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Modeling and Comparison of Machine-Learning Algorithms for Energy Consumption Prediction in Smart Buildings

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Abstract. One-third of global energy demand is attributed to consumption in buildings, with HVAC and lighting systems as the primary contributors. This study presents the development and comparison of several machine-learning algorithms for predicting energy consumption in a building simulated using EnergyPlus and following the Team Data Science Process (TDSP) methodology. Feature-selection techniques (feature selection and feature importance) were applied to identify the most influential variables. Five predictive models were trained: MLP, SVR, XGBoost, Random Forest and Keras Regressor. Results demonstrate that the MLP model achieved the highest accuracy, while XGBoost showed greater stability. Additionally, traditional statistical models (ARIMA and SARIMAX) were compared to machine-learning models for multi-horizon prediction.

Keywords. Energy consumption prediction, smart buildings, energy optimization, predictive models, machine learning.

1 Introduction

According to various studies, buildings worldwide consume between 30 % and 40 % of total energy produced (Arballo et al., 2019; La et al., 2016), and these figures are expected to increase due to population growth and urbanization trends. Within buildings, heating, ventilation and air conditioning systems (HVAC) account for 50 % to 70 % of energy consumption (Montalvo García, 2020), followed by traditional lighting systems; their lack of adaptability contributes to inefficient energy use (Bastidas Paz & Chinchero Villacís, 2023).

Smart energy management incorporates demand-side management techniques (Molla et al., 2018), and the implementation of machine-learning (ML) algorithms emerges as a promising alternative.

These algorithms enable the analysis of large volumes of data to identify patterns that support the development of automated strategies for energy optimization. This study proposes the use of ML algorithms to predict energy consumption in smart buildings.

Various variable-selection techniques are applied to construct predictive models, and the performance of five ML algorithms: MLP, SVR, XGBoost, Random Forest and Keras Regressor, is compared. Additionally, these models are evaluated against traditional statistical methods. The resulting models aim to support decision-making processes and contribute to the development of strategies for energy optimization.

Section 2 presents a review of the state of the art regarding energy prediction and optimization techniques. Section 3 describes the theoretical framework related to energy consumption and machine learning. Section 4 details the dataset used, the variable-selection process, and the construction of the predictive models. Section 5 provides a comparative analysis of the prediction results. Finally, Section 6 discusses the conclusions derived from the results.

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2 Background

In the context of smart-building development, machine-learning (ML) algorithms play a crucial role in forecasting and enhancing future energy efficiency. Various strategies have been explored, ranging from predictive-control techniques to the implementation of reinforcement-learning algorithms, which address the complexity of dynamic-system behavior (Papaioannou et al., 2024).

Several studies have demonstrated that significant energy savings can be achieved using ML techniques. For instance, some investigations have reported that optimizing energy use in buildings can result in savings of up to 26 % while maintaining acceptable thermal comfort conditions (Arballo et al., 2019).

Energy optimization in buildings has progressed substantially in recent years, particularly through the integration of artificial-intelligence techniques. Many studies have focused on predicting energy consumption to support decision-making processes aimed at improving efficiency while preserving user comfort in indoor environments.

2.1 Energy Consumption Prediction Using Machine-Learning Algorithms

Numerous studies have focused on forecasting energy consumption using ML, particularly emphasizing the use of neural networks and regression-based methods.

For example, Freire et al. (2023) compared artificial neural networks (ANN) with gated recurrent units (GRU) for predicting energy generation in a hydroelectric plant, showing higher accuracy with ANN models.

Zhong et al. (2019) proposed a vector-field-based support-vector-regression (SVR) model, which outperformed classical approaches in predicting the energy demand of a building in Tianjin. Similarly, Cai et al. (2023) implemented an SVR model enhanced with metaheuristic-optimization algorithms to identify the optimal combination of hyperparameters, leading to improved accuracy in predicting thermal loads in buildings.

Yu et al. (2021) introduced a hybrid approach combining ARIMA, generative adversarial networks (GAN) and wavelet transforms. This methodology captures both the linear and non-linear components of energy demand, resulting in enhanced predictive performance compared with standalone models.

2.2 Implementation of Metaheuristic Algorithms for Enhancing Predictive Models

An important aspect of improving the performance of ML algorithms lies in the optimization of hyperparameters. In this regard, Le et al. (2019) evaluated the performance of artificial neural networks optimized using Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Imperialist Competitive Algorithm (ICA), and Artificial Bee Colony (ABC) to predict heating loads in buildings, showing that these techniques can significantly enhance prediction accuracy.

Similarly, Deepanraj et al. (2022) applied the Wild Geese Algorithm to optimize hyperparameters in LSTM models, reducing short-term prediction errors. These types of studies, which combine ML models with metaheuristic-optimization techniques, demonstrate the potential for improving forecasting performance through hybrid approaches.

2.3 Deep Learning

Another approach to predicting energy consumption is through deep-learning models such as convolutional neural networks (CNNs), long short-term memory (LSTM) networks and bidirectional LSTM (BiLSTM) networks. Kavitha et al. (2022), for example, proposed a hybrid model combining these architectures to forecast heating and cooling loads using structural building data, achieving high predictive accuracy.

Conversely, Bendaoud et al. (2022) explored the use of CNNs trained on load profiles to forecast energy demand in Algeria. However, their results indicated that the effectiveness of this approach may vary depending on the data structure and context, as the use of load profiles did not consistently improve prediction accuracy.

2.4 Current Trends

Smart buildings already benefit from the integration of advanced technologies such as the Internet of Things (IoT) and machine learning (ML) to optimize energy consumption. This is achieved through the deployment of intelligent sensors and devices that collect real-time data on energy usage, occupancy and environmental conditions, enabling deep analysis and dynamic adaptation of consumption patterns (Muniandi et al., 2024; Udendhran et al., 2023).

These studies demonstrate the strong potential of ML to transform energy-management decision-making in buildings. However, there are still challenges to address, including the integration of intermittent renewable-energy sources, model scalability and the need for validation in real-world environments.

3 Theoretical Framework

This section defines the key concepts related to energy consumption in smart buildings.

Smart buildings are equipped with sensors, actuators and interconnected systems designed to optimize resource usage and reduce environmental impact without compromising user comfort. One essential component is the energy-management system, which coordinates and optimizes the operation of various subsystems to minimize overall energy consumption (Muniandi et al., 2024).

According to the review by Silva et al. (2023), energy optimization refers to maximizing the use of energy generated from sustainable sources while minimizing energy consumption and losses, all while maintaining the same level of performance. In other words, it is the ability to achieve equivalent outcomes using less energy.

Machine learning is a fundamental approach that enables machines to learn from data and improve performance through experience. It enables the identification of patterns and the generation of predictions to inform decision-making about energy management (Castillo de la Barrera, 2023).

To evaluate the performance of predictive models, the following metrics are used:

– Root Mean Squared Error (RMSE): Penalizes large errors and quantifies the deviation between predicted and actual values.

– Mean Absolute Error (MAE): Denotes the average of absolute errors between predicted and actual values.

– Mean Absolute Percentage Error (MAPE): Useful for interpreting prediction errors in relative percentage terms.

4 Methodology

The Team Data Science Process (TDSP) is an agile, iterative methodology for organizing the development cycle of data-science projects, from problem understanding through to model deployment (M., 2017). In this study, the TDSP framework was followed to structure the workflow as described below (see Fig. 1).

4.1 Business Understanding

In this stage, relevant literature was analyzed to identify key elements such as the machine-learning algorithms used for energy-consumption prediction, the variables commonly employed, and the modeling approaches adopted in related works.

4.2 Data Acquisition and Understanding

The EnergyPlus tool, developed by the U.S. Department of Energy (EnergyPlus, n.d.), was used to simulate energy-consumption data for a prototype school building (see Fig. 2). The simulated model includes detailed structural and operational characteristics, along with environmental input variables provided by the U.S. Department of Energy (n.d.).

The resulting dataset comprises 8,760 hourly records, representing a full year of building operation.

The variables obtained include:

– Consumption variables: HVAC, fans, lighting, internal equipment, refrigeration, and total building consumption.

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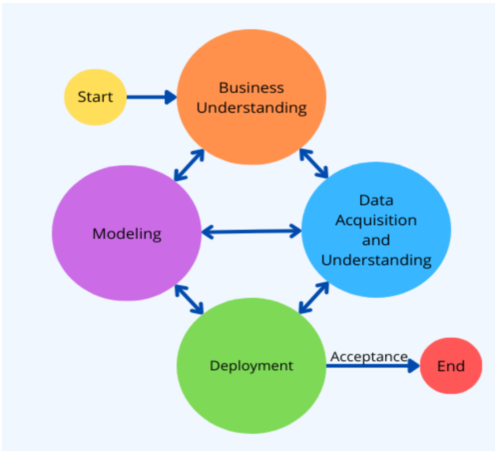

Fig. 1. Team Data Science Process methodology (M., 2017)

- Environmental variables: sky temperature, humidity, wind speed, and infrared radiation.
- Operational variables: estimated total occupancy per hour.
- Energy production: photovoltaic energy generated by the building.

Energy consumption values were standardized to kWh for consistency.

To facilitate a deeper understanding of the dataset, the following analyses were performed:

- Descriptive statistical analysis: to explore central tendency measures, data distribution, and percentiles.
- Seasonality analysis: to identify temporal patterns in energy consumption (see Fig. 3).
- Autocorrelation analysis: to detect lagged relationships in consumption.
- Correlation analysis: using Spearman's coefficient to assess relationships between variables.
- Causality analysis: to estimate the influence of input variables on total consumption, accounting for climatic confounders.

From these analyses, the most relevant variables identified were: HVAC, Fans, Total Occupancy, Interior Lighting, and Ambient Temperature.

4.3 Modeling

This stage comprises two phases: the first involves applying various feature-selection techniques, and the second focuses on training and comparing machine-learning models.

4.3.1 Variable Selection

In the first phase, identifying the most relevant variables from the dataset is essential. Two complementary approaches were employed: feature-selection and feature-importance techniques.

Feature-selection techniques employ statistical criteria to identify variables that offer significant explanatory power for the target variable: The following methods were applied:

- Backward Elimination: Uses p-values as a reference to iteratively remove variables that exceed the defined threshold (Simplilearn, 2022). In this study, a threshold of 0.05 was set, and the 10 most significant variables were selected.
- Mutual Information: Evaluates the dependency between variables and quantifies the amount of information each one provides about the target variable (McClure, 2020). This method is capable of capturing non-linear relationships.
- Variance Threshold: Removes variables with low variance, which are often constant or redundant in the dataset (KoshurAI, 2024).
- Recursive Feature Elimination (RFE): Iteratively removes variables with high multicollinearity or low contribution, aiming to find the optimal subset of features that maximizes model performance (Yellowbrick v1.5 documentation, n.d.).

Feature-importance approaches score and rank variables based on their contribution to a predictive model (Terence, 2024). The techniques implemented include:

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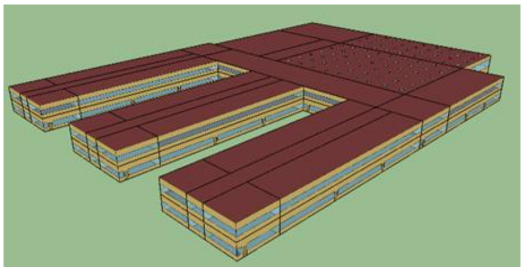

Fig. 2. Secondary school prototype (The U.S. Department of Energy, n.d.)

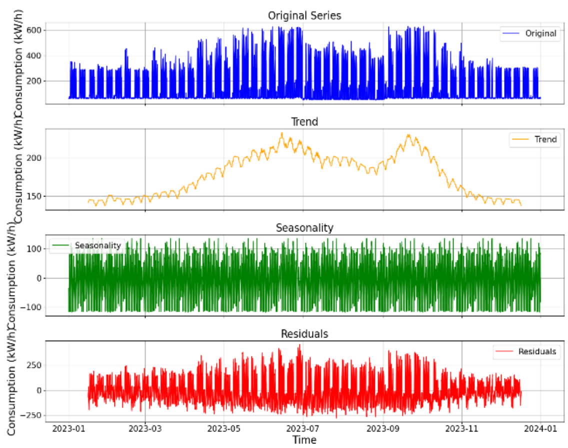

Fig. 3. Seasonality analysis (Elaborated by the authors)

– Decision Tree: A single decision tree with a maximum depth of 5. Feature importance is derived from the reduction in mean squared error achieved when a variable is used to split nodes.

– Extra Trees: An ensemble of 100 trees with a maximum depth of 10; the importance of each variable is determined by averaging the reduction in impurity across all trees using randomly generated splits.

– Random Forest: An ensemble of 100 trees with a maximum depth of 10, selecting the optimal split at each node; the average reduction in impurity across all trees is used to compute feature importance.

– LASSO (Least Absolute Shrinkage and Selection Operator): Applies L1 regularization to a linear regression model, effectively eliminating irrelevant features. The ten variables with the largest absolute coefficients are selected.

– Greedy Selection: Using Random Forest as the base model, this technique sequentially incorporates variables and evaluates model performance at each step, selecting the combination of ten variables that yields the best results.

4.3.2 Characteristics of Machine Learning Algorithms

In the second phase, machine-learning algorithms were trained to predict the building's energy consumption and to evaluate their performance. The models and their configurations are detailed below:

– Multilayer Perceptron (MLP):

  - Architecture: Two hidden layers with 64 and 32 neurons, respectively.
  - Activation function: ReLU (default).
  - Optimization algorithm: Adam.
  - Maximum number of iterations: 500.
  - Fixed random seed for reproducibility: random_state=42.

– Support Vector Regressor (SVR):

– Kernel used: Radial Basis Function (RBF), suitable for capturing non-linear relationships.

– Default parameters were used for C and ε as defined by Scikit-learn.

– Requires input normalization due to its sensitivity to feature scale.

– XGBoost Regressor:

  - Number of estimators (trees): 100.
  - Maximum tree depth: 5.
  - Learning rate: 0.1.
  - Objective function: squared error loss (reg:squarederror).
  - Ensemble technique: sequential correction of residual error.

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– Random Forest Regressor:
  - Number of trees: 100.
  - Splitting criterion: reduction of mean squared error (MSE).
  - No restriction on tree depth, allowing flexible segmentation.
  - Random seed: random_state=42.
– Keras Regressor:
  - Two hidden dense layers with 64 and 32 neurons, respectively.
  - ReLU activation functions in hidden layers.
  - Output layer: one neuron with linear activation, suitable for regression tasks.
  - Loss function: mean squared error (MSE).
  - Optimizer: Adam.
  - Training over 50 epochs, with a batch size of 32.

4.4 Implementation

In this stage, algorithms were implemented to predict the building's energy consumption across different time horizons, and these models were then compared with traditional statistical methods—specifically ARIMA and SARIMAX.

Two forecasting strategies were applied:

– Autoregressive models, which predict the next value recursively based only on the previous value of the target variable. The output from each step is used as the input for the next prediction.

– Exogenous-variable models, which use multiple external input variables to predict the total energy consumption.

To ensure a fair comparison, the ARIMA model was evaluated against an LSTM model under the autoregressive strategy, whereas SARIMAX was compared with XGBoost in the exogenous-variable setting.

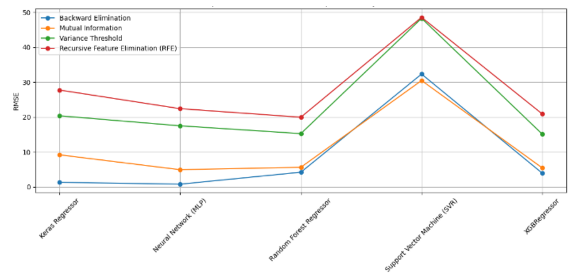

Fig. 4. Results using Feature Selection (Elaborated by the authors)

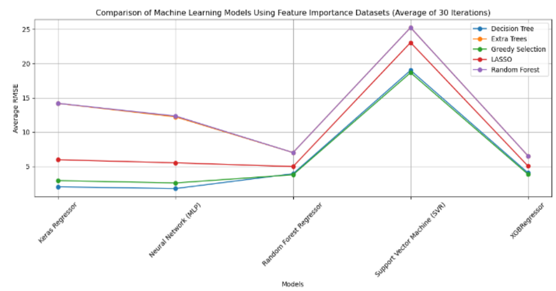

Fig. 5. Results using Feature Importance (Elaborated by the authors)

Predictions were generated for three-time horizons: one day, one week and one month.

5 Results and Comparison

For model training, the data set was randomly divided into 70 % for training and 30 % for validation. Each model–data set combination was evaluated over 30 repetitions to ensure statistical robustness. The target variable for all experiments was the building's total energy consumption, labelled 'Facility (kWh)'.

5.1 Evaluation of Predictive Models

The results obtained using data sets selected by feature-importance techniques are shown in Figure 5, while those using feature-selection techniques are presented in Figure 4.

The results indicate that the MLP model consistently achieved the best predictive accuracy. However, the XGBoost Regressor proved to be the most stable across multiple data sets, exhibiting the lowest variance. It showed a slight advantage

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Table 1. Exogenous variable predictions (Elaborated by the authors)

	SARIMAX			XGBOOST		
	Day	Week	Month	Day	Week	Month
RMSE	6.87	15.61	17.94	3.65	3.28	2.93
MAE	4.21	10.93	12.35	2.29	2.09	1.93
MAPE	2.27%	9.28%	9.77%	1.31%	1.60%	1.61%

Table 2. Autoregressive predictions (Elaborated by the authors)

	ARIMA			LSTM		
	Day	Week	Month	Day	Week	Month
RMSE	33.33	32.94	34.2	13.93	29.68	84.66
MAE	26.56	25.9	26.97	10.33	20.84	51.09
MAPE	22.30%	20.99%	20.94%	4.69%	9.92%	32.92%

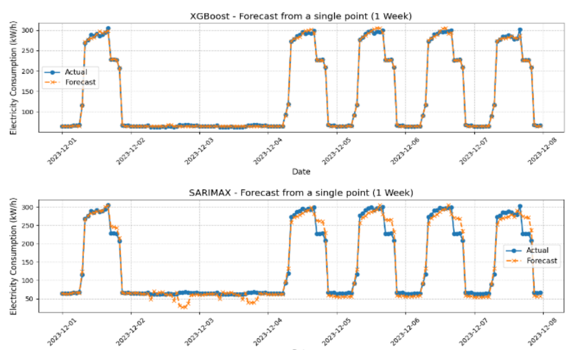

Fig. 6. Comparison between SARIMAX and XGBoost for one-week predictions (Elaborated by the authors)

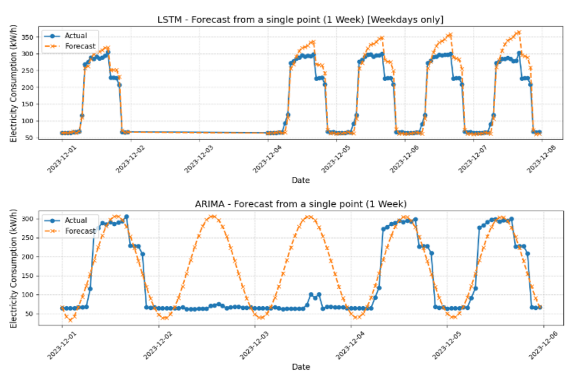

Fig. 7. Comparison between ARIMA and LSTM for one-week predictions (Elaborated by the authors)

over the Random Forest Regressor, particularly in terms of performance consistency across different input configurations.

5.1 Multi-Horizon Forecast

5.1.1 Predictions with Exogenous Variables

Regarding the predictions made using exogenous variables, the results are summarized in Table 1, where it can be observed that both models perform reasonably well. However, the machine learning model (XGBoost) demonstrates greater stability across different prediction horizons.

As shown in Figure 6, the SARIMAX model exhibits a marked decline in accuracy, particularly during periods of low-energy demand, during which it exhibits recurring errors and tends to overestimate evening-consumption patterns.

5.1.2 Autoregressive Predictions

The results obtained for the autoregressive forecasting models are presented in Table 2. It can be seen that the ARIMA model maintains consistent performance across time horizons, whereas the LSTM model shows increasing error margins as the prediction horizon lengthens.

As illustrated in Figure 7, the ARIMA model tends to underperform during periods of low-energy demand, where it fails to adapt. Additionally, due to its moving-average structure, ARIMA struggles to capture daily consumption patterns. In contrast, the LSTM model captures daily trends more effectively but tends to overestimate periods of high demand, especially in longer prediction horizons.

6 Conclusions

The results confirm that the application of machine-learning algorithms to predict energy consumption in smart buildings is highly effective. By simulating and analyzing data generated with EnergyPlus, we identified consumption patterns and determined the key variables that most strongly influence a building's overall energy usage.

Among the variables analyzed, HVAC, fans, total occupancy, interior lighting and outdoor temperature exhibited the highest correlation and

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causal impact on total energy consumption. These variables also demonstrated robustness across statistical tests—including confounding analyses—and were consistently selected by various feature-selection and feature-importance techniques.

Among the models evaluated, the Multilayer Perceptron (MLP) produced the most accurate predictions, followed closely by the XGBoost Regressor, which additionally demonstrated higher stability across different data sets. In contrast, methods such as SVR showed lower predictive performance due to their limited flexibility in modeling complex and non-linear relationships.

Overall, machine-learning models outperformed traditional statistical methods such as ARIMA and SARIMAX, particularly in complex scenarios. ML algorithms offered greater adaptability to daily consumption patterns, which is especially relevant when energy consumption is affected by fluctuating climatic conditions, occupancy levels and operational settings.

The developed models provide accurate consumption forecasts, which can serve as the foundation for strategic applications such as dynamic adjustment of HVAC and lighting systems, demand-based energy management, and planning for infrastructure use and renewable-energy integration.

These findings reinforce the viability of machine learning as a powerful tool for predicting energy consumption. Its predictive capabilities lay the groundwork for the development of intelligent strategies for energy management and optimization in smart buildings.

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