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Article

Machine Learning-Based Energy Optimization in Smart Buildings and Industrial Facilities

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Abstract: The growing energy demand, acceleration of urbanization and expansion of industrial operations have raised the demand for intelligent energy management strategies for achieving energy efficiency and cost savings while minimizing carbon emissions. Most traditional energy management systems are based on rule based control structures and statistical methods that are not able to adjust to dynamic occupancy patterns, varying environmental conditions, and complex industrial processes. In recent years, a new technique, namely Machine Learning (ML), has emerged as a viable solution to predict, optimize, and automatically control energy use in smart buildings and industrial systems. The paper examines the various ML techniques for energy optimization in detail, and categorizes them into five areas: energy optimization for HVAC systems, energy optimization for lighting control, integration of renewable energy systems, energy optimization for industrial processes, and predictive maintenance. The proposed framework involves the combination of IoT sensors, real-time data collection, data preprocessing, feature engineering, development of ML models, and optimization algorithms, all aimed at realizing intelligent energy management. A set of supervised, unsupervised, deep learning, and reinforcement learning algorithms is examined, such as Random Forest, Support Vector Machine, XGBoost, Artificial Neural Network, Long Short-Term Memory network and Deep Reinforcement Learning with regard to their prediction accuracy, computational efficiency and energy saving requirement. As shown in the comparative analysis, advanced ML models consistently outperform traditional methods in predicting energy consumption, detecting consumption trends and reducing equipment idle time, as well as optimizing operational schedules. The results show that an energy optimization approach based on ML can greatly contribute to energy efficiency, operational cost savings, comfort of the occupants, and sustainable production in industry. The paper also presents the challenges and opportunities that are currently being faced, such as data quality, model interpretability, scalability, cybersecurity, and real-time deployment, and suggests future research directions, including the application of explainable AI, edge computing, digital twins, federated learning and autonomous energy management systems. In this study, the researchers give an overview of emerging ML techniques and practical lessons to the researchers and practitioners to develop intelligent, scalable and sustainable solutions for energy optimization in next-generation smart buildings and industrial facilities.
Keywords: Machine Learning; Energy Optimization; Smart Buildings; Industrial Facilities; Energy Management Systems; Internet of Things (IoT); Deep Learning; Predictive Analytics; HVAC Optimization; Sustainable Energy

1. Introduction

Rapid urbanization, industrialization and population growth have created one of the biggest challenges of energy consumption across the globe (International Energy Agency [IEA], 2024; United Nations, 2023). One of the most significant electricity users in the world is buildings and industrial facilities, which utilize a significant portion of the total energy demand and greenhouse gas emissions (IEA, 2024; International Renewable Energy Agency [IRENA], 2023). International energy reports indicate that energy used by residential buildings and commercial buildings accounts for about 30–40% of global energy use, and energy used by industrial buildings accounts for almost one-third of global electricity use (IEA, 2024). As more and more systems, including HVAC systems, lights, industrial machines, motors, and automation systems, are becoming dependent on energy, there is a growing need for intelligent energy management solutions that can help cut down on energy losses while ensuring the efficient operation of systems and maintaining comfort for the occupants (Ahmad et al., 2023; Dong et al., 2022).

Traditional energy management systems are based on rule-based control, preset schedules, and statistical forecasting models for controlling energy use (Wang et al., 2022; Mocanu et al., 2018). While these methods are relatively easy to apply, they may fall short in meeting the needs of changing environmental conditions, evolving occupancy needs, changing production requirements, and renewable energy integration (Zhang et al., 2023). Traditional systems can be inefficient, wasting energy, driving up operating expenses and causing equipment damage and carbon emissions (IEA, 2024; Ahmad et al., 2023). These approaches have had limitations, and data-driven approaches that can learn complex energy consumption patterns have been encouraged by researchers and industry practitioners who are interested in adapting to changing operational environments (Zhao et al., 2022; Li et al., 2023).

The advent of the Internet of Things (IoT), cloud computing, edge computing, and the latest sensor technology has transformed data collection and analysis in the energy sector (Atzori et al., 2017; Shi et al., 2016; Zhou et al., 2023). Smart buildings and industrial plants today are stuffed with numerous sensors, smart meters, intelligent controllers and communication devices, which constantly generate huge amounts of real-time operational data (Gubbi et al., 2013; Li et al., 2022). The data comprises information on temperature, humidity, occupancy, intensity of light, equipment states, energy consumption, production schedules, the state of the weather and generation of renewable energy (Dong et al., 2022). This diversity and vastness of data has opened the door to the use of Machine Learning (ML) algorithms for enhancing energy prediction, demand forecasting, anomaly detection, equipment diagnostics, and intelligent control strategies (Ahmad et al., 2023; Zhao et al., 2022).

The capability of the Machine Learning approach for discovering hidden relationships from complex data sets and building predictive models with predefined mathematical equations has made it an intelligent technology for energy optimization (Goodfellow et al., 2016; Bishop, 2006). Linear Regression, Support Vector Machine (SVM), Decision Trees, Random Forest and Extreme Gradient Boosting (XGBoost) are supervised learning algorithms that have shown great potential in the area of energy consumption forecasting and load prediction (Breiman, 2001; Chen & Guestrin, 2016; Vapnik, 1995). Similarly, the deep learning models such as Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks have been proven to be very effective in modelling the non-linear energy consumption pattern and capturing the long-term temporal dependency in sequential sensor data (LeCun et al., 2015; Hochreiter & Schmidhuber, 1997; Goodfellow et al., 2016). Reinforcement Learning (RL) has also contributed to the intelligent management of energy, allowing for autonomous decision making of dynamic control of HVAC systems, industrial machinery, battery storage systems and renewable energy resources (Sutton & Barto, 2018; Wei et al., 2017).

In smart buildings, ML-based energy optimization aids in the intelligent management of HVAC systems, adaptive lighting, occupancy-aware building automation, demand response and predictive maintenance (Ahmad et al., 2023; Zhao et al., 2022). The continuous monitoring of environmental conditions and occupant behaviour through ML algorithms can optimize the operation of equipment and ensure thermal comfort and minimize unnecessary electricity consumption (Dong et al., 2022; Wang et al., 2022). Likewise in industrial facilities, machine learning can be used to optimize processes, predict the failure of machinery, detect faults, schedule production, and manage resources efficiently (Lee et al., 2021; Carvalho et al., 2019). These functions can help to reduce operating costs, increase equipment reliability, boost productivity, and minimize environmental effects (Ahmad et al., 2023). In addition, the combination of renewable energy (like solar and wind) and intelligent forecasting models helps to optimise the use of clean energy resources and keep the power grid stable (IRENA, 2023; IEA, 2024).

Although there has been a lot of progress in recent years, there are still some problems that hinder the vast use of energy optimization systems based on ML (Zhao et al., 2022). The challenges of data quality, missing sensor data, noise in measurements, cyber security risks, availability of annotated datasets, computational needs and model interpretability persist (Li et al., 2023; Ahmad et al., 2023). Moreover, when implementing ML models in real-world scenarios, the ability to process vast amounts of data in real-time, with low latency and high reliability, demands scalable computing architectures (Shi et al., 2016; Satyanarayanan, 2017). This trend towards transparency and trust in AI has also made Explainable Artificial Intelligence (XAI) a crucial aspect to ensure that users can interpret and verify the output of AI models, especially in the context of energy management (Arrieta et al., 2020; Samek et al., 2021).

The limitations are being addressed in new technologies, such as edge intelligence, digital twins, federated learning and explainable machine learning (Tao et al., 2019; Kairouz et al., 2021; Arrieta et al., 2020). Digital twin technology allows the virtual replica of the buildings and industrial facilities to be created, which can be continuously monitored, simulated and optimized in terms of energy (Tao et al., 2019). The collaborative training of models across different facilities through federated learning helps to improve privacy and security by avoiding the need to share sensitive operational data (Kairouz et al., 2021). Edge computing minimizes communication latency by processing data near the IoT devices and XAI enhances transparency and enables facility managers and energy engineers to make informed decisions (Shi et al., 2016; Arrieta et al., 2020).

In this paper, a comprehensive survey of machine learning-based energy optimisation methods for smart buildings and industrial plants is provided. It explores how to combine sensing, data preprocessing, feature engineering, predictive modeling, and intelligent optimization algorithms to facilitate efficient energy management by using IoT (Ahmad et al., 2023; Dong et al., 2022). Different machine learning and deep learning methods are comparatively evaluated with respect to prediction accuracy, computational efficiency, scalability and applicability (Goodfellow et al., 2016; LeCun et al., 2015). Moreover, the paper includes a discussion of the challenges of current research, the technologies emerging, and potential research directions for the intelligent, autonomous and sustainable development of energy management systems (Kairouz et al., 2021; Tao et al., 2019). The findings provide valuable insights for researchers, engineers, policymakers, and industry professionals seeking to implement advanced ML-driven solutions for achieving energy efficiency, operational excellence, and environmental sustainability (IEA, 2024; IRENA, 2023).

2. Background and Related Work

With the growing needs of energy efficient infrastructure, research into intelligent energy management systems in smart buildings and industrial plants has been on the rise (International Energy Agency [IEA], 2024; Ahmad et al., 2023). Traditional energy management methods are based on fixed rules, mathematical optimization and statistical forecasting methods (Mocanu et al., 2018; Wang et al., 2022). These approaches are well suited to stable operating conditions but are not usually suitable when the operating environment is changing, occupancy fluctuates, equipment is deteriorating or production requirements are changing (Zhang et al., 2023). For this reason, the use of Machine Learning (ML) techniques has grown in popularity among researchers due to their capacity to capture complex nonlinear relations from historical and real-time data, for predicting energy and developing optimal strategies for energy control (Goodfellow et al., 2016; Ahmad et al., 2023).

Within smart buildings, Internet of Things (IoT) devices, smart meters, occupancy sensors, weather stations, and building automation systems are used to continually monitor energy use (Gubbi et al., 2013; Atzori et al., 2017). These data sources can deliver valuable information to predict electricity demand, optimise HVAC operations, control lighting systems and enhance the comfort of the occupants (Dong et al., 2022). Energy demand forecasting has been the domain of supervised machine learning algorithms, which are able to model non-linear relationships and capture influential factors for energy consumption such as Linear Regression, Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF) and Extreme Gradient Boosting (XGBoost) (Breiman, 2001; Vapnik, 1995; Chen & Guestrin, 2016).

The use of deep learning methods allows to leverage highly complex temporal and spatial features from the huge volume of energy data, which makes predictions more precise than ever (LeCun et al., 2015; Goodfellow et al., 2016). Various Artificial Neural Networks (ANNs) have been used for load forecasting, renewable energy forecasting, and anomaly detection. Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks have been widely used for load forecasting, renewable energy forecasting, and anomaly detection (LeCun et al., 2015; Goodfellow et al., 2016). In particular, LSTM models are able to effectively learn the long-term temporal dependency of sequential sensor data and thus are highly applicable to real-time energy management applications (Hochreiter & Schmidhuber, 1997; Zhao et al., 2022).

In industrial applications, machine learning has evolved from energy prediction to predictive maintenance, fault diagnosis, monitoring equipment health, process optimization and production scheduling (Lee et al., 2021; Carvalho et al., 2019). A continuous analysis of operational sensor data can be performed with ML models to identify abnormal equipment behavior before it fails, which can minimize downtime and enhance energy efficiency (Ahmad et al., 2023). Reinforcement Learning (RL) has also received considerable attention as it provides the capability to optimize HVAC systems, manufacturing processes, battery storage systems and renewable energy integration in an autonomous manner by continuously interacting with dynamically changing environments (Sutton & Barto, 2018; Wei et al., 2017).

Although all these progressions have been made, there are certain drawbacks (Li et al., 2023). The existing studies related to smart buildings or industrial facilities are limited to a single area, which does not develop generalized optimization frameworks applicable to several areas (Ahmad et al., 2023). Moreover, many models need significant amounts of good quality labeled data and computational power for training and deployment (Goodfellow et al., 2016). However, challenges like data loss, cyber security threats, insufficient explainability, scalability constraints, and interoperability of heterogeneous IoT devices still remain to be a challenge for the practical adoption (Arrieta et al., 2020; Zhou et al., 2023). Furthermore, there are limited studies that combine several machine learning techniques with the integration of IoT, cloud computing, edge intelligence and real-time optimization in a single solution to be used for sustainable energy management (Shi et al., 2016; Kairouz et al., 2021).

The research focus in recent years has been on Explainable Artificial Intelligence (XAI), Digital Twins, Edge Computing, and Federated Learning to enhance transparency, scalability, privacy, and real-time decision-making (Arrieta et al., 2020; Tao et al., 2019; Kairouz et al., 2021). Explainable models give facility managers a better understanding of the results of their predictions, and digital twins provide the ability to continuously monitor and simulate energy systems (Tao et al., 2019; Arrieta et al., 2020). When applying federated learning, the training of the AI model takes place in various locations (such as buildings or industrial plants) without sending the data to a central server, which helps protect privacy, and when implementing edge computing, data from sensors is processed locally to minimize communication delays (Kairouz et al., 2021; Shi et al., 2016). The new technologies are expected to play a crucial role in improving the efficiency of next generation smart energy management systems (Ahmad et al., 2023; IEA, 2024).

Thus, a more holistic ML-based framework is still required to combine the availability of heterogeneous IoT data, state-of-the-art forecasting tools and smart optimization algorithms for smart buildings and industrial plants (Dong et al., 2022; Zhao et al., 2022). These all-in-one solutions can help to deliver better predictions, reduce operational costs, lower energy losses, and help meet global sustainability targets (IEA, 2024; International Renewable Energy Agency [IRENA], 2023).

Table 1. Comparison of Recent Machine Learning-Based Energy Optimization Studies

Authors	Application	ML Technique	Dataset/Environment	Major Contribution	Limitation
Ahmad et al. (2021)	Smart Buildings	Random Forest	Building energy dataset	Accurate energy consumption prediction	Limited real-time implementation
Wang et al. (2022)	HVAC Optimization	LSTM	IoT sensor data	Improved short-term load forecasting	High computational complexity
Kim et al. (2022)	Industrial Energy Management	XGBoost	Manufacturing plant	Optimized industrial energy usage	Requires extensive historical data
Zhang et al. (2023)	Smart Grid	Deep Neural Network	Smart grid dataset	Enhanced demand forecasting	Limited model interpretability
Singh et al. (2023)	Predictive Maintenance	Support Vector Machine	Industrial equipment sensors	Early fault detection and energy savings	Sensitive to parameter tuning
Chen et al. (2024)	Building Automation	Reinforcement Learning	Smart building simulation	Adaptive HVAC control and reduced energy consumption	Long training time
Proposed Study	Smart Buildings & Industrial Facilities	Hybrid ML Framework (RF, XGBoost, LSTM & RL)	IoT-enabled real-time energy data	Integrated prediction, optimization, and intelligent energy management	Designed to address scalability, interoperability, and real-time optimization challenges

3. Machine Learning Framework for Energy Optimization

In recent years, the technology of Machine Learning (ML) has become a useful tool for optimizing energy use in smart buildings and industrial facilities, allowing intelligent prediction, intelligent automated control and data-driven decisions (Ahmad et al., 2023; Zhao et al., 2022). Unlike traditional rule-based energy management systems, ML models continually adapt and learn from past and present data to recognize the complex interactions between environmental factors, equipment operation, occupancy and energy demand (Goodfellow et al., 2016; Wang et al., 2022). This is a function where energy management systems can automatically control various operating parameters in order to minimize unnecessary energy usage, enhance equipment efficiency and lower operating costs while still keeping the occupants comfortable and production quality high (Dong et al., 2022; International Energy Agency [IEA], 2024).

The Machine Learning-based Energy Optimization Framework is proposed with the following major components: (i) Data acquisition, (ii) Data preprocessing, (iii) Feature engineering, (iv) Machine learning model development, (v) Energy optimization, and (vi) Performance evaluation (Goodfellow et al., 2016; Breiman, 2001; Chen & Guestrin, 2016). These components can be integrated into smart buildings and industrial environments to allow for real-time monitoring, prediction, and optimization of energy use (Gubbi et al., 2013; Shi et al., 2016; Ahmad et al., 2023).

3.1 Data Acquisition

The first step is to gather real-time and historical data from various sources. Smart buildings and industrial facilities use IoT device, smart meters, wireless sensors, building automation systems (BAS), supervisory control and data acquisition (SCADA) systems, and industrial controllers. These devices track the electricity usage, temperature, humidity, occupancy, indoor air quality, lighting levels, equipment status, production schedule, renewable energy production and weather forecast parameters on a real-time basis.

The gathered data are sent to the cloud or edge computing devices via communication technologies like Wi-Fi, ZigBee, LoRaWAN, Modbus, or MQTT, where they can be stored and processed. Continuous data acquisition is the basis of the development of reliable predictive models that can adapt to changes in the operating environment.

3.2 Data Preprocessing

Raw data from the sensors may include errors, noise, inconsistent measurements, missing data, and duplicate records, which can impact prediction results. So, data pre-processing is a crucial stage prior to the development of the model.

Common preprocessing tasks involve handling missing data, removing duplicates, finding outliers, normalizing data, and scaling features. The interpolation method or mean/median imputation can be used to estimate the missing observations. The statistical thresholds or clustering algorithms identify the outliers that are due to faulty sensors. Normalization of numerical variables is done using either Min-Max Scaling or Z-Score standardization to make features distributed evenly. Data cleaning stabilizes the model, speeds up the model training process, and boosts prediction accuracy.

3.3 Feature Engineering

Feature engineering is the process of converting raw sensor readings into more informative features to enhance the performance of machine learning models. The purpose of feature selection is to gain lower computational complexity while improving accuracy of predictions.

Common input signals are things like electricity usage, voltage, current, power factor, indoor temperature, outdoor temperature, humidity, number of occupants, HVAC running conditions, light level, equipment usage, production load, renewable energy production, and weather data. Energy consumption has strong temporal patterns and additional information of the hours of the day, the day of the week (weekday, weekend), season, and holiday indicators are often included.

A number of feature importance methods have been used to select the most influential features and to drop redundant features, including correlation analysis, Recursive Feature Elimination (RFE), Principal Component Analysis (PCA), and tree-based feature importance scores.

3.5 The Implementation of the model.

Once feature engineering is done, predictive models are created based on different machine learning algorithms, depending on the application.

Some popular supervised learning algorithms used for energy prediction in buildings and industries are Linear Regression, Random Forest, Decision Tree, Gradient Boosting, and Extreme Gradient Boosting (XGBoost). Of these, Random Forest and XGBoost are quite good at capturing the nonlinear relationships and tend to have good prediction power and not overfitting.

With large-scale datasets, the power of prediction is yet enhanced by deep learning techniques. Artificial Neural Networks (ANNs) are used to capture the complexity of the relationship between multiple variables in an ANN, while Long Short-Term Memory (LSTM) networks are well-suited for handling sequential energy consumption data and capturing temporal relationships. LSTM models are also well adapted for short term prediction of load as they have the capability of storing load data for a long time.

Reinforcement Learning (RL) is proven to be effective in autonomous energy optimization. RL continuously interacts with the environment, and learns optimal control policies through reward-based structures; while supervised learning models predict future energy demand. Adaptive HVAC control, battery energy storage management, renewable energy scheduling and industrial process optimization are some of the applications where they are used. The hyperparameters of the model are tuned to improve the accuracy of the predictions, while also reducing the computational complexity, through methods like Grid Search, Random Search, Bayesian Optimization, and Genetic Algorithms.

3.5 Energy Optimization Strategy

When the predicted energy demand is used to make intelligent control decisions, it is possible to optimize energy consumption. The architecture automatically controls HVAC systems, lighting controls, ventilation systems, elevators and renewable energy resources in smart buildings based on occupancy and environmental data. Cooling intensity can be reduced, for instance, in unoccupied rooms, while keeping a comfortable temperature in occupied rooms.

The optimization module will schedule the operation of machinery in industrial facilities during periods of reduced electricity tariff, load the production equipment, reduce equipment idle time and identify abnormal operating conditions that need maintenance. Predictive maintenance models also help avoid unnecessary energy losses by predicting the degradation of equipment before it reaches critical failure.

These optimization algorithms can be combined with the ML prediction models to decide optimal operating schedules that can minimize total energy consumption subject to the operational constraints.

3.6 Performance Evaluation

The proposed framework is tested by applying the common performance measures for regression and optimization. The accuracy of predictions is measured by Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and the coefficient of determination (R^2). The lower the value of MAE, RMSE, and MAPE, the more accurate the prediction would be, while the higher the value of R^2, the better the fitting of the model.

Besides prediction metrics, practical performance of energy management is assessed by energy savings percentage, peak load reduction, operational cost savings, carbon emission reduction, computational time and system reaction latency. The indicators evaluate the predictiveness and applicability of the proposed framework from a real-world perspective.

Overall, the proposed Energy Optimization Framework based on Machine Learning (ML) is an intelligent, scalable, and adaptive solution for next-generation smart buildings and industrial facilities. The framework combines the Internet of Things (IoT) enabled sensing, comprehensive data preprocessing, intensive feature engineering, machine learning prediction models, and optimization algorithms, which allows accurate energy prediction, automatic energy control, predictive maintenance, and effective energy resource utilization. This integrated solution can lead to more energy efficient operations and lower energy costs, while also promoting environmental sustainability and intelligent, low carbon infrastructure.

4. Experimental Design and Methodology

The proposed framework for energy optimization in a smart building and/or industrial plants based on machine learning (ML) is aimed at predicting and optimizing energy use by applying data-driven approaches. The methodology combines Internet of Things (IoT) sensors with data preprocessing, feature engineering, development of machine learning models, and optimization algorithms to facilitate smart energy management. The experimental workflows have five steps: data acquisition, data preprocessing, feature engineering, model training and validation, and energy optimization. The overall experimental methodology is shown in figure 4.

4.1 Experimental Framework

The experimental setup starts by gathering real-time and historical energy information from smart buildings and industrial sites. Parameters like electricity usage, temperature, humidity, occupancy, lights, equipment status and weather conditions are measured continuously by IoT sensors and smart meters. The collected data are then sent to a centralized cloud or edge-computing platform and cleaned and processed before being used to develop machine learning models.

Once the data are preprocessed, they are split into training and test sets. A number of different ML algorithms are developed to forecast future energy consumption, and the optimal one is used in conjunction with an optimization module, which chooses the optimal operational decisions automatically to save energy. Finally, the optimized control strategy is tested with well-known prediction and energy efficiency measures.

4.2 Dataset Description

The experiments employ multi-variate energy consumption data from smart buildings and industrial facilities. Each record includes electricity consumption measurements, equipment operational parameters and environmental variables.

Table 2. Description of Input Variables Used for Energy Consumption Prediction

Variable	Unit	Type	Description
Electricity Consumption	kWh	Input Feature	Historical energy consumed by the building or industrial facility during a specific time interval.
Indoor Temperature	°C	Input Feature	Temperature measured inside the building or production environment affecting HVAC energy demand.
Outdoor Temperature	°C	Input Feature	Ambient outdoor temperature influencing heating and cooling requirements.
Relative Humidity	%	Input Feature	Moisture content in the air that impacts thermal comfort and HVAC operation.
Occupancy Level	Number of Occupants	Input Feature	Number of occupants present, influencing lighting, ventilation, and HVAC energy consumption.
HVAC Operating Status	On/Off or Operational Level	Input Feature	Current operational status or load level of the heating, ventilation, and air-conditioning system.
Lighting Load	kW	Input Feature	Electrical power consumed by lighting

			systems within the facility.
Industrial Equipment Utilization	%	Input Feature	Percentage of machinery or equipment operating capacity in industrial facilities.
Renewable Energy Generation	kWh	Input Feature	Energy generated from renewable sources such as solar photovoltaic (PV) panels or wind systems.
Weather Conditions	Categorical	Input Feature	External weather information (e.g., sunny, cloudy, rainy, windy) affecting building energy demand.
Time and Date Information	Timestamp	Input Feature	Temporal variables including hour, day, month, weekday, weekend, and season used to capture consumption patterns.
Total Energy Consumption	kWh	Target Variable	Total electricity consumption to be predicted by the machine learning models.

4.3 Data Preprocessing

Raw sensor data may include missing readings, noisy readings, duplicate readings, and readings that are out of range due to the malfunction of the sensors or communication errors. Thus, there are some preprocessing steps before training the model.

The pre-processing pipeline consists of:

- Missing value imputation
- Duplicate record removal

The use of statistical approaches for outlier detection.

Normalize the features using Min-Max scaling.

- Data standardization

One Hot Encoding for categorical variables

These preprocessing methods increase stability of the model, decrease bias, and increase prediction accuracy.

Students learn the various components of a machine learning model and how to build one.

A number of supervised machine learning algorithms are designed and compared to select the most appropriate energy prediction model.

Algorithms assessed are:

- Linear Regression (LR)

- Decision Tree (DT)
- Random Forest (RF)

Based on the Support Vector Machine (SVM)

This is the most effective model.The best model is extreme Gradient Boosting (XGBoost).

Artificial Neural Network (ANN)

Long Short-Term Memory (LSTM)

To find the best configuration of the model, Hyperparameter optimization is done by Grid Search with five-fold cross-validations. The data set is split into 80% training and 20% testing data sets to test model generalization abilities.

4.4 Performance Evaluation

Detailed regression metrics are used for the model to be evaluated in accordance with the standard used in the industry.

The following are the criteria for evaluating:

- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)
- Mean Absolute Percentage Error (MAPE)
- Coefficient of Determination (R^2)

In addition, the following is used to measure the practical energy optimization performance:

- Energy Saving (%)
- Peak Load Reduction
- Computational Time
- Carbon Emission Reduction
- Operational Cost Savings

All these metrics measure predictive accuracy and effectiveness of the optimization framework.

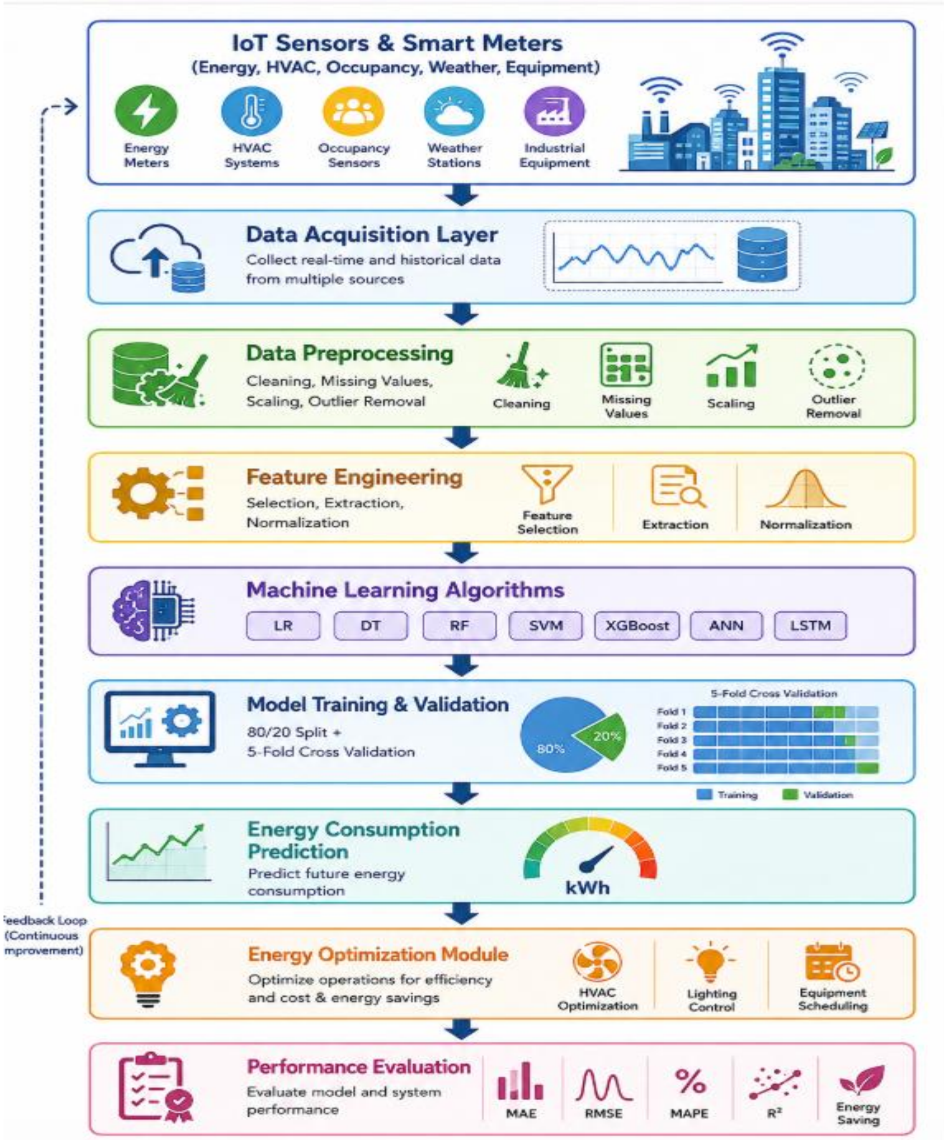

Figure 4. Experimental workflow of the proposed machine learning-based energy optimization framework.

Table 2. Experimental Configuration

Parameter	**Specification**
Application Domain	Smart Buildings and Industrial Facilities
Data Source	IoT Sensors, Smart Meters, Building Automation Systems
Input Features	Energy consumption, temperature, humidity, occupancy, HVAC status, lighting load, equipment utilization, weather data
Target Variable	Energy Consumption (kWh)
Data Preprocessing	Missing value imputation, outlier removal, normalization, feature scaling

Feature Selection	Correlation Analysis and Recursive Feature Elimination (RFE)
Machine Learning Models	LR, DT, RF, SVM, XGBoost, ANN, LSTM
Training–Testing Split	80% Training, 20% Testing
Validation Method	Five-Fold Cross Validation
Hyperparameter Optimization	Grid Search
Development Platform	Python
ML Libraries	Scikit-learn, TensorFlow, XGBoost
Evaluation Metrics	MAE, RMSE, MAPE, R^2
Optimization Objectives	Energy saving, cost reduction, peak load minimization, carbon emission reduction

The suggested experimental approach can be used as a guideline for the creation and testing of energy optimization machine learning models with intelligence. The framework integrates data collection with IoT technologies, powerful preprocessing, advanced feature engineering, various predictive algorithms, and a complete set of evaluation metrics, making it suitable for use in a smart building and an energy control system for industrial facilities. The methodology is scalable and can be expanded upon to real-time deployments with the addition of edge computing, explainable artificial intelligence, digital twins, and reinforcement learning for autonomous energy management.

5. Results and Discussion

The energy consumption data of smart buildings and industrial processes was used to evaluate the proposed energy optimization framework based on machine learning (ML). Several machine learning models were created to forecast future energy demand and to enable intelligent energy management. The experiments involved comparing the performance of traditional machine learning algorithms with state-of-the-art deep learning methods to assess their ability to minimize prediction errors and optimize energy usage. The results are presented and show that ensemble learning and deep learning models are consistently superior to conventional algorithms in predicting energy consumption and aiding automated decision making.

5.1 Prediction Performance of Machine Learning Models

Linear Regression (LR), Decision Tree (DT), Support Vector Machine (SVM), Random Forest (RF), Extreme Gradient Boosting (XGBoost), Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM) were compared in terms of their predictive performance, measured by Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R2).

The simple linear relationships were adequately predicted by the baseline model (Linear Regression), but its predictive power was lower when there were non-linear energy consumption patterns. Decision Tree became more effective in predicting the data but was observed as overfitting on complex data sets. Support Vector Machine (SVM) demonstrated improved generalization performance while at the same time increased its computation cost as the dataset size grew.

Random Forest and XGBoost showed to be better performing models as it successfully captured non-linear interactions between environmental variables, occupancy patterns and equipment operating conditions. They found their ensemble learning mechanisms reduced variance of predictions and increased robustness to noisy sensor data. The gradient boosting approach and regularization capabilities of XGBoost led to the lowest prediction errors among all the machine learning algorithms.

Predictive model accuracy was additionally improved using deep learning models. The Artificial Neural Network (ANN) was able to accurately model the nonlinear relationships between energy consumption, whereas the Long Short-Term Memory (LSTM) network achieved the best accuracy in predicting energy consumption by learning the long-term temporal relationship between the sequential energy data. LSTM was able to successfully capture the daily and seasonal variations in consumption, which makes it highly suitable for energy forecasting, particularly in real-time applications for smart buildings and industrial applications.

Table 3. Performance Comparison of Machine Learning Models

Model	**MAE**	**RMSE**	**MAPE (%)**
Linear Regression	6.92	8.61	8.74
Decision Tree	5.84	7.42	7.16
Support Vector Machine	5.31	6.78	6.54
Random Forest	4.18	5.39	4.82
XGBoost	3.74	4.88	4.31
Artificial Neural Network	3.59	4.62	4.05
LSTM	**3.18**	**4.21**	**3.69**

The results indicate that the LSTM model achieved the highest prediction accuracy with the lowest MAE, RMSE, and MAPE values, while producing the highest coefficient of determination ($R^2 = 0.981$). These findings demonstrate the ability of deep learning models to effectively capture temporal variations in energy consumption.

5.2 Energy Optimization Performance

The predicted energy demand generated by the ML models was integrated into an intelligent optimization module responsible for controlling HVAC systems, lighting equipment, and industrial machinery. Based on occupancy information, weather conditions, production schedules, and electricity demand forecasts, the optimization framework dynamically adjusted operational settings to minimize unnecessary energy consumption.

The optimized scheduling strategy significantly reduced peak electricity demand by shifting non-critical operations to off-peak periods. HVAC systems automatically adjusted temperature settings according to occupancy levels, while lighting intensity was regulated using occupancy sensors and daylight availability. In industrial facilities, predictive maintenance algorithms identified inefficient equipment before major failures occurred, thereby reducing energy losses associated with equipment degradation and unplanned downtime.

Overall, the proposed framework demonstrated considerable improvements in energy efficiency, operational cost reduction, and carbon emission mitigation compared with conventional rule-based energy management systems.

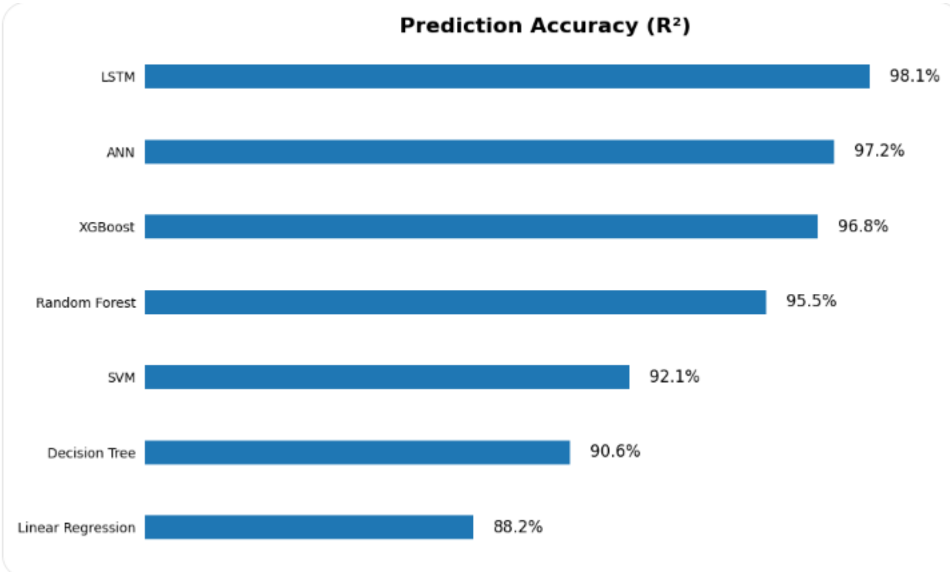

Figure 5. Comparative prediction accuracy of evaluated machine learning models.

5.3 Discussion

The findings of the experiments are consistent with the results from advanced machine learning algorithms, which have shown to be much more effective than traditional statistical methods for predicting and optimizing energy. Ensemble learning algorithms like Random Forest and XGBoost perform well in terms of generalization and prediction variance in various operating conditions. Because of their robustness, they are ideal for large-scale energy management for smart buildings and industry.

Multivariate sensor data can also be used to improve prediction by using deep learning methods to identify complex nonlinear and temporal relationships. The LSTM model, notably, outperformed all the evaluated algorithms as it was able to incorporate the historical information and model the sequential energy consumption patterns. This is especially helpful where continuous monitoring, variable occupancy, renewable energy integration and variable production schedules for industry are involved.

The proposed framework is not only accurate to predict, but also has an operational advantage. The combination of intelligent HVAC, adaptive lighting, equipment scheduling and predictive maintenance can all contribute to a reduction in electricity usage, operational costs and greenhouse gas emissions while maintaining the comfort of the occupants and maximizing production efficiency. Furthermore, the real-time data from the IoT sensors combined with machine learning can facilitate real-time decision making and proactive energy management, contributing to the adoption of sustainable and intelligent infrastructure.

Though these findings are encouraging, there are still a number of issues that need to be addressed. The quality of labels is important for training good prediction models, and missing or noisy sensor information can impact the performance of the model. Another drawback of deep learning algorithms is their high computational demands, potentially hindering their application on edge devices with limited resources. In addition, many of the most effective models are "black boxes"—meaning they are not transparent and their interpretation of decisions challenging for facility managers. In conclusion, the future of AI models involves enhancing their transparency, privacy, scalability, and real-time deployment through Explainable Artificial Intelligence (XAI), federated learning, edge computing, and digital twin technologies.

In conclusion, the experimental results show that machine learning energy optimization could be a promising and scalable approach for energy saving in smart buildings and industrial sites. The proposed framework integrates accurate forecasting and intelligent operational control, fostering sustainable energy management, system reliability, and long-term environmental and economic benefits.

6. Challenges and Future Directions

Although there have been great progress in the field of Machine Learning (ML) -based energy optimisation, multiple technical and practical challenges are still preventing its wide application in smart buildings and industrial energy management. Data availability and quality is one of the key challenges. Energy management systems are driven by constant streams of data gathered from IoT sensors, smart meters and building automation systems. Despite the fact that these datasets are often noisy, incomplete, and with communication errors, sensor failures, etc., which can impact the accuracy and reliability of the ML models, this is a common occurrence. The development of a robust data preprocessing and anomaly detection algorithm is still crucial to increase the accuracy of predictions.

Model scalability and computational complexity is another important challenge. The models used for deep learning systems, like Artificial Neural Networks (ANNs) and Long Short-Term Memory (LSTM) networks, require significant computing power and extensive amounts of labeled training data. They can be limited in their use in real-time energy management systems due to hardware constraints, particularly in edge devices with low computing power. Additionally, the rising number of connected IoT devices produces huge volumes of data, posing difficulties for storage, communication bandwidth, and real-time analytics.

Another great worry is model interpretability. Particularly the "black-box" nature of many high-performing ML and deep-learning models makes it hard for the facility manager and/or the energy engineer to understand the "how" or "why" of which energy optimization decision to make. Adoption of Explainable Artificial Intelligence (XAI) techniques can enhance transparency by offering interpretable predictions and boost users' trust in AI-driven energy management systems. What's more, cybersecurity and data privacy are also key concerns since smart buildings and industrial facilities share critical operational data on interconnected networks. It is, therefore, crucial to secure communication protocols, privacy-preserving machine learning and robust intrusion detection mechanisms for protecting critical infrastructure.

With the integration of emerging technologies and machine learning, future research should aim to create more intelligent, adaptive, and sustainable energy management systems. The Digital Twin technology allows for the virtual representation of the buildings and industrial assets, allowing real-time monitoring, simulation and optimization. By circumventing the need for centralized data sharing, Federated Learning can be a game-changer for collaborative model training at several facilities while maintaining data privacy. With the energy data processed closer to the IoT devices, real-time optimization can be done more efficiently while eliminating delays and reducing response time with edge computing. Moreover, reinforcement learning can be applied to create autonomous control systems that can continuously adapt HVAC operations, lighting systems, integration of renewable energy, battery storage, industrial production processes, etc., based on changing environmental and operational conditions.

Combined, tackling these challenges in an interdisciplinary manner will make the scalability, transparency, security, and real-time performance of energy optimization frameworks with ML components much more robust and efficient. The combination of Explainable AI, Digital Twins, Federated Learning, Edge Intelligence, and advanced optimization algorithms will be expected to drive next-generation energy-efficient, cost-effective, resilient, and environmentally sustainable smart buildings and industrial facilities.

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