SMART HOME ENERGY OPTIMIZATION SYSTEM

by

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The proposed system outlined a scientific project aimed at developing a machine learning-based system to optimize home energy usage and optimization. The proposed system leverages occupancy patterns, weather forecasts, and energy consumption data to create predictive models to recommend energy-efficient actions to homeowners. By utilizing advanced machine learning techniques, this research study aims to contribute sustainable energy practices and reduce energy costs for homeowners while minimizing environmental impact. The proposed system was developed to analyze the data using exploratory data analysis approaches. Pre-processing approaches are applied to prepare the data for model development. Weather correlations are identified with the usage of energy for home appliances. Groups are created based on the division of the date column data such as month-wise, weekly, daily, and hourly. The algorithms for the data forecasting used moving average, persistence algorithm, ARIMA, auto ARIMA, LSTM univariate and LSTM multivariate. The performance of the proposed system was evaluated by showing the graphical representation, which was very satisfactory. The LSTM multivariate algorithm outperforms the smart home energy optimization dataset compared to other algorithms. The outcome in the graphical representation of the evaluation shows much satisfaction.

Key words: *energy optimization, smart home appliance, energy forecasting, machine learning energy forecasting, ARIMA*

Introduction

Energy usage is increasing daily due to the high volume of energy used in every region. People's lifestyle is changing, and energy consumption is rising. There is a need to replace traditional household appliances with the smart system. Connect the system to smart home devices like thermostats, lights, and appliances. Use machine learning to predict occupancy based on historical data and forecasted events. The system learns the occupants' preferences and adjusts energy usage accordingly [1]. For instance, it can optimize heating or cooling schedules, suggest energy-efficient appliance settings, and even estimate potential energy savings.

In an era of rapid urbanization, technological advancement, and environmental consciousness, the concept of a *Smart Home* has emerged as a promising solution enhance the comfort and sustainability of modern living. Within this transformative landscape, the optimization of energy consumption in residential spaces has taken center stage. The *Smart Home Energy*

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Optimization System represents a pioneering endeavor to revolutionize how we manage and utilize energy within homes [1].

As populations swell in cities worldwide, the energy demand has escalated, putting immense pressure on existing infrastructure and contributing to GHG emissions. Traditional energy consumption patterns are no longer sustainable, compelling us to seek innovative solutions that reduce carbon footprint and empower homeowners with greater control over their energy usage and costs [2].

This project aims to address these pressing challenges by harnessing the power of cutting-edge technologies, including artificial intelligence, the IoT, and data analytics, to create a comprehensive and intelligent system. The *Smart Home Energy Optimization System* will monitor and optimize energy usage and adapt to each household's unique preferences and needs, providing a personalized and sustainable energy management solution.

This introduction will provide an overview of energy consumption in residential spaces, highlighting the need for a more efficient and eco-conscious approach. We will also outline this project's objectives, scope, and significance, demonstrating how it aligns with the broader vision of creating smarter, more sustainable homes for the future. Additionally, we will offer a brief glimpse into the key components and technologies employed in developing this innovative system, setting the stage for a detailed exploration of its functionalities and benefits in the subsequent sections of this project report [3].

As the energy demand continues to rise, optimizing energy consumption in residential buildings is critical for cost savings and reducing the carbon footprint. This project aims to address this challenge by developing a machine learning-based system that [2] leverages three key components:

Occupancy patterns

Understanding when and how residents are present in a home is crucial for optimizing energy usage. We will collect occupancy data using sensors or smart home devices to build occupancy profiles.

Weather forecasts

Weather conditions have a significant impact on home energy consumption. By integrating weather forecasts, we can proactively adjust energy usage for temperature, humidity, and other environmental factors [2].

Energy consumption data

Historical energy consumption data will be collected to create a baseline for each home. This data will be the foundation for developing predictive models [3].

Project objectives

A system that optimizes home energy usage by analyzing occupancy patterns, weather forecasts, and energy consumption data. The proposed system has some key objectives, which are discussed:
- To develop a predictive system that optimizes home energy usage by analyzing occupancy patterns, weather forecasts, and historical energy consumption data [4].
- To create machine learning models that provide energy-efficient recommendations to homeowners based on real-time data inputs [5].

– To evaluate the system's performance and usability through controlled experiments and user feedback [6, 7].

Project aspects

The importance of the *Smart Home Energy Optimization System* project cannot be overstated, as it addresses critical challenges in modern living related to energy consumption, sustainability, and quality of life. This project is paramount for several reasons. First and foremost, the project directly contributes to a more sustainable future. In a world grappling with the devastating consequences of climate change, the need to reduce GHG emissions and conserve energy resources has never been more urgent. This project is pivotal in mitigating environmental impact by optimizing energy consumption in residential spaces. It aligns with global sustainability goals and represents a proactive step toward reducing the carbon footprint associated with homes [8].

Additionally, this project is essential for achieving energy efficiency in households. Traditional homes often exhibit significant energy wastage due to outdated appliances, inefficient heating and cooling systems, and imprudent energy use habits. By integrating cutting-edge technologies such as artificial intelligence and the IoT, the *Smart Home Energy Optimization System* rectifies these inefficiencies. It paves the way for smarter and more efficient homes, translating to substantial energy cost savings for homeowners over time. This financial relief is significant in an era of increasing energy prices [9].

Furthermore, the system's user-centric approach is crucial for enhancing the quality of life for homeowners. It adapts to individual preferences and needs, offering a personalized and convenient way to manage energy consumption. This level of automation and customization increases comfort and encourages homeowners to make eco-conscious choices effortlessly. Real-time monitoring and data-driven insights empower users to reduce energy waste actively, fostering a culture of environmental responsibility [10].

On a broader scale, the project's impact extends to the resilience of the electrical grid. Integrating with the grid and participating in demand response programs contributes to grid stability during peak demand periods and emergencies. This grid resilience is increasingly essential in an interconnected world, where energy supply disruptions can have far-reaching consequences [11].

The *Smart Home Energy Optimization System* project embodies the convergence of technology, sustainability, economics, and user-centric design. Its importance lies in its potential to reduce energy consumption and costs and in its role as a catalyst for a more sustainable and resilient future. Addressing the pressing challenges of time exemplifies a commitment to improving the well-being of homeowners, the environment, and society at large [12].

System analysis

System perspective

The home energy optimization system (HEOS) is a standalone software application that interfaces with various data sources, including occupancy sensors, weather forecast API, and energy consumption data sources. It provides recommendations to homeowners based on analyzed data.

System functions

The primary functions of the HEOS system include:

– Data collection from occupancy sensors (open-source), weather forecasts, and energy consumption sources.
– Data pre-processing and feature engineering.
– Development and training of machine learning models.
– Real-time analysis of occupancy patterns and weather forecasts.
– Energy-efficient recommendations to homeowners.
– User model views allow homeowners to interact with the system.
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User classes and characteristics

Homeowners

The primary users of the system who will receive energy-efficient recommendations. Homeowners are responsible for initiating and interacting with the *Smart Home Energy Optimization Syste*m through various user interfaces, such as a mobile app or a web portal. Homeowners configure their energy preferences and priorities within the system. This includes setting desired temperature ranges, lighting preferences, and energy usage constraints. They regularly monitor their home's energy consumption data and receive recommendations or alerts from the system. When the system suggests energy optimization actions, homeowners can review these recommendations and decide whether to accept or modify them based on their preferences. Homeowners provide feedback on the system's recommendations and effectiveness, contributing to ongoing learning and improvement [11].

System administrators

Responsible for maintaining the system and ensuring data integrity. System administrators are responsible for the maintenance, upkeep, and smooth operation of the *Smart Home Energy Optimization System*. They offer user support and assistance to homeowners regarding technical issues, system inquiries, and updates. System administrators ensure the security and privacy of user data, implementing robust cybersecurity measures to protect sensitive information. They oversee system updates, ensuring all software components are current and security patches are applied promptly. Administrators troubleshoot and resolve issues to minimize downtime during system malfunctions or technical glitches [12].

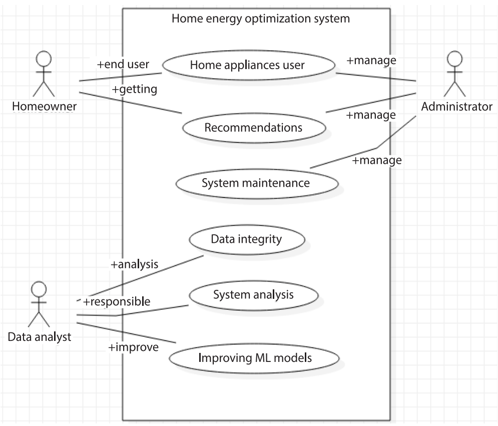

Figure 1. Use case diagram for the proposed system

Data analysts

Responsible for analyzing system performance and improving the machine learning models. Data Collection: Data analysts oversee the collection of energy consumption data from various smart devices and sensors installed in the homes connected to the system. They analyze the collected data to identify patterns, trends, and opportunities for energy optimization within the homes. Data analysts may work on developing and fine-tuning the algorithms that power the system's energy optimization recommendations. They continuously monitor the system's performance, ensuring it meets energy efficiency goals and user expectations.

Data analysts collaborate with other team members to improve the accuracy and relevance of energy optimization recommendations [13].

Figure 1 shows the use case diagram where the proposed system enclosed data analyst responsibilities, administrator, and homeowner. All the actors' roles are clearly defined in fig. 1. The data analyst analyzes data integrity and is responsible for the system analysis and improving the machine learning models applied during the development [14].

Operating environment

The HEOS system will operate in residential environments with internet connectivity. It will interact with external data sources, including occupancy sensors, weather forecast APIs, and energy consumption data from utility providers [5].

Design and implementation constraints

The system must be compatible with a wide range of occupancy devices and smart home devices. The system must adhere to data privacy and security regulations. The machine learning models must be scalable and efficient for real-time analysis.

User documentation

Comprehensive user documentation, including user guides and FAQ, will be provided to homeowners to help them interact with the system effectively.

Assumptions and dependencies

The availability of reliable occupancy sensors and smart home devices. Access to weather forecast API and historical weather data. Access to historical energy consumption data from utility providers.

Software requirements specifications

External interfaces

User interfaces

The system will provide a user-friendly interface for homeowners to access energy-efficient recommendations and system settings.

External data interfaces

The system will interface with the following external data sources:
- Occupancy sensors and smart home devices.
- Weather forecast dataset.
- Historical energy consumption data from utility providers.
-

Functional requirements

Data collection and pre-processing

Open-source data is collected [15], with all the necessary features for weather data and energy consumption:
- The system shall collect real-time occupancy data from sensors.
- The system shall retrieve weather forecasts and historical weather data.
- The system shall acquire historical energy consumption data.
- Data pre-processing shall include cleaning, normalization, and feature engineering.

Machine learning models

The system shall develop and train machine learning models for energy consumption prediction. Models shall be updated periodically to maintain accuracy. Models shall consider occupancy patterns, weather conditions, and historical data.

Real time analysis and recommendations

The system shall analyze real-time occupancy patterns. The system shall consider weather forecasts in real-time analysis. Based on analysis, the system shall provide energy-efficient recommendations to homeowners [6].

Performance requirements

The system shall provide recommendations with a response time of less than 5 seconds. Machine learning models shall maintain an accuracy rate of at least 90%. The system shall support concurrent access by multiple homeowners.

Design constraints

The system architecture shall be scalable to accommodate growing users and data sources. Data storage and transmission shall comply with data privacy regulations (*e.g.*, GDPR – general data protection regulation) a European Union law designed to protect individuals' privacy and personal data by regulating how organizations collect, store, and use it.

Software system attributes

Reliability

The system shall have a backup and recovery mechanism for data.

Security

Data transmission and storage shall be encrypted. User authentication and authorization shall be implemented.

Scalability

The system shall be able to scale horizontally to handle increased data volume.

Usability

The user interface shall be intuitive and user-friendly.

Maintainability

The system shall be maintainable with regular updates and bug fixes.

Architecture diagram

High level architecture of the HEOS system will follow a three-tier architecture [7]:
- *Presentation layer*: The web-based or simple user interface for homeowners.
- *Application layer*: Responsible for data collection, pre-processing, machine learning, and real-time analysis.
- *Data layer*: Stores historical data and machine learning models.

Figure 2 shows the architectural diagram of the proposed system, where three layers are designed to represent the complete structure [17].

System data flow

Figure 3 shows the proposed system's data flow diagram, where the system's complete data flow is designed in detail. A few necessary points are discussed:
– Data from occupancy sensors, weather forecasts, and energy consumption sources will be collected.
– Data pre-processing will occur in the application layer.
– Machine learning models will be applied for real-time analysis.
– Recommendations will be provided to homeowners through the user interface.

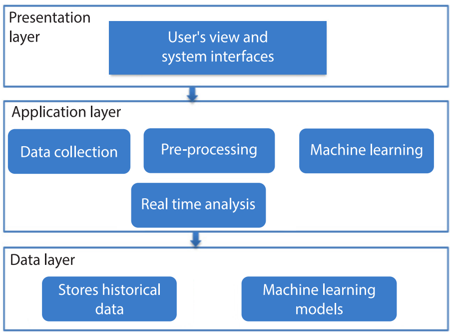

Figure 2. Architectural diagram

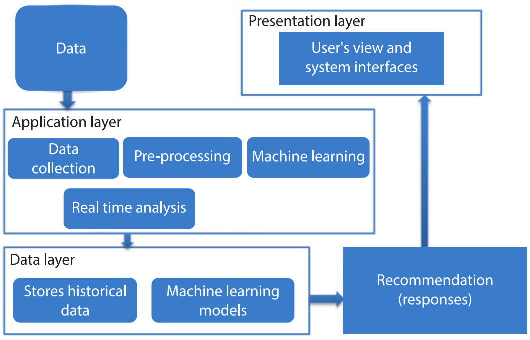

Figure 3. Data flow diagram

System implementation

This project can be implemented smoothly, and it is easy to understand the machine learning concepts. Please follow the points given to develop the model. Certainly! Here are the essential steps to build a system that optimizes home energy usage using machine learning.

Data collection

The proposed method used the open-source smart home dataset, which included weather information. This dataset was gathered using IoT devices. This dataset contains the reading with a period of 1 minute of the house appliances in KW. This data was collected from a smart meter and weather conditions [18].

Occupancy data: Install occupancy sensors or utilize existing smart home devices to monitor when occupants are present. This data will be anonymized and securely stored [18].

Weather data: Collect weather forecasts and historical weather data for the region where the home is located. This information will include temperature, humidity, precipitation, and daylight hours [18].

Energy consumption data: Gather historical energy consumption data from the homeowners' utility bills, smart meters, or energy monitoring devices. This data will be used to train and validate the machine-learning models [18].

Data pre-processing

Clean and handle missing values in collected data. Align timestamps and integrate data sources.

Machine learning models

Feature engineering: Create relevant occupancy, weather, and energy consumption data features. These features included occupancy profiles, weather conditions, and energy usage patterns.

Model development: Develop machine learning models, such as regression, time series analysis, and deep learning, to predict future energy consumption based on the input features. Models are trained to optimize energy usage while ensuring comfort levels. The following machine learning algorithms are used to train the model:
– *ARIMA basic*: This model is used to get the forecasting and time series data. It is the combination of AR and MA models.
– *ARIMA dynamic*: The ARIMA Dynamics analyzes and forecasts the more complex time series and adjusts quickly compared to the basic ARIMA.
– *SARIMA*: It is the variation in the ARIMA model to handle the seasonal data with time series.
– *SARIMAX*: It is the same as the SARIMA model but has more ability to handle seasonal data, which also affects the external data variables.
– LSTM univariate: This deep learning recurrent model is mainly used for the time series data. It works for a single variable, so it's called univariate.
– *LSTM multivariate*: This deep learning recurrent model is mainly used for the time series data. It works for multiple variables, which is why it's called multivariate.
– *SARIMAX with exons*: This algorithm is the advanced form of SARIMA and has additional external variables.

Recommendation engine: Build a recommendation engine that provides actionable suggestions to homeowners, such as adjusting thermostat settings, turning off lights, or running appliances during off-peak hours.

Model evaluation and testing

Performance metrics: Use energy savings, cost reductions, and user satisfaction metrics to assess the system's performance.

User feedback: Collect feedback from homeowners through surveys and interviews to understand the usability and acceptance of the system.

Real-world testing: Conduct controlled experiments in real homes to validate the system's effectiveness under varying conditions.

System outcomes

A machine learning-based system that optimizes home energy usage and reduces energy costs for homeowners. Energy-efficient recommendations tailored to individual occupancy patterns and weather conditions. Validation of the system's effectiveness through experiments and user feedback.

Energy correlation

Energy consumption was the key point in the proposed system, and it was needed to determine the correlation between energy consumption and energy consumption. Figure 4 shows the correlation in energy consumption, where the energy features were used to draw the given correlation. Correlation shows that the home furnace consumed more energy than other appliances. Content values are shown in the center of the graph. Some columns in the data are much more correlated than others and may be the same data.

Figure 5 shows that the energy-related columns have the same data and overlap. The blue line shows energy usage, and the orange line shows house energy usage. Gen and solar lines overlap, showing the energy columns overlap due to the same data.

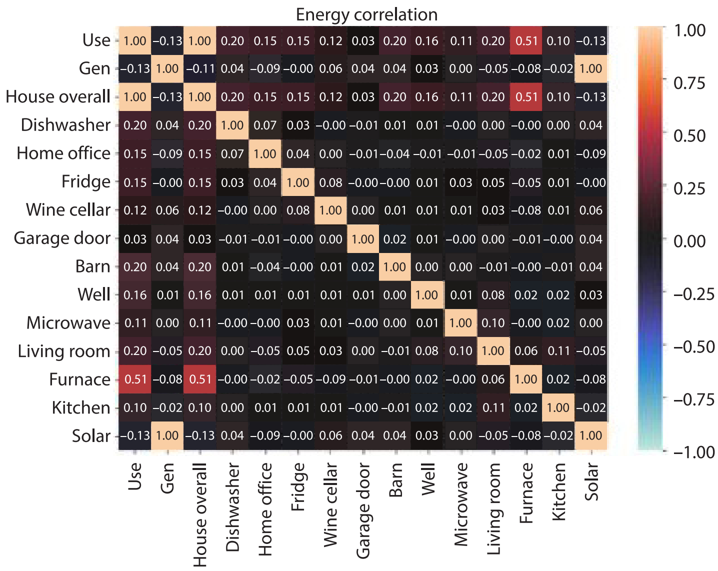

Figure 4. Energy features correlation

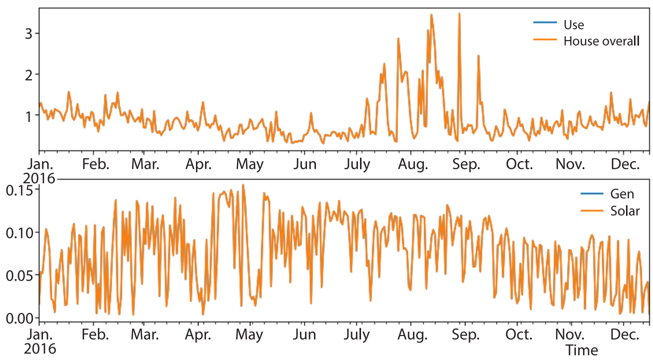

Figure 5. Correlated energy columns

Weather correlation

The weather significantly impacts energy consumption, especially for smart home appliances, which reflect the significant impact of weather conditions. Weather correlation is shown in fig. 6, where the weather features' significant changes can easily be seen. Temperature features have a significant impact compared to other features.

Figure 6 shows the correlation between temperature, apparent temperature, and dew point type of energy columns. The relationship between these features is clearly shown where the change in the variation of these values can be seen but almost all the values are not significantly different.

The humidity feature is also shown in the bottom graph in fig. 6. This data analysis gives insights into the proposed system's selected data. The temperature difference in correlation with the weather data is also shown in tab. 1. Temperature has greater values than other features. Figure 6 shows the in the form of confusion matrix in between the weather features.

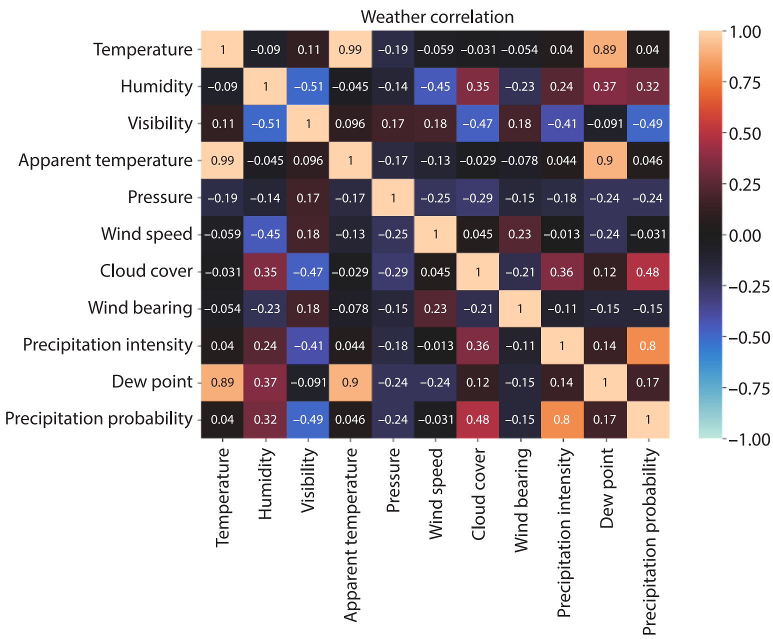

Figure 6. Weather features correlation

Table 1. Correlation between T_{diff} (temperature, aparent temperature) and weather columns

Weather	$T_{\text{diff\_corr}}$
Temperature	0.732693
Humidity	0.188441
Visibility	0.018984
Apparent temperature	0.807018
Pressure	0.029497
Wind speed	0.465971
Cloud cover	0.013172
Wind bearing	0.180131
Precip intensity	0.055953
Dew point	0.753312
Precip probability	0.068525

Figure 7 shows the first six energy columns that show the change in energy consumption. The overall graph shows a change in the values. The dishwasher has an almost static change in the graph, and the home office also has some minor changes, the fridge has significant fluctuations in the graph, wine cellar changes can be seen on the single point with high but other places were exact, and garage door not very high energy consumption changes. These six columns have significant changes and impact on energy consumption, whereas other energy columns have some changes in their graph but have no significant effect.

Figure 7 shows the weather data columns and the change in each column due to the shift in energy forecasting.

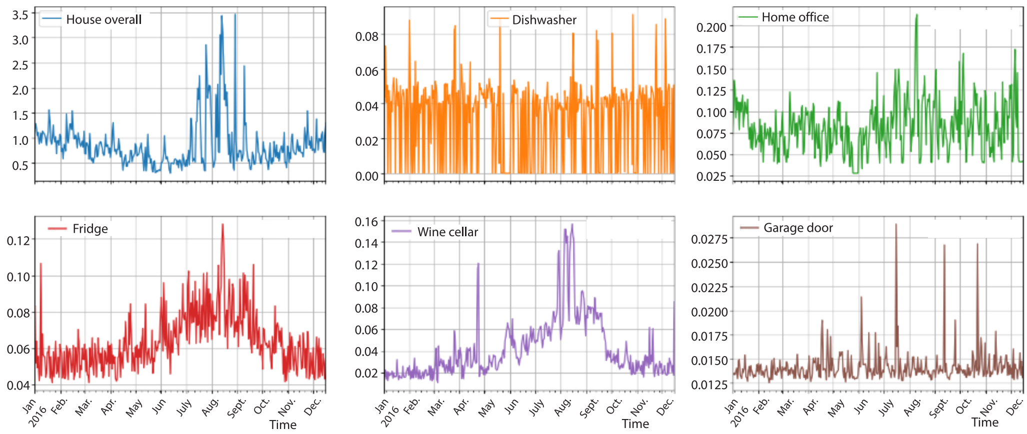

Figure 7. Six energy columns change energy consumption

Energy consumption by monthly, weekly and daily

Energy consumption was significantly impacted due to the weather conditions and depended on the appliances. So, the consumption was divided into monthly, weekly, and daily amounts. Figures 8-10 show the monthly, weekly, and daily energy consumption. The change in monthly energy consumption, weekly consumption, and daily consumption can be seen in these figures.

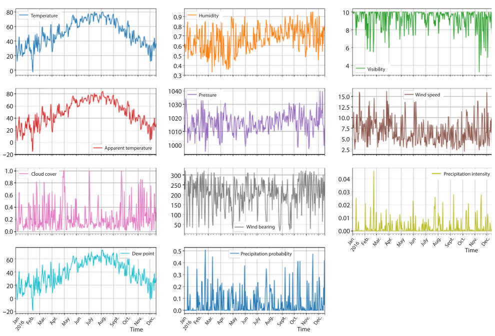

Figure 8. Weather data visualization

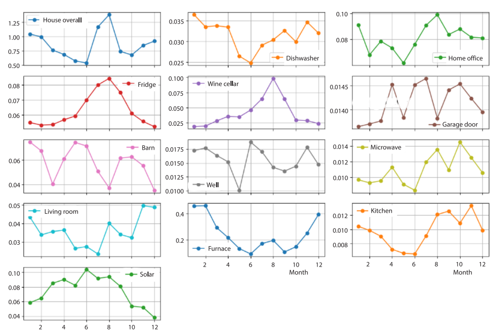

Figure 9. Energy consumption monthly

Figures 8-10 mainly show the change in energy consumption in monthly, weekly, and daily, respectively. The purpose was to analyze the energy consumed on which day or see the energy consumed in which week or month. So, we have all the variations to analyze the energy consumption.

Figure 11 shows the correlation between weather data and energy, which we can call energy-weather correlation.

The energy-weather correlations, fig. 12, between fridges and wine cellars have the most energy consumption devices, so other devices like Furnaces are also great energy consumers. Still, it is not as much as the fridge. Therefore, it can be analyzed by looking at the graph showing the large energy consumer devices and comparing weather data. So, to achieve low energy consumption, these devices can be changed or reduced.

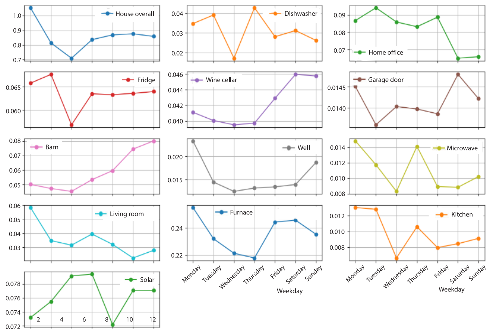

Figure 10. Energy consumption weekly

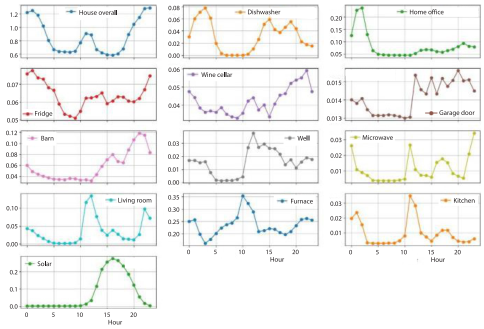

Figure 11. Energy consumption daily

House overall	0.010379	0.011511	–0.002609	0.005560	0.010730	–0.003853
Dishwasher	–0.015716	–0.001868	–0.008064	–0.014547	0.000211	–0.001672
Home office	0.011908	–0.006008	0.020638	0.010856	0.02791	–0.017898
Fridge	0.107466	0.030749	0.009019	0.107064	–0.000517	–0.024886
Wine cellar	0.289168	0.055541	0.030095	0.288882	0.018494	–0.052860
Garage door	0.013511	–0.007399	0.002262	0.013578	–0.000276	0.000419
Barn	–0.017188	–0.002141	0.008376	–0.015189	0.011716	–0.015196
Well	–0.004691	–0.006590	–0.001069	–0.004741	0.002994	0.000677
Microwave	–0.001369	0.012541	–0.18359	0.002265	–0.001248	–0.006129
Living room	–0.049781	0.003189	–0.014494	–0.048981	0.013774	0.013427
Furnace	–0.339845	–0.055172	–0.029998	–0.348868	–0.001174	–0.104223
Kitchen	–0.006106	0.010423	–0.005027	–0.004344	0.003483	–0.010426
Solar	0.090983	0.007608	–0.017650	0.093793	–0.000222	–0.056554

Figure 12. Energy-weather correlations

Moving average algorithm results

Some algorithms were used to get the optimized energy consumption solution, so the moving average is the algorithm that is the baseline model and is used to calculate the evaluation metrics values of the RMSE. Results obtained from the test data are shown in fig. 13, where the house usage overall is compared to the rolling mean. Thus, the RMSE 0.266 value is best, which shows that this model predicts energy consumption based on their calculation.

Persistent algorithms results

The persistent algorithm analyzes the energy consumption compared to the weather data. Figure 14 shows the graphical representation based on the test data for persistent algorithms. The blue line shows the overall house data view, and the orange line shows the persistent algorithm. Therefore, the RMSE value was computed at 0.304, higher than the other algorithms.

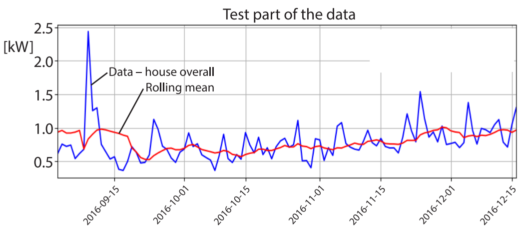

Figure 13. Moving average algorithm test data results

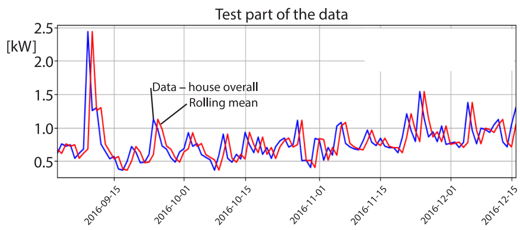

Figure 14. Persistent algorithm results

The ARIMA algorithm results

Figure 15 shows the results of the ARIMA model for energy consumption when comparing weather data. The test data was used to evaluate the model performance shown in fig. 15. The RMSE values were computed in the ARIMA model 0.581. Accordingly, the RMSE values near the 0 values show this model performs best, but if the values are less than this, the model performance on test data can be increased. Train data is shown in the green line, test data is shown in the blue, and the red line shows the predictions.

The SARIMAX algorithm results

Figure 16 shows the SARIMAX model results for energy consumption when comparing weather data. The test data was used to evaluate the model performance shown on fig. 16. The RMSE values were computed in the SARIMAX model 0.319. Therefore, the RMSE values are near the 0 values, which shows this model performs even better than the ARIMA model. If the values are less than this, the model performance on test data can be increased. Train data is shown on the green line, test data in the blue line, and the red line shows the predictions.

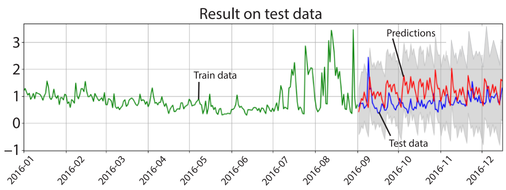

Figure 15. The ARIMA model results

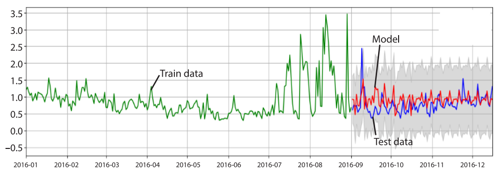

Figure 16. The SARIMAX model results

The LSTM univariate algorithm results

A deep learning model is used to get the energy consumption from the weather data and the house appliances. Figure 17 shows the LSTM univariate model results for the energy consumption when comparing weather data. The test data was used to evaluate the model performance, as shown in fig. 17. The RMSE values were computed in the LSTM Univariate model 0.26583. Consequently, the RMSE values are near the 0 values, which shows that this model performs even if it best performs the ARIMA model. However, if the values are less than this, the model performance on test data can be increased. Train data is shown in the green line, test data is shown in the blue, and the red line shows the predictions.

The LSTM multivariate algorithm results

A deep learning model determines energy consumption using weather data and household appliances. Figure 18 shows the LSTM multivariate model results for the energy consumption when comparing weather data. The test data was used to evaluate the model performance, as shown in fig. 18. The RMSE values were computed in the LSTM Multivariate model 0.14376. Subsequently, the RMSE values are near the 0 values, which shows that this model performs even if it best performs the ARIMA model. However, if the values are less than this, the model performance on test data can be increased. Train data is shown in the green line, test data in the blue line, and the red line shows the predictions.

Therefore, in the end, the RMSE value for the LSTM Multivariate is very low compared to the other algorithms. It performs best as compared to the different algorithms. Table 2 shows the RMSE values for these algorithms with a detailed comparison. Figures 13-16 show the computed results of the Moving average algorithm, Persistent algorithm, ARIMA, SARIMAX, LSTSM Univariate, and LSTSM Multivariate respectively.

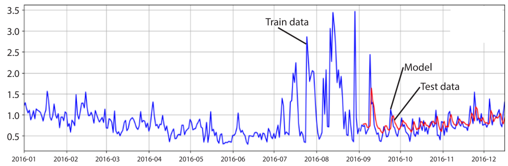

Figure 17. The LSTSM univariate results

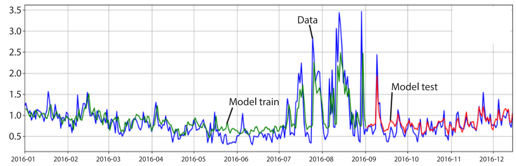

Figure 18. The LSTSM multivariate results

A few of the common forecasting algorithms were tested to develop predictive models, including Moving Average, Persistence algorithm, ARIMA, Auto ARIMA, LSTM Univariate, and LSTM Multivariate. Table 2 shows the computed results with the RMSE values for each algorithm.

Table 2. The RMSE values comparison for the algorithms on test data

Algorithm	RMSE values
Moving average	0.266
Persistence algorithm	0.304
ARIMA	0.581
SARIMAX	0.319
LSTM Univariate	0.265
LSTM Multivariate	0.143

Conclusions

In this research, it has successfully developed a machine learning-based system to optimize home energy usage. The system leverages occupancy patterns, weather forecasts, and energy consumption data to create predictive models recommending energy-efficient actions to homeowners. Employing advanced machine learning techniques, this project contributes to sustainable energy practices, offers a path to reducing energy costs, and minimizes environmental impact.

The proposed methodology involved an in-depth data analysis using exploratory data analysis techniques, followed by appropriate data pre-processing. We established correlations between weather conditions and energy consumption for home appliances and visualized these relationships through graphs. Varying time intervals grouped data: monthly, weekly, daily, and hourly to further scrutinize energy usage patterns.

Various forecasting algorithms were tested to develop predictive models, including moving average, persistence algorithm, ARIMA, Auto ARIMA, LSTM Univariate, and LSTM Multivariate. Performance metrics indicated that the LSTM Multivariate algorithm outperformed the others, boasting a remarkably low RMSE value of 0.143, highlighting its efficacy and accuracy.

The proposed system has shown significant promise in providing actionable, energy-efficient recommendations for homeowners, thereby contributing to sustainability efforts. The successful performance of the proposed system paves the way for future research and real-world applications in optimizing home energy consumption.

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