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Power Predict AI: Intelligent Energy Consumption Forecasting System

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ABSTRACT:

The area of computer architecture has long been a hotbed of research on power consumption. Energy acquisition as a metric in ML is only starting to take shape, but most experiments are still mainly aimed at getting very accurate results with no computing constraints whatsoever. We think that the fact that they don't have easy access to energy usage evaluation tools is one reason for the lack of interest. This study's overarching goal is to assess rules that the machine learning community may utilize to their advantage, allowing them to develop and implement energy estimate techniques for their algorithms. For reliable electricity predictions, we use a variety of ensemble models, including Linear Regression, Random Forest Regression, and Adaboost Regression. Nevertheless, we also cover the most recent software tools that provide principles for electricity estimate, along with two use cases that bolster the investigation of energy fatigue in machine learning. Ultimately, we are able to foretell future energy needs, which is a huge boon to the grid as it allows for more precise energy generation via the installation of smart meters, which allow everyone to see which appliances are using the most power.

PROBLEM STATEMENT

One of the biggest challenges in energy management is power consumption prediction. Since energy suppliers should improve energy distribution, prevent energy waste, and avoid the power system being overwhelmed, accurate electricity consumption forecasts are vital for effective energy management [11]. When it comes to calculating power use, traditional approaches have limitations in terms of accuracy and expandability. Therefore, a reliable and effective way of It is required for power consumption forecasting.

INTRODUCTION

Modern energy consumption is on the rise due to both residential and commercial applications, such as the widespread usage of automobiles, large-scale generators, mobile devices, and kitchen appliances. Similarly, smart meter infrastructure (SMI) continues to expand [1]. All throughout the globe, people were laying the framework to integrate active energy systems into smart meters. The door has been opened to energy demand forecasting and modeling with this introduction; the moment has come to implement a green environment, particularly for residential energy consumers [2]. The electricity market is being affected by consumer behavior and the use of electrical devices. The necessity for innovative solutions to reduce energy consumption in both commercial and residential buildings is being acknowledged by power grid authorities. The sensors in smart homes use a lot of power, but the conveniences they provide, like controlling many electronics from afar with a smartphone app, are worth it. An ensemble regression model combining linear and SVR prediction methods was created to enhance the accuracy of power forecasts [3]. A large amount of resources are wasted each year as a result of this kind of mismanagement, which often leads to the abuse of household equipment [3]. In order to keep it running with reliable demand predictions for the future, cutting down on this energy loss is crucial.

Various prediction algorithms are used in the energy management domain to anticipate power consumption in the next days in order to produce capacity [3]. Nevertheless, there are a number of factors related to the building's structure that can affect energy consumption. These include, but are not limited to, weather conditions, construction materials, and sub-level heating, lighting, and ventilation systems [4]. Consumers have the option to reduce energy consumption by adjusting the load using appliances or by adjusting the number of occupants. [5] The complexity and stability of the building's infrastructure determine the difficulty of this crucial task: energy projection. Efficient use and deployment are made possible by using historical data that includes reported home values from 2006 to 2010 for power consumption forecast. [6].

LITERATURE SURVEY

The literature on energy consumption prediction, smart building optimization, and anomaly detection highlights a strong transition from traditional statistical methods to advanced machine learning and deep learning approaches. Early works focused on data-driven modeling and statistical analysis for understanding building energy behavior. For instance, studies such as Energy and Buildings research by S. P. Corgnati emphasize parameter estimation and building energy modeling using data-driven techniques, which laid the foundation for predictive analytics in smart buildings. Similarly, long-term and short-term forecasting models using artificial neural networks and regression techniques have been explored in journals like Applied Energy, demonstrating the effectiveness of neural networks in capturing nonlinear energy consumption patterns. These approaches, however, often faced challenges in adapting to dynamic user behavior and real-time variations.

With the advancement of machine learning, more sophisticated models such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and hybrid approaches have been introduced to improve forecasting accuracy. Research works in Energy AI and Energy Reports demonstrate that combining statistical techniques with machine learning significantly enhances prediction performance. For example, short-term load forecasting using SVM models has shown improved precision in capturing consumption trends, while hybrid ANN-SVM models provide better generalization across different datasets. Additionally, studies on user behavior learning and time-series decomposition have further refined forecasting accuracy by incorporating temporal patterns and occupant behavior into the models.

Another important dimension of the literature focuses on smart home energy management and optimization techniques. Research published in IEEE Transactions on Smart Grid highlights optimal scheduling of household appliances to minimize energy costs and peak demand. Techniques such as Mixed Integer Linear Programming (MILP), discussed in Journal of Cleaner Production, enable efficient scheduling of appliances while maintaining user comfort. These optimization strategies are crucial for demand-side management in smart grids, where balancing energy consumption and supply is essential. Furthermore, distributed control methods for microgrids have been explored to enhance power dispatch efficiency and ensure reliable energy distribution in decentralized systems.

The integration of Internet of Things (IoT) and intelligent monitoring systems has further expanded the scope of energy management. IoT-based systems enable real-time data collection from sensors, allowing continuous monitoring of energy usage patterns. Studies in Future Generation Computer Systems highlight the role of IoT and blockchain in enabling secure and scalable energy forecasting frameworks. These technologies support decentralized data sharing and improve transparency in smart grid operations. Additionally, regression and machine learning-based prediction models have been applied to large-scale smart environments, enhancing scalability and real-time decision-making capabilities.

A significant portion of recent research also addresses anomaly detection in energy systems, which is essential for identifying faults, inefficiencies, and unusual consumption patterns. Deep learning techniques, particularly autoencoders, have gained prominence in this domain. Research in IEEE Access demonstrates that deep autoencoder models can effectively detect anomalies by learning normal system behavior and identifying deviations. Similarly, IoT-based anomaly detection frameworks using deep learning have been explored in Cluster Computing, showing improved detection accuracy in complex and dynamic environments. These methods are particularly useful for predictive maintenance and ensuring system reliability.

Moreover, several review studies provide a comprehensive understanding of the evolution of energy prediction techniques. For instance, surveys in Renewable and Sustainable Energy Reviews analyze various data-driven approaches and highlight the growing importance of machine learning in energy forecasting. These studies identify key challenges such as data quality, model scalability, and the need for real-time processing. They also emphasize the importance of integrating multiple data sources, including environmental factors and user behavior, to improve prediction accuracy.

In addition to technical advancements, recent research has also explored AI-driven applications in related domains, such as automated decision-making and intelligent systems. For example, platforms like HireVue demonstrate how AI can be used for automated screening and decision support, indicating the broader applicability of AI techniques beyond energy systems. This highlights the potential of integrating intelligent algorithms into various real-world applications, including smart homes and energy management systems.

Overall, the literature indicates that energy consumption prediction and management have evolved significantly with the adoption of AI and IoT technologies. While traditional models provided a baseline for analysis, modern approaches leveraging machine learning, deep learning, and optimization techniques offer higher accuracy, adaptability, and real-time capabilities. However, challenges such as data heterogeneity, scalability, privacy concerns, and integration with emerging technologies like blockchain and edge computing still remain. Addressing these challenges is essential for developing robust, efficient, and intelligent energy management systems in the future.

DESIGN METHODOLOGY

In order to provide continuous values, supervised machine learning models are trained using historical data. Using data like historical data, the model is taught to estimate the likelihood of a new power consumption number.

Proposed Work

We tested the suggested approach on a publicly available dataset from the UCI machine learning repository that includes information on electric power consumption from 2006 to 2010: the individual household power consumption dataset. There are 9 columns and 104,8575 rows in the dataset. Before testing them on the full test set, we train all supervised regressor models on the train set with all characteristics. In order to track progress across time.... Our toolset includes Adaboost Regressor, a scikit-learn implementation of LR and RF, and logistic regression (LR).

Advantages

- It is in-expensive
- It is non-intrusive monitoring system
- Estimates the on/off states of appliances include inverter

Recent advances in the prediction models used to forecast energy usage have been greatly aided by machine learning (ML) techniques. These models significantly enhance the traditional time series forecasting tools' accuracy, resilience, precision, and generalizability.

Existing System:

We evaluate several regression techniques, including multi-layered perceptrons (MLP), radial basis function networks (RBFN), and support vector regression (SVR), to predict how much electricity an air conditioner uses. Nonlinear regression methods such as MLP are considered standard. Therefore, it provides a solid foundation for comparing with other approaches. Each parameter-adjustable basis function in RBFN functions as a hidden unit of MLP. Using kernel functions, SVR excels in high-dimensional spaces. Based on our expectations, RBFN and SVR should outperform MLP.

Disadvantages:

We only did with non-intrusive monitoring system but not for monitoring system.

MODULES

- DATA COLLECTION
- DATA PRE-PROCESSING
- DATA SPLITTING
- EVALUATION MODEL

TESTING METHODS

Functional Testing

In accordance with the business and technical requirements, system documentation, and user guides, functional tests systematically prove that the tested functionalities are accessible.
The following are the main points of functional testing: Identified functions need to be performed. It is necessary to exercise the identified types of software outputs. Procedures and Systems: The system need to function correctly.

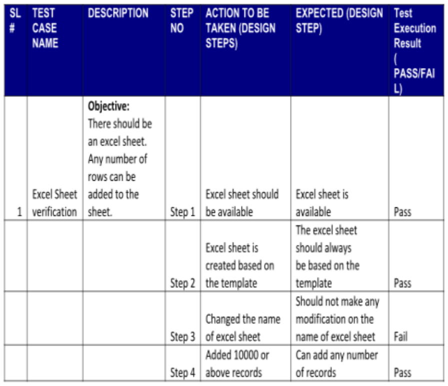
Integration Testing

The goal of software integration testing is to find and fix interface issues by gradually integrating two or more software components on the same platform.

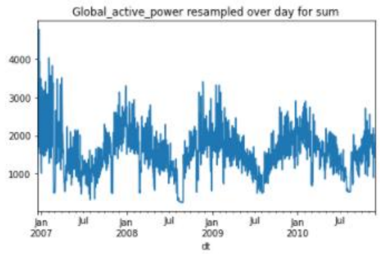
Test Case for Excel Sheet Verification:

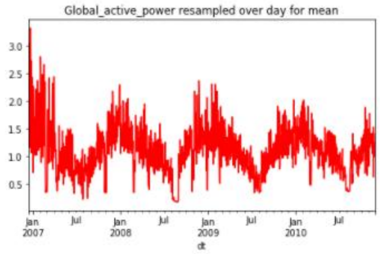
In machine learning, we work with datasets that are in Excel sheet format, so if we need to examine a test case, we can just open the Excel file. The columns of the dataset will be used for categorization later on.

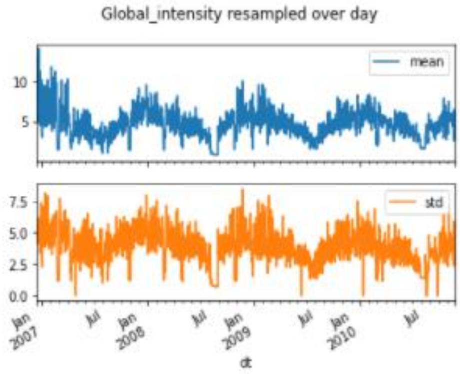
Results

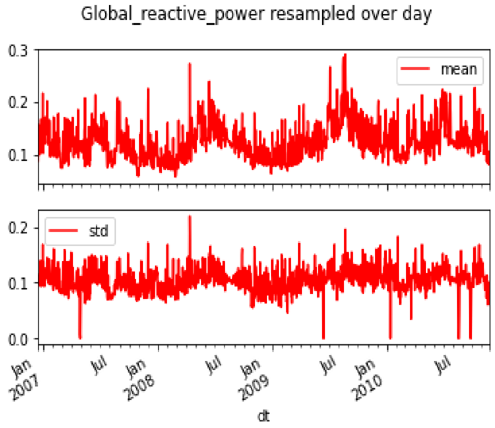


SL #	TEST CASE NAME	DESCRIPTION	STEP NO	ACTION TO BE TAKEN (DESIGN STEPS)	EXPECTED (DESIGN STEP)	Test Execution Result (PASS/FAIL)
1	Excel Sheet verification	**Objective:** There should be an excel sheet. Any number of rows can be added to the sheet.	Step 1	Excel sheet should be available	Excel sheet is available	Pass
			Step 2	Excel sheet is created based on the template	The excel sheet should always be based on the template	Pass
			Step 3	Changed the name of excel sheet	Should not make any modification on the name of excel sheet	Fail
			Step 4	Added 10000 or above records	Can add any number of records	Pass

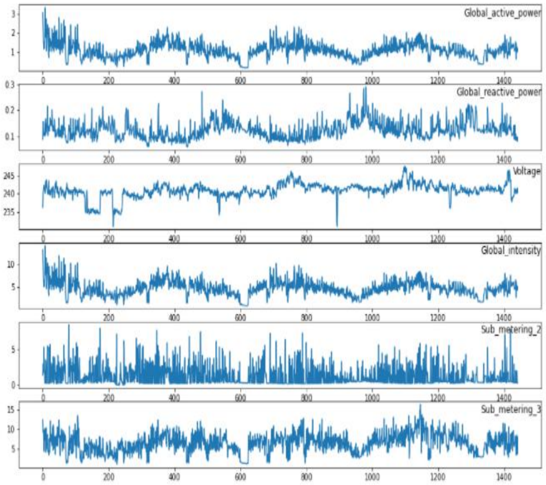


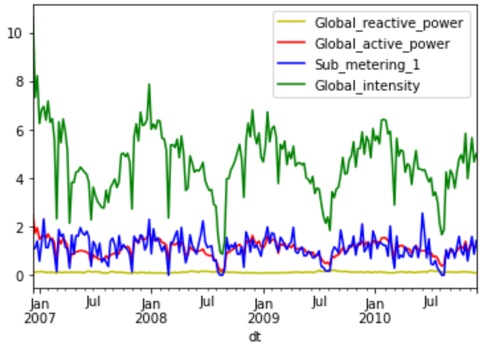




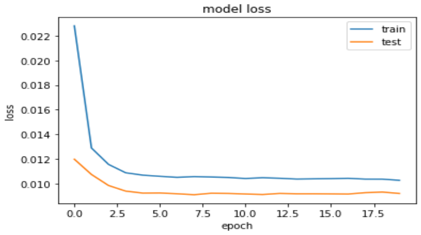


Output Validation:



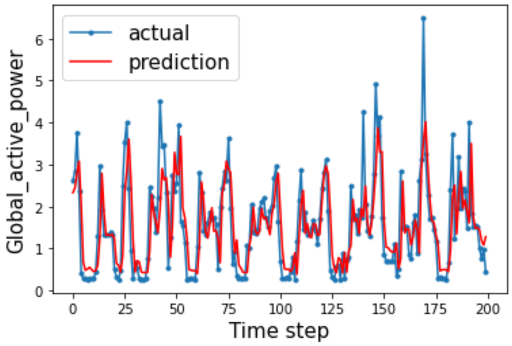


Lstm Result

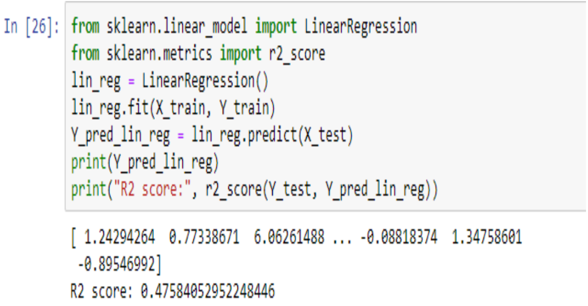


```
Test RMSE: 0.617
```

Future Prediction Result



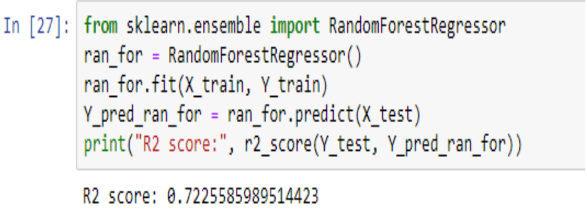
Prediction Result with Linear Regression



```
In [26]: from sklearn.linear_model import LinearRegression
         from sklearn.metrics import r2_score
         lin_reg = LinearRegression()
         lin_reg.fit(X_train, Y_train)
         Y_pred_lin_reg = lin_reg.predict(X_test)
         print(Y_pred_lin_reg)
         print("R2 score:", r2_score(Y_test, Y_pred_lin_reg))

         [ 1.24294264  0.77338671  6.06261488 ... -0.08818374  1.34758601
          -0.89546992]
         R2 score: 0.47584052952248446
```

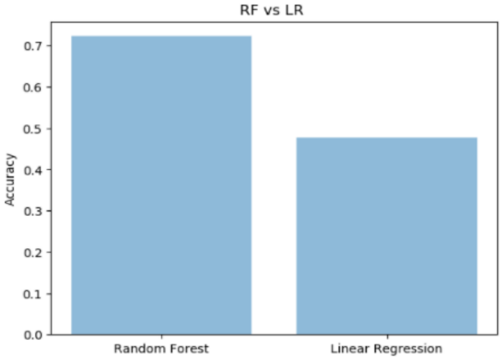
Prediction Result with Random Forest Regression



```
In [27]: from sklearn.ensemble import RandomForestRegressor
         ran_for = RandomForestRegressor()
         ran_for.fit(X_train, Y_train)
         Y_pred_ran_for = ran_for.predict(X_test)
         print("R2 score:", r2_score(Y_test, Y_pred_ran_for))

         R2 score: 0.7225585989514423
```

Comparative Result Graph



CONCLUSION

Power consumption prediction models have lately benefited greatly from machine learning (ML) techniques. Traditional methods of time series forecasting are greatly enhanced by these models in terms of accuracy, resilience, precision, and generalizability. We can estimate future electricity use by analyzing the past data. Here, we employed LSTM for future prediction using one household's electric power consumption data and obtained an accuracy of 72% using linear regression and random forest regression.

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