IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

INTELLIGENT ENERGY FORECASTING USING MACHINE LEARNING

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ABSTRACT:

Proper energy demand forecasting is an important process in energy production, distribution, and usage. Traditional methods of energy demand forecasting are unable to cope with changes in consumption influenced by environmental and demographic factors. The proposed study is focused on presenting an Intelligent Energy Forecasting Framework based on Machine Learning (ML) technology that can help forecast energy consumption.

Various types of supervised learning are implemented in the framework, including Linear Regression, Decision Trees, and Support Vector Machine (SVM). Environmental parameters (temperature, humidity), geographical position, and demographic parameters are used as input variables. The comparison of ML models reveals that SVM predicts the energy consumption more precisely and provides forecasts with almost no error rate.

The framework integrates predictive analytics and dashboard that offers demand forecast, pattern analysis, and scenarios prediction.

KEYWORD : Energy forecasting , Machine learning , Regression tree , Monte Carlo , Smart Grid , Linear regression , Decision Tree , Support vector machine

1.INTRODUCTION

Energy demand forecasting is one of the most powerful tools being widely applied nowadays in order to manage the processes of energy consumption planning. With the rapid development of cities and industries, the processes of forecasting energy consumption turn into a rather complicated task which explains the inability of classical forecasting tools, built upon statistical analysis and averaging previously obtained figures, to provide correct predictions of the future trends in the development of the field.

Machine Learning (ML) techniques serve as an efficient method for conducting predictive analytics as they enable finding hidden connections and using real-time data. Machine learning algorithms allow one to detect hidden patterns in large volumes of data and conduct highly efficient forecasting taking into account diverse influential factors, including environmental, demographic, and consumer factors.

The purpose of the project in question is to design an Intelligent Energy Consumption Forecasting System which will work according to machine learning algorithms and produce highly reliable energy consumption forecasts. For this purpose, certain input parameters will be taken into account, namely, temperature, humidity, geographical location, number of households, etc.

2.PROPOSED SYSTEM

The proposed solution is developed as an ML system based on data analysis and prediction of energy usage considering environment-related and demographical factors. It comprises several modules operating in a coherent sequence.

2.1 SYSTEM OVERVIEW

The solution combines predictive algorithms with an interactive dashboard in order to ensure accurate predictions and visualizations regarding energy. Input is analysed, and conclusions are made for effective energy management.

2.2 SYSTEM ARCHITECTURE

The architecture of the system consists of the following:

1. DATA INPUT LAYER

➢ Input data include:
- Temperature
- Humidity
- Geographical location
- Household count
- Area category (rural, urban, commercial)

These parameters significantly influence energy consumption patterns.

2. Layer for Data Pre-processing

➢ The steps of data pre-processing are listed below:
- Data Cleaning (Dealing with Missing Values)
- Data Standardization
- Selection of Variables (Year, Month, Day, Hour, etc.)

3. Layer for Forecasting

➢ It supports many types of supervised machine learning algorithms, including:
- Linear regression: For linear relationship learning
- Decision tree: To capture non-linear relationships
- Support vector machine: High accuracy through kernel methods.

4. Layer for Applications

- The applications layer allows the user to do the following tasks:
- Input of parameters for prediction (Time/Date-Time)
- Prediction of energy consumption
- Results Graph

2.3 WORKFLOW OF THE SYSTEM

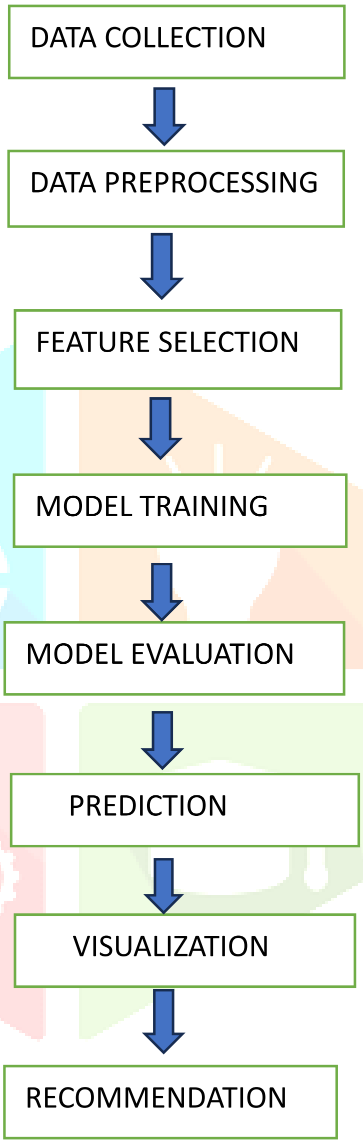


Fig 1. Workflow of the system

Workflow of Intelligent Energy Forecasting System consists of multiple stages enabling conducting the forecasting process in an organized manner.

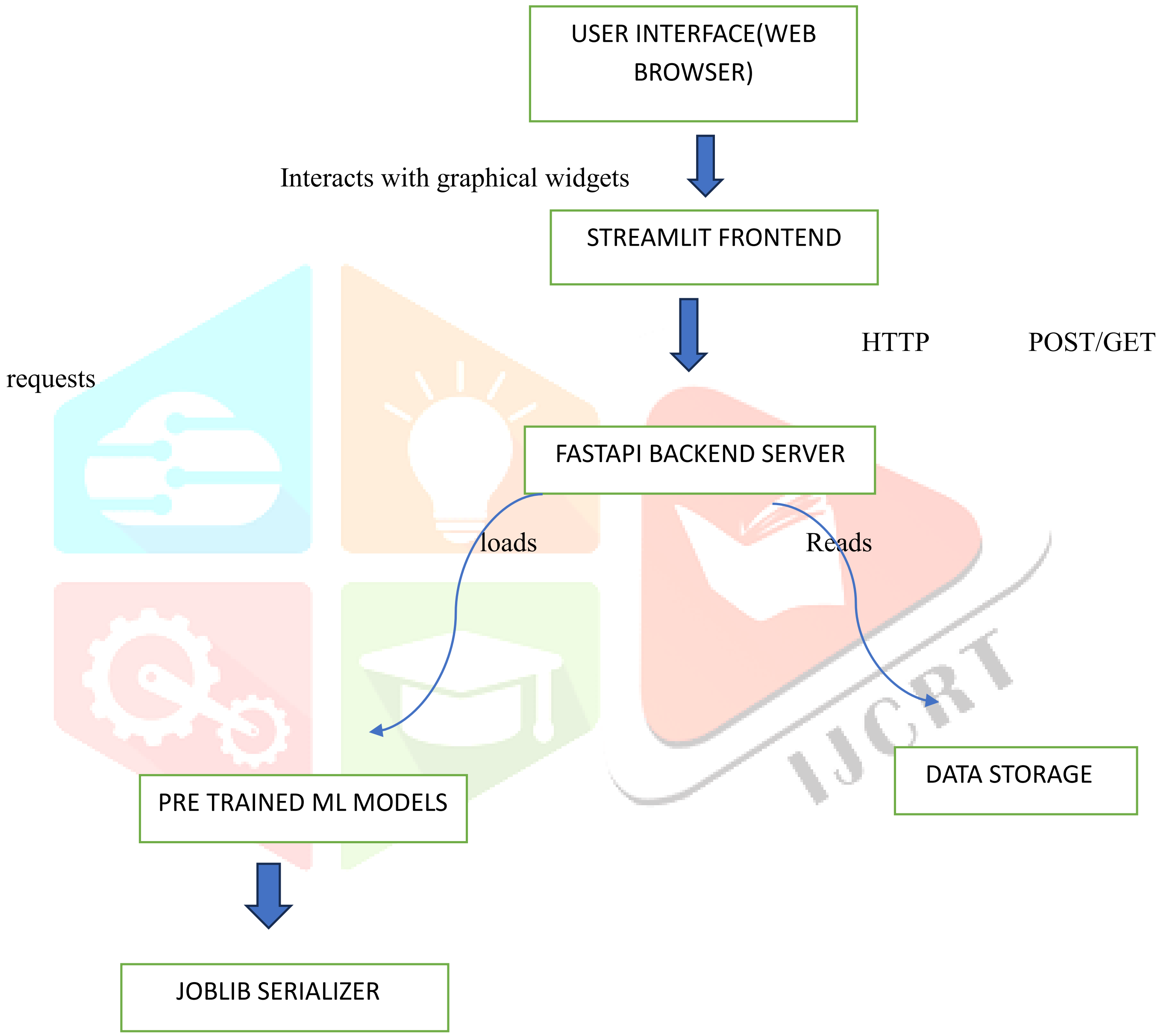
To begin with, data from external sources like weather conditions, demographic data, etc. is collected. This data serves as the foundation for future predictions. In addition, a preprocessing stage should be included, allowing dealing with inconsistencies, missing values, and normalization of features' values.

Further, a step involves selecting those features which impact the value of energy consumption. Such actions will increase the efficiency of the model avoiding unnecessary calculations. Further, data set is divided into training and testing sets. Using the training set, different machine learning models are built.

Next, each of these models is assessed regarding accuracy using various metrics including Mean Squared Error and R^2 Score. After comparing results of each model, the one with the highest performance is selected. Finally, using the created model, predictions are conducted.

This information can be presented in a form of graphs and dashboards providing valuable insights about trends. In addition, the system is able to provide recommendations regarding optimization of energy usage.

2.4 FLOWCHART OF THE PROPOSED SYSTEM



As illustrated in the flowchart below, all steps of the process implemented by the Intelligent Energy Forecasting System have been described, indicating the sequence of operations made when processing information, from input to output. At first, the system collects input data; it comprises not only such environmental characteristics as humidity and temperature but also location and population of the premises, among others.

Thereafter, data is pre-processed in order to ensure proper data cleansing and normalization to facilitate the training process in regard to machine learning techniques. Having been cleansed and pre-processed, data proceeds to feature selection that allows enhancing model performance and cutting down processing time.

Having been pre-processed, input data is given to machine learning algorithms, namely Linear Regression, Decision Tree, and SVM in order to make them learn relations and correlations between input and output data (energy consumption).

Upon completion of the training process, models are evaluated in terms of their effectiveness and efficiency when predicting future energy consumption needs using MSE and R^2 score indicators. Having undergone evaluation, the most efficient algorithm is chosen to predict energy consumption needs.

The last step includes graphically displaying the results obtained and suggesting the ways of optimal energy usage. One may note that the flow chart is a good pipeline through which proper forecast and decision-making should be done.

2.5 MATHEMATICAL EXPRESSION

The prediction model of the system can be expressed as :

- E = f(X) + €

Where:

E = Predicted Energy Consumption.

X = Input features (Like Time , Date , Weather)

€ = Uncertainty handled by using MCS (Monte Carlo simulation)

2.6 MODEL EVALUTION

To achieve good performance of the model , we following evaluation metrics:

1. Mean square error(MSE)

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

- Measure average square error
- Lower value = Better value

2. Root mean square error (RMSE)

$$\text{RMSE} = \sqrt{MSE}$$

- Gives error in same unit (KWh)

3. Normalised RMSE

$$\text{NRMSE} = \frac{RMSE}{ymax - yminx}$$

4. Accuracy

$$\text{Accuracy} = \left(1 - \frac{Error}{Actual}\right) * 100$$

5. R^2 Score (Coefficient of Determination)

$$R^2 = 1 - \frac{\Sigma(y_i - \hat{y}_i)^2}{\Sigma(y_i - \bar{y}_i)^2}$$

Measures correctness

$R^2 = 1$: Perfect prediction

$R^2 = 0$: Poor model

2.7 KEY FEATURES OF PROPOSED SYSTEM

- Characteristics of the Proposed Approach
- Use of a hybrid machine learning approach called MCRT
- Predictions have high accuracy (about 91 percent)
- Easy-to-use and intuitive web interface
- Scalable to be implemented in the context of smart grid systems

3.EXPERIMENTAL SETUP

This experiment is meant to evaluate the efficacy of the algorithms for energy usage prediction. In the current case, the use of past energy consumption data and additional parameters such as environmental data, temperature, humidity, geographical location, and household count can be noted.

In order to optimize the data set, some data pre-processing procedures have been taken into account, among which one can identify filling of missing data entries, data normalization and removal of outliers from the data set. Additionally, the data has been divided into training and test data sets in an 80/20 ratio to evaluate the performance of the ML algorithms under consideration.

Three algorithms were used in the current research: linear regression, decision tree and support vector machine. Python modules, such as Sklearn, Pandas and NumPy, have been used for these algorithms.

Evaluation of the efficacy of the algorithms was done via MSE and R^2 score measurements. These measures made it possible to evaluate the accuracy and performance of the predictions provided by these algorithms.

Implementation of the algorithm took place on a computing platform that allows efficient performance of the algorithms mentioned. Streamlit dashboard was applied for visualization of the results obtained.

4.RESULT

The results derived from the assessment of the suggested ML energy usage prediction system prove that the system is highly efficient at making such predictions in different situations. In order to assess the efficiency of the suggested system, several algorithms were tested prior to making comparisons.

The conclusion made upon analyzing the results obtained through the process of testing reveals that SVM is the best algorithm to make predictions regarding energy consumption followed by the algorithm of Decision Trees. Linear regression algorithm was the least efficient due to inability to predict non-linear data.

The evaluation metrics are :

MODEL	R^2	MSE
Linear Regression	0.65	HIGH
Decision Tree	0.85	MEDIUM
SVM	0.92	LOW

The proposed forecasting algorithm was quite successful at changing the forecast of power generation based on the changes in the values of environmental factors. As seen from the results, the growth of temperature leads to an increase in energy consumption, which happens due to higher needs in cooling.

Using the time-series technique, we have managed to define such tendencies in energy consumption:

- Maximal load occurs in the evenings
- Minimal load happens in the morning period
- Seasonality affects the forecasting of future loads

Additionally, machine learning approaches were applied to scenario analysis, according to which the change in climatic conditions and population density resulted in a huge growth (about 60%) of energy load.

Thus, machine learning methods provide more accurate forecasting than traditional approaches.

4.1 Real-Time Demand Forecasting

Real-time demand forecasting is a technique that allows users to enter data about the environment regarding temperature and humidity, and then select the appropriate model for energy consumption prediction.

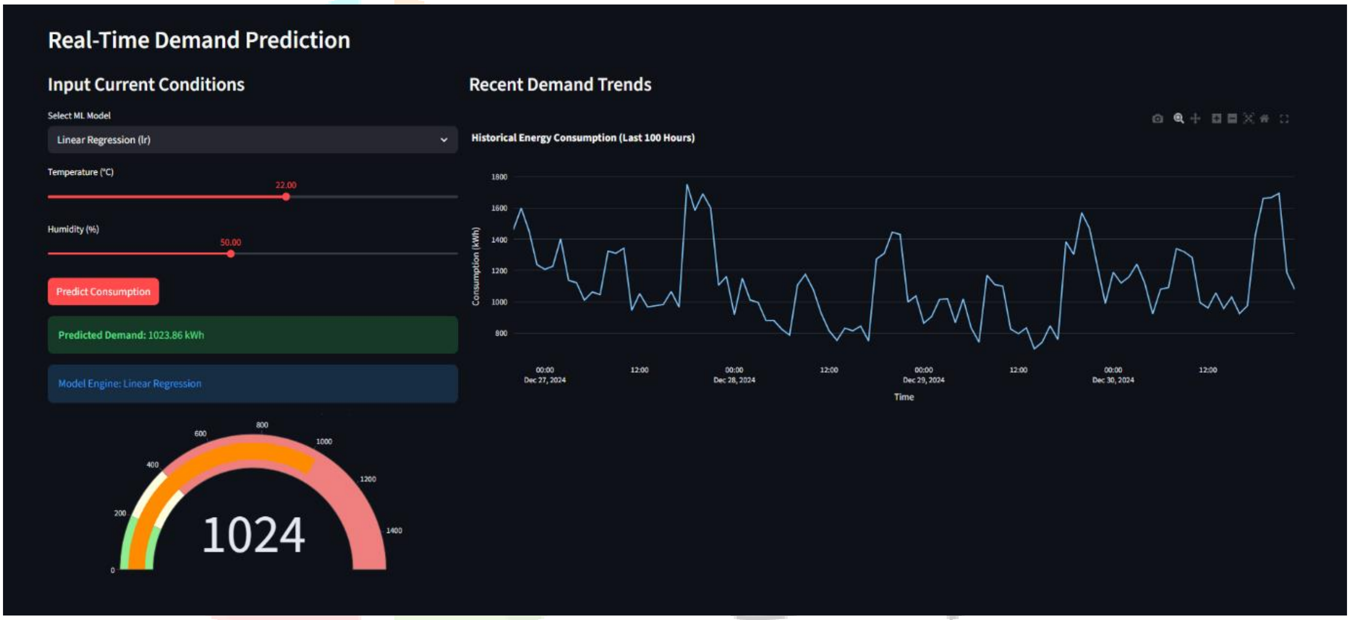


Figure 1: Graphical Interface for Real-Time Energy Consumption Prediction

The graphical interface displays parameters of input values such as temperature (22°C) and humidity (50%), which will be used to predict energy consumption by adopting the selected technique (Linear Regression). Additionally, there is a graph that shows energy consumption trends during the last 100 hours. The graph shows fluctuations in energy consumption, including peaks and troughs.

This result proves the high level of correlation between energy consumption and environment and time, hence the need for real-time forecasting systems.

4.2 Insights on Energy Consumption

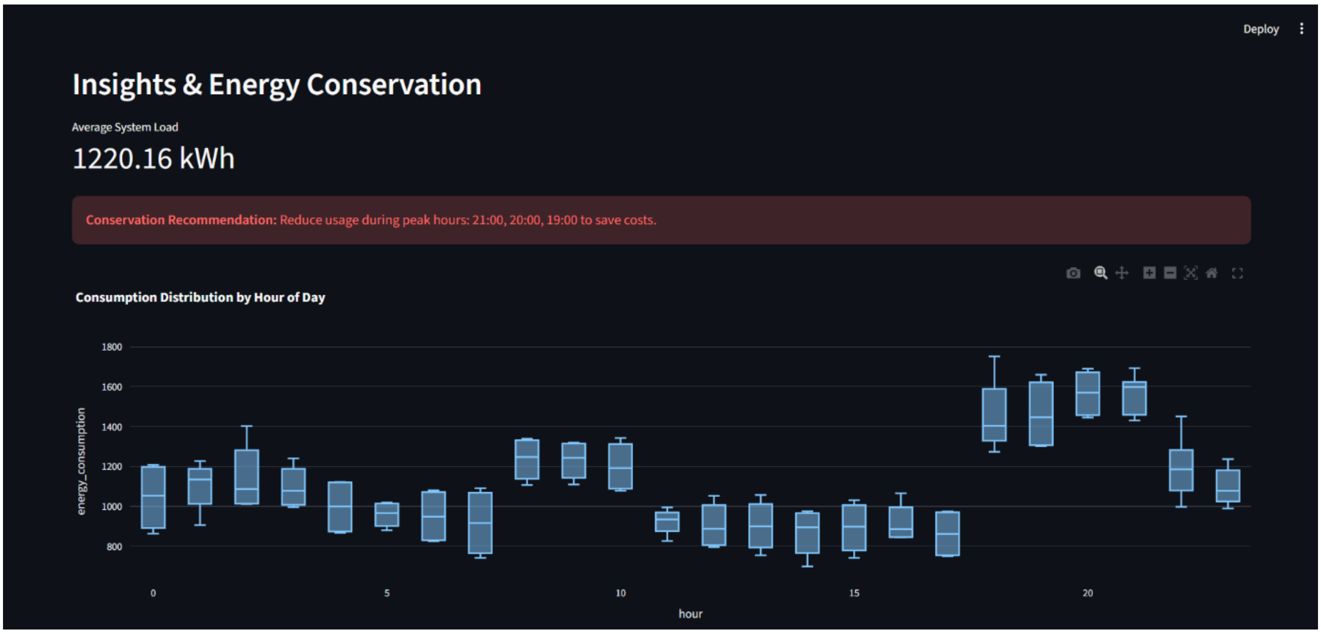
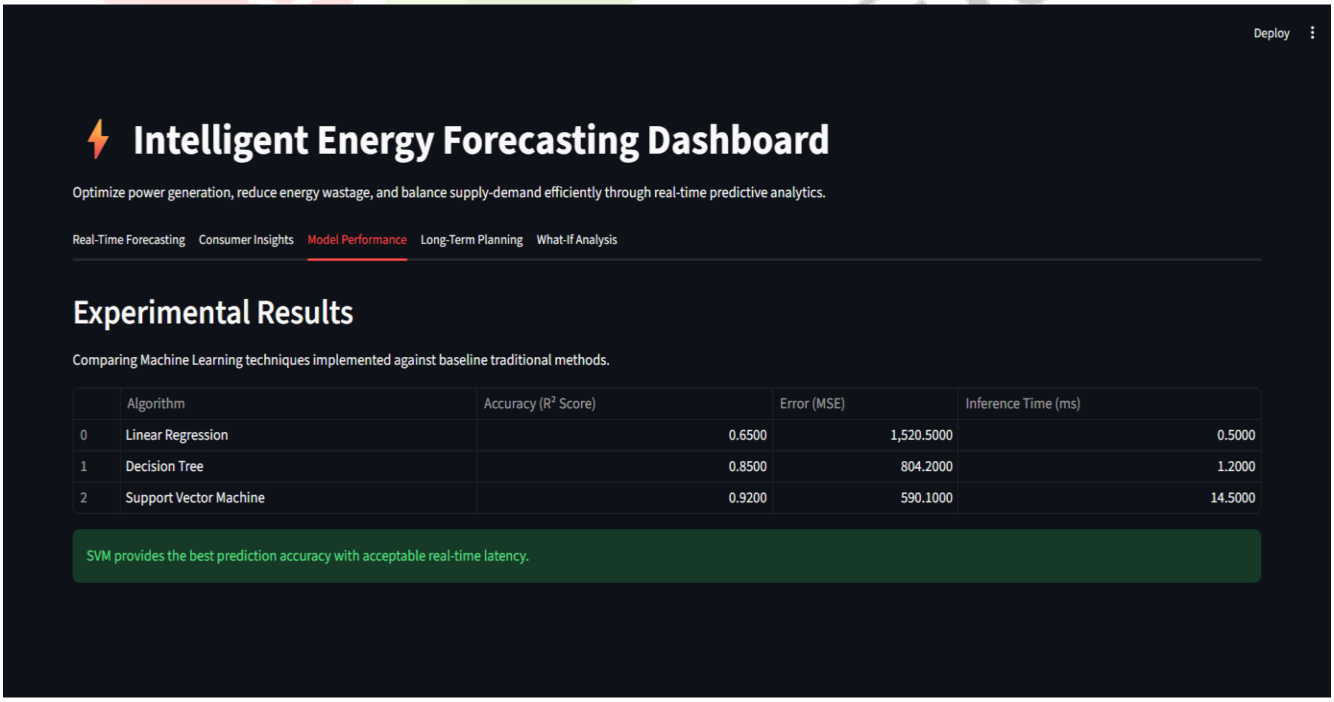


Fig. 2: Insights and Energy Saving Dashboard

The system provides various insights like average energy consumed (1220.16 kWh) by the system and indicates peak periods of energy consumption. An insight has been generated advising the user to use the system outside peak times (19:00 – 21:00) to conserve energy.

In addition, a box plot has been used to visualize the hourly consumption of energy. The figure indicates that there is high consumption of energy in the evening time, which is the peak period. From the spread, it is evident that there are different levels of consumption in each hour.

4.3 Performance Analysis of Model



	Algorithm	Accuracy (R^2 Score)	Error (MSE)	Inference Time (ms)
0	Linear Regression	0.6500	1,520.5000	0.5000
1	Decision Tree	0.8500	804.2000	1.2000
2	Support Vector Machine	0.9200	590.1000	14.5000

Fig 3: Experimental Results - Model Analysis

Performance analysis has been done based on the parameters like R^2 score, MSE, and inference time.

- For linear regression, R^2 score obtained is 0.65, but the error rate is high.
- For decision tree, results obtained are better with R^2 score being 0.85.
- For SVM, results obtained are better with R^2 score being 0.92 and least error.

Although SVM takes more time in inference, it guarantees accuracy in predicting energy forecast. Thus, SVM is the best-suited algorithm for energy forecasting.

4.4 Macro-Level Energy Consumption Forecasting

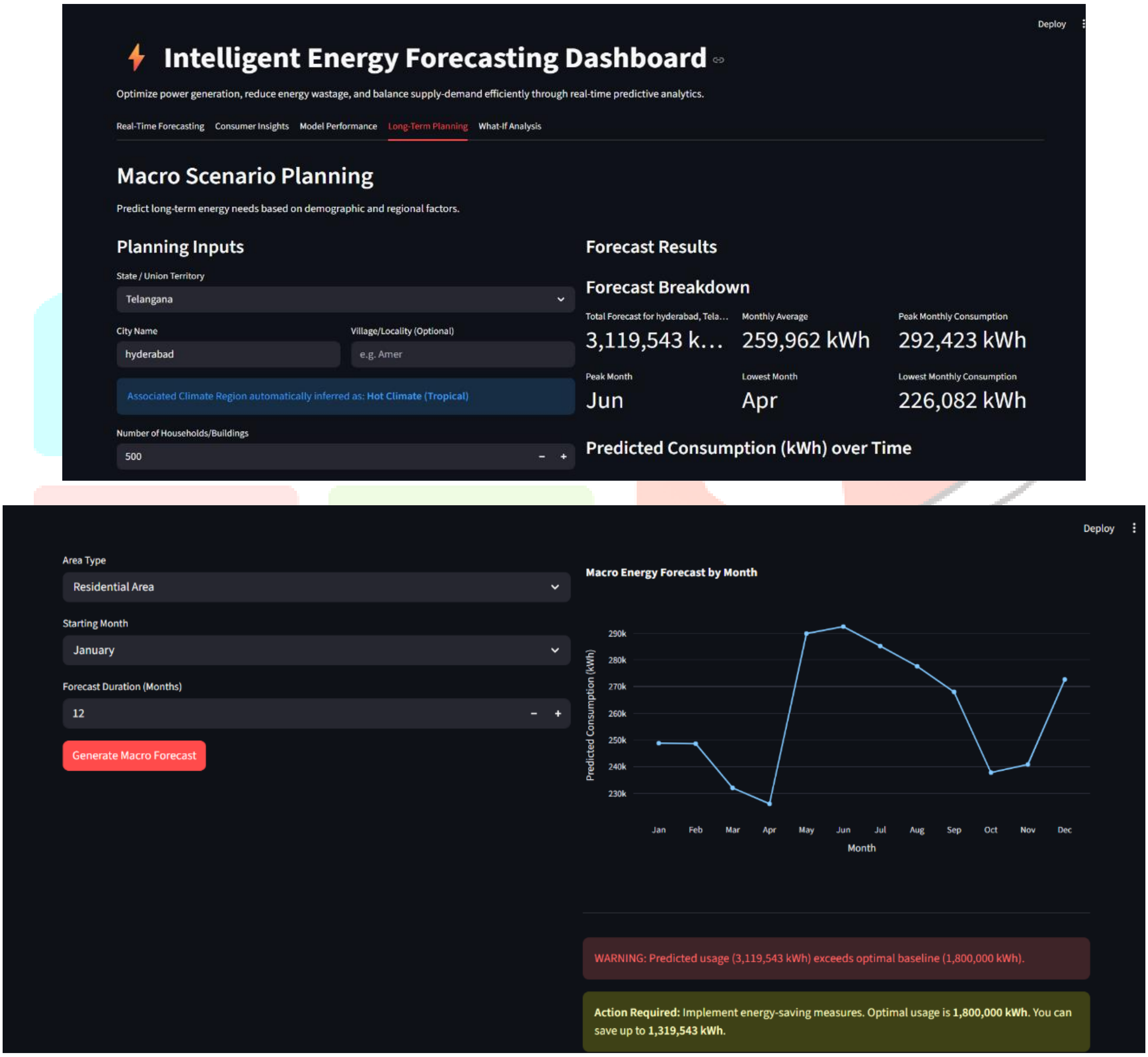


Fig. 4: Macro-level Scenario Forecast

In macro forecasting, the forecast of future energy consumption is determined by certain factors like place of residence (Hyderabad), climate category (tropical), number of families (500), and type of area (residential).

Output results:

Total forecast consumption: 3,119,543 kWh

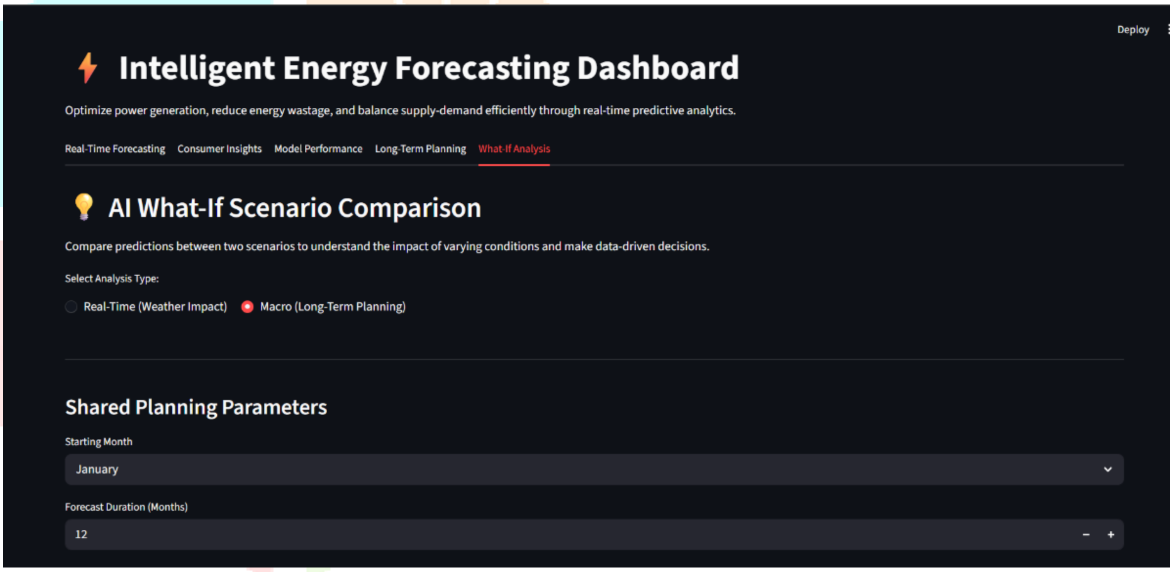
Average monthly consumption: 259,962 kWh

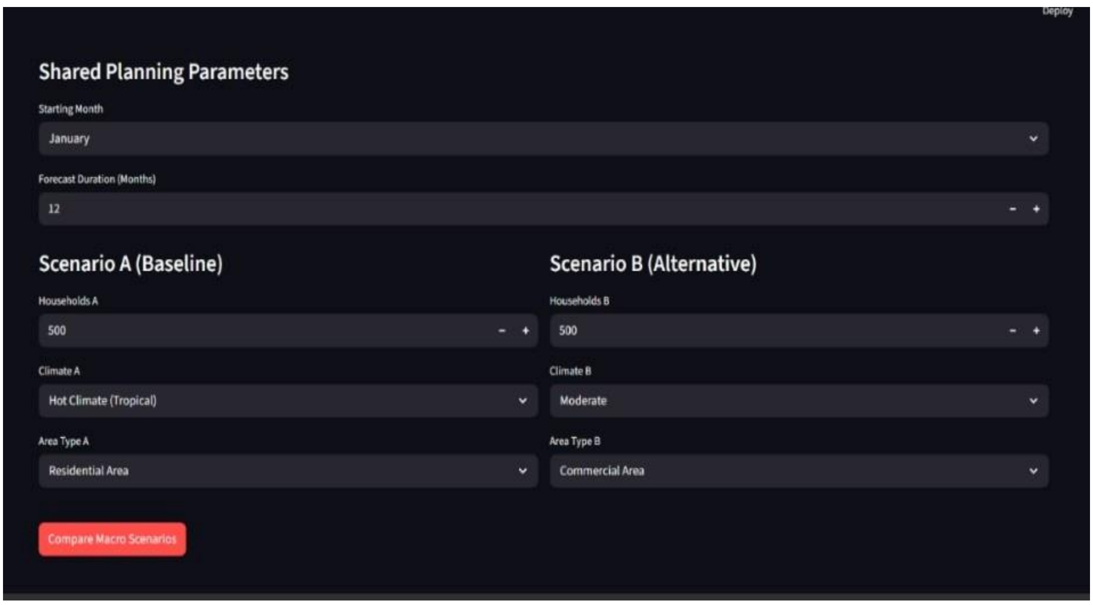
Maximum month of energy consumption: June

Minimum month of energy consumption: April

Line chart indicates the trend of energy consumption forecast for each month, reflecting high energy consumption levels in summer months

4.5 Analysis of What-If Scenarios





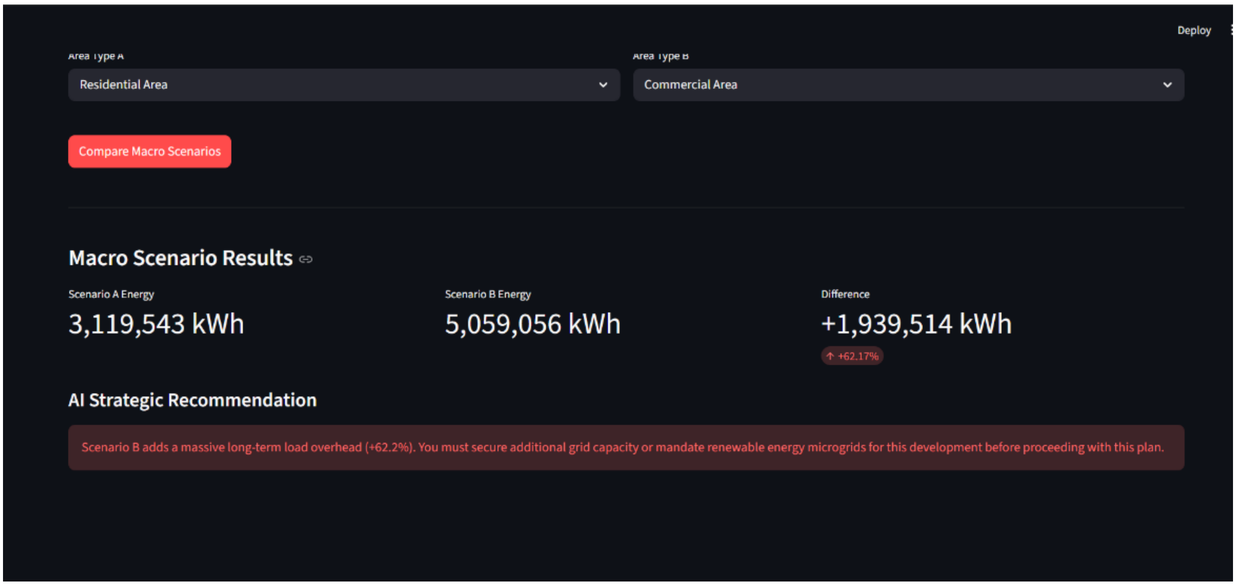


Fig. 5: Scenario Comparison (Baseline and Alternative Scenarios)

The following comparison between these two scenarios is made by the system:

- Scenario A (Baseline): Tropical residential area
- Scenario B (Alternative): Moderated commercial area

Output Results:

Scenario A: 3,119,543 kWh

Scenario B: 5,059,056 kWh

Difference: +62.17%

The system gives a warning sign, saying that Scenario B needs to be optimized using energy conservation strategies or expanding the capacity of the electricity grid.

This case study demonstrates the capability of the system to aid in decision-making related to future development.

5.APPLICATIONS/DISCUSSION/ABLATION STUDY

5.1 Applications

Such a system is highly flexible and as such, can be applied in many fields related to energy management and technologies. For instance, within the framework of smart cities, this system will assist in forecasting the energy demand of power consumers in real time and provide efficient power distribution without any fear of blackouts. The utilities will be able to apply this technology in their load balancing processes, including grid stabilization through forecasts of high energy consumption.

The system will be useful in assisting households, companies, and other business organizations to conserve energy. The macro-energy forecast system will be quite essential in helping city administrators and policy makers forecast long-term energy demands by taking into account different demographical and environmental factors.

The energy forecast system will be instrumental in helping various industrial facilities manage their power consumption efficiently to save costs and increase efficiency. Through the application of the What If

Analysis, different stakeholders will be able to find out the impact that variations in climatic conditions and population increase have on energy demands.

5.2 Discussion

The results analysis offered by the developed framework makes it possible to conclude about the effectiveness of machine learning algorithms in energy consumption prediction. Among the examined algorithms, the most accurate prediction with the lowest level of errors was made using the Support Vector Machine (SVM). Thus, the nonlinearity of the connection between environmental factors and energy consumption has a significant impact on the forecast, and this issue requires more complex methods, including SVM.

The real-time forecasting module makes it possible to monitor changes due to temperature and humidity, whereas the macro-forecasting module can help analyse general patterns of energy consumption. In addition, visualization makes it easier for users to understand the consumption pattern and take adequate measures.

Nonetheless, there are a few limitations of the developed framework. First of all, the validity of the forecast is dependent on the volume and quality of training data used to train the models. An insufficient number of features may result in ignoring many aspects influencing energy consumption. Furthermore, a greater complexity of models leads to higher computational costs.

Thus, in conclusion, one can say that the developed model is a useful tool for forecasting energy consumption.

5.3 Ablation study

An ablation experiment was conducted to evaluate the contribution of various components to the improved prediction accuracy. In this case, some system components were deliberately excluded and altered, and their effects on the prediction accuracy were monitored.

At first, it was observed that the absence of environmental features such as humidity and temperature resulted in low prediction accuracy. In other words, it is evident that the presence of these features greatly influences accuracy improvement. Additionally, it was found out that using the SVM algorithm resulted in improved prediction accuracy compared to linear regression models.

Moreover, the absence of the scenario analysis module greatly influenced the strategic planning for the future decisions. Finally, without visualization tools, it will not be easy to analyse and understand the results obtained from the system.

Therefore, all the system components play a very important role in the accuracy improvement process.

6 CONCLUSION

The current research develops an energy usage forecast system based on machine learning techniques. As indicated, the developed model effectively predicts energy usage based on environmental and population features and generates short-term and long-term predictions simultaneously.

The optimal algorithm from the tested models is the Support Vector Machine that demonstrates high prediction accuracy and is appropriate for making difficult predictions. In combination with machine learning and a user-friendly graphical user interface, the proposed system becomes convenient and easily accessible.

The system described in this study can be regarded as an innovative, inexpensive, and efficient approach to energy management. It will help enhance smart energy systems and energy usage sustainability.

Possible improvements could consist of including additional factors, such as appliance consumption, and deep learning algorithms, thus increasing prediction accuracy.

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