Research on to Develop an AI Based Model for Electricity Demand Projection Including Peak Demand Projection for Delhi Power System

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Abstract - *The increasing complexity of electricity consumption patterns in metropolitan cities such as Delhi has made accurate demand and peak load forecasting a critical requirement for efficient power system planning and operation. Rapid urbanization, climate variability, and rising use of energy-intensive appliances contribute to significant fluctuations in electricity demand, particularly during peak periods. Traditional forecasting techniques often fail to capture the non-linear relationships between demand, weather conditions, and temporal factors.*

This paper presents the development of an AI-based electricity demand projection system designed to forecast both overall load and peak demand for the Delhi power system. Historical electricity consumption and related datasets are analyzed and preprocessed using data science techniques, including feature engineering and normalization. Machine learning models such as Random Forest, Support Vector Machine, and XGBoost are implemented to model complex demand patterns, with SMOTE applied where required to handle data imbalance during peak demand scenarios. Model performance is evaluated using standard error metrics to identify the most accurate forecasting approach.

A Python Flask-based web application is developed to provide interactive visualization of demand forecasts and power analysis results. The proposed system demonstrates improved forecasting accuracy and reliability, supporting better operational planning, peak load management, and sustainable energy management for urban power systems.

Key words: **Electricity Demand Projection, Random Forest, SVM, SMOTE, XGBoost.**

1. INTRODUCTION

Electricity demand forecasting plays a crucial role in the planning, operation, and reliability of modern power systems. In rapidly growing metropolitan cities such as Delhi, the continuous increase in population, urban infrastructure, and commercial activity has led to a significant rise in electricity consumption. Seasonal variations, extreme weather conditions, and changing consumer behavior further contribute to highly dynamic and non-linear demand patterns. Accurate forecasting of electricity demand, particularly during peak load periods, is therefore essential to ensure grid stability, efficient resource utilization, and uninterrupted power supply.

Traditional electricity demand forecasting methods primarily rely on historical averages and linear statistical models. While these approaches have been widely used, they often struggle to capture the complex interactions between multiple influencing factors such as temperature, humidity, holidays, and economic activity. As a result, conventional models frequently produce inaccurate predictions during peak demand periods, increasing the risk of grid stress, power outages, and costly emergency power procurement.

The growing availability of large-scale historical load data, weather information, and advancements in data science have enabled the adoption of Artificial Intelligence (AI) and Machine Learning (ML) techniques for electricity demand forecasting. AI-based models such as Random Forest, Support Vector Machines, and XGBoost are capable of learning complex, non-linear relationships within data, making them more effective for demand and peak load prediction compared to traditional approaches. These models can adapt to changing consumption patterns and provide improved forecasting accuracy under varying operating conditions.

In this context, this paper aims to develop an AI-based electricity demand projection system for the Delhi power system, with a specific focus on peak demand forecasting. The proposed system utilizes historical electricity demand and related datasets to train and evaluate multiple machine learning models. Additionally, a Python Flask-based web interface is developed to visualize demand forecasts and perform power analysis, enabling data-driven decision-making for power system planning and management. The outcomes of this paper contribute toward improving grid reliability, reducing operational costs, and supporting sustainable energy management in large urban power systems.

2. LITERATURE REVIEW

2.1. Kavitha Juliet, et al. paper presents an IEEE-style, AI-based forecasting framework that combines classical machine learning methods with advanced deep learning architectures such as Long Short-

Term Memory (LSTM) networks. Data preprocessing, feature engineering, model selection, and experimental outputs visualization are all part of the work. System design, algorithmic formulation, implementation details, and a discussion of forecasting results with reference to real-time graphical outputs are included in the expanded sections.

2.2. Abdul Aziz et al. proposed an AI-based peak power demand forecasting model that emphasizes the combined impact of economic indicators and climate-related features on electricity consumption patterns. The study highlights that traditional load forecasting approaches often neglect macroeconomic variables, leading to reduced accuracy in peak demand estimation. By integrating machine learning techniques with key economic factors such as GDP growth and population trends, along with climatic parameters including temperature and humidity, the proposed model effectively captures the nonlinear relationships influencing peak power demand. The results demonstrate that AI-based models significantly enhance forecasting precision, particularly during extreme demand periods caused by weather variability. This work underscores the importance of incorporating both economic and climate features into intelligent forecasting systems to improve power system reliability, operational planning, and long-term energy management.

2.3. Ashley Josco C presented a constructive study and AI-based framework for electricity demand and peak load forecasting specifically for the Tamil Nadu power system. The research emphasizes the importance of region-specific load forecasting due to variations in climate, industrial activity, and consumer behavior. The proposed framework utilizes artificial intelligence and machine learning techniques to analyze historical electricity consumption data along with weather and temporal features to predict both overall demand and peak load accurately. The study demonstrates that AI-based models outperform conventional statistical methods in handling nonlinear load patterns and seasonal fluctuations. The results highlight improved forecasting accuracy, making the framework effective for operational planning, demand-side management, and infrastructure development within the Tamil Nadu power system.

2.4. Mustafa Sağlam et al. investigated the application of artificial intelligence techniques for electricity demand forecasting in the isolated power system of Gökçeada Island. The study highlights the limitations of conventional forecasting approaches in small and islanded power networks, where demand patterns are highly sensitive to seasonal tourism, weather conditions, and population variation. AI-based models were employed to analyze historical electricity consumption and climatic factors, enabling accurate short- and medium-term demand prediction. The results demonstrated that artificial intelligence methods significantly improved forecasting accuracy compared to traditional statistical techniques, particularly in capturing nonlinear and seasonal demand behavior. This research emphasizes the effectiveness of AI-driven forecasting models for localized power systems and supports their role in improving energy planning, reliability, and sustainability in isolated grid environments.

2.5. Shuang Dai presented a comprehensive review of machine learning applications in peak demand forecasting, focusing on the theoretical foundations, emerging trends, and practical insights in power systems. The study discusses how traditional statistical forecasting techniques face limitations in accurately predicting peak load due to their inability to model complex nonlinear relationships and extreme demand events. Various machine learning approaches, including support vector machines, decision trees, ensemble learning, and deep learning models such as LSTM, are analyzed for their effectiveness in peak demand prediction. The review highlights the growing importance of feature engineering, data quality, and hybrid modeling approaches to enhance forecasting performance. The findings emphasize that machine learning-based methods offer improved accuracy, adaptability, and scalability, making them essential tools for reliable peak demand forecasting in modern and smart power grids.

2.6. Nguyen Hoang Lan et al. conducted a bibliometric analysis of research published in the Scopus database to examine the application of basic artificial intelligence models in electric load forecasting. The study systematically reviews the evolution of AI-based forecasting methods, highlighting frequently used techniques such as Artificial Neural Networks, Support Vector Machines, decision trees, and ensemble models. The analysis identifies key research trends, influential authors, and dominant application areas, revealing a growing interest in AI-driven load forecasting due to its superior accuracy over traditional statistical approaches. The findings emphasize the increasing adoption of AI models for both demand and peak load forecasting, as well as the need for further research on model optimization and real-world power system implementation. This bibliometric study provides valuable insights into the development and future direction of AI-based electric load forecasting research.

2.7. Kibaek Kim et al. proposed a real-time AI-based power demand forecasting framework aimed at peak shaving and energy consumption reduction through the integration of vehicle-to-grid (V2G) technology and reused energy storage systems. The study demonstrates how artificial intelligence models can accurately forecast short-term power demand in real time, enabling optimal control of distributed energy resources to reduce peak load. Using a business center on Jeju Island as a case study, the system effectively coordinated energy storage and V2G operations based on predicted demand patterns. The results showed significant peak demand reduction, improved energy efficiency, and cost savings, highlighting the practical applicability of AI-driven forecasting for demand-side management and smart energy systems.

2.8. Prof. Madhu Nagraj presented a comprehensive survey on AI-powered energy consumption forecasting and prediction techniques used in modern power systems. The study reviews a wide range of artificial intelligence and machine learning models, including Artificial Neural Networks, Support Vector Machines, decision trees, ensemble learning methods, and deep learning architectures, highlighting their effectiveness in short-term, long-term, and peak load forecasting. The survey emphasizes the role of advanced feature extraction, real-time data analytics, and hybrid AI models in improving forecasting accuracy. It also discusses challenges such as data quality, scalability, and integration with smart grid infrastructure. The findings indicate that AI-based forecasting approaches significantly outperform traditional methods and are critical for efficient energy management, demand response planning, and sustainable power system operation.

2.9. Elmar Ibrahimov examined AI-driven approaches for household-level electricity load forecasting, focusing on key challenges, methodologies, and future research directions. The study discusses the complexity of residential load patterns influenced by occupant behavior, appliance usage, and weather variability, which pose challenges for accurate forecasting. Various artificial intelligence techniques, including machine learning and deep learning models such as ANN, SVM, and LSTM, are reviewed for their effectiveness in capturing nonlinear and high-resolution consumption data. The paper also highlights issues related to data privacy, scalability, and model generalization. The findings suggest that AI-based household load forecasting plays a crucial role in demand response, peak load management, and smart home energy systems, while emphasizing the need for robust and adaptive forecasting models in future smart grids.

2.10. Chowdhury's research presents an integrated AI framework for forecasting and optimizing energy consumption across urban and institutional sectors in the USA, addressing the limitations of traditional energy management methods that often fail to handle dynamic and non-linear consumption patterns. The study utilizes extensive datasets containing electricity usage, peak demand, weather variations, and building characteristics, and applies advanced machine learning models such as Random Forest, XGBoost, Support Vector Regression, and Long Short-Term Memory (LSTM) networks to achieve high-precision demand forecasts. To further enhance energy optimization, the framework incorporates reinforcement learning for adaptive control, along with clustering and anomaly detection techniques to identify consumption patterns and irregular behaviors. This combined approach not only improves forecasting accuracy but also supports sustainable energy planning, operational efficiency, and reduced environmental impact, providing valuable insights for policymakers, urban planners, and facility managers.

3. METHODOLOGY

The proposed system is an AI-based electricity demand and peak load forecasting framework designed for the Delhi power system. The system utilizes historical electricity consumption data along with relevant weather and temporal parameters such as temperature, humidity, day type, and seasonal indicators. The collected data is preprocessed through cleaning, normalization, and feature engineering to enhance data quality and model performance.Machine learning models including Random Forest, Logistic Regression, Support Vector Machine, and XGBoost are employed to learn complex, non-linear relationships between input features and electricity demand. To improve peak load prediction and handle data imbalance during extreme demand conditions, the SMOTE technique is applied where required. The trained models are evaluated using standard performance metrics to identify the mostaccurate forecasting approach.The system also includes a Python Flask-based web application that enables users to visualize electricity demand trends, peak load forecasts, and power analysis results in an interactive manner. By providing accurate demand and peak projections, the proposed system supports effective operational planning, peak load management, and data-driven decision-making for reliable and efficient power system operation.

FLOW CHART

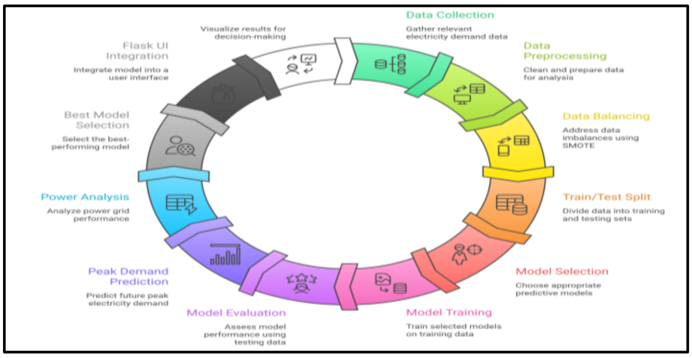


Fig -1: Shows the Flow chart of the system

3.1. WORKING

The system begins by collecting historical electricity demand and weather data for the Delhi power system. The collected data is preprocessed through cleaning, normalization, and feature engineering to improve data quality. If peak demand data is imbalanced, SMOTE is applied to balance the dataset. The processed data is then divided into training and testing sets, and machine learning models such as Logistic Regression, Random Forest, SVM, and XGBoost are trained. The trained models are evaluated using standard error metrics, and the best-performing model is selected for forecasting. The selected model is used to predict electricity demand and peak load, followed by power analysis to study demand trends and peak behavior. Finally, the forecasting results are integrated into a Python Flask-based web application for visualization and user interaction.

3.1.1. SYSTEM REQUIREMENT

SOFTWARE REQUIREMENT:

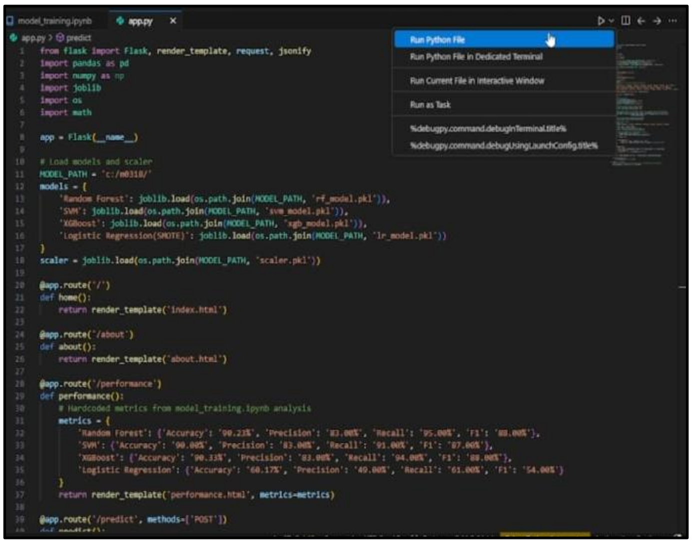
- Python Software

MODULES USED:

- Flask

4. IMPLEMENTATION & RESULT

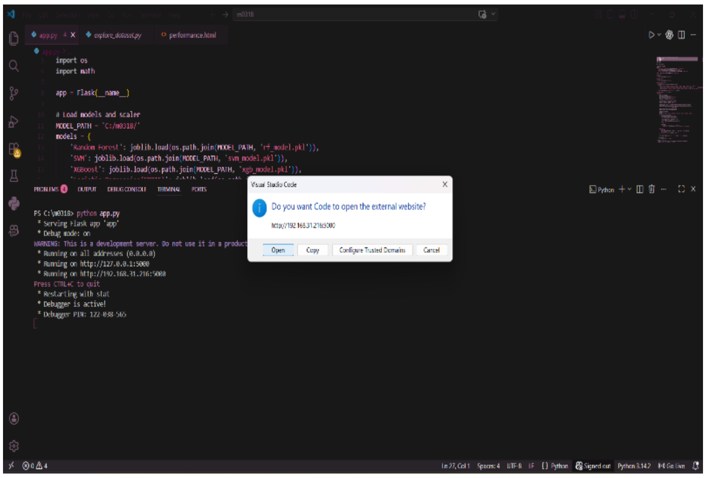
Step 1: Model Integration and Flask Application Setup



```python
from flask import Flask, render_template, request, jsonify
import pandas as pd
import numpy as np
import joblib
import os
import math

app = Flask(__name__)

# Load models and scaler
MODEL_PATH = 'c:/m0318/'
models = {
    'Random Forest': joblib.load(os.path.join(MODEL_PATH, 'rf_model.pkl')),
    'SVM': joblib.load(os.path.join(MODEL_PATH, 'svm_model.pkl')),
    'XGBoost': joblib.load(os.path.join(MODEL_PATH, 'xgb_model.pkl')),
    'Logistic Regression(SMOTE)': joblib.load(os.path.join(MODEL_PATH, 'lr_model.pkl'))
}
scaler = joblib.load(os.path.join(MODEL_PATH, 'scaler.pkl'))

@app.route('/')
def home():
    return render_template('index.html')

@app.route('/about')
def about():
    return render_template('about.html')

@app.route('/performance')
def performance():
    # Hardcoded metrics from model_training.ipynb analysis
    metrics = {
        'Random Forest': {'Accuracy': '90.23%', 'Precision': '83.00%', 'Recall': '95.00%', 'F1': '88.00%'},
        'SVM': {'Accuracy': '90.00%', 'Precision': '83.00%', 'Recall': '91.00%', 'F1': '87.00%'},
        'XGBoost': {'Accuracy': '90.33%', 'Precision': '83.00%', 'Recall': '94.00%', 'F1': '88.00%'},
        'Logistic Regression': {'Accuracy': '60.17%', 'Precision': '49.00%', 'Recall': '61.00%', 'F1': '54.00%'}
    }
    return render_template('performance.html', metrics=metrics)

@app.route('/predict', methods=['POST'])
```

Fig -2: Shows running the Python file to start the Flask application

The Python file of the Flask application is executed using the “Run Python File” option in the code editor. Once the program starts running, the Flask server gets activated and all the required modules and trained machine learning models are loaded into the system. This includes models like Random Forest, SVM, XGBoost, and Logistic Regression. After successful execution, the system becomes ready to accept user inputs through the web interface and perform electricity demand and peak load prediction.



```python
import os
import math

app = Flask(__name__)

# Load models and scaler
MODEL_PATH = 'C:/m0318/'
models = {
    'Random Forest': joblib.load(os.path.join(MODEL_PATH, 'rf_model.pkl')),
    'SVM': joblib.load(os.path.join(MODEL_PATH, 'svm_model.pkl')),
    'XGBoost': joblib.load(os.path.join(MODEL_PATH, 'xgb_model.pkl')),
```

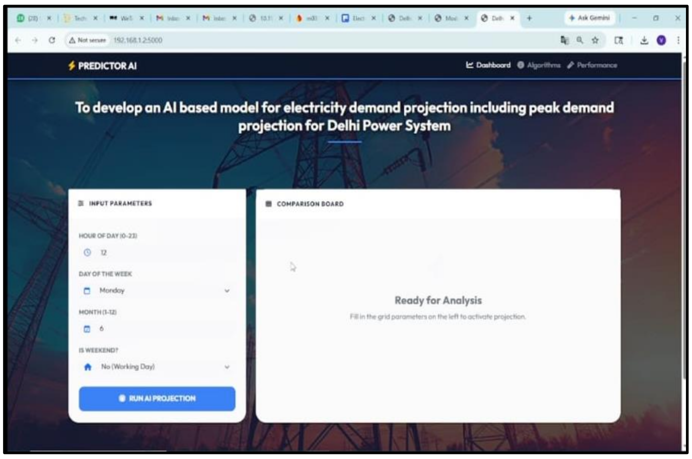
```
PS C:\m0318> python app.py
 * Serving Flask app 'app'
 * Debug mode: on
WARNING: This is a development server. Do not use it in a product
 * Running on all addresses (0.0.0.0)
 * Running on http://127.0.0.1:5000
 * Running on http://192.168.31.216:5000
Press CTRL+C to quit
 * Restarting with stat
 * Debugger is active!
 * Debugger PIN: 122-038-565
```

Do you want Code to open the external website?

http://192.168.31.216:5000

Fig -3: Shows the terminal window

The terminal window shows that the Flask application has started running successfully. After running the Python file, a URL link is generated and displayed in the terminal. By clicking or opening this link in a web browser, the user interface of the application is launched.



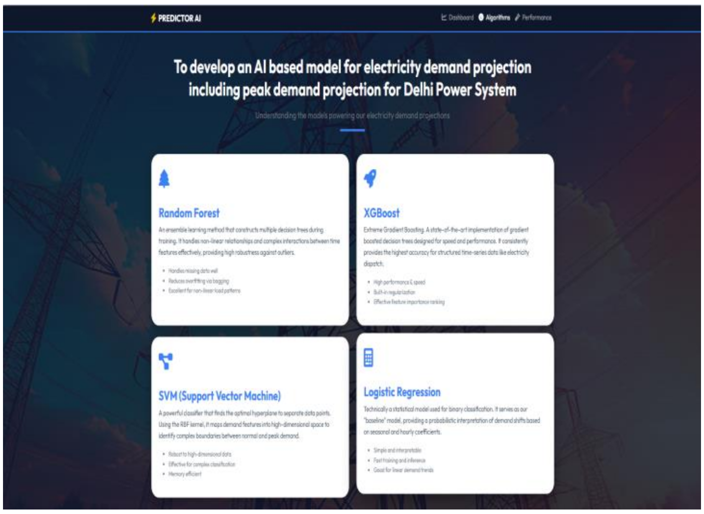
To develop an AI based model for electricity demand projection including peak demand projection for Delhi Power System

HOUR OF DAY (0-23): 12
DAY OF THE WEEK: Monday
MONTH (1-12): 6
IS WEEKEND?: No (Working Day)

Ready for Analysis

Fill in the grid parameters on the left to activate projection.

Fig -4: Shows the dashboard of the system



To develop an AI based model for electricity demand projection including peak demand projection for Delhi Power System

Understanding the models powering our electricity demand projections

Random Forest

An ensemble learning method that constructs multiple decision trees during training. It handles non-linear relationships and complex interactions between time features effectively, providing high robustness against outliers.

- Handles missing data well
- Reduces overfitting via bagging
- Excellent for non-linear load patterns

XGBoost

Extreme Gradient Boosting. A state-of-the-art implementation of gradient boosted decision trees designed for speed and performance. It consistently provides the highest accuracy for structured time-series data like electricity dispatch.

- High performance & speed
- Built-in regularization
- Effective feature importance ranking

SVM (Support Vector Machine)

A powerful classifier that finds the optimal hyperplane to separate data points. Using the RBF kernel, it maps demand features into high-dimensional space to identify complex boundaries between normal and peak demand.

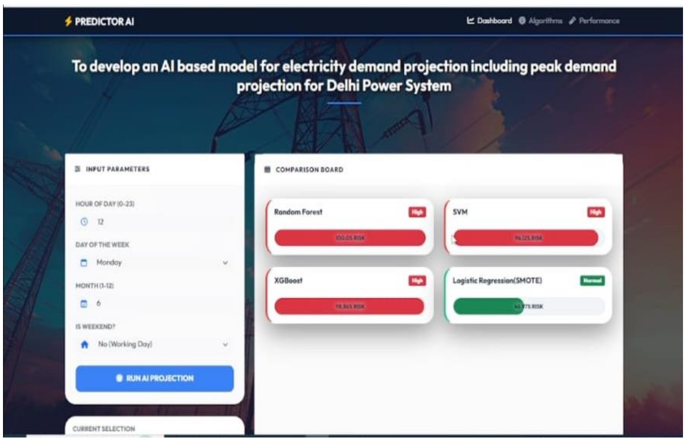
- Robust to high-dimensional data
- Effective for complex classification
- Memory efficient

Logistic Regression

Technically a statistical model used for binary classification. It serves as our "baseline" model, providing a probabilistic interpretation of demand shifts based on seasonal and hourly coefficients.

- Simple and interpretable
- Fast training and inference
- Good for linear demand trends

Fig -5: Shows the web interface displaying the different machine learning algorithms used in the system



To develop an AI based model for electricity demand projection including peak demand projection for Delhi Power System

INPUT PARAMETERS

HOUR OF DAY (0-23): 12
DAY OF THE WEEK: Monday
MONTH (1-12): 6
IS WEEKEND?: No (Working Day)

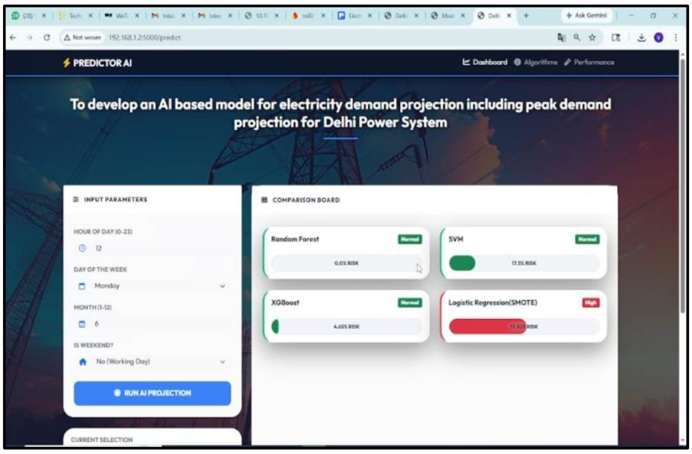
CURRENT SELECTION

COMPARISON BOARD

Random Forest: High
SVM: High
XGBoost: High
Logistic Regression(SMOTE): Normal

Fig -6: Shows the prediction results of different machine learning models displayed on the web interface

The system displays the prediction results after the user enters input parameters and runs the model. The output shows predictions from different machine learning models such as Random Forest, SVM, XGBoost, and Logistic Regression with SMOTE. The Random Forest model predicts a peak demand condition with 100% risk, while the SVM model also indicates peak demand with 96.12% risk. Similarly, the XGBoost model shows a peak condition with 98.86% risk, indicating strong prediction performance. In contrast, the Logistic Regression model with SMOTE predicts a normal demand condition with 46.97% risk. This allows the user to compare the results of multiple models at the same time. The visual representation makes it easy to understand the prediction outcome and clearly shows that ensemble models like Random Forest and XGBoost provide more reliable results for electricity demand and peak load forecasting.



To develop an AI based model for electricity demand projection including peak demand projection for Delhi Power System

INPUT PARAMETERS

HOUR OF DAY (0-23): 12
DAY OF THE WEEK: Monday
MONTH (1-12): 6
IS WEEKEND?: No (Working Day)

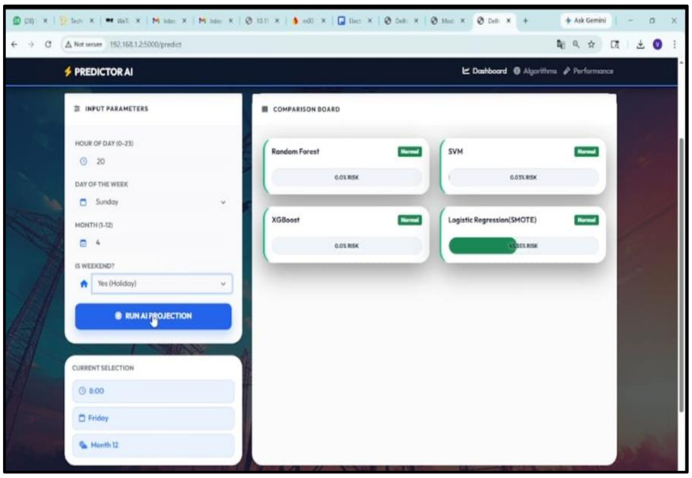
CURRENT SELECTION

COMPARISON BOARD

Random Forest: Normal, 0.0% RISK
SVM: Normal
XGBoost: Normal, 4.65% RISK
Logistic Regression(SMOTE): High

Fig -7: Shows the prediction results with variation among different machine learning models

The system displays prediction results where different models give slightly varied outputs for the same input parameters. The Random Forest model predicts a normal demand condition with around 0.01% risk, while the SVM model also indicates normal demand with approximately 13.5% risk. Similarly, the XGBoost model shows a normal condition with about 4.65% risk. However, the Logistic Regression model with SMOTE predicts a peak demand condition with a higher risk of around 53.67%. This variation highlights the difference in learning capability of models, where ensemble models like Random Forest and XGBoost provide more stable predictions, while Logistic Regression may behave differently due to its linear nature. This step helps in understanding model comparison and reliability in real-world scenari



INPUT PARAMETERS

HOUR OF DAY (0-23): 20
DAY OF THE WEEK: Sunday
MONTH (1-12): 4
IS WEEKEND?: Yes (Holiday)

CURRENT SELECTION

8:00
Friday
Month 12

COMPARISON BOARD

Random Forest: Normal, 0.0% RISK
SVM: Normal, 0.03% RISK
XGBoost: Normal, 0.0% RISK
Logistic Regression(SMOTE): Normal

Fig -8: Shows the prediction results indicating normal electricity demand conditions

The system displays the prediction results for another set of input parameters. The output shows that all machine learning models predict a normal demand condition. The Random Forest model shows a very low risk of around 0.01%, while the SVM model indicates approximately 0.03% risk. Similarly, the XGBoost model also predicts a normal condition with about 0.0% risk. The Logistic Regression model with SMOTE shows a comparatively higher value of around 45.55% risk, but it still falls under the normal category. This result demonstrates that the system is able to identify both peak and normal demand scenarios effectively based on different input conditions, providing reliable and consistent predictions.

RESULT

The developed AI-based electricity demand and peak load forecasting system successfully predicts demand conditions using multiple machine learning models integrated with a Flask-based web interface. The system was tested with different input scenarios, including peak, normal, and mixed conditions. In peak scenarios, models like Random Forest, SVM, and XGBoost showed high prediction confidence with values such as 100%, 96.12%, and 98.86% risk respectively, while Logistic Regression showed comparatively lower confidence. In normal conditions, all models predicted low risk values (around 0.01%–0.03%), indicating stable performance. In some cases, variation was observed where Logistic Regression predicted higher risk compared to other models. Overall, ensemble models such as Random Forest and XGBoost demonstrated better accuracy and consistency in capturing complex demand patterns. The system effectively provides reliable electricity demand and peak load predictions, making it useful for power system planning and decision-making.

5. CONCLUSION

This paper highlights the significant impact of artificial intelligence (AI) and machine learning (ML) in promoting energy sustainability through precise forecasting and intelligent optimization of consumption patterns. By utilizing advanced models such as XGBoost, Random Forest, Support Vector Machine (SVM), and SMOTE. The paper effectively captured both temporal dependencies and non-linear relationships within energy usage data. In conclusion, this research advances sustainable energy management by providing an AI-driven framework that enhances forecasting precision.

6. REFERENCE

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