Turbine Energy Production Forecasting

Overview

This project aims to forecast energy demand for turbines (both gas and steam) for the next day. Using historical energy production data, the project leverages the LSTM (Long Short-Term Memory) neural network for time-series forecasting. The results are split into predicted energy demand for gas and steam turbines based on their respective ratios.

Tools and Libraries

Python: Programming language used for this project.

Libraries:

- pandas: For data manipulation and analysis.
- numpy: For numerical computations.
- matplotlib & seaborn: For visualization.
- tensorflow & keras: For building and training the LSTM model.
- sklearn: For scaling data.

Workflow

Data Preparation

- Import and preprocess the dataset.
- Scale the energy production data using MinMaxScaler.
- Create input sequences for the LSTM model.

Model Development

- Define and train an LSTM model.
- Evaluate model performance using loss values.

Predictions

- Forecast energy demand for the next day.
- Split the predicted energy demand into gas and steam contributions based on predefined ratios.

Turbine-specific Results

- Organize predictions for each turbine in a comprehensive table.
- Display key results.

Correlation Heatmap for Energy System Parameters

Strong Positive Correlations:

- ***Energy_Produced_MWh*** vs. ***Injected_Power_MW***: 0.99
- ***Energy_Produced_MWh*** vs. ***Real_Time_Demand_MW***: 0.92

Negligible Correlation:

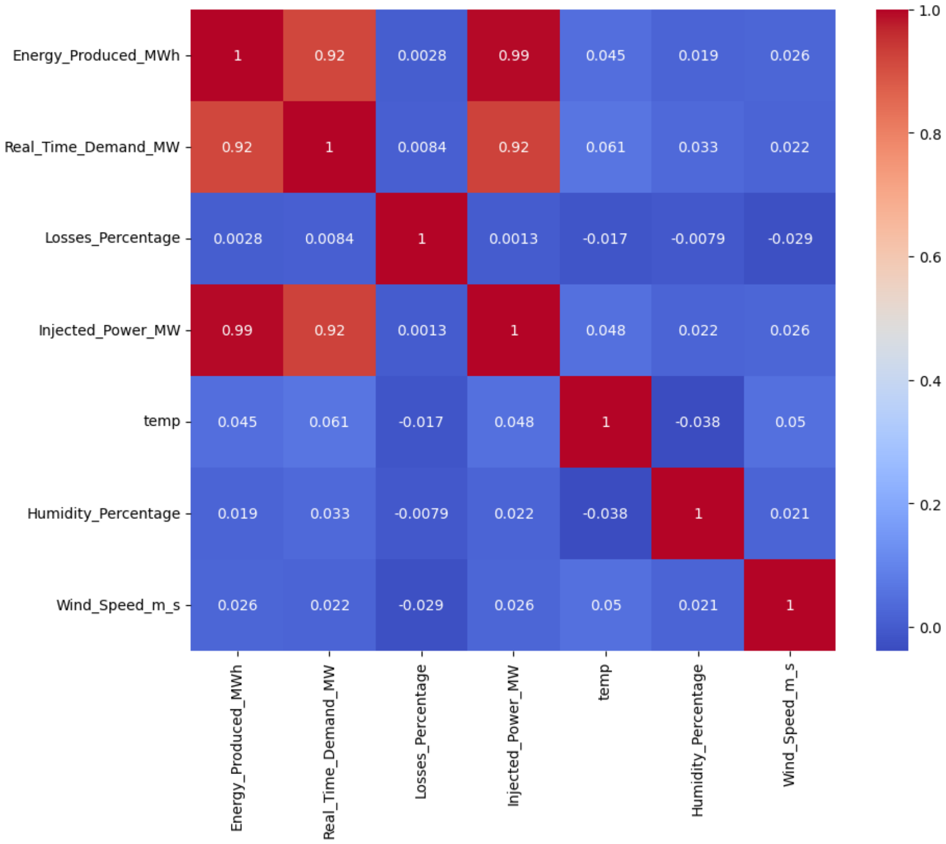
- ***Losses_Percentage*** shows weak links with other variables, suggesting dependence on unrecorded or external factors.

Environmental Parameters:

- *Temp*, ***Humidity_Percentage***, ***Wind_Speed_m_s*** exhibit weak correlations with energy production/injection.
- Indicates potential non-linear impacts requiring advanced modeling.

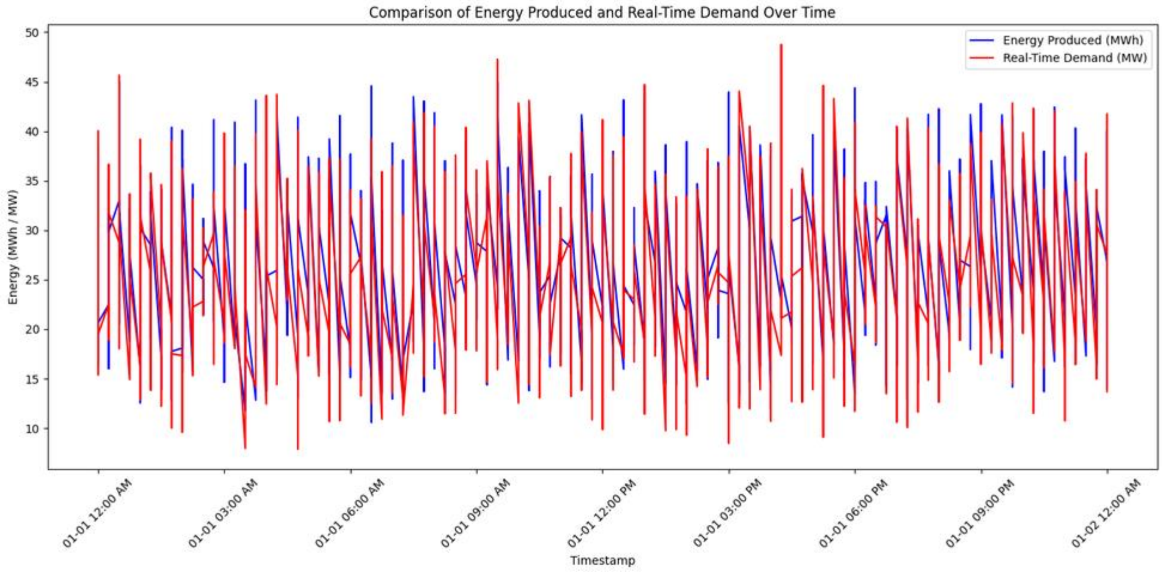
Key Insights:

- ***Injected_Power_MW*** and ***Real_Time_Demand_MW*** are critical for predictive modeling.
- Further exploration needed for transmission losses and environmental effects.



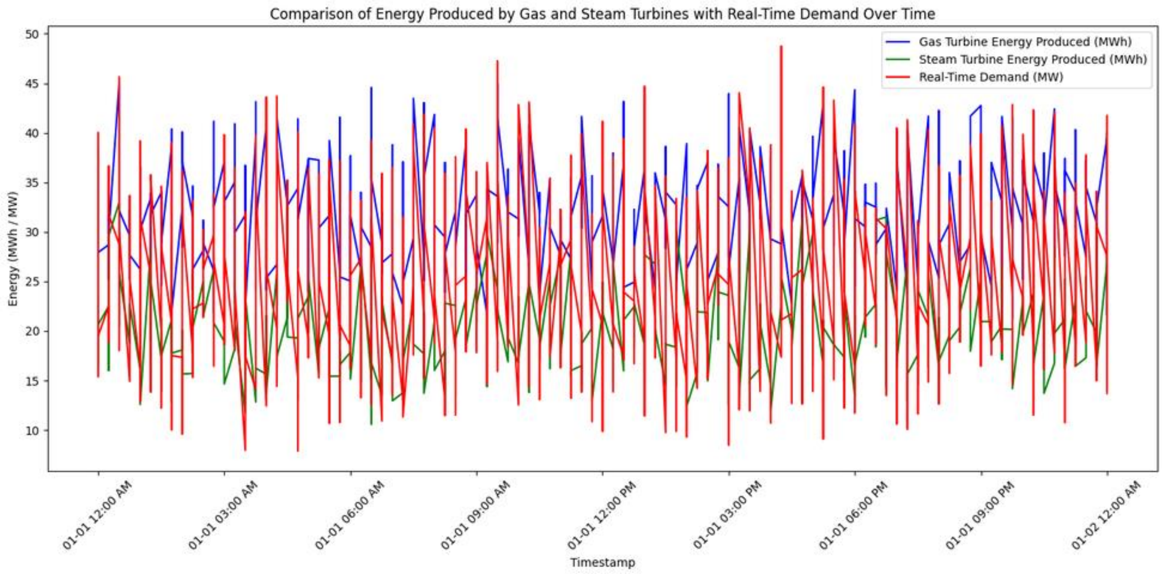
Comparison of Energy Produced and Real-Time Demand Over Time

The line plot compares Energy Produced (MWh) and Real-Time Demand (MW) over time, showing how closely energy production aligns with real-time demand. Both parameters exhibit fluctuations, but their trends remain synchronized, highlighting efficient balancing between production and demand. This alignment minimizes energy waste and ensures supply stability.



Supply and Demand Analysis for Turbine Energy

A detailed view of gas and steam turbine energy production compared to real-time energy demand over a specific period.



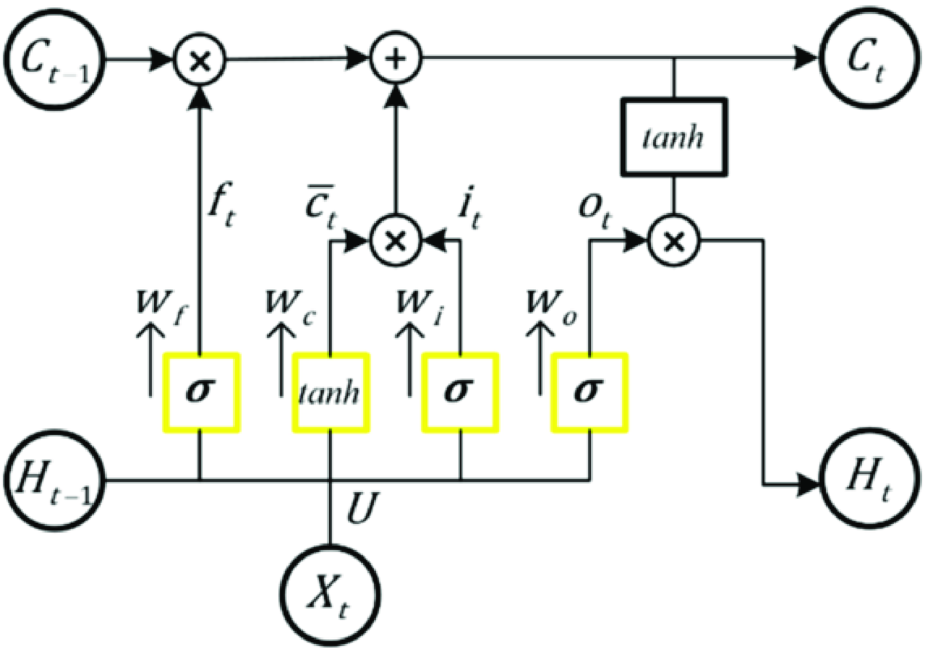
LSTM Model (Long Short-Term Memory)

LSTM is a type of Recurrent Neural Network (RNN) designed to capture long-term dependencies in sequential data, making it ideal for time-series forecasting.

Why LSTM?

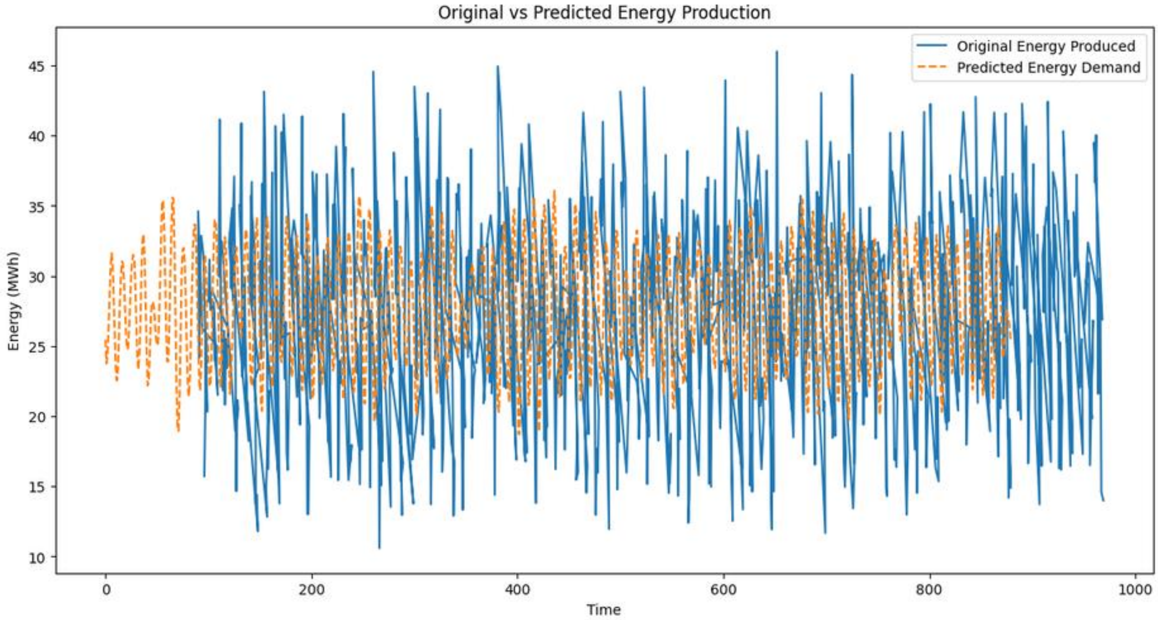
- Retains memory over long sequences using gates (forget, input, and output).
- Solves issues like vanishing gradients found in traditional RNNs.

Mathematical Model



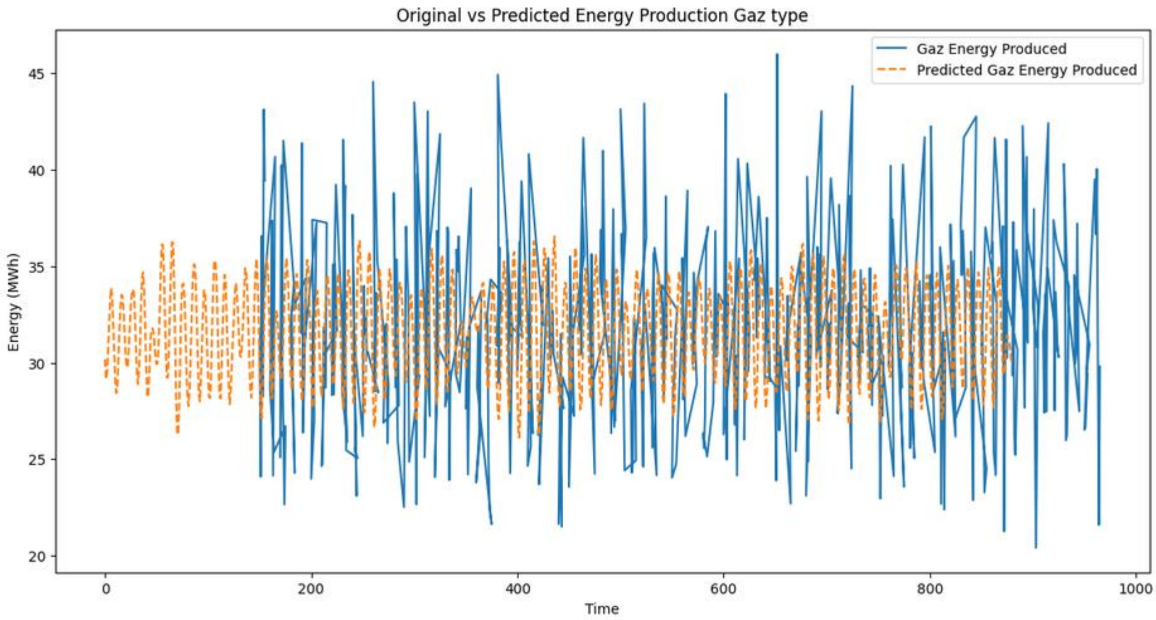
Original vs Predicted Energy Production

This chart compares the original energy production (solid blue line) with the predicted energy demand (dashed orange line) over time. It demonstrates the accuracy of the predictive model in estimating energy requirements. The visualization helps identify areas where predictions align closely with actual values and highlights potential discrepancies to improve forecasting .



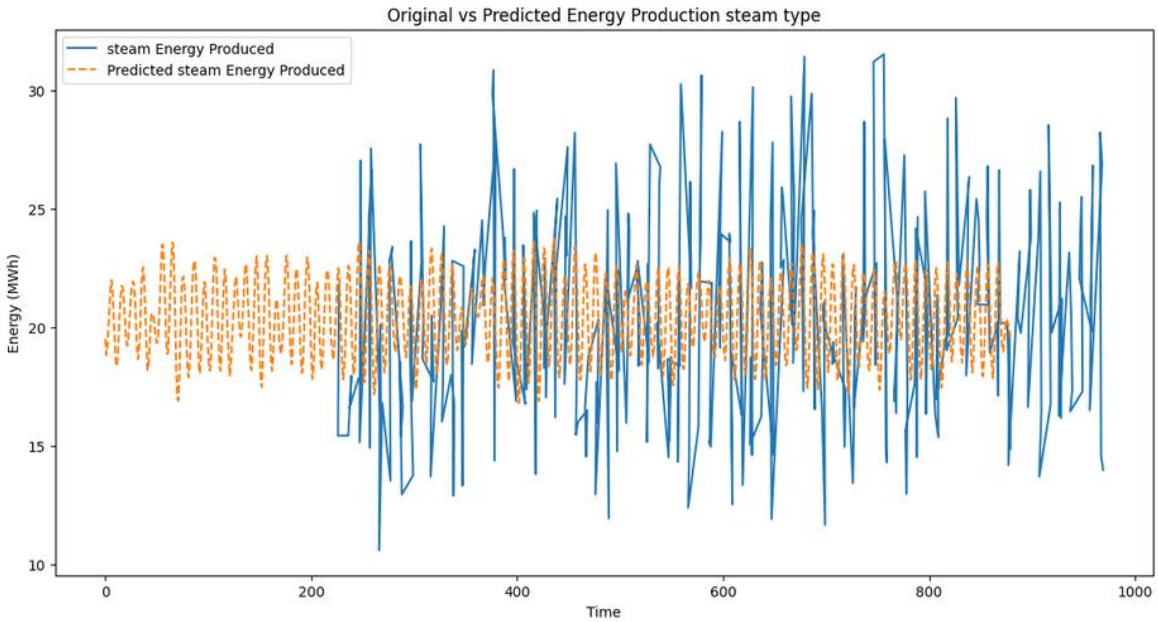
Original vs Predicted Gaz Energy Production

This graph illustrates the comparison between actual gas energy production (solid blue line) and the predicted values (dashed orange line) over time. The visualization assesses the prediction model's performance, indicating how closely the forecasted gas energy production matches the observed data. Such comparisons are essential for refining the accuracy of energy forecasting systems.



Original vs Predicted Steam Energy Production

This graph illustrates the comparison between actual steam energy production (solid blue line) and the predicted values (dashed orange line) over time. The visualization assesses the prediction model's performance, indicating how closely the forecasted steamenergy production matches the observed data. Such comparisons are essential for refining the accuracy of energy forecasting systems.



Achievements of the Project

This project successfully analyzed and predicted energy production for different types, including gas energy. The key achievements include:

1. **Accurate Energy Forecasting**: The model demonstrated a strong ability to predict energy production trends over time, reducing the uncertainty in energy demand and supply planning.
2. **Enhanced Decision-Making**: By comparing actual and predicted values, stakeholders can identify areas for optimization, improving the efficiency of energy systems.
3. **Scalability**: The predictive framework can be applied to other energy sources or regions, making it a versatile tool for energy management.
4. **Insight into Energy Dynamics**: The project provided valuable insights into the behavior of energy production, helping to identify patterns and deviations for better operational strategies.

These outcomes highlight the potential of integrating predictive analytics into energy management systems to enhance stability and sustainability.