Forecasting the Future: Electricity Load and Price Prediction Based on Weather

Team # 8

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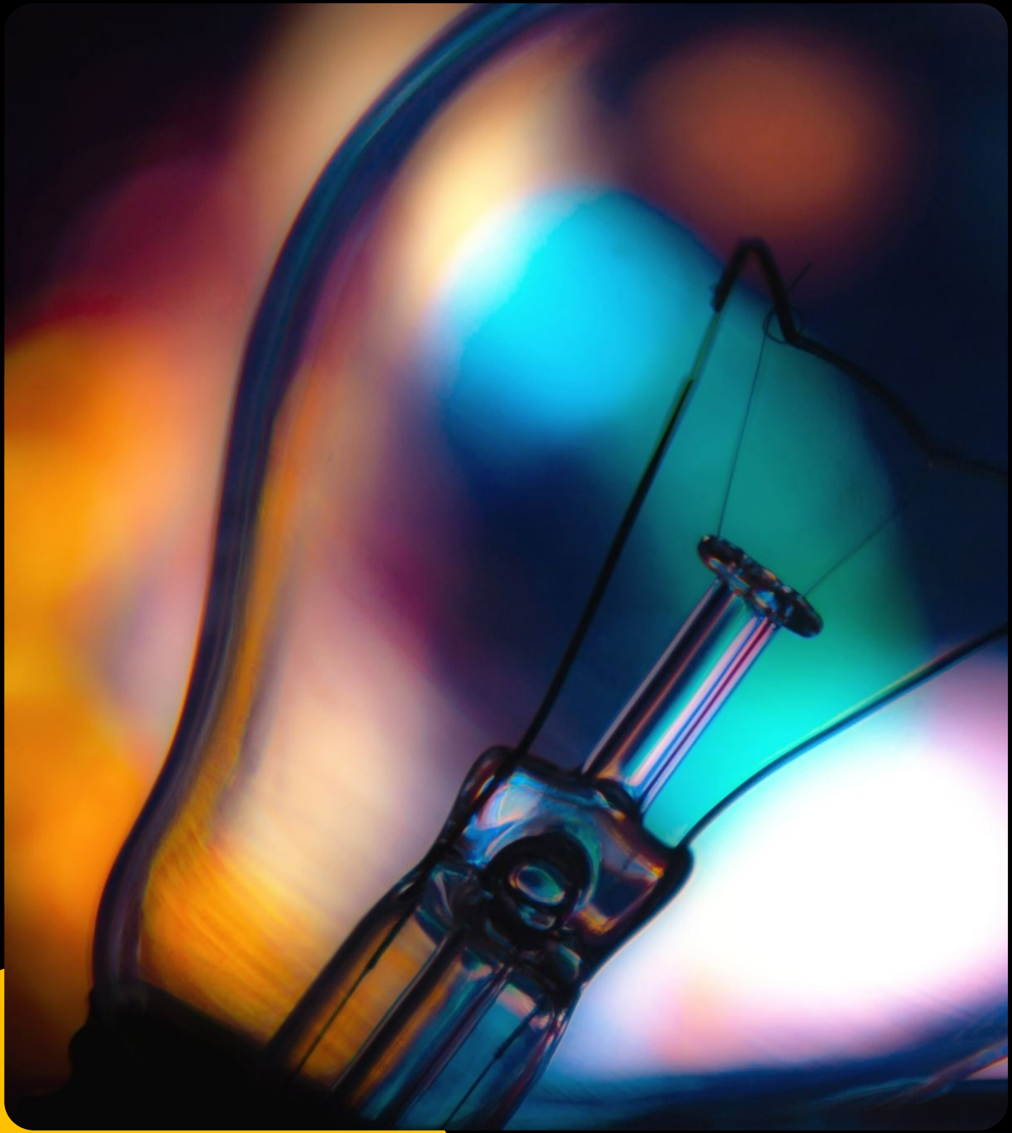
Agenda

- Motivation
- Challenges
- Technical part
- Experimental results
- Conclusion

Motivation



Problem Description:

The issue centers on accurately predicting electricity load and prices, which are significantly impacted by weather conditions.

Importance:

Precise predictions are essential for maintaining the stability and efficiency of the power grid. They also support informed decision-making regarding the allocation of resources and pricing strategies.

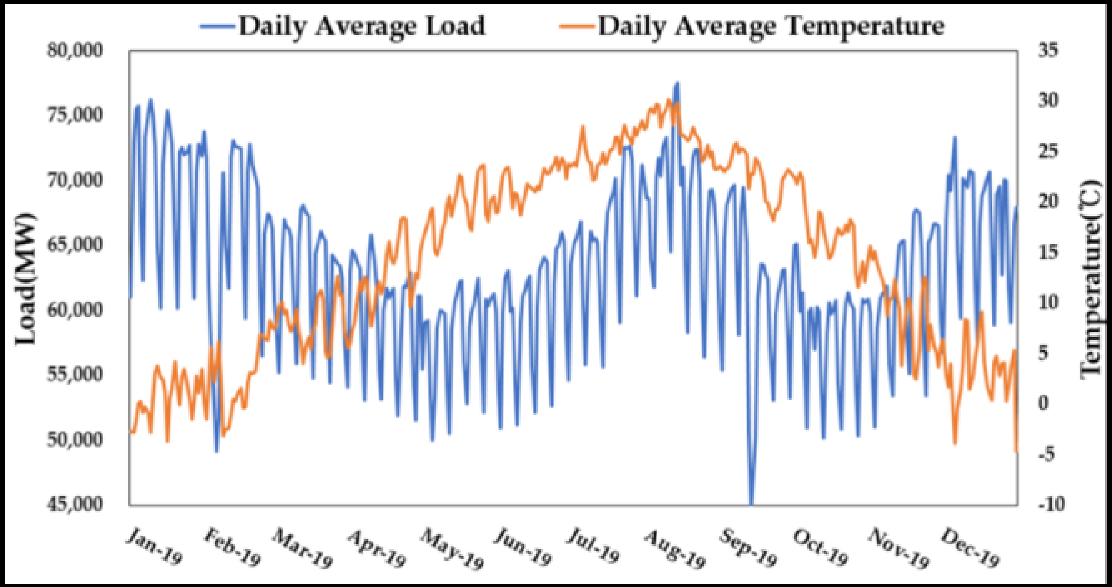
Existing Research:

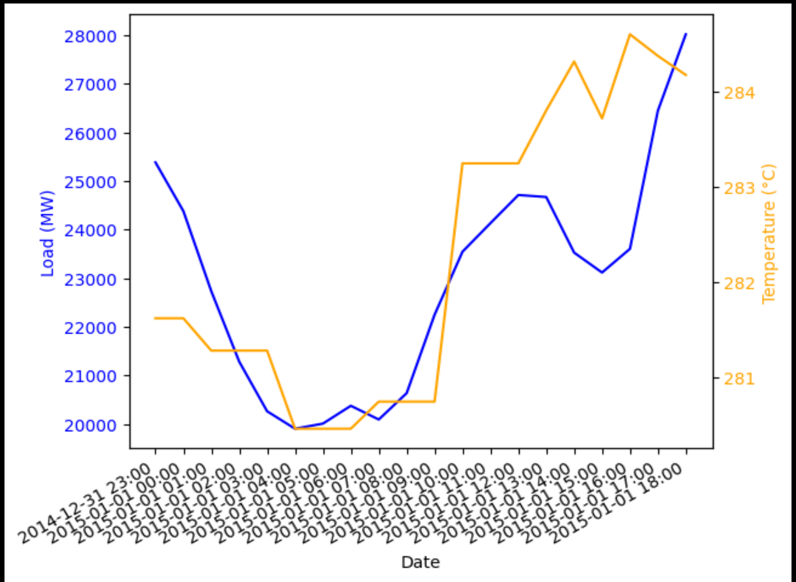
Past studies have utilized a range of approaches to predict electricity load and prices, such as statistical models, time series analysis, and machine learning techniques. Despite these efforts, effectively addressing the complex interplay between weather conditions and energy usage remains a challenge.

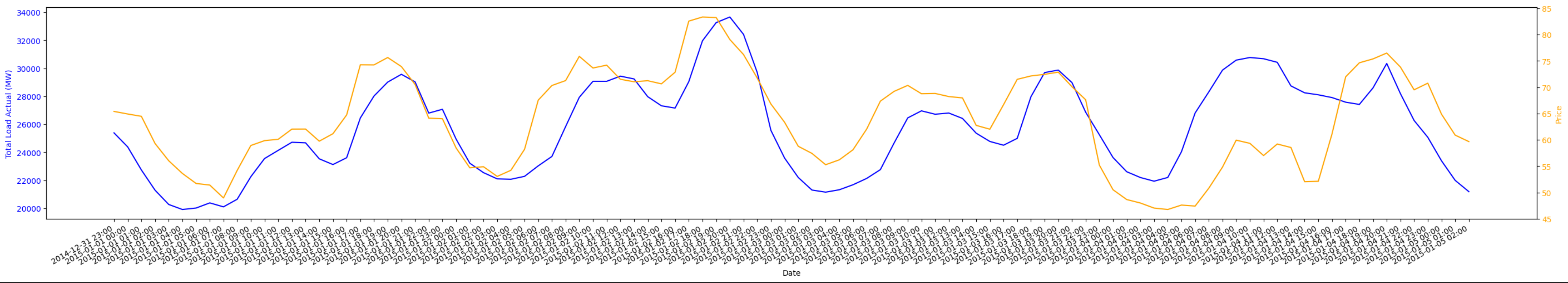
Key Challenge:

The main difficulty is in creating reliable predictive models that can accurately anticipate electricity load and price fluctuations, considering the influence of weather on demand. Traditional approaches often fail to account for the non-linear and dynamic nature of these relationships, underscoring the need for more innovative methods and sophisticated machine learning algorithms.

Image(s)/example(s) to illustrate







Challenges

- **Data Integration and Quality:**
  - Collecting and integrating data from various sources, including weather stations, energy consumption records, and pricing logs, which may not be in compatible formats.
- **Real-time Data Processing:**
  - To be effective, the system might need to process real-time data to forecast demand and pricing accurately.
- **Seasonal and Geographical Variations:**
  - Addressing seasonal variations in weather and energy use patterns, as well as geographical differences in weather impacts.
- **Dynamic Weather Patterns:**
  - Accounting for the increasing unpredictability of weather patterns, possibly due to climate change.

Literature Review

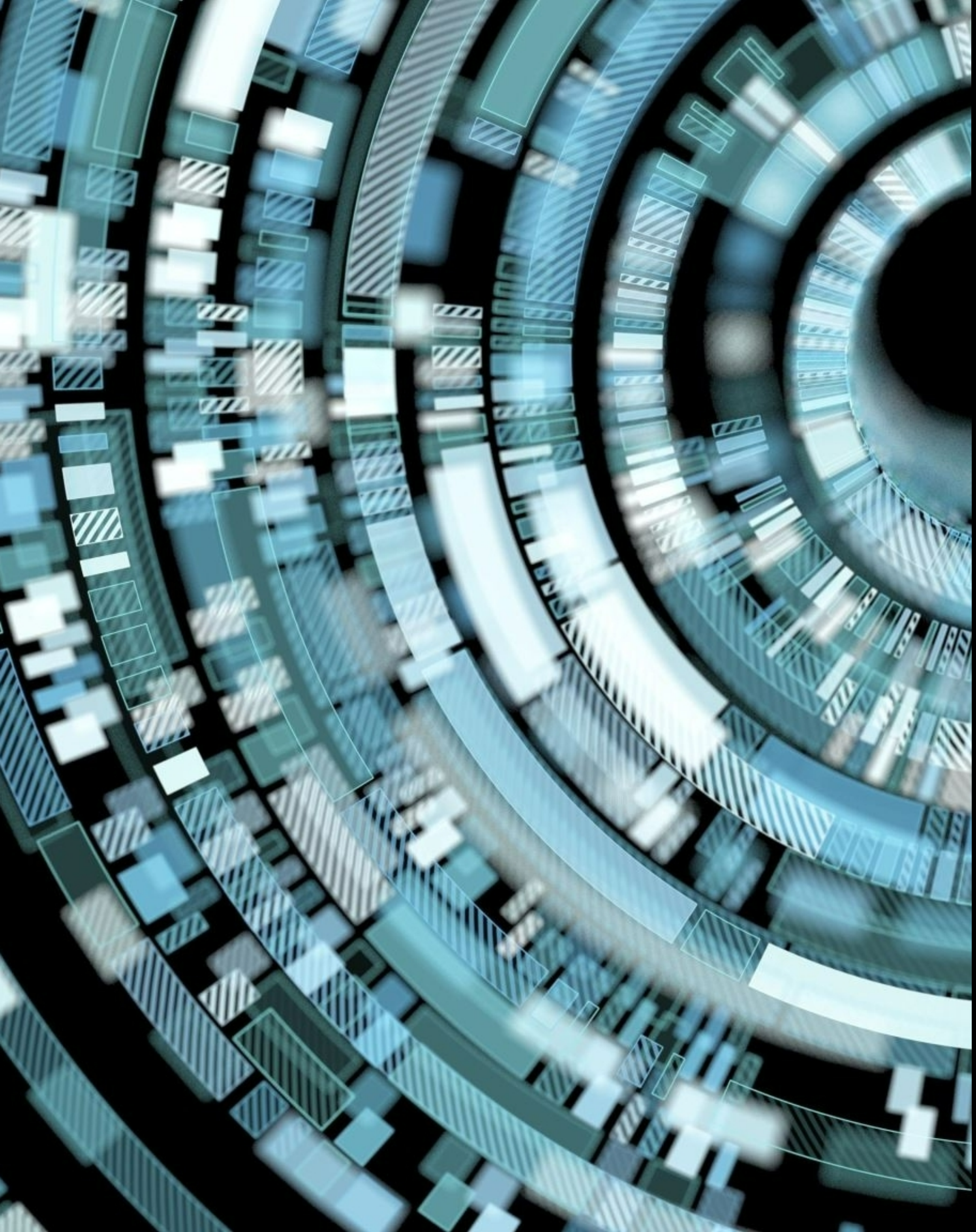
- **Short-Term Electricity Price and Load Forecasting using Enhanced Support Vector Machine and K-Nearest Neighbor**
  - This paper proposes an enhanced approach for short-term electricity load and price forecasting in Smart Grids.
  - It utilizes New York Independent System Operator (NYISO) data, employing Decision Tree for feature selection and Recursive Feature Elimination for extraction.
  - Two classifiers, Support Vector Machine (SVM) and K-Nearest Neighbor (KNN), are used, achieving high accuracies of approximately 89.6% for load forecasting and around 88.3% for price forecasting with the modified SVM, and 89.9% and 85.6%, respectively, with the modified KNN.
- **Day ahead hourly load and price forecast in ISO New England market using ANN**
  - This paper presents a method for day-ahead hourly load and price forecasting in the ISO New England market using artificial intelligence (AI), specifically artificial neural networks (ANN).
  - By utilizing historical temperature, electricity load, and natural gas price data, the ANN model achieves highly accurate forecasts, aiding power producers and consumers in developing effective bidding strategies to maximize profit.

Literature Review(contd.)

- **Electricity load forecasting using fuzzy logic**: Short term load forecasting factoring weather parameterP. Mukhopadhyay;G. Mitra;S. Banerjee;G. Mukherjee. This paper introduces a fuzzy logic-based approach for short-term electricity load forecasting, emphasizing the impact of weather parameters on demand estimation. By integrating weather and temperature data, the model enhances forecast accuracy, facilitating efficient generation planning and reserve management for system operators.Notably, the model excludes season-dependent factors such as agricultural load, focusing solely on short-term load prediction.

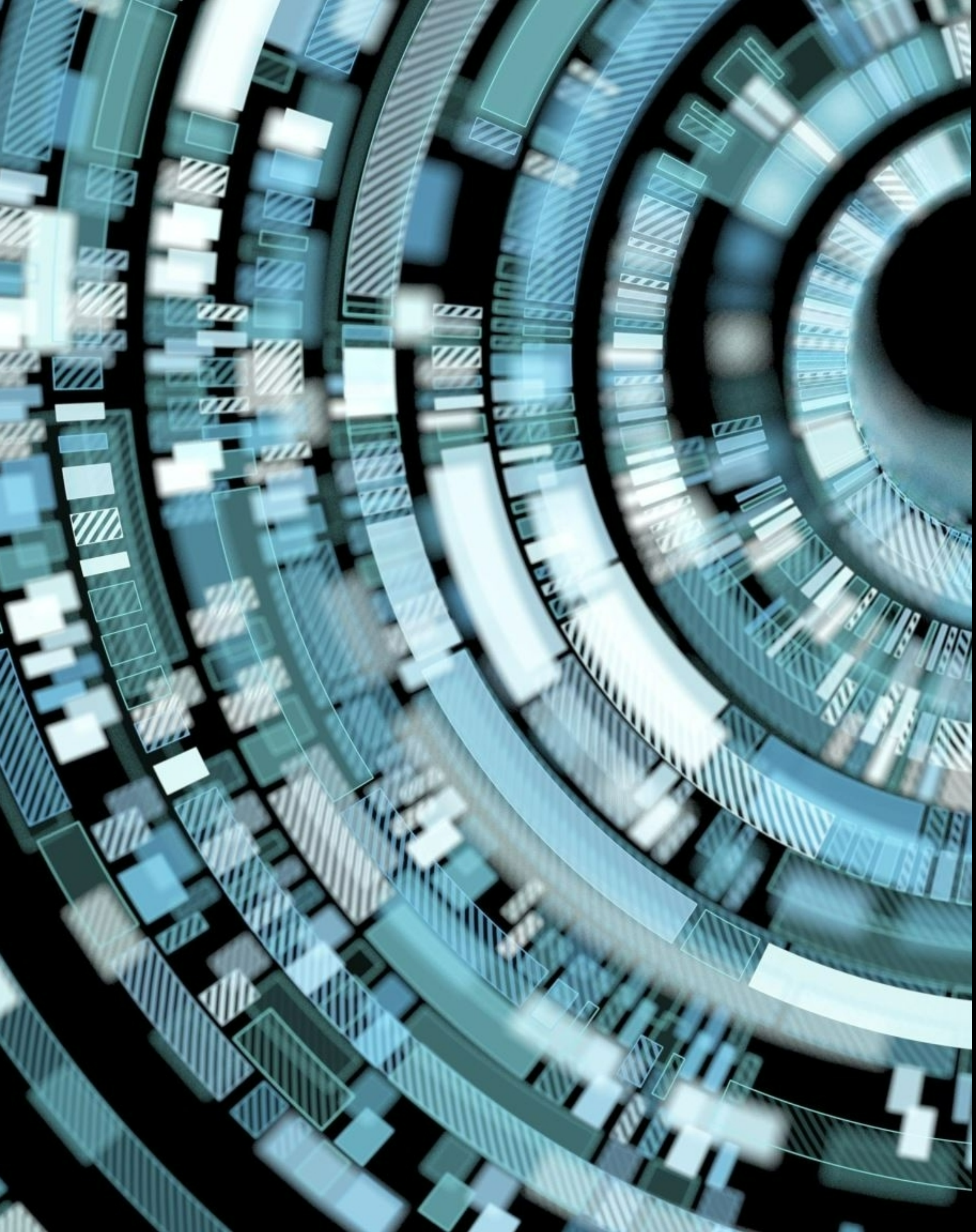
Comparison with Existing Literature

- In comparison to existing literature, this proposal offers a unique and advanced methodology for short-term load and price forecasting. While previous studies have explored techniques such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Artificial Neural Networks (ANN), our approach leverages the power of Long Short-Term Memory (LSTM) and Random Forest algorithms. By directly integrating weather data into the forecasting process, our model aims to capture the complex relationships between weather conditions and electricity demand more effectively. This comprehensive approach holds the potential for improved accuracy in load and price predictions, addressing the limitations of existing methods and providing valuable insights for smart grid management and decision-making.



Technical Part

- Python Environment: Python was used as the primary programming language for data manipulation, analysis, and machine learning.
- LSTM: A type of recurrent neural network (RNN) known for its ability to model sequence data, particularly useful for time-series forecasting tasks.
- Random Forest: An ensemble learning method that combines multiple decision trees to improve predictive accuracy and handle nonlinear relationships.
- Data Processing and Analysis: Data preprocessing steps were conducted using Python libraries such as Pandas and NumPy to clean, transform, and engineer features from the raw datasets.
- Model Development and Training: LSTM and Random Forest models were developed and trained using libraries like TensorFlow and scikit-learn respectively. Considerations for model selection, such as model complexity and performance metrics, were considered during the training process.



Technical Part (contd.)

Data Preparation and Integration

- Datasets Integration: Two datasets merged on time indices to create a comprehensive time series dataset.
- Time Series Features: Hour, Day of the Week, Month extracted from datetime index.
- Weather Variables: Temperature, Humidity, and Wind Speed in Barcelona.
- Target Variables: Total Load Actual (for Load Prediction) & Price Actual (for Price Prediction).

Feature Selection

- Features Used: Temperature, Humidity, Wind Speed, Hour, Day of the Week, Month.
- Target for Load Prediction: Total Load Actual.
- Target for Price Prediction: Price Actual.

Data Preprocessing

- Scaling: Standard Scaler to normalize feature variables.

Technical Part

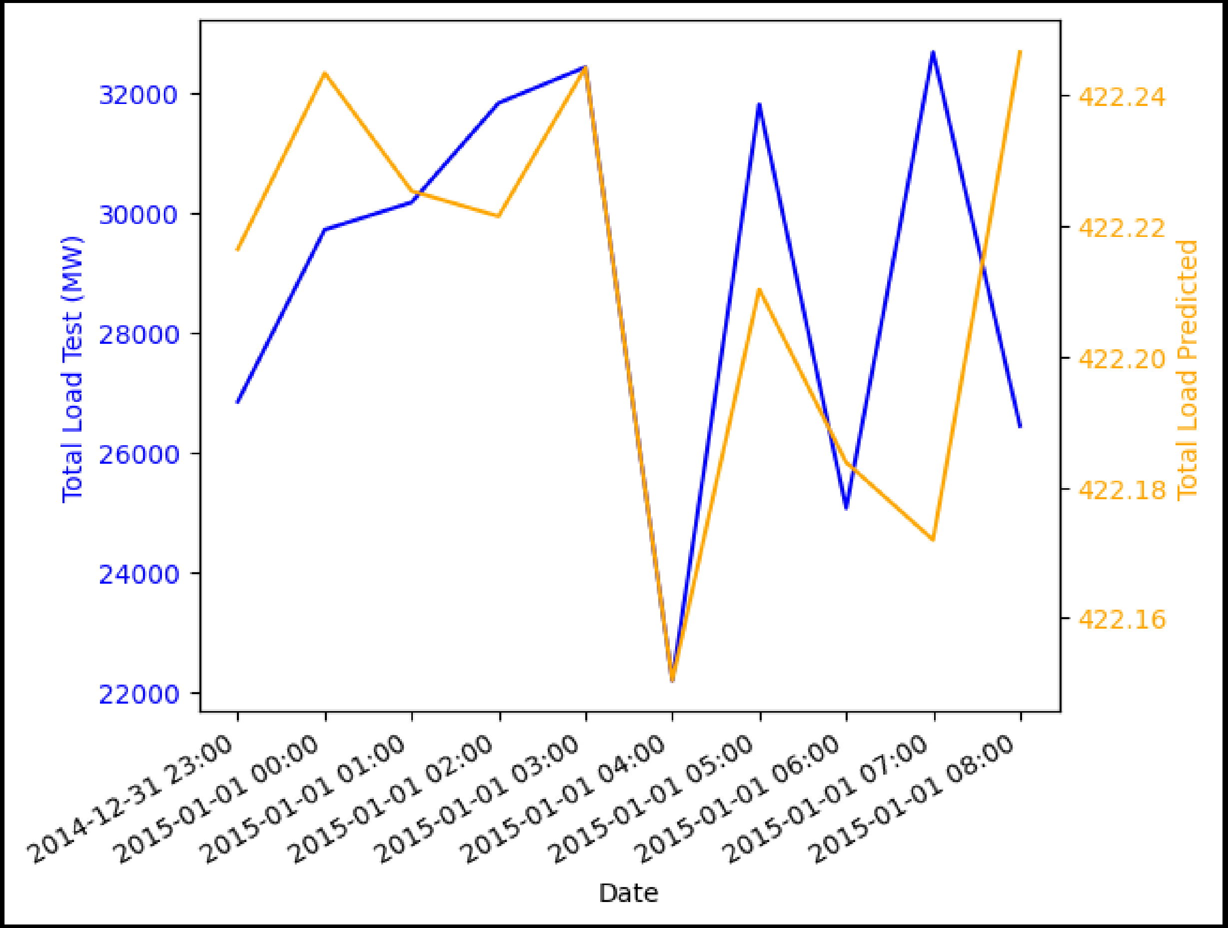
Random Forest Regressor	Long Short-Term Memory(LSTM)
Model Selection • Algorithm: Random Forest Regressor. • Configuration: 100 estimators, random state set to 42 for reproducibility.	**Model Selection** • Algorithm: LSTM. • Configuration: Adam optimizer, learning rate at 0.001, loss as ‘mean_squared_error’
Training and Testing Split • Split Ratio: 80% training, 20% testing. • Random State: 42 to ensure consistent splits.	**Training and Testing Split** • Split Ratio: 80% training, 20% testing. • Random State: 42 to ensure consistent splits.
Model Training • Trained two separate Random Forest Regressor models for Load and Price prediction.	**Model Training** • Trained two separate LSTM models for Load and Price prediction.
Model Evaluation and Results • Evaluation Metric: Root Mean Squared Error (RMSE). • Load Prediction RMSE: 2365.9979 - Reflects the accuracy of electricity load forecasting. • Price Prediction RMSE: 8.5829 - Indicates the precision of electricity price prediction	**Model Evaluation and Results** • Evaluation Metric: Root Mean Squared Error (RMSE). • Load Prediction RMSE: 28735.06497403227 • Price Prediction RMSE: 10.9526863738375

Experimental results

LSTM – Long Short-Term Memory Model Performance

Description:

- The first graph showcases the performance of an LSTM model.
- Y-axes exhibit different scales, with predicted values significantly smaller than actual test values.
- This discrepancy suggests a potential issue with scaling during preprocessing or plotting.
- Despite the scaling concern, LSTM models are renowned for their proficiency in capturing temporal dependencies.



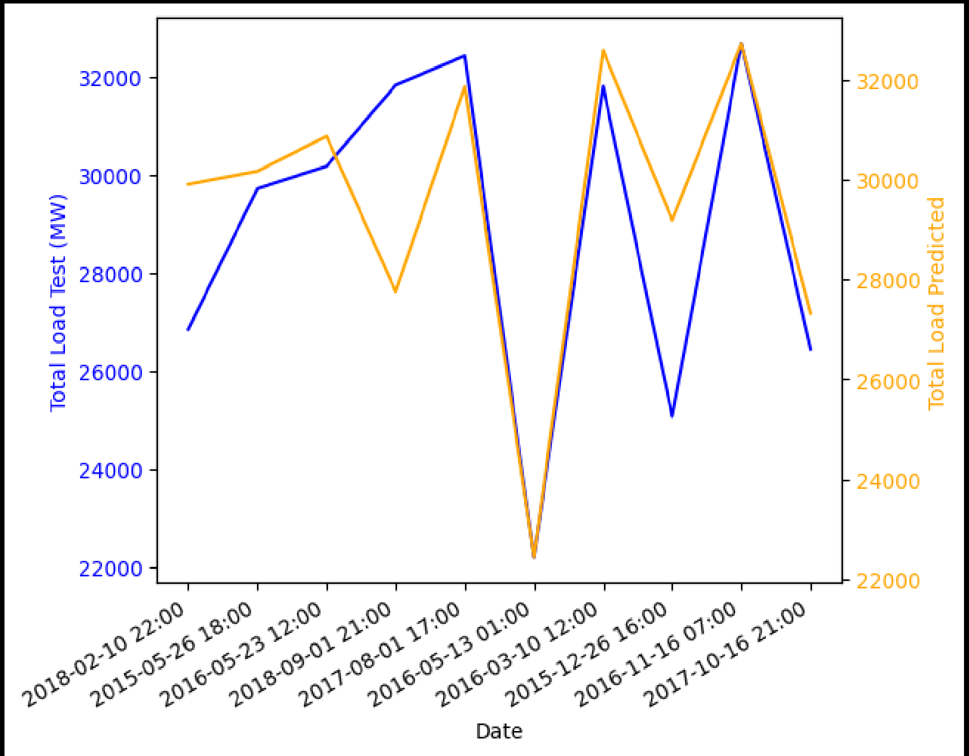
LSTM - Long Short-Term Memory

Experimental results (con't)

Random Forest Model Performance

Description:

- The second graph illustrates the performance of a Random Forest Regressor.
- Predicted and actual values share matching scales, facilitating straightforward comparison.
- The Random Forest model captures the load trend effectively.
- Minor deviations from actual load occur, which is a common characteristic of Random Forest models.



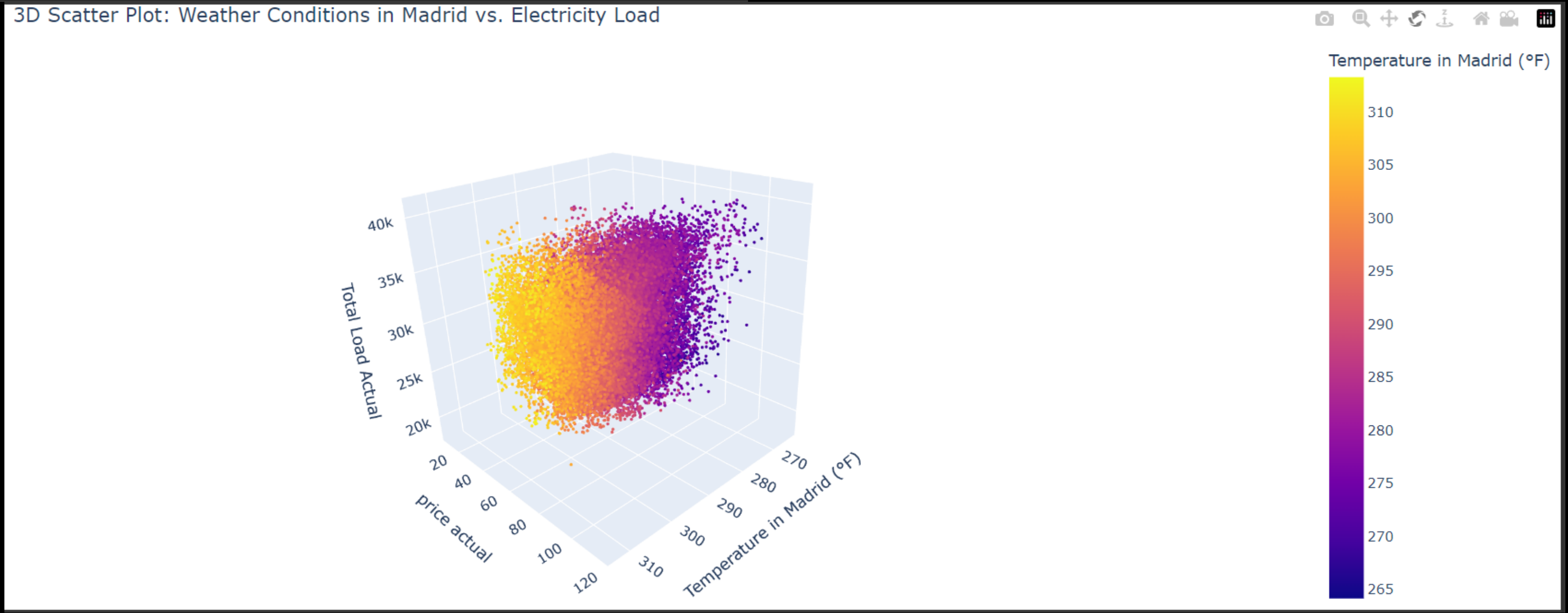
Random Forest Regression

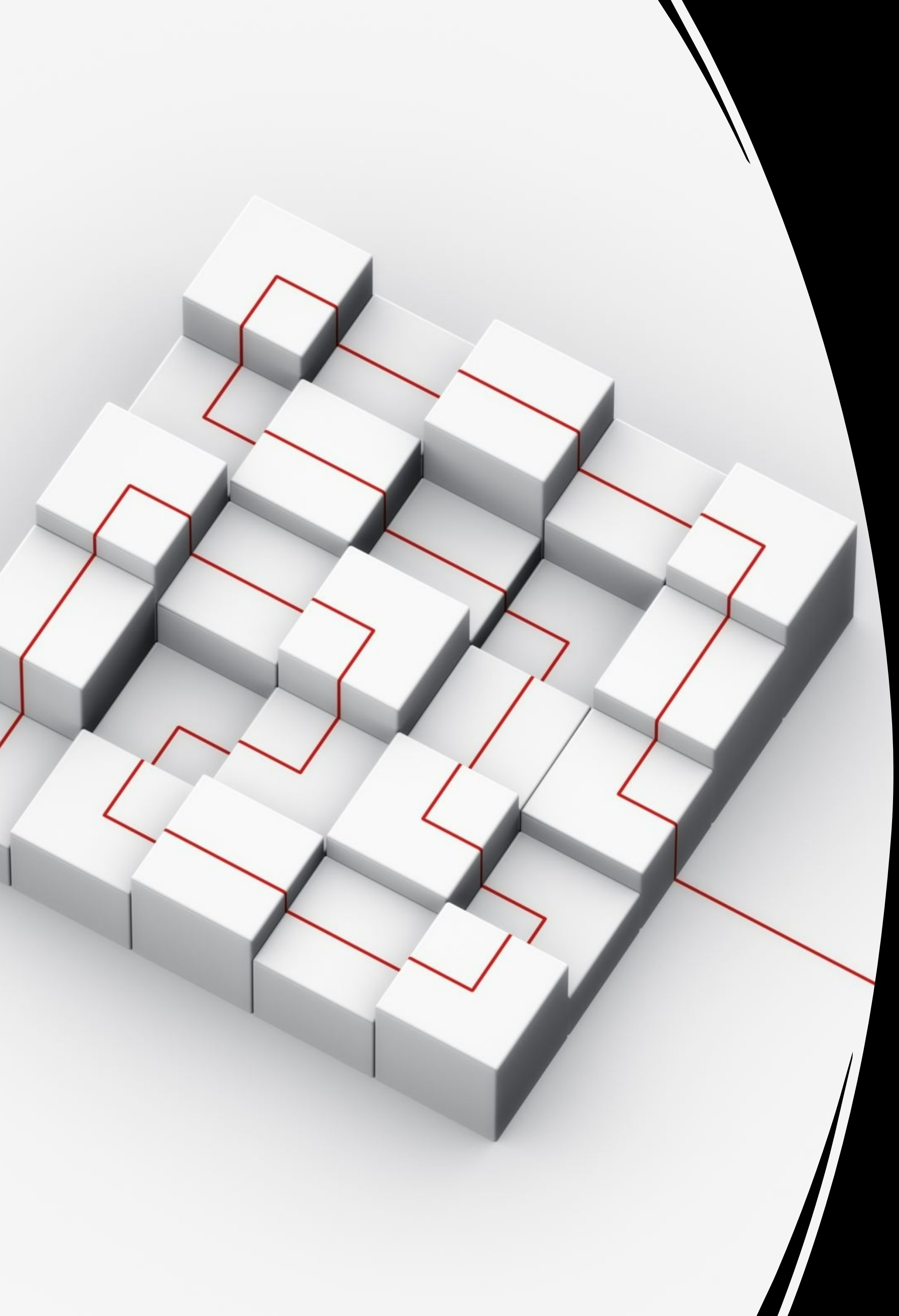
Visualization

```python
import plotly.express as px


fig = px.scatter_3d(merged_dataframe, x='temp_Madrid', y='price actual', z='total load actual',
                    color='temp_Madrid',
                    title='3D Scatter Plot: Weather Conditions in Madrid vs. Electricity Load',
                    labels={'temp_Madrid': 'Temperature in Madrid (°F)',
                            'humidity_Madrid': 'Humidity in Madrid (%)',
                            'total load actual': 'Total Load Actual'})

fig.update_layout(margin=dict(l=0, r=0, b=0, t=30))
fig.update_traces(marker=dict(size=1.5))
fig.show()
```





Conclusion

- Performance on Test Data:
- Both models exhibit a certain level of proficiency in tracking the actual load, as indicated by the trends in the graphs.
- The LSTM model seems to have a smoother prediction curve, potentially indicating a better handling of temporal dependencies within the data.
- Accuracy:
- The Random Forest model appears to have predictions that are more varied in range, possibly suggesting overfitting or a less stable prediction under varying conditions.
- Consistency:
- The LSTM model's consistency suggests it may better capture the time series nature of the data.
- The Random Forest model, while typically strong in handling non-linear relationships, may not be as consistent in this time series context.

Team Member Roles and Contributions

Member Name	Role	Contribution
Naga Vara Pradeep Yendluri	ML Engineer	Training ML Models
Tarun Teja Nallan Chakravertula	ML Engineer	Data Preprocessing
Prathyusha Gangisetty	ML Engineer	Visualization
Kartheek Sure	ML Engineer	Training ML Models
Jayabhi Sankar Reddy Illuri	ML Engineer	Visualization
Sathwik Karthikeya Mannava	ML Engineer	Conclusion

THANK YOU