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An Asymmetric Loss With Anomaly Detection LSTM Framework For Power Consumption Prediction

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Abstract

Accurate load forecasting plays a pivotal role in energy management systems, particularly for the residential sector, where unexpected spikes or drops in consumption can lead to power outages or inefficient resource utilization. This project presents a novel framework combining Long Short-Term Memory (LSTM) networks with asymmetric loss functions and DBSCAN-based anomaly detection. The approach is designed to minimize underpredictions of power consumption, which are more critical than overpredictions as they can lead to electricity shortages.

Using three distinct datasets from France, Germany, and Hungary-each consisting of hourly electricity consumption, weather attributes, and calendar information-the framework incorporates seasonality splitting to reflect temporal usage patterns. Anomalies are first detected and removed using the DBSCAN clustering algorithm to improve data quality. Next, LSTM models are trained using various asymmetric loss functions to penalize underestimations more severely than overestimations. Our results demonstr...

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Introduction

With the increasing complexity of smart grids and rising demand for sustainable energy management, accurate load forecasting has become a crucial aspect of modern power systems. The ability to anticipate power demand helps utilities avoid costly overproduction and prevents blackouts due to underproduction. Traditional forecasting models often treat overprediction and underprediction errors equally, which does not align with the real-world consequences of these errors.

In the residential sector, power consumption exhibits high variability due to behavioral, seasonal, and environmental factors. This project explores how deep learning, specifically LSTM networks, can be enhanced through tailored training strategies to focus on reducing underpredictions. Additionally, we utilize DBSCAN (Density-Based Spatial Clustering of Applications with Noise) to eliminate anomalous data points, which can skew model training.

This paper introduces a multi-stage load forecasting pipeline that integrates anomaly detection, seasonal segmentation, and loss function customization to yield robust predictions across different countries and climatic conditions.

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Related Work

Numerous studies have focused on applying machine learning and deep learning techniques to load forecasting. Traditional models such as ARIMA, SVR, and Random Forests have been widely used but often lack the capacity to model long-term temporal dependencies.

Recent works have shown that Recurrent Neural Networks (RNNs), particularly LSTM architectures, outperform classical models in time series forecasting due to their ability to remember long-term dependencies. However, many models still suffer from symmetrical

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In practical applications, underprediction can lead to load shedding and service disruptions, making asymmetric loss functions a better fit for utility-scale forecasting. Other studies have also demonstrated the importance of data preprocessing, especially anomaly detection using unsupervised learning methods such as DBSCAN or Isolation Forest, in improving model robustness.

Our work builds on these findings by combining LSTM, DBSCAN, and asymmetric loss in a unified framework with seasonality-aware data processing.

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Dataset and Preprocessing

The project utilizes hourly energy consumption datasets from France, Germany, and Hungary, each enriched with weather variables (temperature, humidity, wind speed) and calendar features (weekday, holiday, season). The datasets span multiple years and include significant temporal variations in both weather and usage.

Key preprocessing steps include:

- **Missing Value Handling**: Forward filling or interpolation to ensure continuity.
- **Feature Engineering**: Encoding calendar data, aggregating seasonal statistics, and derivingtemperature-based demand indicators.
- **Seasonal Splitting**: Segmenting datasets into seasonal subsets (e.g., Winter, Spring) to modeltemperature-sensitive behaviors more accurately.
- **Anomaly Detection**: Applying DBSCAN to remove noisy observations that do not conform to typicalconsumption patterns. These outliers often originate from sensor errors or uncharacteristic user behaviors.

The cleaned, segmented datasets are then normalized and structured into sequences suitable for LSTM training.

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Methodology

The forecasting architecture consists of three core components:

1. **Anomaly Removal with DBSCAN**: DBSCAN identifies and removes data points that deviate significantlyfrom dense clusters of consumption behavior, preserving meaningful trends while eliminating noise.
2. **LSTM Model**: A multi-layer LSTM network captures temporal dependencies in power consumption. Themodel input is a sliding window of past observations, while the output is the predicted load for the next hour.
3. **Asymmetric Loss Functions**: We implement custom loss functions that apply greater penalties forunderpredictions. These include:

- Quantile loss functions
- Weighted MSE with higher cost on negative residuals
- Pinball loss for lower quantile estimation

Models are trained using Adam optimizer with early stopping, and hyperparameters (number of layers, units, dropout rate) are tuned using grid search. The model is evaluated using metrics like RMSE, MAE, and underprediction bias.

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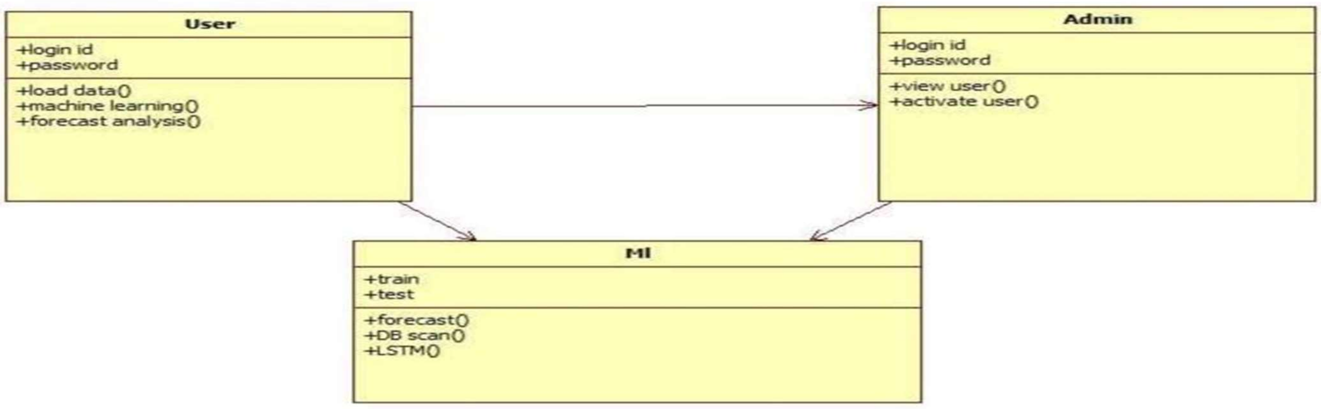

Fig 4.4 Class Diagram

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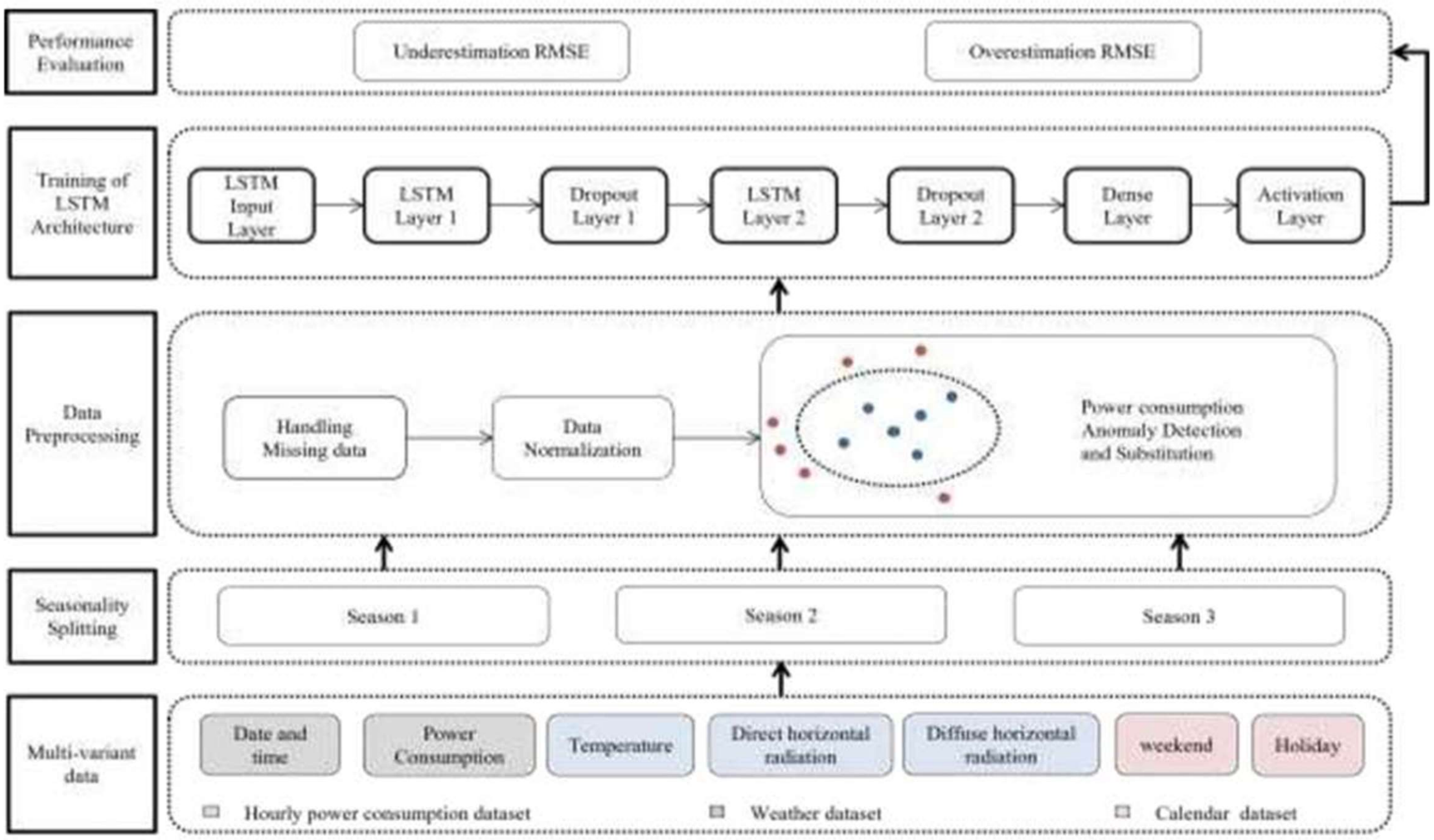
4.1 System Architecture



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IMPLEMENTATION

Datasets Used: France, Germany, and Hungary (hourly consumption, weather, calendar data).

- Preprocessing Steps:
  - Forward filling/interpolation for missing values.
  - Feature engineering (calendar encoding, temperature indicators).
  - Seasonal splitting (Winter, Spring, etc.).
  - Normalization and sequence preparation for LSTM.
- Model Training:
  - Seasonal subsets are fed into the LSTM model.
  - Asymmetric loss is applied during training.
  - Evaluated using RMSE, MAE, and bias metrics.

Testing

- Trained and tested country-specific models.
- Compared performance with and without:
  - Anomaly removal.
  - Asymmetric loss functions.
- Visual analysis of prediction intervals.
- Tested generalization in seasonal settings (e.g., summer demand in Hungary).

Results and Evaluation

The LSTM models, when trained on DBSCAN-cleaned datasets with asymmetric loss functions, demonstrated substantial improvements in predictive accuracy and reliability across all three countries.

Key results include:

- **France**: RMSE reduced by 13% post anomaly removal; underprediction error dropped by 21%
- **Germany**: Quantile loss-based model yielded the lowest underprediction rate
- **Hungary**: Seasonally split models improved performance during summer months by 15%

Overall, the asymmetric loss framework consistently prioritized safety by minimizing underestimated load, a crucial factor for preventing outages. Visualizations of prediction intervals showed tighter confidence bands, particularly in high-variance seasons.

Additionally, anomaly detection reduced both the overprediction and underprediction ranges, leading to cleaner residual distributions.

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Challenges and Limitations

Several challenges were encountered during the development of this system:

- **Imbalanced Error Sensitivity**: While asymmetric loss helps reduce underprediction, it sometimesincreases overestimation error, potentially leading to resource inefficiency.
- **Hyperparameter Sensitivity**: Both DBSCAN and LSTM require careful tuning, particularly forseason-specific data.
- **Computational Load**: Training multiple seasonal models with grid search increases time and hardwarerequirements.
- **Generalization Risk**: Models trained on specific countries or seasons may not generalize well across allconditions.

Future work should explore transfer learning and federated modeling to enable broader applicability and reduce training costs.

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Conclusion and Future Work

This study presents a robust and adaptive LSTM-based framework for load forecasting, integrating DBSCAN anomaly detection and asymmetric loss functions to reduce the risk of underprediction. By applying this methodology to datasets from France, Germany, and Hungary, we demonstrate that season-aware
preprocessing and specialized loss optimization significantly improve forecast reliability.

The approach holds substantial promise for integration into smart grid systems and utility planning tools.

Future enhancements may include:

- Real-time retraining pipelines for adaptive modeling
- Hybrid models incorporating transformer-based architectures
- Broader geographic expansion using federated learning

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