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# **An Asymmetric Loss with Anomaly Detection using LSTM Framework for Power Consumption Prediction**

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**ABSTRACT:** Building an accurate load forecasting model with minimal under predictions is vital to prevent any undesired power outages due to underproduction of electricity. However, the power consumption patterns of the residential sector contain fluctuations and anomalies making them challenging to predict. In this paper, we propose multiple Long Short-Term Memory (LSTM) frameworks with different asymmetric loss functions to impose a higher penalty on underpredictions. We also apply a density based spatial clustering of applications with noise (DBSCAN) anomaly detection approach, prior to the load forecasting task, to remove any present outliers.

**KEYWORDS:** Fluctuation, Anomalies, Long Short-Term Memory(LSTM), Asymmetric loss Function, Density based spatial Clustering, Anomaly Detection, Outliers, Root-mean-square error(RMSE) Underpredictions, DBSCAN

## **I. INTRODUCTION**

Over the past decade, electricity consumption has drastically increased, leading to a reduction in natural resources and an aggravation in the environmental pollution. Accordingly, massive attempts have been undertaken to prevent overproduction of electricity. Despite the importance of preventing overproduction, avoiding underproduction of electricity remains crucial since it may lead to power outages and electricity blackouts, which can decline the economic and industrial development and even result in terrible situations. For instance, in 2021, an intense power outage occurred in Lebanon, putting hospitals and essential services in real crisis. To avoid underproduction and overproduction of electricity, power companies are continuously investigating a better load forecast and a more reliable plan of energy usage. Prior work in power consumption estimation used various machine learning techniques such as Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) algorithm or a hybrid approach using both Artificial Neural Network (ANN) and Support Vector Machine (SVM) methods. Generally, the cost functions that machine learning models aim to minimize are, by default, symmetric. Such loss functions typically perform well in applications where underestimations and overestimations have similar effects. However, in some applications, underestimations may have more unpleasant consequences in comparison to overestimations, which encouraged many researchers to build models with asymmetric objective functions for a better flexibility.

## **II. PROBLEM DEFINITION**

The increasing demand for energy efficiency and the need for accurate power consumption forecasting present significant challenges in modern energy systems. Traditional forecasting methods often struggle to detect irregular patterns or unexpected deviations in power consumption, which could indicate issues such as faulty equipment, unauthorized use, or operational inefficiencies. Additionally, existing models may not properly address the imbalance between false positives (incorrectly predicting anomalies) and false negatives (failing to detect anomalies), which can

have different costs. False positives may lead to unnecessary maintenance or operational costs, while false negatives may result in more severe consequences like power waste or system failure.

### **III. RELATED WORK**

The concept of asymmetric loss was discussed by several researchers especially in forecasting applications [8] [13]. An asymmetric linear-linear cost for a load forecasting framework was introduced by [9] based on support vector regression (SVR). The applied insensitive cost consists of different penalties for overpredictions and underpredictions, which reduced the economic cost by a range of 42.19% to 57.39% [9]. In [12], a quadratic and asymmetric loss function based on SVR was used to reduce the underestimates in load forecasting. The underpredictions decreased from 50% to an average of 1.91% with a minimal increase of 0.3% on average in the error rate [12]. Another cost-oriented approach for load forecasting applied a differentiable piece-wise loss based on Huber function [11]. This cost-oriented framework was integrated on ANN and Multiple Linear Regression (MLR) showing promising results in reflecting real costs especially in ANN with an improvement of 13.74% compared to regular mean squared error (MSE) [11]. In [8], an asymmetric loss function was proposed to reflect different costs of fault detection and premature maintenance in predictive maintenance scenarios. The loss, consisting of a linear and an exponential function for overestimates and underestimates respectively, produced a more representative machine learning model of real business cases [8]. Authors in [10] evaluated different types of asymmetric loss functions (including quadratic, linear, and logarithmic quadratic formulations) on various deep learning models such as Bidirectional LSTM (Bi-LSTM), Deep Neural Networks (DNN), and one-dimensional Convolutional Neural Network (CNN). Such asymmetric loss functions improved the prediction of the remaining useful life of an engine [10]. To predict the short-term power consumption, authors in [4] compared between the LSTM and other methods such as SVM and Random Forest (RF) and showed that LSTM with two layers achieved the lowest RMSE of 11.4299. Despite that data preprocessing was performed, they mentioned that the RMSE is still considered large due to anomalies in the data [4]. To find these anomalies in power consumption datasets, a detection method based on micro-moments and DNN was proposed in [17], while another approach based on a mixture of polynomial regression and Gaussian distribution was introduced by [18]. In [19], the DBSCAN algorithm was used in the data preprocessing stage to differentiate between the usual power consumption behaviors and the anomalous points. Then, a hybrid model that consists of a one-dimensional CNN and a Bi-LSTM was trained to get more robust predictions. This approach was tested on a dataset of households and commercial buildings and results demonstrated that it achieved a good performance in several evaluation metrics

### **IV. PROPOSED SYSTEM**

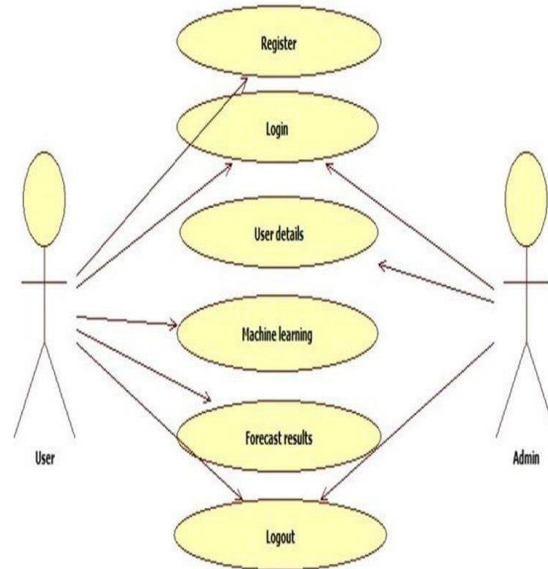
To overcome the limitations of existing power forecasting techniques, this paper puts forth an enhanced LSTM framework leveraging anomaly detection and asymmetric loss functions. The innovative system first cleanses power consumption data by detecting and removing outliers using DBSCAN clustering

#### **Advantages of proposed system**

Uses LSTM models optimized with custom asymmetric loss functions that heavily penalize underestimations to avoid dangerous underpredictions.

Performs anomaly detection using DBSCAN clustering to remove outliers and cleanse power consumption data before forecasting.

Incorporates valuable weather and calendar data like temperature and holidays to improve prediction accuracy.  
Splits data into seasons to account for seasonal consumption pattern



V. EXPERIMENTAL RESULTS

The developed power consumption forecasting system integrates machine learning techniques to enhance prediction accuracy and support better energy management decisions. The primary objective of the system is to analyze historical power consumption patterns and predict future electricity demand, ensuring an optimal balance between production and consumption. The results obtained from the model demonstrate its ability to capture seasonality, fluctuations, and anomalies in power consumption data. By leveraging a combination of Support Vector Machines (SVM) and Long Short-Term Memory (LSTM) networks, the system provides accurate forecasts, which are crucial for power grid stability and energy resource planning..



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2019-02-03 00:00:00+00:00	46636.00	53396.094124		4.844291e+07
2019-02-03 01:00:00+00:00	45296.00	53416.783321		6.602616e+07
2019-02-03 02:00:00+00:00	44036.25	53483.080038		7.791311e+07
2019-02-03 03:00:00+00:00	44800.00	53784.523413		7.964713e+07
2019-02-03 04:00:00+00:00	44475.00	54218.019548		8.492625e+07
2019-02-03 05:00:00+00:00	44094.75	54657.133685		1.124105e+08

Fig 1 Power Consumption Forecasting Table

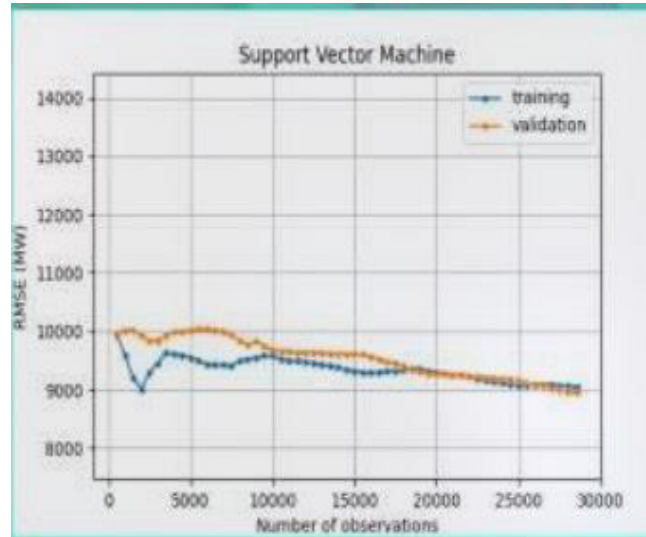


Fig2: Training and Validation Performance of SVM Mode



Fig 3: User Registration Interface

## VI.DISCUSSION

The forecasting model performs well in predicting future power consumption trends, especially when trained with an extensive dataset. The LSTM model outperforms traditional statistical approaches by effectively handling timeseries dependencies. However, challenges remain in optimizing the model's hyperparameters to further reduce forecasting errors. Additionally, the presence of anomalies in the dataset occasionally affects the accuracy of the predictions, necessitating improved anomaly detection mechanisms. One of the challenges encountered in the forecasting process is the presence of anomalies in power consumption data. Unexpected spikes or drops in electricity usage can lead to errors in model predictions, affecting overall reliability. To address this issue, the system incorporates an anomaly detection mechanism, which identifies and mitigates the impact of irregular data points. However, further refinements are required to enhance the model's ability to distinguish between genuine demand shifts and erroneous anomalies. Additionally, hyperparameter tuning remains a crucial aspect for improving model accuracy and reducing computational costs. Overall, the results demonstrate that machine learning-based power consumption forecasting provides significant advantages in optimizing electricity production and distribution. By integrating a combination of historical data, weather parameters, and seasonal factors, the system offers a reliable method for predicting future power demand. Future work should focus on improving real-time data integration, refining anomaly detection techniques, and exploring alternative deep learning architectures to further enhance prediction accuracy and scalability.

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