Methodology

1.Introduction

In this section, we present the methodology adopted to forecast a country's Environmental, Social, and Governance (ESG) values. The approach combines the use of Empirical Mode Decomposition (EMD) technique with a multilayered Long Short-Term Memory (LSTM) model.

2.Data Preprocessing

The data preprocessing step involved decomposing the time series data using Empirical Mode Decomposition (EMD) to extract the underlying components and capture the inherent dynamics within the ESG time series.

First, the time series data was decomposed into multiple Intrinsic Mode Functions (IMFs) using the EMD technique. The EMD method successfully split the ESG time series into discrete oscillatory components representing different fluctuation scales.

Then, each decomposed IMF series was split into training and validation sets to facilitate the model training process. We did a 60/40% split where the initial 60% was used for training, and the remaining 40 % was used for testing or validating our model.

Following the decomposition and data-splitting steps, we constructed windowed datasets suitable for training the EMD-LSTM model. We created a separate windowed dataset for each IMF by applying a sliding window technique. This involved selecting a fixed window of 5 data points and sliding the window along the IMF sequence with a shift of 1 data point at a time.

We applied shuffling to the windowed dataset to ensure the diversity and randomness of the training samples.

Lastly, the windowed datasets were organized into batches to facilitate parallel processing and efficiently utilise computational resources. We set the batch size to 4 to balance training stability and computational efficiency.

By performing these data preprocessing steps, we ensured that the ESG time series data was appropriately decomposed, split into training and validation sets, and transformed into windowed datasets suitable for training the EMD-LSTM model. These steps were crucial for capturing the inherent dynamics and temporal patterns within the ESG values and enabling accurate forecasting using the subsequent model.
LSTM Algorithm

3.Model Training on Decomposed IMFs

To capture the unique patterns and dynamics within each Intrinsic Mode Function (IMF), we trained individual model on the decomposed IMFs. Each model was trained using the same architecture and hyperparameters.

The model architecture consisted of a 1D convolutional layer followed by multiple bidirectional LSTM layers. The convolutional layer was designed with 32 filters and a kernel size of 3, with a padding strategy

set to 'causal' to preserve the temporal order of the data. ReLU activation function was used to introduce non-linearity.
To prevent overfitting, dropout layers were added after each LSTM layer. A dropout layer did not follow the final LSTM layer. The model was concluded with a dense layer with a single output neuron to predict the ESG values.

4.Model Compilation and Training

Each model was compiled using the Mean Absolute Error (MAE) loss function, which measures the average absolute difference between the predicted and actual ESG values. The Adam optimizer with a learning rate of 0.001 was employed to optimize the model's performance. The evaluation metric, Mean Absolute Error (MAE), was used to monitor the model's accuracy during training.

The training process for each model involved fitting the model on the corresponding windowed dataset created from the decomposed IMFs. The windowed dataset allowed the model to learn the patterns and dependencies present in the specific IMF. We trained each model for 500 epochs, ensuring sufficient iterations for the model to converge and capture the distinctive characteristics of the IMF.
The training progress of each model was monitored by observing the MAE metric, which quantified the deviation between the predicted and actual ESG values. The MAE provided insights into the accuracy of each model in capturing the patterns specific to the corresponding IMF.

Analyzing the training results of the individual models enabled us to assess how effectively each model learned the unique patterns within the respective IMFs. The convergence of the MAE value indicated that the model successfully learned the underlying patterns, contributing to accurate forecasts of the ESG values.

By training separate models on the decomposed IMFs, we leveraged the distinctive information contained within each IMF. This approach allowed for a comprehensive understanding of the intricate dynamics and temporal dependencies present in the ESG time series.
The trained models on the decomposed IMFs serve as essential components of our forecasting framework, enabling us to aggregate the predictions from each model and generate an accurate forecast of the overall ESG values.

Overall, training individual models on the decomposed IMFs proved to be an effective strategy to capture the nuanced patterns within each IMF. This approach enhanced the forecasting accuracy and provided a deeper understanding of the underlying dynamics driving the ESG values.

To assess the overall performance of our forecasting framework, we calculated the cumulative loss by summing the final losses obtained from each individual model. The final loss, represented by the mean absolute error (MAE), provides a comprehensive measure of the deviation between the predicted and actual ESG values.This came out to be **0.82** which is our overall training loss.

5.Evaluation and comparison

To evaluate our model , we will use our evaluation set which we split from our time series earlier. This evaluation provided insights into the performance of our forecasting framework and its ability to capture the underlying dynamics of the ESG time series.

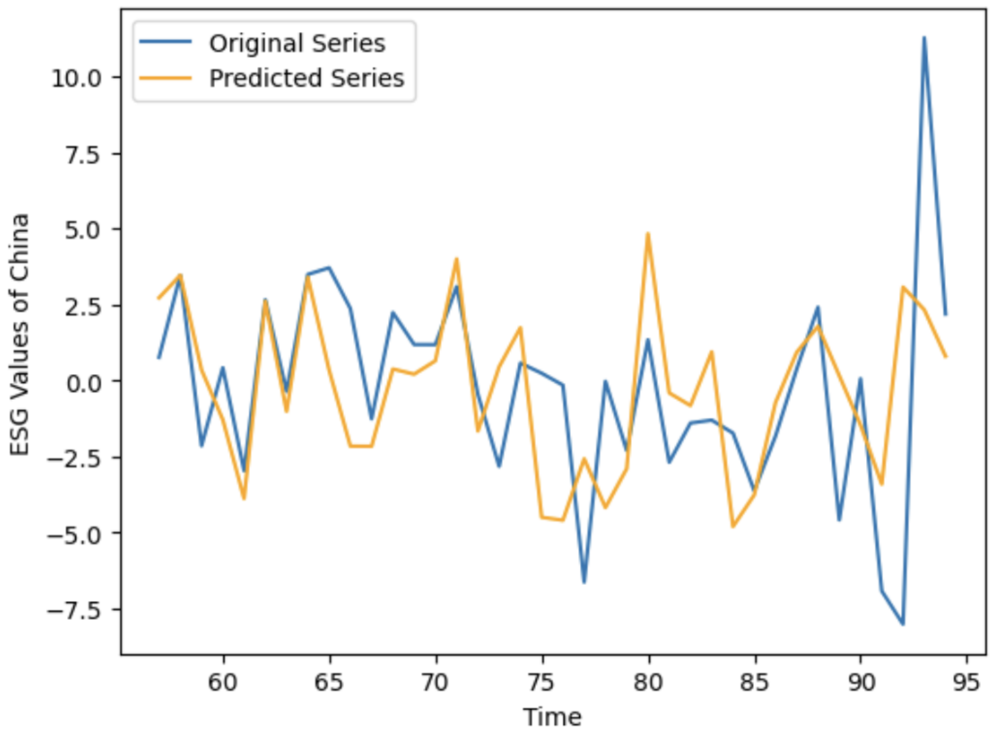
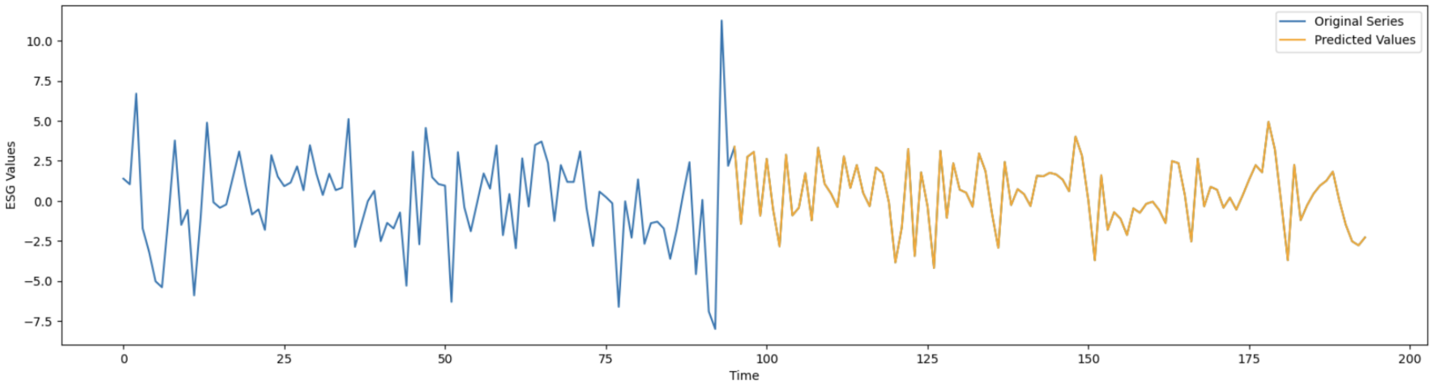


Fig1.This image shows our predictions using the model on the evaluation set.We got an evaluation loss of 2.36 in terms of MAE for this model, which is pretty good.

To assess the forecasting capabilities of our EMD-LSTM model, we generated predictions for future ESG values over a period of 99 days. The predictions were made by applying the trained model to the decomposed Intrinsic Mode Functions (IMFs) of the ESG time series data.



So overall, we have 11 countries, and we have divided them according to 5 IMFs countries and 6 IMFs countries where for each of them, we will just train on 5 and 6 models, respectively.