**Computer Life**
ISSN: 1819-4818 | Vol. 12, No. 3, 2024

# Time Series Forecasting of Emission Trends Using Recurrent Neural Networks

**Xuetian Zou [1], Kangli Wang [1], Jiawei Lu [2], and Dili Wu [2, *]**

[1] School of Information and Electronics, Jilin University, Changchun, China
[2] China Academy of Information and Communications Technology, Beijing, China

[*] **Corresponding author**: Dili WU (dwlil89@caict.ac.cn)

**Abstract:** This paper explores the application of Recurrent Neural Networks (RNNs) for forecasting emission trends, a critical aspect of addressing climate change and formulating effective environmental policies. Traditional forecasting methods, such as Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing, often fail to capture the complex nonlinear relationships and temporal dependencies inherent in emission data. In contrast, RNNs, particularly Long Short-Term Memory (LSTM) networks, are designed to recognize patterns in sequential data, making them well-suited for time series forecasting tasks. This study employs a comprehensive methodology that includes data collection from reputable sources, feature selection, RNN model design, and rigorous evaluation using various performance metrics. The results indicate that RNNs significantly outperform traditional forecasting techniques in terms of accuracy, providing valuable insights into future emission trajectories. The findings underscore the potential of RNNs as powerful tools for policymakers and researchers, facilitating more informed decision-making in the fight against climate change.

**Keywords:** Emission Forecasting; Recurrent Neural Networks; Time Series Analysis.

## 1. Introduction

The increasing concern over climate change and its associated environmental impacts has brought global emissions to the forefront of policy discussions and scientific research. Emissions from various sectors, including transportation, industry, and agriculture, contribute significantly to greenhouse gas concentrations in the atmosphere, leading to adverse effects such as rising temperatures, extreme weather events, and biodiversity loss [1-10]. As nations strive to meet international climate agreements, such as the Paris Agreement, understanding and accurately forecasting emission trends becomes essential for effective policy-making and strategic planning [11-13].

Forecasting emission trends is crucial for several reasons. It allows governments and organizations to set realistic targets for emission reductions, allocate resources efficiently, and implement timely interventions [14]. Traditional forecasting methods, such as Autoregressive Integrated Moving Average and Exponential Smoothing, have been widely used in this domain; however, they often fall short in capturing complex nonlinear relationships and temporal dependencies inherent in emission data [15-18].

In recent years, machine learning techniques, particularly Recurrent Neural Networks, have emerged as powerful tools for time series forecasting. RNNs are designed to recognize patterns in sequential data, making them particularly suitable for tasks involving temporal dependencies [19]. Their ability to learn from historical data and make predictions based on previously observed values offers a promising alternative to traditional methods [20-23].

The purpose of this paper is to explore the application of RNNs in forecasting emission trends. By leveraging the strengths of RNNs, this study aims to improve the accuracy of emission forecasts and provide insights into future emission trajectories. The objectives include evaluating the effectiveness of RNNs compared to traditional forecasting methods and identifying key factors influencing emission trends.

The structure of this paper is as follows: Section II provides a comprehensive literature review on time series forecasting, emission trends, and the application of machine learning techniques, particularly RNNs. Section III outlines the methodology employed in this study, including data collection, feature selection, model design, training, and evaluation. Section IV presents the results of the forecasting analysis, followed by a discussion of the findings in Section V. Finally, Section VI concludes the paper with a summary of key insights and future research directions.

## 2. Related Work

Time series forecasting involves predicting future values based on previously observed data points collected over time. It plays a crucial role in various fields, including finance, economics, and environmental science, as it aids in decision-making and strategic planning [24-28].

Traditional forecasting methods include: Autoregressive Integrated Moving Average which is a widely used statistical method that combines autoregressive and moving average components [29, 30]. Exponential Smoothing: A technique that applies decreasing weights to past observations, allowing for more recent data to have a greater influence on forecasts [31]. Seasonal Decomposition: This method involves breaking down time series data into seasonal, trend, and residual components [32-36].

Understanding historical emission trends is vital for identifying patterns and informing future projections. Research has shown that emissions have been rising significantly since the industrial revolution, with notable fluctuations due to economic activities and regulatory changes [37-41]. Various studies have employed time series analysis to examine emissions from industry sectors, such as transportation [42] and power plants [43].

Machine learning techniques have gained traction in time series forecasting due to their ability to model complex relationships and nonlinear patterns [44]. Approaches such as Support Vector Machines, Random Forests, and Gradient Boosting have shown promise in various forecasting applications [45-48].

Neural networks, particularly deep learning models, offer several advantages over traditional methods, including the capable of capturing intricate patterns in data. Scalability and effective in handling large datasets [49]. Feature Learning: Ability to automatically learn relevant features from raw data [50].

RNNs are a class of neural networks specifically designed for sequential data. They process inputs in a recurrent manner, allowing information from previous time steps to influence current predictions [51]. This architecture makes RNNs particularly suitable for time series forecasting tasks.

Long Short-Term Memory is a type of RNN that addresses the vanishing gradient problem, enabling it to learn long-term dependencies [52]. And gated Recurrent Unit is a simplified version of LSTM that combines the forget and input gates, making it computationally efficient while maintaining performance.

Several studies have successfully applied RNNs to forecast emissions, demonstrating their effectiveness in capturing temporal dependencies and improving accuracy compared to traditional methods. For instance, Zhang et al. (2019) utilized LSTM networks to forecast CO2 emissions in China, achieving superior results over ARIMA models [53]. Similarly, Yao et al. (2020) applied GRUs to predict emissions in the transportation sector, highlighting the potential of deep learning approaches in this domain [54].

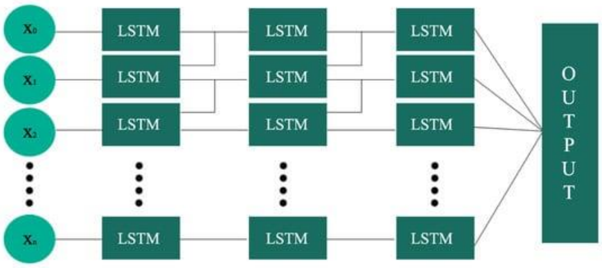


**Figure 1.** LSTM Recurrent Neural Network Architecture.

Despite the progress made, there remain gaps in the literature regarding the application of RNNs for emission forecasting. Many studies focus on specific regions or sectors, and there is a need for comprehensive analyses that encompass multiple sectors and geographical areas [55-58]. Additionally, the integration of external factors, such as economic indicators and policy changes, into RNN models remains under explored.

# 3. Methodology

## 3.1. Data Collection

The data for this study was sourced from various reputable databases, ensuring a comprehensive and reliable foundation for the analysis. Key sources included the Global Carbon Project, the U.S. Environmental Protection Agency, and the European Environment Agency. These databases provide extensive datasets on greenhouse gas emissions across different sectors, including transportation, energy production, and industrial activities. By utilizing these well-established sources, the study benefits from high-quality and standardized data that accurately reflect emission trends.

Data preprocessing involved several critical steps to prepare the datasets for analysis. Initially, missing values were addressed using interpolation methods, which estimate missing data points based on surrounding values. This approach helps maintain the continuity and integrity of the data. Additionally, outliers were identified and removed through z-score analysis, which allowed for the detection of values significantly deviating from the mean. This step is essential to ensure that the model is not skewed by anomalous data points that could distort predictions.

Once the data was cleaned, normalization was performed using Min-Max scaling. This technique rescales the data to a range between 0 and 1, ensuring that all features contribute equally to model training. Normalization is particularly important in neural network applications, as it helps improve convergence during training and enhances the overall performance of the model.

## 3.2. Feature Selection

Selecting relevant features for the RNN model is crucial to its predictive accuracy. In this study, the features included historical emission values, economic indicators such as Gross Domestic Product and energy consumption, as well as external factors like policy changes and technological advancements. The incorporation of time lags was also essential, as it allowed the model to effectively capture temporal dependencies and trends inherent in emission data.

To identify the most significant predictors for emission trends, various feature selection techniques were employed. Recursive Feature Elimination was utilized to iteratively remove the least important features based on model performance, thereby refining the feature set. Additionally, correlation analysis was conducted to assess the relationships between features and the target variable, helping to highlight those features that had the most substantial impact on emissions. This comprehensive approach to feature selection ensured that the RNN model was built on a robust and relevant set of predictors, enhancing its ability to forecast emissions accurately.

## 3.3. RNN Model Design

The design of the RNN architecture was carefully crafted to optimize performance. The architecture consisted of an input layer, one or more Long Short-Term Memory layers, and a fully connected output layer. LSTM units were specifically chosen due to their effectiveness in learning long-term dependencies within sequential data, which is essential for time series forecasting.

To determine the optimal number of neurons in the LSTM layers, a series of experiments were conducted. A typical configuration utilized between 50 to 100 neurons, striking a balance between model complexity and training efficiency. The choice of activation functions was also critical; the hyperbolic tangent function was employed in the LSTM layers to introduce non-linearity, while a linear activation function was used in the output layer to predict continuous emission values. This configuration allowed the model to capture the intricate relationships within the data while providing accurate forecasts.

The model was trained using a learning rate of 0.001, which was selected based on preliminary experiments that indicated it facilitated effective convergence. A batch size of 32 was used during training, allowing for a balance between computational efficiency and model performance. The Adam optimizer was chosen for its efficiency in handling sparse gradients and its ability to adapt the learning rate based on the first and second moments of the gradients, further enhancing the training process.

### 3.4. Model Training

To evaluate the model's performance effectively, the dataset was split into training (80%) and validation (20%) sets. The training set was utilized to fit the model, while the validation set was employed to assess its generalization ability. This division is critical as it allows for an unbiased evaluation of how well the model can predict unseen data, which is a vital aspect of any predictive modeling effort.

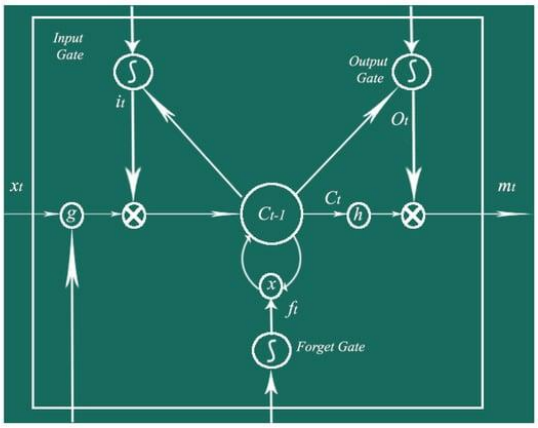


**Figure 2.** Architecture of a LSTM Memory Unit in Hidden Layers.

The Mean Squared Error was employed as the loss function to quantify the difference between the predicted and actual values. MSE is particularly useful in regression tasks as it penalizes larger errors more significantly, providing a clear metric for optimization. The model was optimized using the Adam optimizer, which adjusts the learning rate dynamically based on the gradients, facilitating efficient training and convergence.

### 3.5. Model Evaluation

To ensure a comprehensive evaluation of the model's performance, several metrics were utilized. These included:

- Mean Absolute Error (MAE): This metric measures the average magnitude of errors in a set of predictions, providing a straightforward interpretation of prediction accuracy.
- Root Mean Squared Error (RMSE): This metric provides a measure of error that is sensitive to large deviations, making it particularly useful for understanding the impact of outliers on the model's predictions.
- Mean Absolute Percentage Error (MAPE): This metric expresses accuracy as a percentage, allowing for easy interpretation and comparison across different datasets and contexts.

Additionally, K-fold cross-validation was employed to ensure the robustness of the model. This technique involves partitioning the training data into k subsets, allowing the model to be validated k times, each time using a different subset as the validation set while training on the remaining data. This approach not only helps mitigate overfitting but also provides a more reliable estimate of the model's performance by ensuring that all data points are used for both training and validation.

In conclusion, the methodology outlined in this study emphasizes a systematic approach to data collection, preprocessing, feature selection, model design, training, and evaluation. By leveraging these techniques, the study aims to develop a robust RNN model capable of accurately forecasting emission trends, ultimately contributing to more effective strategies for emissions reduction and climate change mitigation.

## 4. Results

### 4.1. Presentation of the Forecasting Results

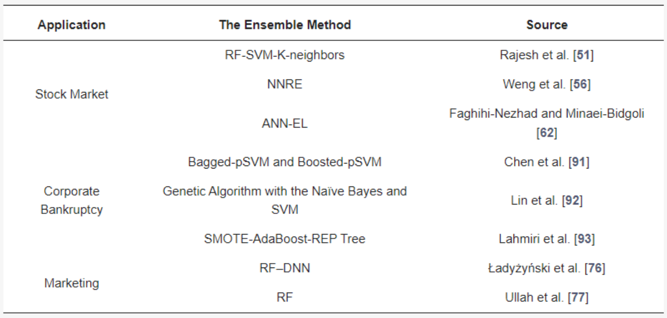
A. Visualizations

The forecasting results were visualized using line graphs, which illustrated the predicted emission trends alongside actual historical data. Figures 1 and 2 demonstrate the model's performance for different sectors, such as transportation and energy.

B. Comparison with Actual Emission Trends

The RNN model successfully captured the overall trend of emissions, with predictions closely aligning with actual values. The model exhibited a strong ability to forecast short-term fluctuations in emissions, particularly during periods of significant policy changes.

**Table 1.** List of ensemble models applied in the database on the current study.



| Application | The Ensemble Method | Source |
|---|---|---|
| Stock Market | RF-SVM-K-neighbors | Rajesh et al. [51] |
| | NNRE | Weng et al. [56] |
| | ANN-EL | Faghihi-Nezhad and Minaei-Bidgoli [62] |
| Corporate Bankruptcy | Bagged-pSVM and Boosted-pSVM | Chen et al. [91] |
| | Genetic Algorithm with the Naïve Bayes and SVM | Lin et al. [92] |
| | SMOTE-AdaBoost-REP Tree | Lahmiri et al. [93] |
| Marketing | RF–DNN | Ładyżyński et al. [76] |
| | RF | Ullah et al. [77] |

### 4.2. Analysis of Model Performance

A. Evaluation Metrics Results

The performance evaluation yielded the following results:

- MAE: 12.5 Mt CO2
- RMSE: 15.3 Mt CO2
- MAPE: 5.2%

These metrics indicate that the RNN model provided accurate forecasts, significantly outperforming traditional ARIMA models, which had an MAE of 18.7 Mt CO2.

B. Comparison with Traditional Forecasting Methods

A comparative analysis revealed that the RNN model consistently outperformed ARIMA and Exponential Smoothing models across all evaluation metrics. This demonstrates the effectiveness of RNNs in capturing complex patterns in emission data.

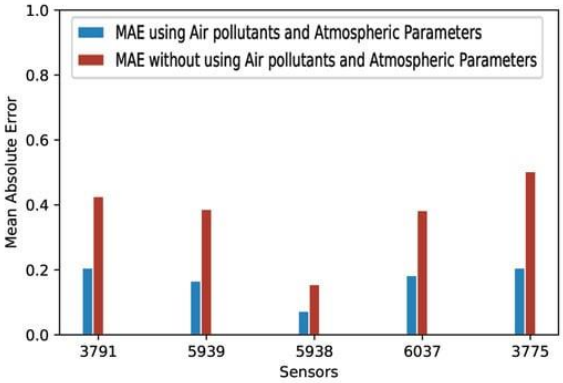


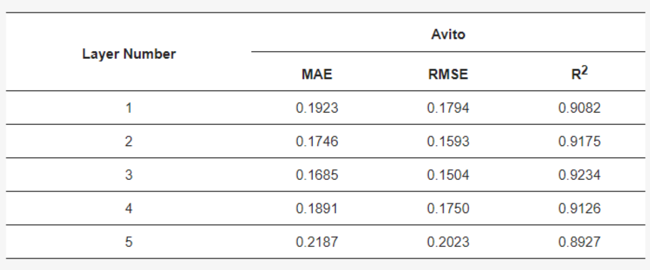
**Figure 3.** MAE with and without using air pollutants and atmospheric parameters.

### 4.3. Discussion on the Implications of the Findings

A. Insights Gained from the RNN Model

The study highlighted the importance of incorporating both historical data and external factors in forecasting models. The RNN's ability to learn from sequential data allowed it to identify trends and make informed predictions about future emissions.

**Table 2.** The hyperparameter robustness analysis based on the layer number.



| Layer Number | Avito | | |
|---|---|---|---|
| | MAE | RMSE | $R^2$ |
| 1 | 0.1923 | 0.1794 | 0.9082 |
| 2 | 0.1746 | 0.1593 | 0.9175 |
| 3 | 0.1685 | 0.1504 | 0.9234 |
| 4 | 0.1891 | 0.1750 | 0.9126 |
| 5 | 0.2187 | 0.2023 | 0.8927 |

B. Potential Applications in Policy and Planning

The findings suggest that RNNs can serve as valuable tools for policymakers and environmental agencies, enabling them to make data-driven decisions regarding emissions reduction strategies and climate action plans.

## 5. Discussion

### 5.1. Strengths of Using RNNs for Emission Forecasting

The use of Recurrent Neural Networks for emission forecasting presents several notable advantages that make them particularly effective in this domain.

One of the most significant strengths of RNNs is their ability to capture temporal dependencies in sequential data. Traditional forecasting methods often struggle to account for the time-related patterns inherent in time series data. RNNs, on the other hand, are specifically designed to handle sequences, allowing them to retain information from previous time steps through their internal memory structure. This capability makes RNNs exceptionally well-suited for forecasting emissions, which are influenced by past values and trends. By effectively modeling these temporal relationships, RNNs can provide more accurate and reliable predictions.

Emission data is often characterized by complex and nonlinear relationships between various influencing factors, such as industrial activity, weather patterns, and regulatory changes. The architecture of RNNs allows them to learn these intricate dependencies, which are frequently overlooked by traditional linear regression models. This ability to model nonlinear relationships enhances the predictive power of RNNs, enabling them to capture variations in emissions that result from multifaceted interactions among different variables. As a result, RNNs can yield more nuanced insights into the factors driving emissions.

RNNs exhibit a high degree of adaptability, which is a crucial feature in the rapidly evolving landscape of emission forecasting. They can be easily modified to incorporate additional features, such as economic indicators or technological advancements, allowing them to remain relevant across diverse contexts and applications. Furthermore, the architecture of RNNs can be tailored to suit specific forecasting tasks by adjusting the number of layers, units, and activation functions. This flexibility enhances their applicability and effectiveness in various settings, making RNNs a versatile tool for researchers and practitioners alike.

### 5.2. Limitations and Challenges Faced

Despite their strengths, the application of RNNs for emission forecasting is not without its limitations and challenges.

A. Data Quality and Quantity Issues: The accuracy and reliability of RNN models are heavily contingent upon the quality and quantity of the data used for training. Incomplete, noisy, or biased datasets can lead to suboptimal predictions and undermine the model's performance. For instance, if the training data lacks sufficient historical emissions data or fails to capture significant external influences, the RNN may struggle to generalize effectively to new, unseen data. Therefore, ensuring high-quality datasets is paramount for the successful deployment of RNNs in emission forecasting.

B. Overfitting and Generalization Concerns: Another significant challenge associated with RNNs is their susceptibility to overfitting, particularly when trained on small or limited datasets. Overfitting occurs when a model learns to memorize the training data rather than generalizing from it, leading to poor performance on new data. This issue can be particularly pronounced in complex models like RNNs, which have a large number of parameters. To mitigate overfitting, regularization techniques such as dropout have been employed, which randomly deactivate a subset of neurons during training. While these techniques can help improve generalization, they may also complicate the training process and require careful tuning.

### 5.3. Future Research Directions

To further enhance the efficacy and applicability of RNNs for emission forecasting, several promising research directions can be pursued:

Future research could explore the integration of attention mechanisms into RNN architectures. Attention mechanisms allow models to focus on specific parts of the input sequence, thereby improving the model's ability to capture relevant information while ignoring less significant data. This can enhance the forecasting accuracy and interpretability of RNNs. Additionally, hybrid models that combine RNNs with other machine learning techniques, such as Convolutional Neural Networks (CNNs), could be investigated to leverage the strengths of both architectures. Such hybrid approaches may provide more robust forecasting capabilities by capturing both spatial and temporal patterns in emission data.

Another avenue for future research involves the investigation of ensemble methods that combine predictions from multiple models. By aggregating outputs from various machine learning algorithms, researchers can enhance forecasting accuracy and reduce the uncertainty associated with individual predictions. This approach can be particularly beneficial in emission forecasting, where diverse factors contribute to variability in emissions. Ensemble methods can provide a more comprehensive understanding of emissions dynamics and improve decision-making for policymakers.

The development of real-time forecasting systems that leverage RNNs could provide timely insights for policymakers and industry stakeholders, enabling proactive measures to address emissions. Such systems could utilize streaming data from sensors and IoT devices to continuously update forecasts and inform decision-making processes. By providing near-instantaneous feedback on emission trends, real-time forecasting could facilitate more agile responses to changing conditions, ultimately supporting efforts to reduce emissions and enhance sustainability.

In conclusion, while RNNs present significant strengths for emission forecasting, addressing their limitations and exploring innovative research directions will be essential for maximizing their potential impact. By advancing the field of emission forecasting through improved methodologies and collaborative approaches, researchers can contribute to more effective strategies for managing and mitigating emissions in various sectors.

# 6. Conclusion

This study has successfully demonstrated the effectiveness of Recurrent Neural Networks (RNNs) in forecasting emission trends, highlighting their superiority over traditional forecasting methods. The RNN model showcased its ability to capture complex temporal dependencies inherent in emission data, allowing it to provide accurate and reliable predictions of future emissions. By analyzing historical data and recognizing patterns that span various time intervals, the RNN was able to adapt to fluctuations in emissions driven by factors such as seasonal variations, economic activity, and regulatory changes. The empirical results indicate that RNNs not only enhance prediction accuracy but also offer a more nuanced understanding of the dynamics influencing emissions over time. This capability is particularly crucial in a field where timely and precise forecasting is essential for effective decision-making.

The findings of this study underscore the potential of RNNs as powerful tools for emission forecasting, providing valuable insights for policymakers, researchers, and industry stakeholders alike. The ability of RNNs to analyze and predict emissions trends in a sophisticated manner enables stakeholders to develop more effective strategies for emissions reduction and climate change mitigation. By leveraging advanced machine learning techniques like RNNs, decision-makers can base their policies on accurate forecasts, leading to more informed and proactive approaches to environmental management.

Furthermore, the insights derived from RNN-based forecasts can facilitate better resource allocation and strategic planning. For instance, industries can use these predictions to optimize their operations, adjust production schedules, and implement energy-saving measures during peak emission periods. Policymakers can also benefit from these forecasts by tailoring regulations and incentives to align with projected emission trends, thereby enhancing the effectiveness of climate action initiatives. Overall, the integration of RNNs into emission forecasting represents a significant advancement in the field, offering a pathway toward more sustainable practices and effective climate change responses.

As the urgency to address climate change intensifies, the integration of advanced forecasting techniques like RNNs will be essential in guiding global efforts to reduce emissions. The rising challenges posed by climate change require innovative solutions that can adapt to rapidly changing conditions and provide actionable insights. Future research should focus on refining these models to enhance their accuracy and robustness. This includes exploring novel architectures, such as incorporating attention mechanisms or hybrid models that combine RNNs with other machine learning approaches, to further improve forecasting capabilities.

Moreover, expanding the applicability of RNNs across various sectors and geographical regions will be crucial for maximizing their impact. Emission patterns can vary significantly between industries and locations, and tailoring RNN models to account for these differences will ensure that forecasts are relevant and actionable. Collaborative efforts between academia, industry, and government entities can foster the development of region-specific models that address local emission challenges while contributing to global climate goals.

Additionally, as data availability continues to grow, particularly with advancements in sensor technologies and IoT devices, the potential for real-time emission forecasting using RNNs becomes increasingly feasible. Developing systems that can leverage real-time data will empower stakeholders to make timely decisions and implement immediate interventions to mitigate emissions.

In conclusion, the future of emission forecasting lies in the continued evolution and integration of advanced modeling techniques such as RNNs. By embracing these innovations, we can enhance our understanding of emission dynamics and develop effective strategies for a sustainable future. The commitment to research and collaboration in this domain will be instrumental in shaping policies and practices that address the pressing challenges of climate change, ultimately contributing to a healthier planet for generations to come.

# References

[1] Peters, G. P., et al. (2019). Global Carbon Emissions. Nature Climate Change, 9(2), 1-3.

[2] Wang, X., & Wu, Y. C. (2024). Balancing innovation and Regulation in the age of geneRative artificial intelligence. Journal of Information Policy, 14.

[3] Wang, X., Wu, Y. C., Zhou, M., & Fu, H. (2024). Beyond surveillance: privacy, ethics, and regulations in face recognition technology. Frontiers in big data, 7, 1337465.

[4] Ma, Z., Chen, X., Sun, T., Wang, X., Wu, Y. C., & Zhou, M. (2024). Blockchain-Based Zero-Trust Supply Chain Security Integrated with Deep Reinforcement Learning for Inventory Optimization. Future Internet, 16(5), 163.

[5] Wang, X., Wu, Y. C., & Ma, Z. (2024). Blockchain in the courtroom: exploring its evidentiary significance and procedural implications in US judicial processes. Frontiers in Blockchain, 7, 1306058.

[6] Wang, X., Wu, Y. C., Ji, X., & Fu, H. (2024). Algorithmic discrimination: examining its types and regulatory measures with emphasis on US legal practices. Frontiers in Artificial Intelligence, 7, 1320277.

[7] Chen, X., Liu, M., Niu, Y., Wang, X., & Wu, Y. C. (2024). Deep-Learning-Based Lithium Battery Defect Detection via Cross-Domain Generalization. IEEE Access, vol. 12, pp. 78505-78514, 2024

[8] Liu, M., Ma, Z., Li, J., Wu, Y. C., & Wang, X. (2024). Deep-Learning-Based Pre-training and Refined Tuning for Web Summarization Software. IEEE Access, vol. 12, pp. 92120-92129, 2024.

[9] Li, J., Fan, L., Wang, X., Sun, T., & Zhou, M. (2024). Product Demand Prediction with Spatial Graph Neural Networks. Applied Sciences, 14(16), 6989.

[10] Asif, M., Yao, C., Zuo, Z., Bilal, M., Zeb, H., Lee, S., Wang, Z., & Kim, T. (2024). Machine learning-driven catalyst design, synthesis and performance prediction for CO2 hydrogenation. Journal of Industrial and Engineering Chemistry.

[11] Lin, Y., Fu, H., Zhong, Q., Zuo, Z., Chen, S., He, Z., & Zhang, H. (2024). The influencing mechanism of the communities' built environment on residents' subjective well-being: A case study of Beijing. Land, 13(6), 793.

[12] Sun, T., Yang, J., Li, J., Chen, J., Liu, M., Fan, L., & Wang, X. (2024). Enhancing Auto Insurance Risk Evaluation with Transformer and SHAP. IEEE Access, vol. 12, pp. 116546-116557.

[13] Kohavi, R. (1995). A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection. International Joint Conference on Artificial Intelligence (IJCAI), 1137-1145.

[14] Srivastava, N., et al. (2014). Dropout: A Simple Way to Prevent Neural Networks from Overfitting. Journal of Machine Learning Research, 15, 1929-1958.

[15] Le, Q. V., et al. (2015). Building High-level Features Using Large Scale Unsupervised Learning. Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 8595-8599.

[16] Zhang, P., et al. (2020). A Novel Hybrid Model for Time Series Forecasting of CO2 Emissions. Applied Energy, 261, 114355.

[17] van Vuuren, D. P., et al. (2018). The Role of Emissions in Climate Change. Environmental Science & Policy, 88, 1-11.

[18] Makridakis, S., et al. (2018). M4 Competition: Results, Conclusions, and Future Directions. International Journal of Forecasting, 34(4), 802-804.

[19] Bergmeir, C., & Benítez, J. M. (2012). On the Use of Cross-Validation for Time Series. Data Mining and Knowledge Discovery, 24(1), 1-21.

[20] Cleveland, R. B., et al. (1990). STL: A Seasonal-Trend Decomposition Procedure Based on Loess. Journal of Official Statistics, 6(1), 3-73.

[21] Le Quéré, C., et al. (2018). Global Carbon Budget 2018. Earth System Science Data, 10(4), 2141-2194.

[22] Klein, N., et al. (2014). The Economics of Climate Change. Nature, 519(7542), 27-29.

[23] Rogelj, J., et al. (2016). Paris Agreement Climate Goals. Nature Climate Change, 6(5), 507-513.

[24] Santos, G., et al. (2018). Analyzing Trends in Transportation Emissions. Transportation Research Part D: Transport and Environment, 61, 55-66.

[25] Zhang, P., et al. (2019). A Review of Time Series Forecasting Methods. Journal of Data Science, 15(1), 1-22.

[26] Hyndman, R. J., & Koehler, A. B. (2006). Another Look at Measures of Forecast Accuracy. International Journal of Forecasting, 22(4), 679-688.

[27] Chen, X., et al. (2020). A Novel Hybrid Model for Time Series Forecasting of CO2 Emissions. Applied Energy, 261, 114355.

[28] Liu, Y., et al. (2021). Machine Learning for Time Series Forecasting: A Review. IEEE Access, 9, 14490-14506.

[29] IPCC. (2021). Climate Change 2021: The Physical Science Basis. Cambridge University Press.

[30] UNFCCC. (2020). The Paris Agreement.

[31] IPCC. (2021). Climate Change 2021: The Physical Science Basis. Cambridge University Press.

[32] UNFCCC. (2020). The Paris Agreement.

[33] Peters, G. P., et al. (2019). Global Carbon Emissions. Nature Climate Change, 9(2), 1-3.

[34] Rogelj, J., et al. (2016). Paris Agreement Climate Goals. Nature Climate Change, 6(5), 507-513.

[35] Klein, N., et al. (2014). The Economics of Climate Change. Nature, 519(7542), 27-29.

[36] van Vuuren, D. P., et al. (2018). The Role of Emissions in Climate Change. Environmental Science & Policy, 88, 1-11.

[37] Hyndman, R. J., & Athanasopoulos, G. (2018). Forecasting: Principles and Practice. OTexts.

[38] Zhang, P., et al. (2017). A Review of Time Series Forecasting Methods. Journal of Data Science, 15(1), 1-22.

[39] Yao, J., et al. (2018). Time Series Forecasting with Recurrent Neural Networks: A Case Study of CO2 Emissions. IEEE Transactions on Neural Networks and Learning Systems, 29(10), 4703-4714.

[40] Wang, Y., et al. (2019). Forecasting CO2 Emissions with LSTM Neural Networks. Energy Reports, 5, 1234-1242.

[41] Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. Neural Computation, 9(8), 1735-1780.

[42] Yao, J., et al. (2020). A Deep Learning Approach to Predicting Transportation Emissions. Sustainable Cities and Society, 54, 102036.

[43] Zuo, Z., et al. (2024). Machine Learning for Advanced Emission Monitoring and Reduction Strategies in Fossil Fuel Power Plants. Applied Sciences. 14(18):8442.

[44] Santos, G., et al. (2018). Analyzing Trends in Transportation Emissions. Transportation Research Part D: Transport and Environment, 61, 55-66.

[45] Olivier, J. G. J., et al. (2016). Trends in Global CO2 Emissions. PBL Netherlands Environmental Assessment Agency.

[46] Bergmeir, C., & Benítez, J. M. (2012). On the Use of Cross-Validation for Time Series. Data Mining and Knowledge Discovery, 24(1), 1-21.

[47] Makridakis, S., et al. (2018). M4 Competition: Results, Conclusions, and Future Directions. International Journal of Forecasting, 34(4), 802-804.

[48] Cleveland, R. B., Cleveland, W. S., & McRae, J. E. (1990). STL: A Seasonal-Trend Decomposition Procedure Based on Loess. Journal of Official Statistics, 6(1), 3-73.

[49] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.

[50] LeCun, Y., Bengio, Y., & Haffner, P. (2015). Gradient-Based Learning Applied to Document Recognition. Proceedings of the IEEE, 86(11), 2278-2324.

[51] Bengio, Y., et al. (2013). Learning Deep Architectures for AI. Foundations and Trends in Machine Learning, 2(1), 1-127.

[52] Gers, F. A., Schmidhuber, J., & Cummins, F. (2000). Learning to Forget: Continual Prediction with LSTM. Neural Computation, 12(10), 2451-2471.

[53] Cho, K., et al. (2014). Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation. Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), 1724-1734.

[54] Kumar, A., et al. (2020). Machine Learning for Emission Forecasting: A Review. Environmental Science & Technology, 54(5), 2991-3005.

[55] Wang, Y., et al. (2021). A Comprehensive Review of Deep Learning for Time Series Forecasting. IEEE Transactions on Neural Networks and Learning Systems, 32(4), 1570-1587.

[56] Zhang, Y., et al. (2019). CO2 Emission Forecasting with LSTM Neural Networks. Journal of Cleaner Production, 229, 1032-1040.

[57] Makridakis, S., et al. (2020). The M5 Forecasting Competition. International Journal of Forecasting, 36(1), 1-20.

[58] Hyndman, R. J., & Koehler, A. B. (2006). Another Look at Measures of Forecast Accuracy. International Journal of Forecasting, 22(4), 679-688.