Forecasting Carbon Emissions in China's Provinces Based on Graph Neural Networks

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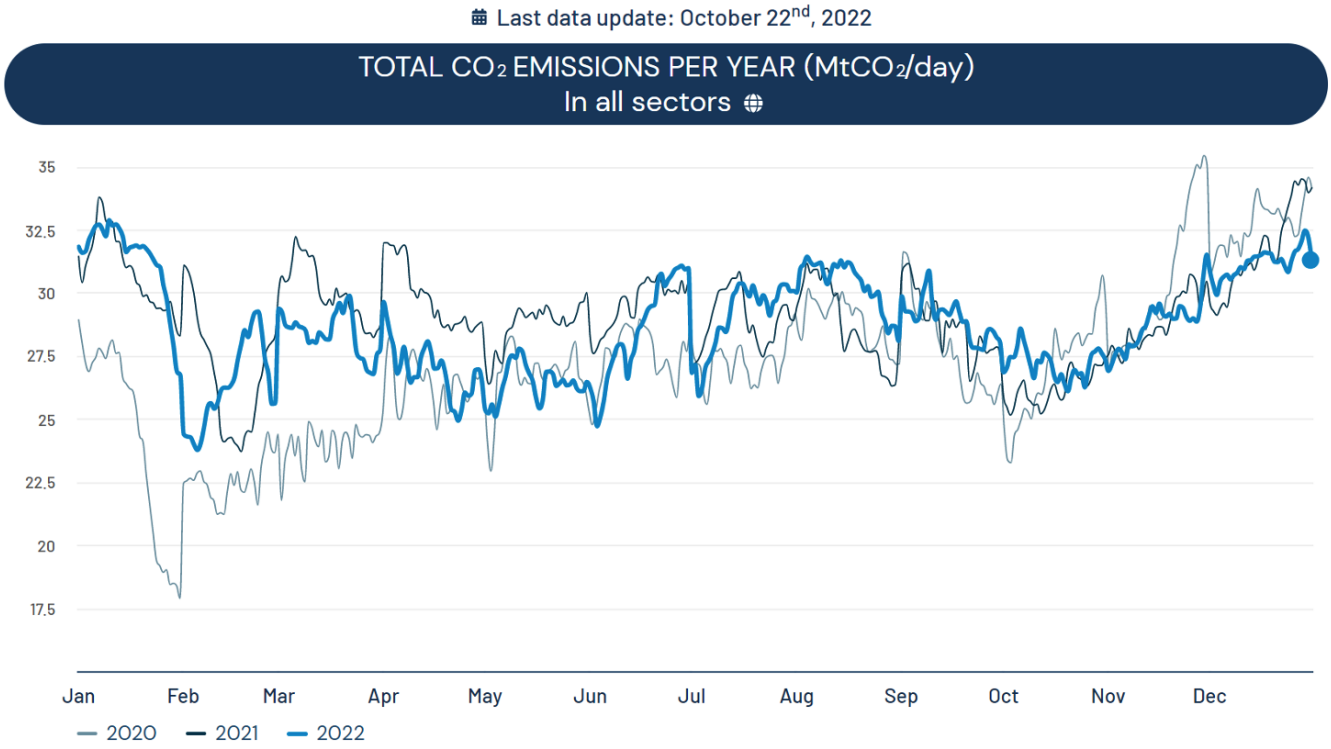

Figure 1: Total Carbon Emissions across Investigated Sectors

ABSTRACT

This is a coursework project submitted to the course *Foundation of Data Science and Analytics*. The project aims to state the effectiveness of Graph Neural Networks (GNN) in carbon emissions forecast, particularly in China's provinces. The project is generally divided into three parts: data preprocessing, model training, and model evaluation. The data preprocessing part includes data cleaning, data integration, and data visualization. The model training part includes the construction of the graph neural network and the training of the model. The model evaluation part includes the evaluation of the model and the analysis of the results. The project is implemented in Python and the source code is available at here. This project demonstrated the effectiveness of GNN in carbon emissions forecast compared to traditional methods such as MLP or LSTM, and the results are promising. In terms of the indivdual contributions, please refer to Table A.1 in the Appendix.

KEYWORDS

Emission prediction, Graph Neural Networks, Carbon Emissions, China's Provinces

1 INTRODUCTION

Global warming, far from being a recent phenomenon, can be perceived from another point as a persisting dilemma that continues to impact both anthropogenic development and the natural ecosystem. The primary agent provoking global warming is attributed to the emissions of greenhouse gases. Empirical studies confirm that carbon dioxide holds the dubious distinction of being the most abundant greenhouse gas in the atmosphere, contributing a staggering 72% to global warming [1].

However, it is noteworthy to mention that China ranks as the preeminent emitter of carbon dioxide on a global scale, discharging in excess of 6 billion tonnes of carbon dioxide annually. Hence, addressing this crisis, intrinsically connected to the existential fate of mankind, became a priority for China. As a concrete commitment to this endeavor, President Xi Jinping, in September 2020, proclaimed China's aim to "reach a peak in CO2 emissions by 2030 and accomplish carbon neutrality by 2060". The challenge of achieving carbon neutrality is multifarious, necessitating a holistic approach, encompassing policy, economy, culture, and technology. This paper opts to focus on the forecasting of carbon emissions, a crucial foundational element for strategic decision-making. Proficient predictions

furnish invaluable data that bolsters informed decision-making. Conversely, if the prognosis proves inaccurate, ensuing plans may fall into the domain of impracticality [2].

The stakeholders who stand most directly impacted by these emissions include governments, investors, and researchers. Government bodies, equipped with foresight into future carbon emissions, can effectuate more meaningful change in climate policy, emergency development, and global cooperation. Conversely, researchers and investors, informed by predictive results, can more effectively design mechanisms such as the Emissions Trading System, Carbon Pricing System, and related technologies. Consequently, the act of forecasting carbon emissions carries significant implications for subsequent research.

Since the year 2011, endeavors have been made to utilize logistic equations in order to prognosticate China's carbon emissions [3]. At present, the primary methodologies employed for the prediction of CO2 emissions can be categorized into three principal clusters, specifically, statistical analysis models, non-linear intelligent models, and grey prediction techniques [4]. Statistical models offer ease of application, yet they necessitate the collection of ample historical data before the models can undergo training. Conversely, machine learning frequently outperforms in forecasting relative to conventional statistical methods.

This study implements the GNNs approach, presenting multiple advantages: Firstly, GNNs are capable of effectively modelling spatial and temporal correlations. Secondly, GNNs have the capacity to integrate additional contextual data, such as socio-economic and policy factors. Thirdly, GNNs can yield an interpretable model structure, thus enabling researchers to derive insights into the relationships between various factors and their subsequent impact on carbon emissions[5].

At this juncture, GNNs have not been extensively explored in the context of predicting carbon emissions. Hence, future research should pivot its focus towards delving into the application of GNNs in carbon emissions forecasting. The unique benefits offered by GNNs should be leveraged to construct models that are both highly accurate and interpretable.

2 DATA DESCRIPTION

Transitioning now to our research endeavor, the initial phase entailed data acquisition from CarbonMonitor CHINA, a repository that chronicles the carbon emission statistics for the past five years. We amassed more than 200 thousand data points spanning from January 1, 2019, to December 31, 2022, systematically segregating the data into 31 distinct states and five sectors respectively.

Subsequently, we performed a rudimentary data analysis, classified according to temporality, sector, and state. A review of the past four years reveals that carbon emissions peaked in the year 2021. Furthermore, a substantial variation in carbon emissions was discerned across different sectors. Additionally, the states of Hebei and Shandong emerged as the leading contributors to the nation's carbon emissions.

3 METHODOLOGY

In this section of the term paper, we systematically explore the technical aspects of three distinct machine learning methodologies

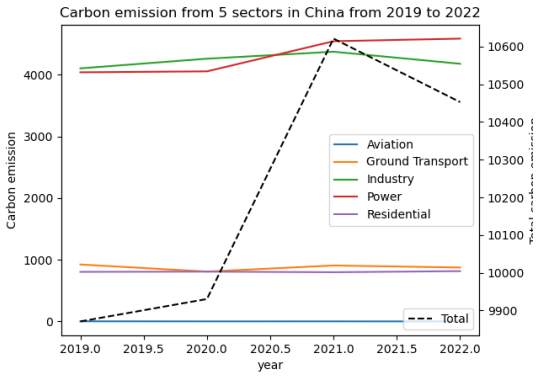

Figure 2: A graphical representation of emissions from five different sectors.

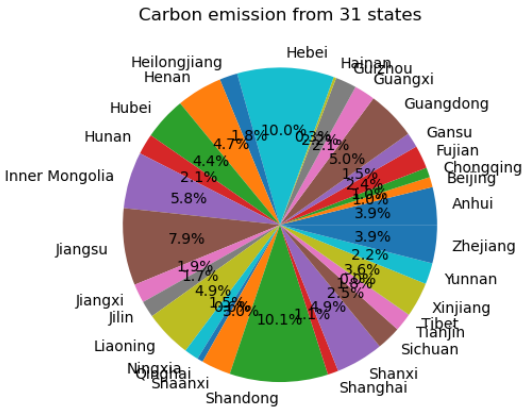

Figure 3: A graphical representation of emissions from 31 different states.

that are used in our study: the Adaptive Graph Convolutional Recurrent Neural Network (AGCRN), Multi-Layer Perceptron (MLP), and Fully Connected Long Short-Term Memory (FC-LSTM).

3.1 Adaptive Graph Convolutional Recurrent Neural Network (AGCRN)

Carbon emissions inherently form a complex, interconnected network due to their origin from various sources and impacts on various regions. This network extends both across different regions (spatial) and over time (temporal), which makes AGCRN uniquely suited for carbon emissions prediction. During the implementation, we mainly refer to the paper [6].

AGCRN's GCN component efficiently captures the interplay between different regions, considering how the carbon footprint in one region might influence and be influenced by the emissions in other regions. Its RNN component focuses on the temporal aspect, modeling how emissions evolve over time, including trends and seasonality, which are common in environmental data. Hence, the

AGCRN model provides a comprehensive, holistic perspective in carbon emissions forecasting.

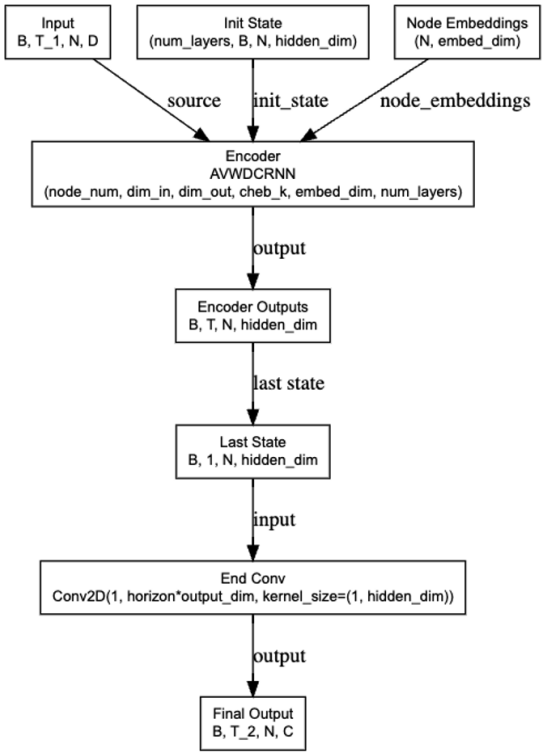

Figure 4: AGCRN workflow.

3.2 Multi-Layer Perceptron (MLP)

MLP is a fundamental form of artificial neural network, effective for capturing non-linear relationships between inputs and outputs. When applied to carbon emissions prediction, the MLP model can take into account various factors influencing emissions, such as industrial production, energy consumption, population density, and others. .

With its multiple layers and the capacity to learn complex mappings from inputs to outputs, MLP can model the intricate interactions between these different variables. Furthermore, the use of ReLU activation functions and dropout regularization enhances the model's ability to generalize from the training data, improving the robustness and reliability of predictions.

3.3 Fully Connected Long Short-Term Memory (FC-LSTM)

FC-LSTM is a recurrent neural network designed to capture long-term dependencies in time-series data, which makes it ideal for carbon emissions prediction. Carbon emissions data typically consist of time-series data, with various factors influencing the emissions evolving over time. We mainly refer to the paper [7].

The LSTM component, with its unique design of gating mechanisms, can efficiently learn and recall past information when needed,

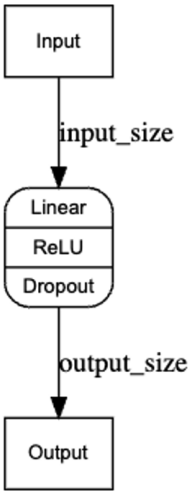

Figure 5: MLP workflow.

making it adept at modeling time-series data with long-term dependencies. These include identifying increasing or decreasing trends in emissions over the years or understanding seasonal variations. The fully connected layer helps in preserving the spatial relationships between different provinces, thereby improving the model's prediction capacity.

In essence, the FC-LSTM model's ability to consider past data and its capability to model time dependencies, along with spatial relationships, makes it highly suitable for predicting future carbon emissions.

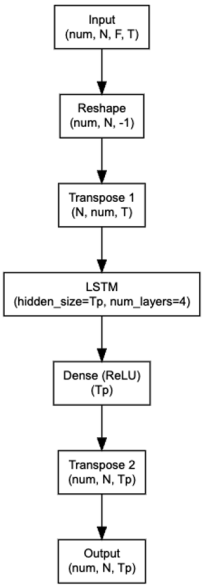

Figure 6: FC-LSTM workflow.

4 DATA PREPROCESSING

The data for this study was sourced from Carbon Monitor which provides daily carbon emissions data across different sectors for all 31 provinces in China. The data spans from 2019 to 2022, resulting in a total of 1461 samples for each province.

4.1 Carbon Emissions Data Preprocessing

Firstly, the raw data was retrieved from Carbon Monitor. For each province, the daily carbon emissions from all sectors were summed up, providing a single comprehensive measure of carbon emissions for each day. This process yielded a time series data set for each province, where each data point represents the total carbon emissions for a specific day.

Algorithm 1 Carbon Emissions Data Preprocessing

```
for each province do
    for each day from 2019 to 2022 do
        Sum up carbon emissions from all sectors
    end for
end for
```

4.2 Province Adjacency Matrix Construction

Next, a shapefile was utilized to calculate the adjacency of the provinces. If two provinces share a border, they are considered adjacent, and the corresponding entry in the adjacency matrix is set to 1; otherwise, it is set to 0. This adjacency matrix serves as the preliminary graph structure, which will be further refined during the training process of the Graph Neural Network (GNN) model.

Algorithm 2 Construction of Province Adjacency Matrix

```
for each pair of provinces do
    if they are adjacent then
        Set the corresponding adjacency matrix entry to 1
    else
        Set the corresponding adjacency matrix entry to 0
    end if
end for
```

The preprocessing of the carbon emissions data, along with the construction of the province adjacency matrix, serves as the foundation for the subsequent application of GNNs for forecasting carbon emissions in China's provinces.

5 EXPERIMENT

In this section, we present the experiment of these three models, AGCRN, MLP and FC-LSTM.

5.1 Evaluation Metrics

To compare the model performance, we implement MAE, MAPE and RMSE to measure these three models.

MAE: MAE measures the average absolute difference between the predicted and actual carbon emissions. It evaluates the model's ability to make accurate predictions.

$$MAE(y, \hat{y}) = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

MAPE: MAPE measures the average absolute percentage difference between the predicted and actual carbon emissions. It is used to evaluate the accuracy of the model's predictions relative to the actual values.

$$MAPE(y, \hat{y}) = \frac{1}{n}\sum_{i=1}^{n}\frac{||y_i - \hat{y}_i||}{||y_i||}$$

RMSE: RMSE is the square root of the MSE and is used to measure the standard deviation of the errors made by the model.

$$RMSE(y, \hat{y}) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Table 1: Parameter settings

Parameter/Setting	Value
Tp	1d
Tr	10d
Loss function	L2Loss
Optimizer	Adam
Percentage of training data	70%
Percentage of validation data	15%
Percentage of test data	15%
Epochs	100
Number of runs	1

Table 2: Average performance comparison of different approaches.

Method	MAE	MAPE	RMSE
AGCRN	0.0151	2.7%	0.0263
MLP	0.0699	8.8%	0.1010
FC-LSTM	0.5447	412.7%	0.4984

5.2 Simulation Results

In the simulation section, the parameter settings are listed in Table. 1, we split the datasets into 70% training data, 15% validation data and 15% test data.

In Table. 2, we exhibit the average performance comparison of different approaches. As you can see, the AGCRN performs the best in the three methods. MAE is 0.0151, MAPE is 2.7% and RMSE is 0.0263.

The AGCRN model outperformed the MLP and FC-LSTM models in our experiment, primarily due to its ability to capture the complex spatiotemporal dependencies of carbon emissions. The graph-based convolutional neural network structure of the AGCRN model enables it to extract features from the spatial and temporal domains simultaneously, resulting in more accurate predictions. In contrast, the MLP and FC-LSTM models are traditional machine

learning models that rely on linear regression and LSTM networks, respectively, to forecast carbon emissions.

5.3 Performance Evaluation

In the experiment, we also visualize the prediction result and evaluate the performance, as shown in Fig. 7 and Fig. 8.

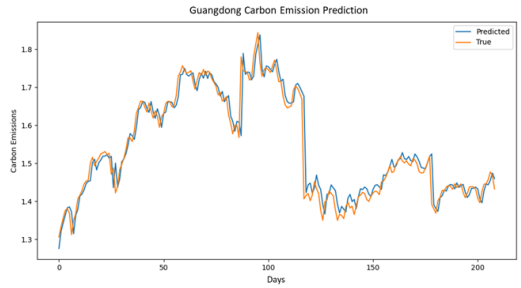

Figure 7: AGCRN.

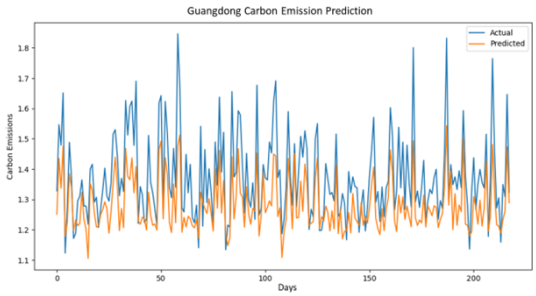

Figure 8: MLP.

From these two pictures of Guangdong carbon emission prediction, we can apparently find that the AGCRN has better prediction results than MLP, which further proves that the AGCRN method is more suitable for carbon emission prediction.

In conclusion, the AGCRN model's superior performance in predicting carbon emissions can be attributed to its unique graph-based convolutional neural network structure, which allows it to capture the intricate spatiotemporal dependencies of carbon emissions. This study's findings offer valuable insights into the development of more accurate and effective models for predicting carbon emissions, which can inform policymakers and stakeholders in their efforts to reduce carbon emissions and mitigate climate change.

6 CONCLUSION AND FUTURE WORK

In this course project, we presented three models, AGCRN, MLP, and FC-LSTM, for predicting the daily carbon emissions of 31 Chinese provinces using historical data from January 1st, 2019 to December 31st, 2022. Our results demonstrated that the AGCRN model outperformed the MLP and FC-LSTM models, indicating its robustness in predicting carbon emissions accurately.

The findings of this project offer a new approach to enhance the precision of carbon emission prediction. The AGCRN model's superior performance can be attributed to its ability to capture the complex spatial and temporal dependencies of carbon emissions. Our study provides valuable insights into the development of more accurate and effective models for predicting carbon emissions, which can inform policymakers and stakeholders in their efforts to reduce carbon emissions and mitigate climate change.

Future work: This project model can help carbon market stakeholders grasp the future trend of the carbon market more accurately and provide a reference for policymakers and investors in decision-making. However, the quality and availability of the carbon emission data are low, which makes it hard to improve the accuracy rapidly.

In future work, we can consider more factors to improve the accuracy of carbon emission prediction such as weather, seasonality, and economic conditions. What's more, it is necessary to improve the computational complexity.

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A APPENDIX

Table A.1: Contribution of each person in the project

Name	Tasks
Xiao FANG	Presenter, Background Investigation, FC-LSTM Training, Model Building
Hanyu GONG	Presenter, Model Evaluation, MLP Training, Model Building
Mingze GONG	Presenter, Data Preprocessing, AGCRN Training, Model Building