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Abstract. Recently, due to global warming, the ice in the arctic ocean is rapidly melting, leading to an increase in the navigable period for ships in the Arctic Ocean. As a result, the number of ships passing through the arctic ocean is also steadily increasing, leading to a rise in the emission of pollutants within the arctic ocean. These environmental changes are exacerbating pollution in the arctic ocean. We aim to analyze the changes in pollutant emissions in the arctic ocean using Arctic Ship Traffic Data (ASTD). Additionally, we aim to conduct long-term predictions of pollutant emissions from ships passing through the arctic ocean to forecast the future pollution levels in the arctic ocean. To achieve this, we propose a neural network architecture called Cross-Dimensional Dependency Network. This model has been proposed to improve the accuracy of long-term predictions of pollutant emissions in the arctic ocean. Compared to existing spatiotemporal data-based long-term prediction models, this model shows an improvement in prediction performance of over 10%. This model is expected to be used as fundamental data for the development of environmental protection policies by predicting future pollution levels in the arctic ocean and comparing them with current IMO regulations and policies.

Keywords: Cross-Dimensional Dependency Network, Arctic Ship Traffic Data, Arctic Ocean Pollutant Emission, Long-Term Forecasting

1 Introduction

Climate change is causing a reduction in ice along the arctic ocean routes, impacting navigation in the arctic ocean [1]. In the past, ships could navigate for five months,

including during the summer. However, in 2020, it was reported that ships could navigate for seven months, and this period is expected to increase gradually [2]. Indeed, over the past decade, maritime activity in the arctic ocean region has increased by an average of 7% per year, with winter navigation activity also significantly increasing [3]. These changes are also accelerating the increase in pollutants emitted from arctic shipping routes.

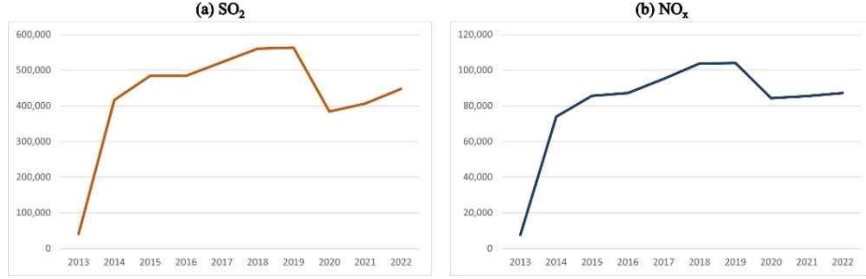


Fig. 1. The trend of changes in the amounts of SO₂ and NO_x emitted along the Arctic route from 2013 to 2022.

Fig. 1 visualizes the emission data included in the Arctic Ship Traffic Data (ASTD). According to this result, although emissions decreased from 2019 to 2020 due to factors such as COVID-19 and the Ukraine conflict leading to a reduction in vessel traffic, there is a consistent upward trend in emissions over the past decade [4].

We utilize the ASTD to perform long-term predictions of pollutants discharged through the arctic maritime routes. Additionally, we propose a novel artificial neural network architecture called Cross-Dimensional Dependency Networks (CDDNet) to enhance the accuracy of long-term predictions of pollutants discharged through the arctic maritime routes. We expected that the proposed CDDNet will contribute to establishing relevant policy regulations by providing accurate long-term predictions of emissions discharged along the arctic shipping routes.

2 Cross-Dimensional Dependency Network

We aim to long-term forecasting the emissions of 7 substances (CO, CO₂, SO₂, NO_x, N₂O, NMVOC, CH₄) at ASTD. Fig. 1 show the overall architecture of the Cross-Dimensional Dependency Networks (CDDNet) used to predict seven emissions from ships navigating in the arctic ocean. CDDNet is composed of n Cross-Dimensional Dependency mapping blocks. Each block consists of an embedding layer composed of linear layers, followed by a temporal layer and a spatial layer arranged in sequence. This structure is designed to learn temporal and spatial feature in the input data.

To generate input data for each network, the location information of the ships collected at the same time and the individual emissions discharged at each location are represented on a 32x32 grid. Subsequently, input data of size $(32, 32, i)$ is generated by considering sequence information of i instances to be trained. Before entering the CDDNet, the input data is partitioned into patches using patch embeddings, with the entire grid divided into patch units

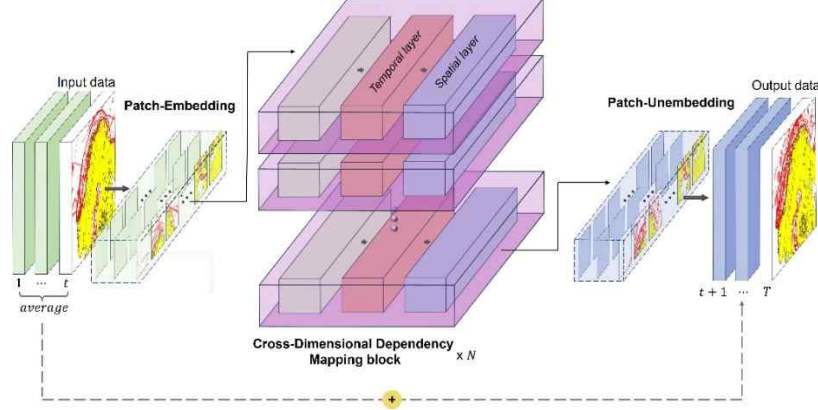


Fig. 2. Architecture of Cross-Dimensional Dependency Networks.

This input data is utilized to train the temporal and spatial features of patch units via the CDDNet. The acquired temporal and spatial features will enable the prediction of emission quantities at the anticipated time points through patch unembeddings. Ultimately, generating a grid set with dimensions of $(32, 32, T)$, where T represents the time points for long-term forecasting.

3 Experiments.

We have conducted comparative experiments between CDDNet and two representative baseline models (ConvLSTM [5], SimVP [6]) commonly used in spatiotemporal prediction to evaluate the predictive performance. The experimental data have been collected from ASTD over a period of 10 years from January 2013 to December 2022. The training and test data have been divided into a 7:3 ratio. The forecasting term has been set at one month and six months ahead for experimentation. For performance evaluation, we utilized metrics including Mean Squared Error (MSE), Mean Absolute Error (MAE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM) MSE and MAE are metrics for evaluating the difference between actual values and predicted values. Smaller values indicate better performance of the prediction model. PSNR and SSIM are metrics for evaluating the similarity between grids containing actual emissions, represented as $(32, 32, i)$, and grids containing predicted emissions, also represented as $(32, 32, i)$. Larger values indicate better performance of the forecasting model.

Table 1 represents the results of the comparative experiments. Initially, on a one-month prediction basis, our proposed model exhibited improved performance across all metrics compared to the existing model. While there were variations across performance metrics, they showed enhancements ranging from 3% to 10%. Furthermore, on a six-month prediction basis, there were performance improvements in all metrics except for the minimum PSNR, with up to a 26% enhancement in prediction performance. These results demonstrate that the structure of our proposed CDDNet is suitable for long-term prediction of pollutants emitted from ships in the arctic route.

Table 1. Table captions should be placed above the tables.

Forecasting Term	Metric	ConvLSTM	SimVP	CCDNet (Our)
One Month (30 days)	MSE	5.074	4.921	4.401
	MAE	2.370	2.587	2.154
	PSNR	44.203	44.267	44.613
	SSIM	0.919	0.917	0.928
Half of Year (180days)	MSE	5.931	5.881	5.757
	MAE	2.550	3.204	2.534
	PSNR	43.651	43.769	43.678
	SSIM	0.911	0.897	0.912

4 Conclusion

Our study presents a new CDDNet artificial neural network architecture for long-term prediction of substances discharged from ships in the Arctic Ocean. We found that the proposed model outperformed existing models, showing up to a 26% improvement in performance, particularly in long-term predictions such as 6 months ahead. By utilizing such predictive models, precise estimations of emissions from ships within the Arctic route can be made, serving as crucial foundational data for environmental regulations. Future research aims to further enhance the existing model structure to develop a model capable of accurate predictions up to 5 years ahead.

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