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Spatiotemporal dynamic network for regional maritime vessel flow prediction amid COVID-19

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ABSTRACT

The COVID-19 pandemic has stifled international trade and the global maritime industry. Its impact on the routing of the regional vessel traffic flow provides supportive data to port authorities, ship owners, shippers, and consignees. This study proposes a spatiotemporal dynamic graph neural network (STDGNN) model that includes the usual primary part of the vessel flow and an auxiliary part of newly confirmed COVID-19 cases near the port. The primary part consists of a time-embedding (TE) block, two dynamic graph neural network (DGNN) blocks, and a gated recurrent unit block, to capture the spatiotemporal dependence in the regional vessel traffic flow. The auxiliary part is made of multiple blocks to exploit the dynamic temporal relationships in hours, days, and weeks. Moreover, the performance of the STDGNN model is verified by utilising real vessel traffic flow data (i.e. inflow, outflow, and volume) and the new cases of COVID-19 near the port of New York, USA, provided by the automatic identification system and the Johns Hopkins University Centre for Systems Science and Engineering. The 2-h prediction result shows a 37.7%, 17.23%, and 11.4% improvement in the mean absolute error (MAE) over the gated recurrent unit (GRU), STGCN, and TGCN models, respectively. The delicate and adaptable prediction of vessel traffic flow could help the port relieve congestion, enhance efficiency, and further assist the recovery of regional maritime industries in the post-COVID era.

1. Introduction

The impacts of COVID-19 on maritime transportation include marine traffic declension, disordered port management, unusual fluctuations in vessel traffic flow, and weakening of the maritime supply chain connections. For example, Shanghai has reported a 17% decrease in port calls in January 2019 from 2020 (Ship-Technology, 2021). Both Europe and Africa suffered the weakening of port connectivity in 2020 (Guererro et al., 2022); distribution volume and goods handling declined owing to the limited workforce (Teoh, 2020). The container throughputs at the ports of Singapore and Los Angeles dropped by 10.6% and 30.9%, respectively (Feng et al., 2021). Maritime shipping, an indispensable integrant of international trade, is under enormous pressure from the impact of COVID-19 and preventive measures implemented by various nations.

A series of managerial issues at ports and their surroundings were observed, especially the issue of delayed cargo handling and sporadic port congestion. These problems and recessions have severely challenged port operation and increased the demand for digitalised intelligent decision support. Hence, exploration into policy making based on big data and the accurate prediction of regional vessel traffic flow amid COVID-19 have become imperative. The spatial and temporal relations in the vessel flow at the port region can provide a foundation for predicting the total vessel traffic volume (referred as the vessel volume hereinafter) and inflow and outflow scenarios, which could forewarn of large inflow to the port, and thus enhance the port operation efficiency.

A growing number of studies are being conducted with a focus on regional vessel flow prediction owing to the development and availability of the automatic identification system (AIS). Statistical and machine learning approaches have been utilised to explore the temporal dependency in vessel traffic flow (Li et al., 2019; Wang et al., 2021). Wang et al. (2019) and Zhou et al. (2020) deemed the flow prediction a spatiotemporal sequence-forecasting problem. However, studies on the prediction framework and method have two demerits. First, they seldom explored non-Euclidean dependencies, and simplified the complex
spatial dependencies as Euclidean dependencies. Second, port management is an indispensable component, especially amid COVID-19 (Shi and Weng, 2021; Shehzad et al., 2020; Notteboom et al., 2021); however, studies could not identify the nonlinear relationships between the pandemic and ship activities with the current methods. They captured the stochastic and nonlinear influences of COVID-19 on shipping decisions rather simplistically and imprecisely.

Previous models that disregarded the non-Euclidean dependency and nonlinear influences may work for small harbours with vessels from limited ports of departure, because the vessel trajectories are simple and clear. The prediction of vessel traffic flow for large ports, however, requires a more sophisticated and comprehensive model that addresses the complex interrelationships in terms of time, space, and features.

This study predicts the regional vessel flow near a port and implements the results to recommend digitalised policies. We used raw data from vessel traffic at New York Port, combined with confirmed cases of COVID-19 around the port as auxiliary data, to predict the vessel volume at the regional level by establishing a deep learning (DL) model with consideration of time, space, and pandemic features. To be specific, the novel prediction model called spatiotemporal dynamic graph neural network (STDGNN) consists of a primary part that captures the dynamic spatiotemporal relationship of the vessel traffic features, and an auxiliary part that extracts the impacts of COVID-19 in different time slices (i.e., hours, days, and weeks).

This study also proposes solutions to the two problems mentioned in the third paragraph of this section by combining the characteristics of regional vessel traffic flows. The solution to the first problem is to dynamically consider the non-Euclidean relations of the traffic flows. The vessel flow in the study area is influenced by its adjacent regions and geographically similar regions. A dynamic weighting approach inspired by the self-attention mechanism is applied to understand the degree of influence of different regions on the current region based on the inputs.

The solution to the second problem is to consider the trends of COVID-19, i.e., its diverse temporal influences, on the vessel flow. For example, the variation of confirmed cases in recent hours, days, and weeks would reveal different impacts on the vessel traffic flow.

This study makes four contributions to the field at large.

1) We capture the impacts of COVID-19 on regional vessel traffic flow by considering the temporal connection of multiple time slices.

2) We propose a model (STDGNN) that exploits the dynamic spatiotemporal dependency in the regional vessel traffic flow prediction. In particular, we design a DGN block to extract the non-Euclidean relationships among the vessel traffic features and also time-embedding (TE) and gated recurrent unit (GRU) blocks to capture the short- and long-term connections, respectively.

3) We obtain real data of New York Port from the AIS system and newly confirmed cases of COVID-19 in the vicinity and utilize them in experiments to provide an intelligent digital reference for policy making.

4) Our findings could provide information and guidance to maritime officials and individual vessel users for drafting long-term strategies or executing short-term decisions. It could help officials dispatch vessels to a certain area and implement disease-prevention measures. It could also alert vessel users of the real-time traffic situation near the port so that they can modify their travel itinerary. The predictions can be used as decision support for policies centred on congestion forewarning, temporary scheduling against emergencies, multiport collaboration, and multimodal transport scheduling.

The remainder of this paper is structured as follows. Section 2 surveys the literature on vessel flow prediction and recent studies on the impact of COVID-19 on seaports. Section 3 defines the problem statement and describes the STDGNN model in detail. Section 4 outlines the dataset processing and the experimental analysis conducted. Section 5 discusses the associated policy implications. Section 6 summarises the study and discusses the limitations, future scope, and application of the findings.

2. Literature review

2.1. Vessel flow prediction

Vessel traffic flow prediction is crucial to efficient maritime transportation management, operation, and coordination. The abundant information of the AIS data allowed us to record the number of ships entering or departing the region. Meanwhile, the prediction methods have developed from simple time series methods to more complex machine learning (ML) and DL methods. The two types of vessel traffic flow prediction methods are statistical and ML and DL methods.

2.1.1. Statistical and ML methods

The most significant studies in the literature have viewed vessel traffic flow prediction as a time-sequence prediction problem by considering the effects of historical timesteps. For instance, the autoregression and moving average (ARMA) method was used to predict ship traffic flow by considering various observations in different time periods (Li et al., 2018). The autoregressive integrated moving average (ARIMA) and wavelet neural network (WNN) were applied to predict the vessel-flow matrices (Liu et al., 2017). However, these methods perform poorly because they merely consider the influence of the historical timesteps on the prediction as a set of linear matrices rather than nonlinear matrices.

A group of ML approaches were proposed to consider the nonlinear characteristics. To be specific, Wang et al. (2017) implemented the back propagation (BP) neural network method to forecast the vessel traffic flow. Improving on this method, Zhang et al. (2019) proposed the PSO-BP mechanism for the same task. However, models related to BP are static feedforward networks, which are incompatible with the complex flexible traffic problem. Li et al. (2015) applied the robust nu-support vector regression model (RSVR) model to compute the nonlinear temporal dependencies of traffic flow. However, the model consumes time in rendering high-quality feature engineering.

2.1.2. Deep learning methods

An emerging branch of the ML, DL methods enjoy the superiority of automated feature engineering. The application of DL in multiple transportation prediction domains, such as traffic flow in the freeway (Lv et al., 2015), metro passenger flow (Liu et al., 2019), and ride-hailing demand (Geng et al., 2019), which gives a new insight on addressing the vessel traffic flow prediction problem in two aspects: temporal dependency and spatial and temporal relationships. Several extensions of methods based on the recurrent neural network (RNN) were applied to consider the temporal dependency. For instance, the long short-term memory (LSTM) network was proposed to consider the short- and long-term changes in vessel traffic flow, with the addition of the influences of water level (Xie and Liu, 2018). Furthermore, as an improvement of the LSTM that has a relatively simple structure, the GRU was combined with Markov residual correction to explore the connections in a time series (Xu et al., 2021).

The vessel traffic flow prediction should be viewed as a spatiotemporal problem owing to the constraints of the spatial structure of the water area and the time-order characteristic. However, these approaches only considered the temporal dependencies. To bridge this gap, a series of spatiotemporal models have been proposed. For instance, the multiple hexagon-based convolutional neural network (MH-CNN) was utilised to predict the vessel traffic flow in a region considering the environmental conditions (Wang et al., 2019). The bidirectional LSTM network was integrated with the CNN (BDLSTM-CNN) to predict the vessel traffic flow in all grids divided by the study domain (Zhou et al., 2020). However, the CNN-based methods were only suitable for capturing the Euclidean space and not the non-Euclidean one.
The development of maritime traffic flow forecasting is less satisfactory than the one for road traffic because of the complexity of data acquisition and processing. With the proposal of aggregating non-Euclidean information in the spatial dimension (Wu et al., 2021), graph neural network (GNN) methods were widely applied to predict the freeway traffic flow. The GNN was further combined with the GRU to learn the topological spatial connection and temporal dependence in traffic forecasting (Zhao et al., 2020). Graph convolution was developed for modelling the spatiotemporal networks using a residual LSTM structure for constructing multiple periodicities (Zhang et al., 2020). Nevertheless, the traditional GNN approaches only construct fixed matrices when acquiring spatial information, which restricts the extraction of dynamic spatial relationships.

We propose the DGNN block for modelling the non-Euclidean relationships (i.e. spatial connections and featural dependency), which captures the stable relationships between two unit grids on the spatial or featural networks and considers the possible dynamic influences from all unit grids to the node under study. Meanwhile, a self-attention mechanism is added in this block to weigh the corresponding influence from all unit grids to the current one flexibly. Time-embedding (TE) and GRU blocks were developed for modelling the short- and long-term periods, respectively, and they were then integrated with the DGNN block to obtain the spatiotemporal relationships in the vessel traffic flow.

2.2. Influence of COVID-19 on maritime ports

Recently, several studies have focused on exploiting the influencing factors of the pandemic on maritime transportation and proposed corresponding policy recommendations in the fields of global maritime mobility (Millefiori et al., 2021), maritime port connection (Guerrero et al., 2022), and maritime transportation security and resilience (Brew et al., 2021). As the nodes of the global maritime network, seaport plays a vital role in commercial intercourse and activity (Kuo, 2020). News reports and research studies related to the effects of COVID-19 on seaports and their policies are abundant. For example, the growth of India’s cargo and vessel traffic at a seaport were hit by the COVID-19 outbreak, which was analysed by comparing the performance before and during the pandemic (Narasimha et al., 2021). The merchant ship count and utilisation frequency the Shanghai port plummeted during the pandemic, which was evaluated by comparing the AIS data in Feb 2019 and 2020 (Shi and Weng, 2021). Italy’s blockade policies during COVID-19 caused a plunge in vessel activities and passenger traffic in Veneto, revealed by comparing the vessel activities during the 2020 lockdown with that during the same period in 2017 (Depellegrin et al., 2020). Such studies had attempted to reveal the impact of the pandemic by comparing the performance before and after it through a comparative analysis. However, they assumed the degree of influence to be static and constant, which is unrealistic.

In contrast, other studies have analysed the influence of the pandemic on the vessel flow by treating time as a continuum. The exogenous effects on the shipping industry from the outbreak were studied using an exponential smoothing model (Zhao et al., 2022), but it overlooked the fact that the progress of the pandemic varied with region. Xu et al. (2021) analysed the effects of macroeconomy, disease severity, and governmental disease control measures on port operations. Millefiori et al. (2021) studied using an exponential smoothing model (Zhao et al., 2022), but it overlooked the fact that the predicted value was related not just to one or two previous assumed linear influences, whereas the pandemic had a stochastic and nonlinear influence over time. Furthermore, they also overlooked the fact that the predicted value was related not just to one or two previous timetables, but also to various historical observations over short- and long-term time periods, e.g. recent time intervals, daily periodicity, or weekly trends. The week sequence, as long-term data, contains the influence from weekly periods.

In summary, various methods have been used to study the impact of the pandemic on maritime flow, primarily focusing on the linear influence of COVID-19. They assumed that the influence was constant over time. The spatiotemporal vessel traffic flow amid the pandemic, especially at seaports, lacks investigation. This study designed a spatiotemporal dynamic network DL framework to explore the impact of the pandemic on the seaport vessel traffic flow by modelling the large database of AIS and COVID-19, owing to the prowess of DL in extracting nonlinear and variable factors.

Vessel traffic flows prediction is essential in efficient maritime transportation management, operation, and coordination. The popularity acquisition of the AIS data allows us to recode the number of ships entering or leaving in the region. In the meantime, the prediction methods have developed from simply time series method to nowadays machine learning and deep learning methods. The reviews of vessel traffic flow prediction are expressed by two aspects below.

3. Methodology

This section first mathematically defines the problem statement and constructs vessel graph networks to capture the non-Euclidean relationships. Next, the construction of the framework is detailed. Finally, the major blocks of the proposed framework are analysed, and their design with respect to the problem statement is explained. The TE, DGNN, and GRU blocks were combined to dynamically and adaptively capture the complex temporal, spatial, and featural dependencies, respectively.

3.1. Problem statement

The objective of the prediction framework is to produce real-time and adaptive spatiotemporal prediction amid COVID-19. The historical vessel features were considered the primary inputs and contain the vessel inflow, outflow, and volume, which respectively signify the number of vessels entering the area, leaving the area, and staying in the area between each pair of adjacent time slices. In addition, we considered multiple types of COVID-19 data consisting of three types of time sequence: 1. The recent hour, 2. Day, and 3. Week sequences. These types historical confirmed COVID-19 cases were further considered as auxiliary inputs simultaneously. A sequence of primary inputs $\mathbf{X}^p = (X_{t-1}^p, ..., X_{t-2}^p, ..., X_0^p) \in \mathbb{R}^{N \times F \times T_h}$ and auxiliary input $\mathbf{X}^e = (X_{t-1}^e, ..., X_{t-2}^e, ..., X_0^e) \in \mathbb{R}^{N \times F \times T_h}$ were collected, where $N$ denotes the number of unit grids in the given region, $T_h^p$ and $T_h^e$ denote the number of historical timesteps in the primary and auxiliary tensors, respectively, and $F$ denotes the number of features. The aim is to design a forecasting model $f$ to predict the future $T_p$ steps

$$X_{t+i}^p = f(X_{t+i}^e, X_{t+i-1}^p)$$

3.2. Vessel graph networks

We considered the non-Euclidean relationships in the framework to fully utilize the spatial information. Consider the scenario depicted in Fig. 1. The vessel traffic flow in a region such as $C$ is typically affected by its spatially adjacent neighbours, regions $A$ and $B$. Region $C$ will correlate with $D$ if there is a clear planning route, but the connection between $C$ and $E$ will be weak if the route is uncertain.

We formulated the non-Euclidean relationships on multiple graphs and structured them together in a time series. Two networks (i.e. the vessel spatial and featural networks) were represented as graphs $G_i = (V_i, A_i, W_i)$ and $G_t = (V_t, A_t, W_t)$, describing the non-Euclidean relationships in terms of space and features, respectively, where $V$ denotes a set of vertices. $|V_i|$ equals $N$ in graph $G_i$, and $|V_t|$ equals $F$ in graph $G_t$. $N$ and $F$ denote the number of spatial regions and vessel features, respectively.
A, W ∈ R^{V×V} denote two adjacent matrices, of which A is filled with the values ‘0’ and ‘1’ ('0' indicates that there is no edge between the two vertices, whereas ‘1’ indicates that there is an edge-bridging between two vertices). The value of W_{ij} in matrix W ranges from ‘0’ to ‘1’ and signifies the strength of the edge that connects vertices i and j.

### 3.3. Framework of STDGNN

We propose a general spatial-temporal forecasting model named STDGNN, mainly contains two paratactic parts: one is the primary part and the other one is the auxiliary part, as shown in Fig. 2. The former that consists of a TE block, two different dynamic DGNN blocks and a GRU block could learn the featural, spatial and temporal relevance in primary input \( X_p \). The latter that is composed by multiple parallel TE and GRU blocks could learn the multiple temporal correlations (i.e. previous hours, days, and weeks) in the auxiliary input \( X_a \). Moreover, an attention aggregation layer is added to dynamically assign different weights on multiple primary results \( O^p_a, O^d_a \) and \( O^h_a \) in order to obtain a more accurate result \( O^p \). Meanwhile, residual links and layer normalizations are added to ensure the effectiveness of the proposed STDGNN model. The final output \( \hat{Y}^p \) is the combination of the outputs of primary part \( O_p \) and the auxiliary part \( O_a \).

The TE block is proposed in both parts to obtain the local trend. The GRU block is employed to obtain the global drift information in as a time series. Additionally, the DGNN block is structured by two parallel DGNN layers and an attention aggregation layer to dynamically extracting the non-Euclidean relationships (i.e. the spatial connection and the featural dependency). To adaptively learn the rich and complex relationships, each DGNN layer was equipped with a dynamic predefined graph \( g_{dp} \) and a dynamic undefined graph \( g_{np} \). The attention aggregation layer was also outlined in each DGNN block to integrate the results of the two DGNN layers with different weights. The TE block, DGNN blocks, and GRU block are detailed in the following sections.

### 3.4. TE block

The purpose of the TE block is to extract the local trends in the temporal domain provided the following three conditions are met: the latest observation should be highly correlated to the present in a time series; a high amount of internal information of COVID-19 is mapped in a set of layers to capture the flexible and various temporal dependencies; and multiple temporal inputs (recent, day, and week inputs) need to be simultaneously modeled. To satisfy these conditions, we designed the TE block, as shown in Fig. 3.

We employed causal convolution in the TE block to capture the consecutive and preceding positions in the temporal relationship (Fig. 3). Specifically, each TE block is deployed to address one feature of the input \( X = (X_{f1}, X_{f2}, ..., X_{fF}) \in \mathbb{R}^{N \times T_h \times F} \) and includes a causal...
convolution function and an activation function ReLU(·). The TE blocks were further stacked to create hidden states $H = (H_1, H_2, ..., H_m) \in R^{N_x \times T_x \times F_M}$, where $M$ denotes the number of output channels in the causal convolution. The input of each layer $X_t \in R^{N_x \times T_x}$ was treated as the stacking of several time sequences from the corresponding unit grids. The convolution kernel $\Gamma \in R^{k \times 1 \times C}$ was utilised with the same weight among the unit grids to aggregate $K_t$ adjacent moments in each sequence.

### 3.5. DGNN block

Spatial and featural relationships are variable and non-Euclidean, which means 1) the nodes in the spatial and featural dimensions appear as non-Euclidean distributions, and 2) the connections among these nodes are continuously changing. The DGNN block is significant in the whole model, which is designed to address the spatial and featural relationships by constructing two dynamic non-Euclidean graphs, the dynamic predefined graph and the dynamic undefined graph, respectively. The DGNN was expressed in four aspects, which are the definitions of the basic GNN, dynamic predefined GNN (DPGNN), dynamic undefined GNN (DNGNN), and attention aggregation layers. Detailed explanations about the motivations and procedures are provided in the following sections.

#### 3.5.1. GNN

GNN-related approaches are widely used to handle unstructured relationships owing to their ability to update the current vertex by collecting information on the associative vertices in the graph (Khosrawy and Wagner, 2019; Qin et al., 2019). The definition of a GNN operation is as follows:

$$GCN(H^{n-1}) = \sigma\left(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}H^{n-1}W^{(m)}\right)$$  \hspace{1cm} (2)

where $H^{(m)} \in R^{V \times D_k}$ denotes the inputs in layer $m$, $V$ is the number of vertices in the graph, $W^{(m)} \in R^{D_k \times D_k}$ is the parameter of a linear projection, $\tilde{A} = A + I_c \in R^{V \times V}$ is the adjacency matrix with added self-connections, and $\sigma(·)$ denotes an activation function.

However, the adjacency matrix $A$ in the GNN model is always fixed, meaning the graph is predefined. This causes the GNN approaches to miss the variable and fixed relationships in the vessel flow prediction problem. To preserve the superiority and avoid the weakness of the GNNs, the proposed DGNN block contains two varieties that use two different dynamic graphs to replace the fixed ones in the GNNs.

#### 3.5.2. DPGNN layer

The adjacency matrix in the traditional GNN approach is fixed, which means the connections between each two vertices in the graph are known. In other words, structuring a predefined graph in the GNN approach based on the official rules would always result in stable performance. For instance, the vessel flow shifts among the adjacent nodes is an approved regular pattern when considering the spatial dependency. Therefore, the predefined graph alone cannot structure dynamic relationships due to the fixed adjacency matrix.

A DPGNN layer containing a self-attention adjacency matrix was proposed that dynamically learned the influential weights from data and maintained the intrinsic connections among nodes. In other words, the self-attention mechanism could choose relatively more influential parameters of the current state by learning the weights from the inputs. It uses the factor $\frac{1}{\sqrt{D}}$ to scale the dot product, where $D$ denotes the dimension of the inputs. The scaling equation is as follows:

$$Self−Attention(Q, K, V) = \text{soft max}\left(\frac{QK^T}{\sqrt{D}}V\right)$$  \hspace{1cm} (3)

A self-attention score matrix $S_{dp}$ was employed to automatically estimate the affective scores of different nodes based on their inputs. The new self-attention adjacency matrix score was calculated by an element-wise dot-product operation connection $S_{dp}$ with the inherent matrix. We replace the original static matrix with a new adjacency matrix to dynamically learn the accepted relationships:

$$S_{dp} = \text{soft max}\left(\frac{X^{(n-1)}X^{(n-1)^T}}{\sqrt{D}}\right) \in R^{V \times V}$$  \hspace{1cm} (4)

$$DPGNN(X^{(n-1)}) = \sigma\left(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}} \odot S_{dp}X^{(n-1)}W^{(m)}\right)$$  \hspace{1cm} (5)

#### 3.5.3. DNGNN layer

More potential relationships are needed in addition to predefined graphs to capture the flexible and dynamic non-Euclidean relationships in the vessel flow. We employed an undefined matrix to exploit the hidden spatial and featural dependencies from the original data. The ReLU(·) activation function was executed to remove the weak connections, and the SoftMax function was used to conduct the corresponding weighting of the existing connection.

Hence, the self-learned matrix $W_{np}$ is calculated based on the hidden input $H^{(n-1)}$ as follows:

$$W_{np} = \text{soft max}\left(\text{relu}\left(\frac{H^{(n-1)}H^{(n-1)^T}}{\sqrt{D}}\right)\right) \in R^{V \times V}$$  \hspace{1cm} (6)

where the weight matrix $W_{np}$ was utilised as an adjacency matrix in the DNGNN layer to dynamically capture more possible connections.
tween vertices. The definition is as follows:

\[ DNGNN(H^{m-1}) = \sigma(W_{dp} H^{m-1} W^{m}) \]  

(7)

3.5.4. Attention aggregation layer

The attention aggregation layer is created to dynamically combine the results of DPGNN and DNGNN by learning their weights based on the inputs. The final outcomes of DGN block are picked after the attention aggregation layer as follows:

\[ Out_{dgnn} = W_{dpgnn} \odot Out_{dpgnn} + W_{dngnn} \odot Out_{dngnn} \]  

(8)

where \( \odot \) is the Hadamard product, \( W_{dpgnn} \), \( W_{dngnn} \) are the weight learned from the corresponding two outputs.

3.6. GRU

The GRU is a special RNN structure that adds a gated mechanism to memorise the possible influencing factors from the long-term information. To obtain the temporal relationship from the entire time sequence, we employed the GRU block as it preserves useful information from the relationship and has a simple structure and fast training speed.

Equations (9)-(12) are the equations of the GRU, where \( h_{t-1} \) denotes the output at time \( t-1 \), \( u_t \), and \( r_t \) represent the reset gates at time \( t \), respectively, and \( h_t \) is the output at time \( t \). The weights and biases are represented by \( W \) and \( b \) in these operations, respectively.

\[ u_t = \sigma(W_t [O_{dgnn}, h_{t-1}] + b_u) \]  

(9)

\[ r_t = \sigma(W_t [O_{dgnn}, h_{t-1}] + b_r) \]  

(10)

\[ c_t = \tanh(W_t [(r_t \odot h_{t-1})] + b_c) \]  

(11)

\[ h_t = u_t \odot h_{t-1} + (1 - u_t) \odot c_t \]  

(12)

The complete structure and other details are presented in Fig. 4. The left-hand side of the figure illustrates the process of the GRU function and the right-hand side the specific structure of a GRU cell. In each GRU cell, \( h_t \) is the hidden output at time \( t \), \( r_t \) and \( u_t \) are the reset and update gates, respectively, used to control the extent of holding and missing information from the previous moments.

4. Case study on New York Port

To evaluate the performance of the proposed model, we conducted several experiments on real datasets of regional vessel traffic flows. We first introduce the dataset and experimental settings. Next, we discuss the results of proposed model, followed by the comparison between the results with other closely related DL-based solutions.

4.1. Datasets

4.1.1. Input data processing

Three important components of the input data are introduced in this section, namely the vessel-flow features, the experimental seaport region, and the COVID-19 feature. First, the AIS dataset was collected with a high frequency. Next, the position of the ship was recorded in real time. The sailing patterns were reported for all types of vessels. The AIS data were used to optimise the maritime intelligent transportation system by predicting the probable vessel flows. Vessel-flow features including ‘vessel inflow’, ‘vessel outflow’, and ‘vessel volume’ were calculated over 2, 4, and 6 h. The total vessel traffic volume (vessel volume) in the unit grid is the number of vessels that ever existed in a specific observation time.

New York Port (lower bay) was chosen as the study area considering its ideal navigation conditions. The upper bay of New York Port is a bustling area with ship docking and loading-unloading operations. The Atlantic Ocean is an open ocean. The lower bay was selected because it is the only area that connects the upper bay of New York Port and the Atlantic Ocean, and the only way in to (out of) the port (world). The prediction of the vessel traffic flow in the lower bay area is the crucial key to managing the traffic flow in the port region. The coordinates of the left upper boundary of the location are (40.622°N, 74.238°E), and those of the right lower boundary are (40.422°N, 73.938°E). As illustrated in Fig. 5, the port region is divided into 10 × 10 grids, according to the geocoding information. The unit grid was assumed to be several non-Euclidean distribution grids divided from the experimental seaport region based on the information on MMSI, Base Date Time, Lat., Lon., Vessel type, and Status of the AIS data. Considering the data validity, 62 grids were deleted because there is little to no vessel traffic in these grids. Finally, 38 grids remained for the final study area (Fig. 6).

As for the COVID-19 feature, we collected the reported cases from 14 COVID-19 monitoring points near the port as the experimental data, as represented by the yellow dots in Figs. 6 and 7. We cleaned the original data by deleting the evidently unusual error records and mapped the newly confirmed cases of COVID-19 from the 14 dots on to the 38 grids as the auxiliary prediction input by considering the reciprocal of geodistance area. A fraction of the initial input data are displayed in Table 1, where the vessel-flow features and COVID-19 cases are recorded at grid No. 5 from June 2nd to 4th.

4.1.2. Description of dataset

After processing the original AIS data and COVID-19 data, we selected the 12-month experimental data from June 2020 to May 2021. The data were grouped into training, validation, and testing sets according to the time sequence. The training section contained 244 days from June 2020 to January 2021, the validation section 60 days from February to March 2021, the test section 61 days from April to May 2021.
Additionally, data were transformed using Z-score normalisation methods.

### 4.2. Settings

All subsequent experiments adopted the mean absolute error (MAE), root-mean-square error (RMSE), and mean absolute percentage error (MAPE) as the evaluation metrics. The definitions of these three metrics are as follows:

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} |\hat{y}_i - y_i| \tag{13}
\]

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2} \tag{14}
\]

\[
MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{\hat{y}_i - y_i}{y_i} \right| \times 100\% \tag{15}
\]

For a feasible comparison in these experiments, the same historical data over the past 12 timesteps were input into the proposed and baseline models and the vessel traffic volume for all unit grids were predicted for the next 2, 4, and 6 h, respectively.

### 4.3. Analysis of results

#### 4.3.1. Performance of the STDGNN

To demonstrate the prediction of the proposed STDGNN model, especially the capabilities of its primary part in capturing the spatio-temporal relationships and its auxiliary part in capturing the multiple temporal connections, we discuss the results from three perspectives: predictions in different time slices of all unit grids to illustrate the temporal dependency; and the results of different unit grids over a week to explain the spatial dependency. The last one compares the STGNN primary (STGNN-Pri) with the STDGNN to demonstrate the impact of the auxiliary part. Fig. 7 presents the details using examples of five-unit grids, from Nos. 28 to 37. The ground truth and prediction are represented by green and red lines.

1) **Temporary dependency performance:** In Fig. 7b, STDGNN achieves accurate predictions for all 38 grids during the next 2, 4, and 6 h. The results prove that the temporal dependency is well-pitched by the STDGNN model. Additionally, the result for 2 h is better than those for 4 and 6 h in all unit grids.

2) **Spatial dependency performance:** To prove the accuracy of the spatial prediction, four unit grids from Apr (2021) were chosen to highlight the superiority of screening multiple spatial relationships. The ground truth and prediction are represented by blue and red lines in Fig. 7. Unit grid Nos. 6 (Fig. 8a) and 38 (Fig. 8d) are marginal points located at the South and North of the selected area, respectively. Nos. 21 (Figs. 8b) and 28 (Fig. 8c) are located at the central port of the region. The prediction accuracies of the central points (i.e. Nos. 21 and 28) are higher than those of the marginal ones (i.e. Nos. 6 and 38), owing to the richer spatial connections, which indicates
that considering the spatial relationships is significant to the regional vessel traffic flow prediction.

3) Impact of auxiliary part: We recorded the remarkable performance of the auxiliary part in terms of the 2-, 4- and 6-h prediction intervals (Fig. 7a). The prediction results of the STDGNN were closer to the ground truth than those of the STDGNN primary. Hence, the impact of the auxiliary part is proved. Thus, considering the new cases of COVID-19 to perform an accurate vessel flow prediction is significant.

4.3.2. Baseline experiments

To assess the model performance, we compared it with that of the baseline models in terms of vessel volume prediction:

- GRU (Fu et al., 2016): Temporal framework, Gated Recurrent Unit, a special RNN model.
- STGCN (Yu et al., 2018): A spatial-temporal graph convolution model based on the spatial method.
- Graph WaveNet (Wu et al., 2019): A combination of graph and temporal convolutions to adaptively capture spatial-temporal dependencies.
- TGNC (Zhao et al., 2020): A spatial-temporal framework that combines a graph convolutional network and a gated recurrent unit.

The improvements in MAE, RMSE, and MAPE obtained by different models are compared in Fig. 9 and Table 2. As can be seen, the results of the 6-h period are inferior to those of the 2- and 4-h periods. As displayed in Fig. 9(a) and (b), the GRU model produces unsatisfactory results because it does not consider the spatial relationships. The MAE results of the STGCN and TGNC are better than those of the GRU because the fixed matrix in the GRU fails to capture the dynamic spatial dependencies. All the evaluation metrics results of our model are slightly lower than those of the Graph WaveNet because the latter fails to consider the effect of feature dependency. In general, the proposed STDGNN model achieved the best overall prediction for all three periods.

4.3.3. Ablation experiments

The two sets of ablation experiments in this section were designed to evaluate the functions of the primary and auxiliary parts in the STDGNN model.

1) Primary part performance: We designed four variants of the model, each based on one block: STDGNN (no-TE), STDGNN-no-DGNN-F (structured by vessel featural network) STDGNN-no-DGNN-S (structured by vessel spatial network), and STDGNN (no-GRU). The results are displayed in Table 3.

- STDGNN-no-TE: The TE block is replaced with a block of stacked fully connected layers.
STDGNN-no-DGNN-F: The DGNN block is replaced by a fully connected layer when capturing the featural dependency.
STDGNN-no-DGNN-S: The DGNN block is substituted with a fully connected layer when capturing the spatial connection.
STDGNN-no-GRU: The GRU block is substituted with a stack of fully connected layers.

The MAE, RMSE, and MAPE of the ablation experiment of the primary part are illustrated in Fig. 10(a), (b), and (c). The STDGNN (no-TE) model performed worse than the STDGNN model, especially with respect to the MAPE of the 4-h period, proving that the TE block can capture the local information in the temporal dimension. Moreover, STDGNN performed markedly better than STDGNN (no-DGNN-F) and STDGNN (no-DGNN-S) in the 4-h and 6-h periods, implying the necessity of the two DGNN blocks. Specifically, the ability of a DGNN block to extract the changes in the vessel traffic flow from different regions was better than the ability of the DGNN block to capture the transformation among multiple vessel traffic flows. Additionally, STDGNN performed better than STDGNN (no-GRU) in the 4-h and 6-h predicted periods, indicating that the GRU block performed more effectively than the fully connected layers owing to its ability to identify the historical time periods vital to the target prediction.

2) Auxiliary part performance: We added three models (STDGNN-Aux-recent, STDGNN-Aux-day and STDGNN-Aux-week) to evaluate the performance of the auxiliary part. The MAE, RMSE, and MAPE of the ablation experiment of the auxiliary part are illustrated in Fig. 11(a), (b), and (c). The STDGNN (no-TE) model performed worse than the STDGNN model, especially with respect to the MAPE of the 4-h period, proving that the TE block can capture the local information in the temporal dimension. Moreover, STDGNN performed markedly better than STDGNN (no-DGNN-F) and STDGNN (no-DGNN-S) in the 4-h and 6-h periods, implying the necessity of the two DGNN blocks. Specifically, the ability of a DGNN block to extract the changes in the vessel traffic flow from different regions was better than the ability of the DGNN block to capture the transformation among multiple vessel traffic flows. Additionally, STDGNN performed better than STDGNN (no-GRU) in the 4-h and 6-h predicted periods, indicating that the GRU block performed more effectively than the fully connected layers owing to its ability to identify the historical time periods vital to the target prediction.

Table 2
Comparison of the baseline models.

|                | MAE    | RMSE   | MAPE   |
|----------------|--------|--------|--------|
|                | 2 h    | 4 h    | 6 h    | 2 h    | 4 h    | 6 h    | 2 h    | 4 h    | 6 h    |
| GRU            | 1.73   | 1.73   | 1.73   | 2.56   | 2.56   | 2.56   | 35.65  | 35.68  | 35.69  |
| STGCN          | 1.73   | 1.73   | 1.73   | 2.56   | 2.56   | 2.56   | 35.55  | 35.57  | 35.72  |
| TGCN           | 0.98   | 1.03   | 1.03   | 1.48   | 1.53   | 1.54   | 34.90  | 37.89  | 38.68  |
| Graph WaveNet  | 0.89   | 0.97   | 0.97   | 1.30   | 1.40   | 1.39   | 28.78  | 30.75  | 29.47  |
| STDGNN-Pri     | 0.90   | 0.99   | 1.00   | 1.33   | 1.45   | 1.47   | 28.49  | 29.47  | 29.85  |
| STDGNN         | 0.89   | 0.99   | 1.00   | 1.31   | 1.43   | 1.45   | 28.16  | 28.89  | 28.82  |

Table 3
Ablation experiment of the primary part in STDGNN.

|                | MAE    | RMSE   | MAPE   |
|----------------|--------|--------|--------|
|                | 2 h    | 4 h    | 6 h    | 2 h    | 4 h    | 6 h    | 2 h    | 4 h    | 6 h    |
| STDGNN-no-TE   | 0.98   | 1.04   | 1.01   | 1.39   | 1.45   | 1.46   | 28.07  | 29.16  | 28.94  |
| STDGNN-no-F    | 0.93   | 1.03   | 1.02   | 1.34   | 1.47   | 1.49   | 28.00  | 28.99  | 29.25  |
| STDGNN-no-N    | 0.93   | 1.01   | 1.02   | 1.33   | 1.45   | 1.47   | 28.14  | 29.86  | 29.87  |
| STDGNN-no-GRU  | 0.92   | 1.02   | 1.01   | 1.37   | 1.47   | 1.49   | 27.46  | 29.11  | 29.40  |
| STDGNN         | 0.89   | 0.99   | 1.00   | 1.31   | 1.43   | 1.45   | 28.16  | 28.89  | 28.82  |
5. Discussion and policy implications

This section summarises the experimental results and discusses the policy implications for improving the operational efficiency at seaports amid COVID-19. Two aspects, real-time ship scheduling and pandemic prevention, along with several application scenarios for the proposed method, are discussed.

5.1. Real-time ship scheduling

1) A forewarning policy can improve port utilisation and relieve heavy congestion. This policy requires the maritime department to create alternate routes for vessels in advance when the prediction indicates a sudden surge in the flow. With the help of the vessel flow prediction, the forewarning policy can also allow the port authority to adjust the docking arrangement with advance notice, and the ship owner could change the sailing plan in a timely fashion.

2) A temporary scheduling policy can prevent the further congestion of the port. With real-time vessel flow prediction, this policy can dynamically and flexibly allocate information, workforce, and equipment at the port to improve the port loading and unloading efficiency amid the pandemic.

3) A multiport collaboration policy can be initiated through intelligent data support. An efficient, joint, and green information platform can be constructed for the port cluster by integrating standard and uniform data from multiple ports. Additionally, a Just-In-Time (JIT) arriving multiport linkage strategy can be formulated to address the challenges related to the irregular distribution of transport resources (i.e., ships and containers) among multiple ports and to promote the green and sustainable development of the maritime industry.

4) A multimodal transport scheduling policy can be implemented using the spatiotemporal vessel prediction results. The results will identify both the rush hours and busy regions of vessel transportation. Furthermore, it can smartly assist the port management with allocating in advance multi-dimensional transport resources. Railway, roadway, airway, and maritime transportation can be seamlessly connected through data support to avoid backlogs at the seaport terminals.

5.2. Pandemic prevention

The port authority should consider the influence of the pandemic through a combination of different sets of historical data when formulating pandemic-prevention policies, instead of focusing on the recent history. The STDGNN provides an adaptive prediction algorithm for the vessel traffic flow at ports, based on which the policies can be drafted for the long run, regularly assisting the pandemic-prevention efforts. A flexible pandemic-prevention policy will be vital in controlling the sources of infection and severing the channels of transmission. To restore international trade and maritime transportation in the post-COVID era, port authorities should dynamically modify their pandemic-prevention decisions based on the severity of regional confirmed cases instead of following a unified and nationwide fixed policy.

5.3. Application scenarios for the proposed method

The following are six application scenarios for the proposed method.

1) Vessel traffic pattern analysis, such as shipping tracking, ship emissions inventory, ship fuel consumption, and maritime traffic accidents.
2) Emergency coordination of maritime shipping in case of contingencies.
3) COVID-19 prevention decision in the maritime shipping field.
4) Recovery of international trade in the post-COVID era.
5) Information sharing among international maritime organisations.
6) Technical support for an intelligent and unmanned port system.

6. Conclusion

We investigated the regional vessel traffic flow forecasting problem by identifying its dynamic spatial, temporal, and featural dependencies under the temporal influence of COVID-19. This research could assist in the allocation and enhancement of port operations along with scheduling and management on a digital platform.
First, the vessel volume around the port region is proved to be potentially affected by both the static and dynamic trends of COVID-19. Multi-temporal impacts of COVID-19 on the regional vessel traffic flow were also considered to enhance the prediction results. Second, a general DL model STDGNN that adaptively encodes the non-Euclidean correlations among the dimensions of space and features using multigraphs was proposed. The outputs of each graph were gathered by a self-attention mechanism, and the short- and long-term relationships were extracted by different sub-blocks. Real-world datasets, including the AIS database on New York Port, and the newly confirmed cases of COVID-19 near the port region were applied to demonstrate the superiority of the proposed approach. Finally, big data and intelligent prediction-based policy recommendations for multiple parties in the port region were highlighted. At a macro-level, the vessel volume results combined with the trends of COVID-19 could be shared among the local government, public health organisation, and port authority to agree on the pandemic prevention and trade promotion methods. At a micro-level, to relieve port congestion caused by emergencies, the prediction results can assist port officers or individual ship users with effectively scheduling or arranging ship sailing and docking in a timely and practical manner.

However, this method has a few disadvantages. First, although the proposed model considers the impact of COVID-19, more external influences such as the weather conditions, marine environment, and politics should be taken into consideration in future studies. Second, the number of sub-blocks tested here limits the accuracy of the model. Therefore, more sub-blocks should be discussed and tested to further improve the prediction accuracy.

Data availability
Data will be made available on request.

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