# Elucidating US Import Supply Chain Dynamics: A Spatial-Temporal Graph Neural Network Approach

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***Abstract*—To enhance the understanding of congestion points at ports and provide visibility into the incoming container ships in the USA, this study focuses on maritime ports and corresponding terminals, using several ports along the East Coast of the United States as case studies.**

**We analyzed Automatic Identification System (AIS) data from January 2015 to September 2023, deriving comprehensive historical berthing data. This analysis enabled us to build several port congestion prediction models, such as Extreme Gradient Boosting (XGBoost), Long Short-Term Memory (LSTM), and a more sophisticated Spatial-Temporal Graph Neural Network (ST-GNN) model. Additionally, this research traced the historical routes of container ships and accurately mapped the sectors where ships' berth within terminals, thereby providing deeper insights into ship scheduling.**

**This study offers considerable value to stakeholders in the supply chain industry, contributing to both theoretical and practical applications in maritime logistics.**

***Index Terms*—Automatic Identification System (AIS), High-performance Computing, ST-GNN, XGBoost, LSTM**

## I. Introduction

With an increasing level of international cooperation, the vulnerability of supply chains to disruptions also grows. In the last few years, supply chains have been affected by several global events, such as the COVID-19 pandemic and the Suez Canal obstruction, which, in turn, led to interruptions in goods flows, increased volatility of demand and supply, and increased costs for all participants. To reduce the negative impact of future disruptions on supply chains in the United States and, also, to provide greater visibility of goods flows for key stakeholders to increase cooperation between them, on March 15, 2022, the Biden-Harris Administration and U.S. Department of Transportation (U.S. DOT) announced the launch of a major supply chain initiative, Freight Logistics Optimization Works (FLOW).

Ports are critical nodes in international trade and global supply chain networks. This is also the case in the United States, where ocean ports are integral parts of supply chain networks. Every US $ of trade flowing through a port will directly or indirectly generate an additional US $4 of global industry output [1].

Moreover, the ports are major entry points for containers of imported goods arriving in the U.S. The visibility envisioned by the FLOW initiative can help to make those movements more efficient. However, it is impossible to achieve a reasonable level of visibility without having the necessary information about logistics in ports, congestion status, port sequencing, and terminal scheduling. Without such data, it is challenging to manage and optimize the flow of goods effectively.

This study's objective is to enhance the understanding of congestion points at ports. Our method for the prediction of port congestion status provides an estimation of the container ship flow into the USA, possible delays, and the possibility to re-route shipments.

In this study, we studied the Automatic Identification System (AIS) data, which collects vessel information throughout maritime voyages via radio frequency, and then selected and compared different statistical and machine learning models to predict port congestion by predicting the number of ships at berth and awaiting berthing areas.

The aim of our work is to create a spatial-temporal model of the supply chain dynamics within global ocean logistics networks. To achieve this, we focused on container terminals at ports along the East Coast of the USA, as listed in Table I, and developed descriptive and predictive models for port congestion within the work's scope.

TABLE I
List of Ports and Terminals

| **Port** | **Terminal** |
|---|---|
| New York / New Jersey | APM Terminals |
| New York / New Jersey | Maher Terminals |
| New York / New Jersey | The Red Hook Container Terminal |
| New York / New Jersey | Port Newark Container Terminal |
| New York / New Jersey | Port Liberty Bayonne Terminal |
| New York / New Jersey | Port Liberty New York Terminal |
| Boston | Conley Terminal |
| Savannah | The Port of Savannah |
| Norfolk | Norfolk International Terminals |
| Baltimore | The Seagirt Marine Terminal |

In this research, we utilized AIS data, where timestamps and coordinate points of vessels provide us insights into the routes of vessels crossing the ocean and the actual time spent at anchorage areas, ports and terminals. We also retrieved historical routes from AIS data. Moreover, the AIS data gave us insider information about other aspects impacting traffic flow, such as straits, channels or artificial obstacles on the routes. We also analyzed the port at the terminal level and developed an algorithm to identify berthing positions of ships, which proved effective for several terminals in New York / New Jersey and Los Angeles / Long Beach. We built and compared several methodologies, such as statistics, machine learning, and neural network models, to identify the most accurate prediction model.

## II. State of Practice

Several research studies have delved into predicting vessels' behaviors, addressing challenges related to congestion and traffic flow and to optimizing port operations. In addition to traditional statistical models, more advanced methodologies have been applied in transportation research, such as Neural Networks and Transformer, showing promising results in predicting congestion of the port.

Reference [2] demonstrated that eXtreme Gradient Boosting (XGBoost) combined with Shapley Additive Explanation (SHAP) can effectively predict port congestion status and improve the accuracy of predicting time spent in port. Reference [3] stated that for predicting the traffic flow rate, the XGBoost algorithm had the lowest error for hour-ahead forecasts in comparison to Holt-Winters, Transformer, and Graph Neural Network (GNN) models. We used the XGBoost algorithm as a benchmark to compare it with our target model.

We built our model based on the work of [4]. The work proposed the utilization of a Spatial Temporal Graph Neural Network (ST-GNN) for traffic prediction. This algorithm captured comprehensive spatial data, which is necessary in the maritime network of the East Coast of the USA, where two major ports - New York / New Jersey and Savannah significantly influence traffic and goods flows in the rest of the East Coast ports. The ST-GNN model also captures temporal patterns by incorporating sequential components, making it well-suited for our study's requirements.

## III. Methodology

We approached the prediction of port congestion through several steps. First, we identified the areas within the scope of our work, including specific terminals, ports, and waiting areas.

We then developed several statistical models aimed at predicting berth occupation in several terminals and ports, as well as the number of container ships in waiting areas. These statistical models provided us a benchmark for evaluating the performance of our ST-GNN model.

Next, we built, trained, and tested our ST-GNN model. This involved several stages, including data processing, layer structuring, and model architecture design. We then analyzed the results and proposed next steps to enhance the value of the model for the stakeholders.

### A. Constructing the Network

In this section, we describe our approach for detecting and describing points of interest and creating nodes for the graph of the ST-GNN model.

*1) Data Handling:* We used AIS data for container ships in the vicinity of the USA coastline from year 2015 through 2023, filtered by the IMO number of container ships. AIS data collects vessel information throughout maritime voyages via radio frequency, enhancing safety and traceability in global ocean logistics. The data includes the International Maritime Organization (IMO) number, a unique identifier for each vessel; dynamic geographical data such as longitude and latitude, which enables tracking of ship trajectories; and static vessel information such as length and beam [5]. The International Maritime Organization's International Convention for the Safety of Life at Sea requires AIS to be fitted aboard international voyaging ships with 300 or more gross tonnage, and all passenger ships, regardless of size [6].

As shown in Table II, AIS data collects a variety of vessel information at regular intervals throughout the voyage.

TABLE II
AIS Data Information

| Field Name | Description |
|---|---|
| MMSI | Maritime Mobile Service Identity, unique nine-digit identification number for each vessel |
| BaseDateTime | Date and time of the AIS signal |
| LAT, LON | Geographical coordinates of the vessel |
| SOG | Speed over ground in knots |
| Draught | Draught of ship |
| COG | Course over ground in degrees from true north |
| IMO | IMO ship identification number, a unique and permanent seven-digit identification number |
| Static data | Length, width, draft, etc. |

To narrow our research, we filtered data by speed over ground, assuming that ships in anchorage and berth areas are spending some time with drift speed or on full stop (berthed, anchored). This filtering allowed us to focus on periods during which ships were either waiting or being processed at the ports, which are key factors in assessing and identifying port congestion.

*2) Addressing Ship Positions:* For the purpose of our models and detecting ship positions, we applied several techniques for different areas and points of interest:

- Berthing: Some ports, for example, Los Angeles / Long Beach and New York / New Jersey, have several terminals situated closely to each other and a complicated geometry of the berth. To address this issue, we constructed a multi-line using the coordinates of points at the beginning and end of each terminal's berth, as well as points where the orientation of the berth changes. We assumed that ships were berthing if the distance to the nearest sector of the line was less than 60 meters. Given that the heading data in AIS is sometimes unreliable and the message frequency and time of berthing are smaller compared to the time discrepancy of the model (one day), this approximation was deemed sufficient for identifying berthing ships.
- Berthing positions in terminals: We defined an algorithm to detect berthing position sectors along the berth line

for ships inside a particular terminal. This allowed us to accurately pinpoint specific berthing locations within each terminal.

- Waiting (Anchorage) area: This area is defined as a polygon surrounding a manually identified and classified cluster, determined by a clustering algorithm. All container ships that appeared inside the polygon were counted toward the total number of vessels that spent some time in the area prior to entering the port.
- Harbor area: This area is a manually identified polygon encompassing the water area from the harbor entrance and all areas of the harbor open to container ships, including terminals.

*3) Building Features:* To generalize the model, we analyzed the list of container ships that visited ports in the USA and categorized them based on major operators and ship sizes:

- We split the container ships into categories of operators, focusing on major operators with more than 10 ships. This grouping helped us align the ships with the terminals preferred by each operator. Ships from less significant operators were combined into a single group.
- We also grouped ships by size, specifically by length and width, by applying k-means clustering [7]. Apart from generalization, this clustering allowed us to decrease the number of features and simplify computations.

For our models, we utilized a 7-day history of the number of ships at each particular node (terminal) and the number of ships heading to such nodes. Additionally, we incorporated time series data, such as the month and day of the week, to capture temporal patterns.

### *B. Statistical and Machine Learning Models*

We built several models to predict the occupation of berth and anchorage areas for terminals based on historical data. We applied this method to predict congestion at all modeled terminals and used them as benchmarks for the ST-GNN model.

*1) Random Forest Regression:* Random Forest, or Random Decision Forest, is a method used for classification or regression by constructing and combining multiple decision trees. This approach was introduced by [8].

*2) LSTM Networks:* The Long Short-Term Memory (LSTM) Networks, introduced by [9], are one of the most widely known and commonly used methods for handling time series data. As described by [10], LSTM networks are particularly effective for forecasting and are well documented.

*3) XGBoost:* XGBoost is a scalable and efficient solution for tree ensemble learning, consisting of multiple decision trees that are combined to form robust predictive models. The XGBoost algorithm assigns scores to the i-th leaf of each decision tree and sums these scores for the corresponding leaves to achieve the final prediction. To optimize the performance of the model, XGBoost minimizes a regularized objective function, as detailed by [11]. This method enhances prediction accuracy and model robustness, making it a valuable benchmark for comparison with the ST-GNN model.

### *C. Spatial Temporal Graph Neural Network*

For the purpose of this work, we utilized the ST-GNN model, a subclass of the more general model, Graph Neural Networks (GNN), which are known for predicting traffic intensity due to their ability to capture spatial information.

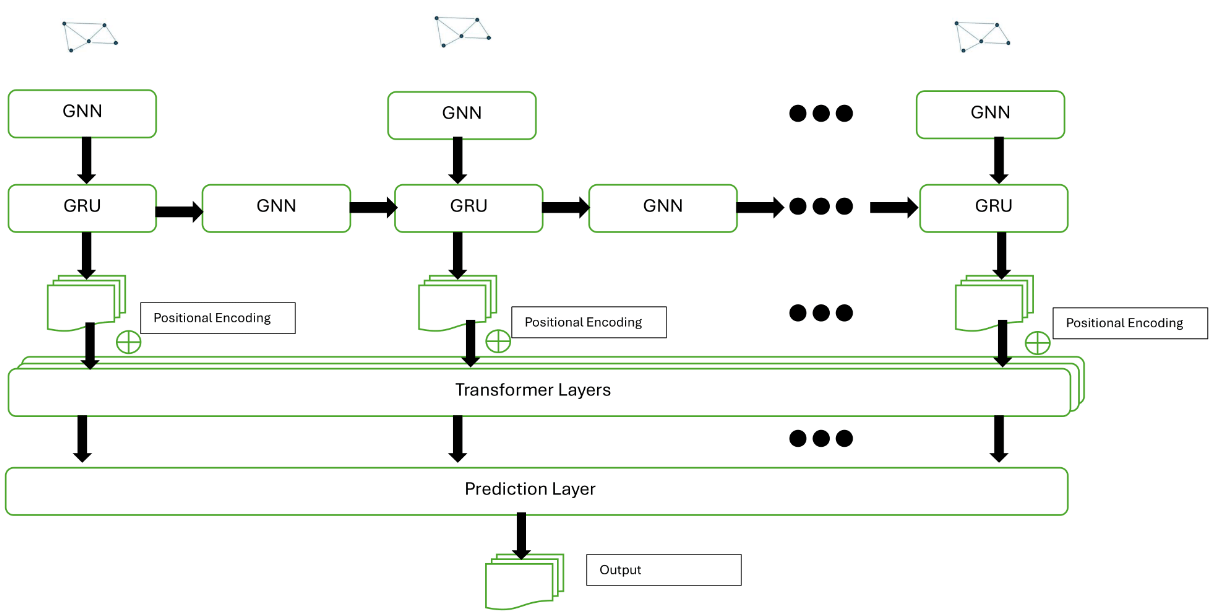


Fig. 1. ST-GNN Model representation, redrawn from [4]

The framework for our model was proposed by [4] and initially used to predict road traffic and has demonstrated robust performance in handling dynamic changes over time and space.

We selected the ST-GNN model for this study due to its advantages in modeling complex spatial and temporal dependencies, which are crucial for predicting maritime transportation patterns. The model's graph-based representation effectively captures interactions between different elements of the transportation system, such as ship locations and port layouts. Our motivation was to test whether the successful techniques used in traffic prediction could be adapted to maritime transportation, thereby providing insights into the applicability of ST-GNN in a new domain.

*1) Layers:* The framework consists of four layers, as shown in Fig. 1:

- GNN layer: Captures spatial information by processing the graph structure of the data.
- Gated Recurrent Unit (GRU) layer: Captures local temporal dependencies by handling sequential data.
- Transformer layer: Captures global temporal dependencies.
- Multi-layer feed-forward network: Outputs the final predictions.

*2) Building the Graph Neural Network:* For our model, we used three types of nodes:

- Ports: Represent physical ports like Boston or New York. These nodes are connected by bidirectional edges.
- Waiting zones of ports: Represent zones where container ships wait for berthing. Each port node is linked to its waiting zone by a unidirectional edge.
- Terminals in ports: Represent terminals within each port. Waiting zones are connected to every terminal in the port by unidirectional edges. Terminals in the port are also interconnected bidirectionally, representing the possibility of ships using multiple terminals, and are linked to the port node, indicating entering and exiting the port.

Edges in the model are represented by an adjacency matrix defined by the physical distance between nodes, capturing the spatial relationships and constraints within the network.

## IV. Results

This section is dedicated to the results of the statistical and machine learning models we built to meet our research objectives. In our work, Random Forest Regressor, LSTM, XGBoost, and ST-GNN models were applied to predict the number of vessels in each area.

### A. AIS Data Analysis

By performing a statistical analysis of AIS data for the Boston port area (berth, anchorage areas), we observed no significant seasonal or time-related effects. We confirmed with port authorities that the primary reason for ship timing in the wait area, aside from unrelated issues to the port such as technical issues or rescheduling, was traffic inside the harbor.

To address the problem of vessel berth identification, we selected points at the end of each berth and the change in


Fig. 2. New York / New Jersey Maher Terminal

geometry of each terminal/port included in this work. Apart from coordinate identification, this gave us the direction (heading) of the berth. By using both coordinates and headings, we were able to identify the mooring of ships by calculating the distance between the ship and the berth line and comparing the heading of the ship with the berth direction. The analysis of AIS data showed that some ships had problems transmitting the correct heading data. Therefore, our approach is to detect the start and end times of berthing by filtering ships with a distance less than the width of the berth. We assumed a potential error margin of no more than 10-15 minutes, which is acceptable to our model given our time discrepancy of 1 day.

To detect ships' berthing positions inside the terminal, we considered all ships at berth within a particular terminal and split them into time windows of specified length (e.g., 3 or 6 hours, starting from 00:00 each day). We then identified the time frame with the greatest number of ships staying more than half of the time window length, which specified the maximum number of positions inside the terminal. To define the positions, we used initial coordinates and headings of sequential ships in the eastward and then northward directions. Subsequently, for each time frame, we sequenced the ships and assigned them to the closest positions, updating position coordinates if necessary. The results for New York / New Jersey Maher terminal (Fig. 2) and Long Beach Pacific Container Terminal (Terminal J) (Fig. 3) matched the actual berthing positions observed in satellite images of the terminals.

### *B. Congestion Prediction Models*

We built several models for the terminals under consideration to predict congestion at those locations. These models were used as a benchmark for our ST-GNN model. For training, we used data from 2015/01/01 to 2023/08/31, and we predicted congestion for the next 30 days, from 2023/09/01 to 2023/09/30 (this period served as our test data).

As an input for the models, we used the number of vessels at the berth per day at terminals, the number of ships heading to the particular terminal from other terminals in the model in the last 7 days, and, additionally, time series categories like month and day of the week. As an output, we predicted the number of vessels at terminals. By analyzing benchmarking models, we used such error metrics as Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Symmetric Mean Absolute Percentage Error (SMAPE).

Although Random Forest Regression achieved the smallest prediction error, the features it relied on appear to have no meaningful relationship with the predicted outcomes. In this case, the chosen features shared coincidentally similar values with the target variable, leading to misleadingly low error rates. Therefore, we excluded this model from the comparison.

Table III displays errors for three different models across various terminals in our testing dataset. The results indicate that the best-performing model varies by terminals. To understand this phenomenon, additional research into the differences between terminals and incoming traffic should be conducted. This further study could reveal additional insights into improv-


Fig. 3. Long Beach Pacific Container Terminal (Terminal J)

ing the models.

TABLE III
ERRORS BY TERMINALS, MODELS

| Port Terminal | Model | MAE | MAPE | SMAPE |
|---|---|---|---|---|
| APM Terminals | LSTM | 1.57 | 37.64 | 47.08 |
| | ST-GNN | 1.52 | 55.16 | 41.05 |
| | XGBoost | **0.52** | **12.28** | **12.82** |
| Port Liberty Bayonne Terminal | LSTM | 0.70 | 50.68 | 84.62 |
| | ST-GNN | **0.51** | **37.75** | **45.18** |
| | XGBoost | 0.67 | 58.92 | 54.50 |
| The Red Hook Container Terminal | LSTM | **0.36** | **57.94** | 158.42 |
| | ST-GNN | 1.39 | 79.62 | 147.71 |
| | XGBoost | 0.94 | 72.32 | **146.14** |

*Note.* Bold numbers represent the best-performing error metric per terminal.

## V. CONCLUSION

In this section, we summarize the key findings from our research on AIS data and port congestion. We also propose recommendations for future research or practical applications.

- Incorporate additional maritime data: To increase prediction capability, it is essential to incorporate information about ships departing from the destination ports outside the USA, as this will give more precise information for the first port of entry. Additionally, incorporating information about the Panama Canal is crucial for accurately diagnosing disruptions in ship flows.
- Understand model performance differences: Further research should investigate why models perform differently across various terminals in the system; that is why some models excel with certain terminals while performing poorly with others. Understanding these differences can help tailor models to specific terminal or port characteristics.
- Incorporate port operations data: Knowledge of port operations, such as port yard utilization and the ability to serve ships quickly, could enhance the predictive models. This information could be obtained directly from the ports or be received indirectly. Additionally, it might be helpful to analyze historical port berthing schedules. We could either derive a reward function by utilizing Inverse Reinforcement Learning (IRL) or propose an assumed reward function to apply a forward Reinforcement Learning (RL) model for every port of interest, in order to predict ship serving sequence and time spent in the area.
- Apply dynamic graph neural networks: For stakeholders, utilizing dynamic graph neural networks could help predict potential ship diversions and route changes. Several studies, such as [12] and [13], have addressed changes in graphs, which could potentially improve prediction accuracy and adaptability in maritime logistics problems.

Our research in this paper developed a promising algorithm to detect ship berthing spots in specific port terminals. We also demonstrated that advanced machine learning models, including XGBoost, LSTM and ST-GNN models, can effectively predict port congestion. Furthermore, by implementing our recommendations and potential improvements, future research can be built on this paper, developing more robust and accurate models to predict port congestion and optimize port operation.

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