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Modeling Dynamic Behavior of Navigable Inland Waterways

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Abstract

The inland waterway freight system is a valuable and underutilized asset within the United States (U.S.) transportation system, providing an economical and environmentally sound mode for moving cargo. Container on Barge (COB) transportation is an intermodal freight transport mode that moves shipping containers via barges on navigable inland and intracoastal waterways. During the past twenty years, COB has been a growing mode of container shipping globally due to its low-cost, eco-friendly, and congestion-reducing characteristics. Europe and China are currently in leading positions in global COB transportation, and the U.S. may have the potential to achieve economic benefits through the implementation of COB within its intermodal transportation system. In this project, three contributions are made: 1) a literature review to systematically describe the development and status of COB transportation research, 2) a Value-Focused Thinking-based decision model to assess the feasibility of implementing COB at inland waterway ports within the United States, and 3) a machine learning study to perform container volume forecasting for COB transportation within the United States. This research assists maritime transportation decision-makers and individual inland waterway port/terminal operators to: 1) adopt success experience from global COB development, 2) comprehensively and practically assess the feasibility of COB development based on values identified from successful implementation, 3) forecast future container throughput volume at major seaports to infer the demands in connecting inland waterway ports via COB, and 4) form suitable port development and operational strategies based on forecasted demand to increase the overall rate of successfully developing COB transportation.

Keywords: Inland water transportation, Maritime industry, Freight transportation, Literature Review, Evaluation and assessment, Machine learning

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1.0 Introduction

The navigable inland waterway system in the U.S. consists of approximately 12,000 miles of navigable inland waterways, 13,000 miles of intracoastal deep channels, 236 lock chambers, and 191 lock sites and serves 41 out of 50 states (U.S. Army Corps of Engineers (USACE), 2021). The system is managed and maintained by the USACE. Exhibit 1 presents a map of the U.S. navigable inland waterway system. The four major inland waterways in the U.S. are the Upper Mississippi River, Lower Mississippi River, Gulf Intracoastal Waterway, and Atlantic Intracoastal Waterway.

The navigable inland waterway system plays an essential role in the U.S. freight transportation network. The U.S. inland waterways transport approximately 260 billion ton-miles (5%) of nation's freight annually (U. S. Department of Transportation (USDOT), 2021a). The Bureau of Transportation Statistics has predicted that, by the year 2045, inland waterway freight will increase 49.6% in value to $1,031 billion and will increase 18.2% in weight to 1,183 million tons (USDOT, 2021b). The past data and future predictions indicate that U.S. inland waterway transportation has great potential and provides an excellent opportunity to accommodate planned growth in freight for the next two decades.

Exhibit 1. U.S. Navigable Inland Waterway System

Source: USACE Navigation Data Center GIS Viewer

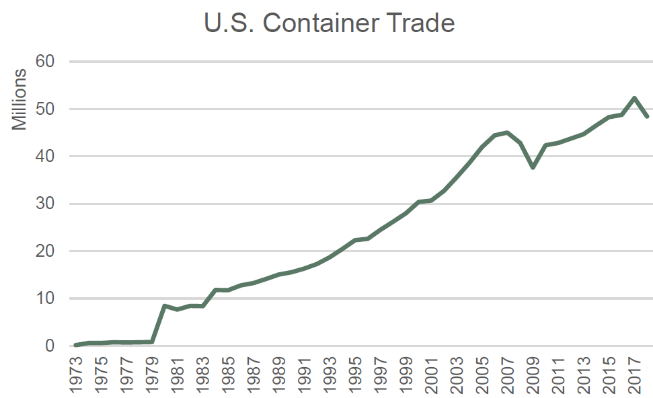
Container on Barge is an intermodal container transportation mode that utilizes barges to move containers between seaports and inland waterway ports via navigable intracoastal and inland waterways (Shobayo and van Hassel, 2019). With the booming market of global container shipping in the last three decades, significant seaports and their connected inland waterways in both Northwestern Europe (Netherlands, France, Germany, and Belgium) and China have taken the lead in container transportation modal shifting from road (truck) to inland waterway (barge), and intermodal container transportation efficiency has been significantly increased in these regions (Notteboom *et al.*, 2020).

One of the most significant advantages of COB transportation is a significant reduction in fuel consumption. On average, a barge can move a ton of cargo for 576 miles while consuming only one gallon of fuel, while the equivalent is 413 miles for a train and only 155 miles for a truck (ODOT, 2017). As a result, barge container transportation decreases 40% of CO_2 emissions compared to train and 270% compared to the truck (ODOT, 2017). In addition, the infrastructure cost of COB transportation is far less than truck or train container transportation where COB transportation brings economy of scale, offering an alternative to truck container transportation and alleviating port area road congestion (Zweer *et al.*, 2019; Fazi *et al.*, 2015; Ypsilantis and Zuidwijk, 2019).

While COB transportation in Northwestern Europe and China continues to grow and contribute economic benefits, COB development in the U.S. lags due to existing infrastructure, policy support, financial support, coordinated behavior between maritime container shipping stakeholders, and other factors (Liu *et al.*, 2017; Clott *et al.*, 2015; Konings *et al.*, 2010). However, as shown in Exhibit 2, with the continued growth of the U.S. container trading market and increased containerized imports from Asia, container traffic in the U.S. is exceeding 50 million annually (American Association of Port Authorities (AAPA), 2017). The considerable growth of container traffic at significant seaports such as the Port of New Orleans and Port of Houston puts dramatic pressure on port container handling and inventory capacity, significantly increased port area road congestion due to truck container shipping. As a reliable, low-cost, eco-friendly alternative transport mode to truck container shipping, COB is receiving increasing attention in the United States. In 2020, the U.S. Department of Transportation's Maritime Administration granted a $9.5 million award to Illinois, Indiana, Kentucky, Louisiana, Tennessee, New York, and

New Jersey to support maritime highway COB development projects (MARAD, 2020). These latest developments may mark the new phase of COB transportation in the United States.

Exhibit 2. United States Container Trade



Source: American Association of Port Authorities, 2017

The overall goal of this research project is to comprehensively assess the feasibility of developing COB transportation as a mode of containerized intermodal transportation for individual U.S. inland waterway ports and predict the potential container traffic flows in the U.S. inland waterway system in order to assist decisionmakers and port stakeholders to generate well-considered investment plans and operation strategies to increase the possibility of a successful COB development.

The overall goal is fulfilled by achieving the following three objectives:

Research Objective 1: This work aims to describe the status of global COB research, summarize information related to vital aspects of COB research among different regions in the world, and provide a literature database for future COB studies and development.

Research Objective 2: This research aims to provide a comprehensive and integrated decision support tool that enables U.S. inland waterway ports decision-makers to identify values of COB development from multi aspects, practically assess COB success factors with available quantitative and qualitative data, and generating better development plans by considering limitations, opportunities, and conditions.

Research Objective 3: This study aims to discover the driving factors that contribute to the massive growth of COB throughput volume in the Northwestern European and Chinese in the past two decades. The research seeks to quantify the impacts on COB throughput volume as well as to model the mathematical relations between the COB container traffic volume and the identified factors.

2.0 Literature Review

To support this research, a comprehensive literature review and comparative analysis of Container on Barge (COB) research was conducted and published in the *Maritime Economics & Logistics* journal (Bu and Nachtmann, 2021). The purpose of the published review and comparative analysis is to describe the status of COB research, summarize information related to key aspects of COB research among different regions in the world, and provide a literature database for future COB research and development. The article examines the similarities and differences of 135 existing COB studies and classifies each reviewed article to enable future researchers to efficiently locate COB transportation information of interest. The findings are organized in the seven sections that follow: 1) Annual Publication Count of COB Articles, 2) Journals Publishing COB Research, 3) Geographic Region of COB Research, 4) Research Questions Studied in COB Literature, 5) Methodological Approaches Employed in COB Research, 6) Advantages of COB, and 7) COB Success Factors. Each section describes a key aspect found to be important in describing and understanding COB literature with the goal of informing and motivating future growth in the research and development of COB transportation.

The overall findings are summarized here with additional detail provided in the full article (Bu and Nachtmann, 2021).

- The number of COB articles published per year fluctuated between zero and three from 2000 to 2010 before it began to increase gradually until reaching its peak in 2020 with nineteen articles published. The overall conclusion is that COB research is receiving increasing attention from scholars.
- Related to journals publishing COB research between 2000 and 2021, COB publications appear most frequently in the Journal of Transportation Geography (10), European Journal of Operational Research (9), Transportation Research Part E: Logistics and Transportation

Review (9), Maritime Economics & Logistics (7), and Transportation Research Record (7). The wide array of publication types indicates that scholars across a wide array of domain expertise (including engineering, computer science, and business) are researching COB.

- The geographic reach of COB research is reflected in the regional scope of the published articles. The majority of articles with a regional focus (102) focused on the Netherlands (26%), followed by China (13%), Germany (10%), Belgium (10%), and the United States (8%).
- The research questions studied in COB literature were reviewed and found to be widely varied. The most common research questions were intermodal transportation network design (16%), followed by ship routing problem (14%), barge container terminal operation (13%), comparative strategies for COB development (12%), barge handling efficiency (10%), and empty container repositioning by barge (6%).
- The review also examines the methodological approach employed in each reviewed article. The most frequently applied methodological approach to COB research was simulation (23%), followed by case study analysis (19%) network optimization (11%), economic analysis (10%), and mixed-integer programming (10%).
- The most frequently published advantages of COB were found to be low cost (19%), environmentally friendly (11%), reliability of COB (7%), reducing road congestion (5%), and economies of scale (5%).
- The key success factors of COB were found to be infrastructure investment (8%), container market growth (7%), navigability of inland waterways (5%), availability of inland waterways (4%), terminal operations efficiency (4%), hinterland access of major seaports (4%), and enabling government policies (4%).

3.0 Value-Focused Thinking Assessment of Container on Barge Maritime Transportation Readiness

3.1 Introduction

Value-focused thinking (VFT) is a decision analysis philosophy developed by Keeney (1992) that contrasts the traditional decision alternative-focused thinking. Keeney (1992) describes values as the aspects that decision-makers care about and spend time and effort thinking about when making decisions. Instead of thinking carefully about the values important to the decision, decision-makers often skip this step in the decision process and simply compare available alternatives to make a choice. However, in the framework of VFT, the decision analyst begins with thinking about and understanding the values relevant to the decision problem first in order to identify the important decision objectives. Rather than simply choosing between presented alternatives, values can guide creative thinking to generate better alternatives to meet the decision objectives. As Keeney (1992) emphasizes, decisions can only be better if decision makers have better alternatives and choosing between poor alternatives can only lead to a poor final decision.

Researchers have applied VFT to conduct feasibility and assessment studies in maritime transportation. Merrick et al. (2004) formulated a multi-objective decision analysis (MODA) model with the application of VFT to perform a comprehensive watershed evaluation in Richmond, VA. The MODA modal enabled decision-makers to see social, economic, and environmental values to make practical plans to improve watershed management effectiveness in maritime transportation. Nachtmann and Pohl (2013) developed a Transportation Readiness Assessment and Valuation for Emergency Logistics (Travel) scorecard based on the VFT framework to assist county or state-level decision-makers in evaluating emergencies and generating better emergency operation plans in utilizing transportation resources. Tong et al. (2015) presented a VFT-based cargo value decreasing rate model to evaluate the total value loss of cargo transported in inland waterways when disruptive events occur in any cargo shipping segment of the network. Wilby et al. (2019) built a waterborne investment assessment model based on the VFT framework to support the U.S. Army Corps of Engineers in forming better investment strategies for inland waterway and seaborne infrastructure maintenance. Boudhoum et al. (2021) constructed a VFT-based qualitative model for inland waterway stakeholders in the U.S. to assess project investment to achieve optimal benefits from multiple aspects including environmental protection, flood protection, recreational benefits, water supply, and hydropower production.

3.2 Methodology and Application

The value-focused thinking-based methodology and the COB Readiness Assessment Scorecard implementation are described and illustrated with a step-by-step assessment example performed at the Port of Shanghai. This section also introduces the nine global ports that are assessed by the COB Readiness Assessment Scorecard in this study.

The nine global ports presented in Exhibit 3 were selected to demonstrate the application of the COB Readiness Assessment Scorecard. There are two types of COB development status among the ports as shown in Exhibit 3; "Developed" where COB is currently functioning as a mature container shipping mode at the port and "In Development" where COB is still being developed at the port and has not yet become a primary container shipping mode.

Five "Developed" ports are located in the Netherlands, Belgium, and China. These three countries were identified by Bu & Nachtmann (2021) as the global leaders in COB transportation, and the Port of Shanghai, Port of Rotterdam, and Port of Antwerp have the most developed COB transportation according to the literature (Notteboom *et al*., 2020). Therefore, assessing these ports provides case analyses of the COB readiness of highly developed COB ports and comparative benchmarks for other less developed ports and future analyses. In addition, four U.S. "In Development" ports were chosen for study as shown in Exhibit 3. These four ports were chosen by the U.S. federal government to receive funding for COB development in 2020 (Maritime Administration, 2020) and provide examples of the readiness of less developed COB ports. In summary, these nine ports allow for a comparison between ports with varying levels of COB development status and demonstration of the COB Readiness Assessment Scorecard capability.

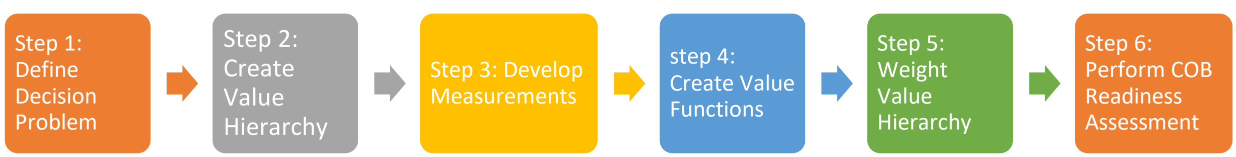
Exhibit 3. Ports Selected for Study

Port Name	Country	COB Development Status
Port of Shanghai	China	Developed
Port of Ningbo-Zhoushan	China	Developed
Lianyungang Port	China	Developed
Port of Rotterdam	Netherlands	Developed
Port of Antwerp	Belgium	Developed
Port of Greater Baton Rouge	U.S.	In Development
Port of New Orleans	U.S.	In Development
America's Central Port	U.S.	In Development
Port of New York	U.S.	In Development

3.3 COB Readiness Assessment Scorecard Development and Implementation

In this section, a customized six step VFT-based process (Keeney, 1992; Parnell *et al.*, 2013; Nachtmann & Pohl, 2013) employed by the COB Readiness Assessment Scorecard (see Exhibit 4) is described. Additionally, each step is illustrated with a case analysis performed on the Port of Shanghai.

Exhibit 4: Container on Barge Readiness Assessment Process



Step 1: Define Decision Problem

In Step 1, the decision problem is defined to generate value measures that address stakeholder values before the decision alternatives are selected. This decision problem for COB readiness provides a comprehensive and integrated decision support tool that assesses relevant factors and measurements for limitations, opportunities, and conditions for ports/terminals that want to evaluate COB implementation. In the illustrative case analysis, the decision problem is to assess the COB readiness for the Port of Shanghai.

Step 2: Create Value Hierarchy

In Step 2, we utilize a value hierarchy (Parnell et al., 2013) with three layers as shown in Exhibit 5 to categorize and organize objectives for the decision problem defined in Step 1. The fundamental objective is COB Readiness Assessment, as shown in the top layer. The middle layer subdivides the fundamental objective into four supporting objectives that are mutually exclusive and exhaustive. A brief description of each supporting objective is presented in Exhibit 6. The third layer contains the minimum number of attributes that can be measured to evaluate the performance of their connected supporting objective. The research team created the value hierarchy by reviewing 135 COB publications (Bu & Nachtmann, 2021) and identifying the most important stakeholder values in COB transportation.

Exhibit 5. COB Readiness Assessment Scorecard Value Hierarchy

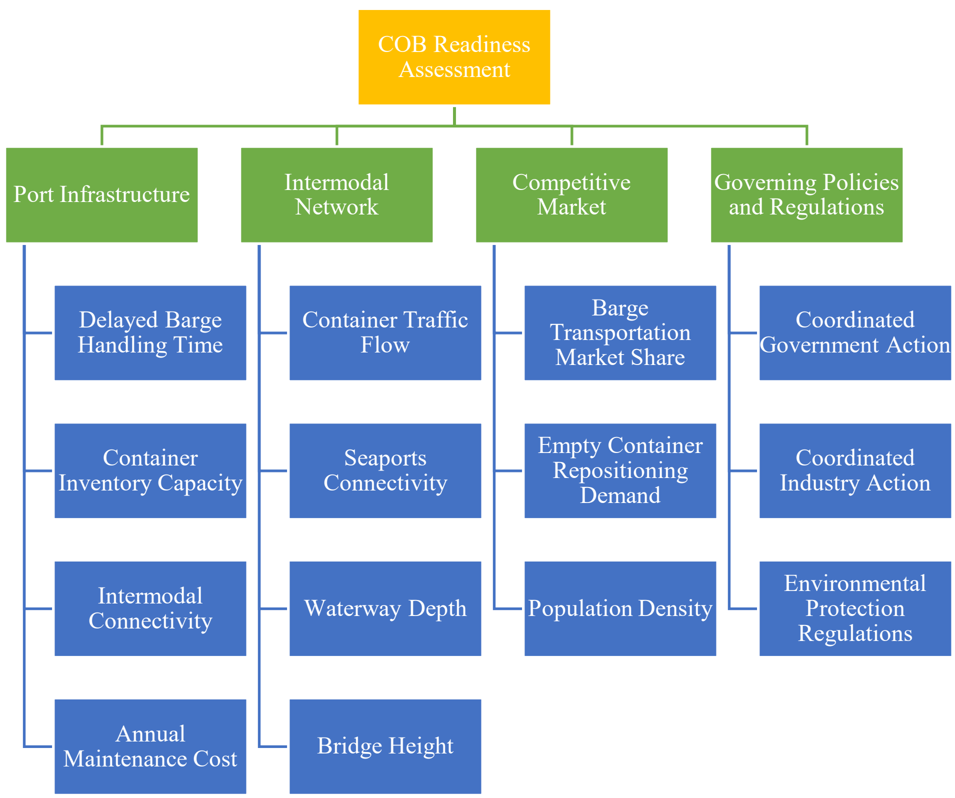


Exhibit 6. Supporting Objectives

Supporting Objective	Description
Port Infrastructure	Evaluate the conditions of existing port infrastructure that is necessary to develop COB transportation
Intermodal Network	Assess the intermodal network of the port since the development of COB is heavily reliant on container throughput volume in the network
Competitive Market	Evaluate the market potential for COB transportation in the port-located area
Governing Policy and Regulations	Assess the level of support a port can gain from the local governing policies and regulations and also assess the coordination level among industrial stakeholders of the port

Step 3: Develop Measurements

Step 3 develops measurements to evaluate each attribute on the third layer of the value hierarchy developed in Step 2. This is a crucial step to implementing VFT and building a scorecard (Keeney, 1992). Measurements can be classified as natural or constructed where a natural measure is widely utilized and generally interpreted, such as MPH (miles per hour) and a constructed measure is used when natural measures are unavailable or unsuitable for the case. An example of a constructed measure is the five-star scale created by the Kelley Blue Book (https://www.kbb.com/) to measure automobile valuation.

After discussions with stakeholders with various backgrounds, the research team decided to use and design constructed measures for all attributes. The constructed measurements are tailored to evaluate the attributes, and in this application, are more feasible to reflect value preferences from stakeholders when assessing the COB readiness of a port. The measurements were determined through comprehensive review of the relevant literature (Bu & Nachtmann, 2021), adjusted by discussing and consulting with stakeholders, and finalized by the research team. Exhibit 7 presents the measurement scales of each attribute the research team developed based on the related qualitative and quantitative data. COB Readiness Assessment Scorecard users can use Exhibit 7 to perform the assessment and obtain a Score for each attribute defined in the Value Hierarchy. In this step, all fourteen attributes in the Value Hierarchy must be assessed using the port's data, and associated scale levels must be chosen for each attribute.

For instance, when assessing the Port of Shanghai using information provided in Exhibit 7, the attribute *Population Density* was assessed as follows. The Rural-Urban Continuum Code (RUCC) is used to assess the population density of port located county as the defined measurement of *Population Density*. There are five different scales for *Population Density*. Because Shanghai is a megacity with a population larger than 24 million (Information Office of Shanghai Municipality, 2019), its RUCC is equivalent to 1. Therefore, a Score of 5 should be assigned for the Port of Shanghai on *Population Density*. Following the same method, the remaining attribute Scores of the Port of Shanghai are assessed and can be found in Exhibit 11.

Exhibit 7. Measurements and Scales for Attributes

Attribute	**Measurement Scales**	**Score**
Delayed Barge Handling Time	0-25% daily average late departures	4
	26-50% daily average late departures	3
	51-75% daily average late departures	2
	76-100% daily average late departures	1
Container Inventory Capacity	213 inventory slots and above	5
	171 to 212 inventory slots	4
	155 to 170 inventory slots	3
	125 to 154 inventory slots	2
	124 inventory slots and below	1
Intermodal Connectivity	Two Direct access modes	5
	One Direct access mode and one Indirect access mode	4
	Two Indirect access mode	3
	One Indirect access mode	2
	No access modes	1
Annual Maintenance Cost	Annual maintenance cost < Annual maintenance budget	3
	Annual maintenance cost = Annual maintenance budget	2
	Annual maintenance cost > Annual maintenance budget	1
Container Traffic Flow	10 or more commodities groups	5
	7 to 9 commodities groups	4
	4 to 6 commodities groups	3
	1 to 3 commodities groups	2
	0 commodities groups	1
Seaports Connectivity	2 or more seaports connected within 300 miles	3
	1 seaport connected within 300 miles	2
	No seaports connected within 300 miles	1
Waterway Depth	Deeper than 12 feet	3
	9 to 12 feet deep	2

	Lower than 9 feet deep	1
Bridge Height	Above 27 feet high	3
	Above 18 feet high but below 27 feet high	2
	Below 18 feet high	1
Barge Transportation Market Share	11.6% and above of market share	4
	4.5% to 11.5% of market share	3
	0.5% to 4.4% of market share	2
	0.4% and below of market share	1
Empty Container Repositioning Demand	0.67 and above imbalance ratio	5
	0.51 to 0.66 imbalance ratio	4
	0.30 to 0.50 imbalance ratio	3
	0.16 to 0.29 imbalance ratio	2
	0.15 and below imbalance ratio	1
Population Density	Rural-Urban Continuum Code (RUCC) = 1	5
	RUCC = 2 or 3	4
	RUCC = 4 or 5	3
	RUCC = 6 or 7	2
	RUCC = 8 or 9	1
Coordinated Government Action	9 components present	5
	6-8 components present	4
	3-5 components present	3
	1-2 components present	2
	no component present	1
Coordinated Industry Action	8 components present	5
	6-7 components present	4
	3-5 components present	3
	1-2 components present	2
	no component present	1
Environmental Protection Regulations	5 components present	5
	4 components present	4
	2-3 components present	3
	1 component present	2
	no component present	1

Step 4: Create Value Functions

Due to the complexity of assessing the COB readiness of ports, directly using scale scores defined in Exhibit 7 is insufficient to distinguish different value preferences from decision-makers accurately. Thus, we create value functions to transfer and normalize scale scores obtained from

Step 3 to a unified range of values from 0 to 100. A Value of 0 indicates the least preferred result, and a Value of 100 indicates the most preferred result. The large value range of 0 to 100 allows more sensitivity by reflecting slight differences in value preferences from COB Readiness Assessment Scorecard users. The general expressions for value functions are:

$$v_i = c_i(s_i), \qquad i = 1, \ldots, n \tag{1}$$

where v_i is the Value of the ith attribute, s_i is the Score of the ith attribute obtained from Step 3, and c_i is the single-dimensional value function that converts s_i to v_i.

COB Readiness Assessment Scorecard users can flexibly modify any value functions based on their preferences. By working together with the contacted COB experts (C. Tian, private contact, March 2022; J. Yi, private contact, March 2022), the research team developed six types of value functions to transfer Scores to Value for all attributes defined in the Value Hierarchy. Exhibit 8 presents the six value functions developed for the COB Readiness Assessment Scorecard, and Exhibit 9 shows which value function is used to measure values for each attribute.

When performing Step 4 on the Port of Shanghai, for example, a Score of 1 was obtained for the attribute *Delayed Barge Handling Time* in Step 3. We first look at Exhibit 9 and find out that this attribute should be assessed by the Type A value function. Next, we use the Type A value function plotted in Exhibit 8 and obtain a Value of 50 for the Score of 1. This process is repeated to obtain value scores for the remaining attributes, and the results of the Port of Shanghai analysis are presented in Exhibit 11.

Exhibit 8. Value Function Types

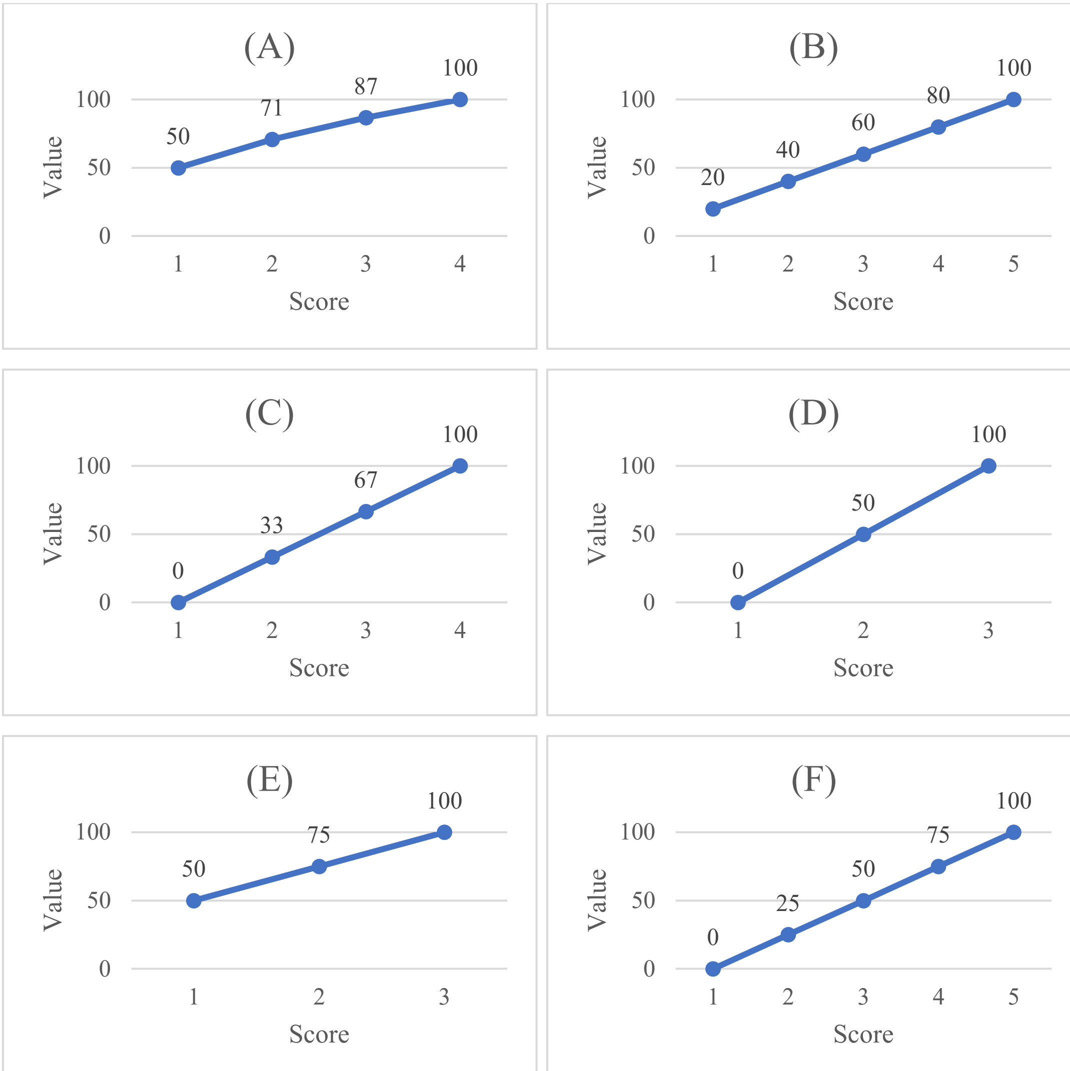


Exhibit 9. Value Function Type Assigned to each Attribute

Type	Attributes
A	Delayed Barge Handling Time
B	Container Inventory Capacity
C	Barge Transportation Market Share
D	Annual Maintenance Cost, Bridge Height, Seaports Connectivity
E	Waterway Depth
F	Container Traffic Flow, Coordinated Government Action, Coordinated Industry Action, Empty Container Repositioning Demand, Environmental Protection Regulations, Intermodal Connectivity, Population Density

Step 5: Weight Value Hierarchy

Step 5 aims to assign weights to the Value Hierarchy attributes to distinguish their importance levels in assessing COB readiness. In the COB Readiness Assessment Scorecard, the Swing Weight Matrix (Parnell et al., 2013, pp. 201-203) is implemented to conduct the weight-assigning process. The research team worked with the contacted COB experts to rank the importance levels and determine swing weights for the attributes. Next, the swing weights are normalized as:

$$w_i = \frac{f_i}{\sum_{i=1}^{n} f_i} \tag{1}$$

where f_i is the assigned swing weight for the *i*th attribute, w_i is the normalized weight for the *i*th attribute, and $i = 1$ to n is the attribute's index. The resulting swing weights and normalized weights for each attribute are presented in Exhibit 10. These are applicable to the Port of Shanghai case analysis and to all other ports studied in this work. COB Readiness Assessment Scorecard users can change the attribute swing weights according to their preferences.

Exhibit 10. Swing Weights and Normalized Weights for Attributes

Attribute	**Swing Weight (f_i)**	**Normalized Weight (w_i)**
Seaports Connectivity	100	0.12
Barge Transportation Market Share	80	0.09
Container Traffic Flow	75	0.09
Intermodal Connectivity	75	0.09
Coordinated Government Action	75	0.09
Annual Maintenance Cost	75	0.09
Bridge Height	60	0.07
Container Inventory Capacity	60	0.07
Coordinated Industry Action	60	0.07
Empty Container Repositioning Demand	50	0.06
Population Density	50	0.06
Waterway Depth	40	0.05
Delayed Barge Handling Time	35	0.04
Environmental Protection Regulations	30	0.03
	Total	1.0

Step 6: Perform COB Readiness Assessment

Step 6 calculates a final COB Readiness Score for the port being assessed. This COB Readiness Score ranges from 0 to 100, where 0 indicates no readiness and 100 indicates perfect readiness conditions to develop COB transportation at the port.

The final COB Readiness Score can be obtained as:

$$v(x) = \sum_{i=1}^{n} v_i w_i \tag{2}$$

where *v(x)* is the COB Readiness Score for port *x*, w_i is the normalized weight for the *i*th attribute, and v_i is the Value score of the *i*th attribute. The defined readiness levels associated with the COB Readiness Score are as follows:

- Very Ready: 86 to 100
- Ready: 75 to 85
- Minimally Ready: 60 to 74.
- Not Ready: 0 to 59.

The illustrative results from Steps 3 through 6 of the Port of Shanghai case analysis are presented in Exhibit 11. We calculated the weighted value ($w_i v_i$) for each attribute. For example, the normalized weight (w_i) and the value (v_i) of *Delayed Barge Handling Time* (as defined in Appendix A) are 0.040 and 50 respectively. Thus, this attribute's weighted value ($w_i v_i$) is calculated as 0.04*50 = 2. This process is repeated to obtain the weighted values for all attributes. Then, the Port of Shanghai's total COB Readiness Score is calculated by summing up the weighted Value scores for all attributes. As indicated in the last row in Exhibit 11, the Port of Shanghai scored 92 out of 100 on its COB Readiness Score.

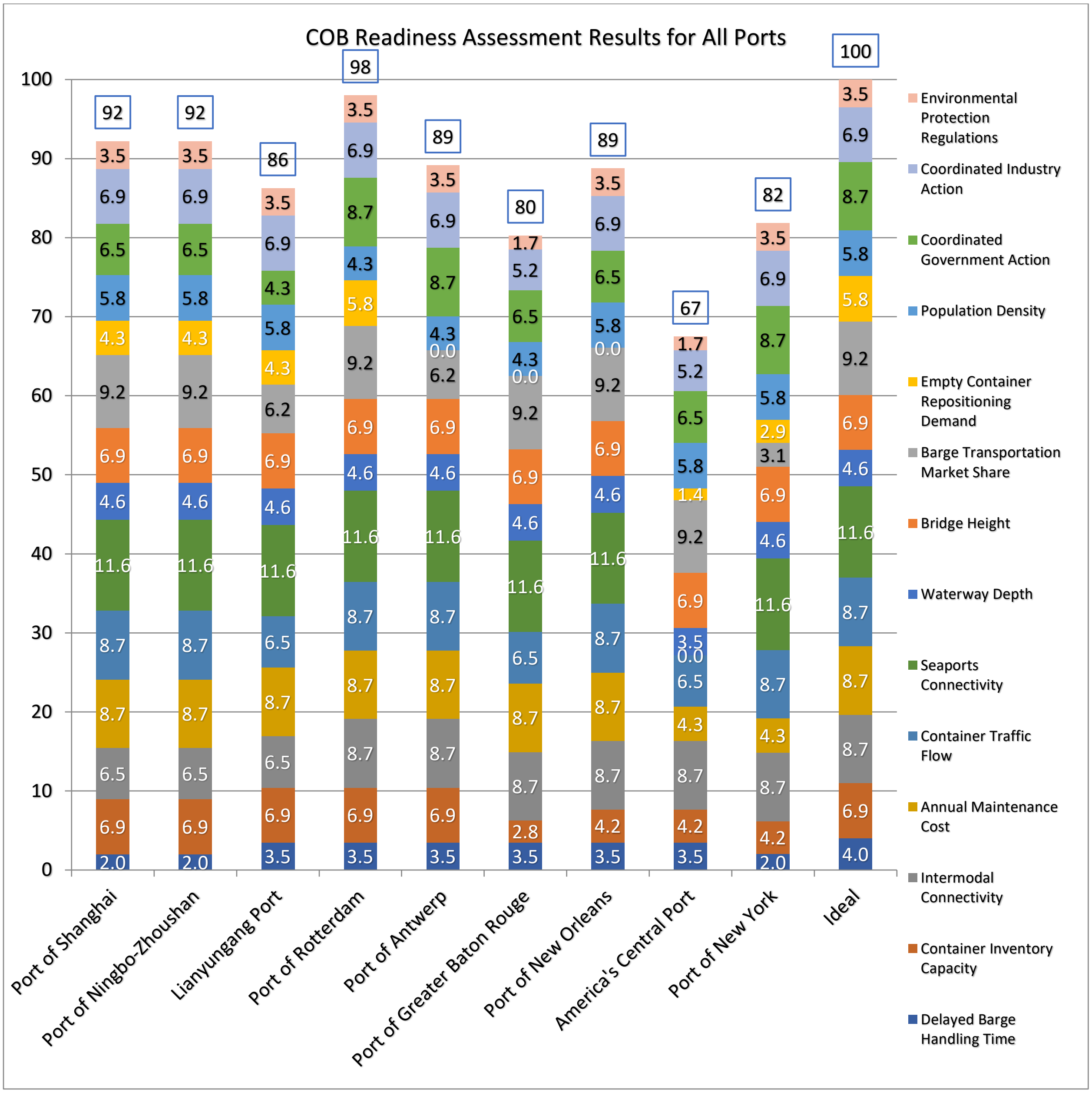
Exhibit 11. Assessment Results for the Port of Shanghai

Attribute	Score	Value	Normalized Weight	Weighted Value
Delayed Barge Handling Time	1	50	0.040	2
Container Inventory Capacity	5	100	0.069	7
Intermodal Connectivity	4	75	0.087	7
Annual Maintenance Cost	3	100	0.087	9
Container Traffic Flow	5	100	0.087	9
Seaports Connectivity	3	100	0.116	12
Waterway Depth	3	100	0.046	5
Bridge Height	3	100	0.069	7
Barge Transportation Market Share	4	100	0.092	9
Empty Container Repositioning Demand	4	75	0.058	4
Population Density	5	100	0.058	6
Coordinated Government Action	4	75	0.087	7
Coordinated Industry Action	5	100	0.069	7
Environmental Protection Regulations	5	100	0.035	3
			COB Readiness Score	92

3.4 Assessment Results and Analysis

The remaining eight ports were assessed following Steps 3 through 6 as demonstrated in the Port of Shanghai case analysis discussed in the previous section. The results of all nine ports are presented in Exhibit 12. We adopted a stacked column chart and added an additional “Ideal Port” that indicates the ideal maximum COB Readiness Score a port could earn. The readiness of each port to develop COB is measured by the total COB Readiness Scores as presented in Exhibit 12.

Exhibit 12. COB Readiness Assessment Results for All Ports



In this study, six out of the nine ports have a COB Readiness Score above 86 and are Very Ready to develop Container on Barge. Among these, the Port of Rotterdam received the highest assessment result (98), which concurs with the literature indicating that the Port of Rotterdam is in the leading position of global COB development (Notteboom *et al.*, 2020). Examining Exhibit 12, it can be seen that the attribute preventing the Port of Rotterdam from getting a perfect 100 is *Delayed Barge Handling Time*, which scored 2 out of 4 due to its moderate daily delay in barge handling processes. Next, the Port of Shanghai and the Port of Ningbo-Zhoushan are tied for second place with a COB Readiness Score of 92. The two Chinese ports received the maximum weighted value on most attributes. However, compared to the Port of Rotterdam, they scored less on *Delayed Barge Handling Time* due to the even heavier daily barge delays. They also scored less on the attribute *Empty Container Repositioning Demand* due to the fewer empty container repositioning demands. Furthermore, the two ports scored lower on *Coordinated Government Action*, because during China's One Road, One Belt development, Chinese maritime ports have had fewer supportive policies from the government with their modal shifting incentives in favor of rail transportation over barges. Following these in COB readiness are the Port of Antwerp and the Port of New Orleans, which both scored 89. When comparing these two ports, Port of New Orleans is in a less ready position than the Port of Antwerp in terms of *Coordinated Government Action* and *Container Inventory Capacity*. Nevertheless, the Port of New Orleans is located in a more population-dense area with more container shipping demands than the Port of Antwerp. Thus, it has more opportunities for future COB development. Last, Lianyungang Port scored 86. This result is slightly less than the other five ports in the 85 to 100 range, because Lianyungang Port does not have enough *Intermodal Connectivity* and *Container Traffic Flow* advantages.

Next, two ports scored in the 75 to 85 range, indicating Ready to develop container on barge. They are the Port of New York with a COB Readiness Score of 82 and the Port of Greater Baton Rouge with a score of 80. The disadvantages and advantages of the Port of New York are shown in Exhibit 12. This port has the lowest value score on *Delayed Barge Handling Time* and *Barge Transportation Market Share* and the highest score on *Coordinated Government Action* and *Environmental Protection Regulations* among all ports. On the other hand, the Port of Great Baton Rouge scored the lowest value scores on *Container Inventory Capacity* and *Empty Container Repositioning* and managed to score at relatively good levels on the rest of the attributes.

With a COB Readiness Score of 67 (Marginally Ready), America's Central Port holds the lowest readiness position among the nine ports assessed in this study. It is the only port that scored below 75. The most considerable drawback is that the port is not connected to any significant seaports within 300 miles. Moreover, the port is also significantly behind the others in terms of *Environmental Protection Regulations* and *Annual Maintenance Cost*. America's Central Port was already chosen by the U.S. government and awarded federal funding to develop its COB transportation. However, based on its COB Readiness Score (67), the port will likely face upcoming COB development challenges since it scored relatively low on some highly weighted attributes.

Overall, ports in the EU and China tend to outperform their U.S. counterparts on multiple attributes: *Container Inventory Capacity*, *Empty Container Repositioning Demand*, *Coordinated Industry Action*, and *Environmental Protection Regulations*. These regions exhibit a higher container stacking capacity, which is critical for sustaining port container throughput growth. Additionally, high demand for empty container shipping is a vital element in creating strong demand for COB business. Moreover, enhanced coordination among container shipping stakeholders can significantly increase COB market growth, which benefits long-term COB development. Furthermore, tight environmental regulations in these regions encourage a rapid shift from truck and train to barge container shipping (Bu & Nachtmann, 2021). Consequently, these four attributes emerge as pivotal success factors for EU and Chinese ports and simultaneously highlight areas for improvement in U.S. ports. As COB matures differently across these regions, reducing these gaps becomes important for the advancement of U.S. ports in COB development.

On the other hand, U.S. ports uniformly score 8.7 out of 8.7 in *Intermodal Connectivity*, indicating a robust connectivity in the intermodal shipping network with potential for facilitating a shift from trucks and trains to barges. While the success of this transition depends on future market growth, it remains a distinct advantage for U.S. ports. Additionally, U.S. ports are on par with EU and Chinese ports regarding *Coordinated Government Action*, reflecting recent increases in U.S. government support to expedite COB development. Should this support extend to additional U.S. ports, such sustained governmental efforts are anticipated to further advance U.S. COB development.

In summary, every port has its advantages and disadvantages related to COB readiness, as discussed above. Except for America's Central Port, all studied ports have demonstrated Very Ready or Ready conditions for COB development. On average, ports in China and the EU have higher total assessment scores than the U.S. This result concurs with the fact that these foreign ports have successfully executed COB transportation for decades. Nevertheless, we believe that the U.S. ports studied in this work are in good stages of readiness to develop successful COB transportation. In addition, their conditions should further improve in the future as they allocate more resources to COB development.

3.5 Summary

This project contributes a value-focused thinking-based scorecard to assist transportation stakeholders in evaluating COB development readiness at maritime ports in the United States. The COB Readiness Assessment Scorecard is developed based on three foundations: 1) a literature review of global COB transportation conducted by Bu & Nachtmann (2021), 2) the philosophy and framework of VFT (Keeney, 1992) combined with the decision analysis methodologies created by Parnell et al. (2013), and 3) port assessment data collected by the research team and contacted COB experts. To demonstrate the application of the COB Readiness Assessment Scorecard and to test its capability and practicality, a step-by-step case analysis of the Port of Shanghai is presented along with an assessment of nine global COB ports in total.

The COB Readiness Assessment Scorecard implements all constructed measures, including direct and indirect measures. It utilizes qualitative and quantitative data, which can be retrieved from government databases or port websites to assess COB readiness effectively. This advantage helps break through the bottleneck of assessing the preconditions of COB development when the U.S. ports lack real-world industry data and COB success stories. The COB Readiness Assessment Scorecard can be implemented to evaluate seaports and inland waterways, and additionally, it can assess both developed and developing COB ports around the world. From the assessment results of the EU and Chinese ports, the validated performance of the COB Readiness Assessment Scorecard successfully reflects the industry status of world-leading COB ports. The results indicate that U.S. ports, in general, have shortcomings in *Coordinated Industrial Action*, *Empty Container Repositioning Demand*, and *Container Inventory Capacity* as compared to ports located in the EU and China. In general, the total COB readiness of U.S. ports is found to be lower than non-U.S. ports as reported in the literature. This effort has resulted in a manuscript currently under review at the Engineering Management Journal.

4.0 Container Traffic Forecasting for Container on Barge Transportation in the United States

4.1 Introduction

Starting in the 1980s, there has been a growing body of research focused on predicting container traffic volume (CTV), signifying notable advancements in this area of study (Yang & Chang, 2020). The application of machine learning (ML) in predicting CTV with time series data is also becoming increasingly popular because of its ability to handle complex data patterns and making accurate predictions. A common practice of implementing ML for forecasting is to collect historical CTV data to train and test the machine learning models, then make predictions on future CTV. This is due to the fact that historical time series CTV data can reveal important trends or patterns for the future.

Here, we explore machine learning and deep learning algorithms designed to predict target variables using only independent variables as inputs. These models present a compelling alternative to conventional methods that depend on historical data of the target variable, offering an innovative approach to predictive analytics. Pan et al. (2021) utilized a ridge regression (RR) model to forecast carbon emissions in China, based on four independent variables: population, working-age population ratio, Engel coefficient, and the proportion of secondary industry employees. Their research validated the model's capability in accurately predicting CO2 emissions, underscoring the significance of selecting relevant variables. Fan et al. (2021) demonstrated the effectiveness of support vector regression (SVM) in predictions using independent variables. They observed that with appropriate kernel function selection and parameter tuning, SVM could effectively model complex, non-linear relationships between variables, thereby improving prediction accuracy. Li et al. (2022) applied long short-term memory (LSTM) neural networks to forecast dengue cases, comparing models with and without historical dengue data inputs. Their results suggested that while the absence of historical data slightly reduced accuracy, the models still achieved commendable forecasting performance. Furthermore, Zeng et al. (2017) developed a (back propagation neural network) BPNN model leveraging economic indicators to predict energy demand. Their findings indicated consistent and reliable results, supporting the prevalent use of economic factors for national energy demand forecasting.

Kharfan et al. (2021) employed a random forest (RF) model to predict seasonal fashion product demand without historical sales data. They found that the flexibility of the RF model enabled superior predictive accuracy, surpassing linear regression and SVM models. Finally, Qiu et al. (2022) implemented an eXtreme Gradient Boosting (XGBoost) algorithm for solar radiation prediction. The study illustrated that, despite lacking historical data, the XGBoost model maintained high accuracy, rivaling other empirical methods. This exploration of various models highlights the potential and versatility of machine learning and deep learning techniques in forecasting scenarios where historical data is not available.

While many studies employ various methods for this task, the focus predominantly lies on seaports. In contrast, research addressing inland waterway transportation, and inland ports remains notably sparse. Tang et al. (2019) utilized grey models, RR, and BPNN to predict container volumes at Lianyungang and Shanghai Ports, where BPNN emerged as the most effective, particularly when multiple years of historical data were incorporated. Ding et al. (2019) assessed the performances of BPNN and SVM in forecasting container traffic at Ningbo and Wenzhou Ports. While SVM slightly outperformed BPNN, a hybrid approach combining SVM with BPNN reduced the average error to below 1.5%. In addition, multiple studies have confirmed that LSTM or CNN+LSTM models can achieve stable and high accuracy in CTV forecasting (Yang & Chang, 2020; Shankar et al., 2020; Shankar et al., 2021). The related articles showed that LSTM is a flexible model to combine with other methods and can take historical container volume data alone as input or in conjunction with other independent variables to maintain a high forecasting accuracy level. Moreover, Awah et al. (2021) employed a RF model to forecast CTV at Douala Port, achieving an MAPE of less than 1%. Notably, RF models yielded the two best results in forecasting accuracy among the ten models compared in the study. Recently, Jin et al. (2023) applied the XGBoost model to predict daily in and out container movements at the Beilun terminal of Ningbo Zhoushan Port. The results were found to be comparable to those obtained using the ARIMA model.

Limited research has been conducted on forecasting CTV for inland waterway transportation. Bernacki and Lis (2021) used a linear regression model to forecast small and medium-sized ports in the Polish waterway system which covers multiple inland waterway ports. The author mentioned that the forecasting on the total inland waterway CTV could be achieved relatively easily because the competition among multiple ports in the same system does not need to be considered in this case. In addition, Van Meir et al. (2022) focused on the Rhine River, using data from gateway seaports like the Port of Antwerp and Port of Rotterdam, along with the Industrial Production Index (IIP) and water level data, for their forecasts. The authors emphasized the scarcity of research in this area but acknowledged the growing importance of inland waterway transportation, calling for more comprehensive container traffic forecasting studies in the future.

It is a common practice to employ multiple machine learning methods in one study to predict container volumes and compare their performances to obtain the best forecasting accuracy (Ding et al., 2019; Tang et al., 2019; Awah et al., 2021). This comparative approach serves dual purposes: 1) it allows for the identification of the most effective model by leveraging the unique strengths and mitigating the weaknesses of each method, and 2) it provides additional validation and credibility to the forecasting results and thereby bolsters the reliability of the forecasted outcomes.

4.2 Economic Indicators

Numerous economic indicators play important roles in CTV forecasting. In various studies, they are called by different names including attributes, predictors, independent variables, inputs, explanatory variables, etc. But in this research, we uniformly refer to them as features. Academic literature reveals that researchers often incorporate a variety of features in addition to historical CTV data to enhance the accuracy of their forecasts. Furthermore, it is standard practice to review prior published studies to identify important features that have been empirically validated as being highly correlated with CTV. This approach helps us to gain a better understanding of container traffic forecasting, and it is even more important if no historical data is used for the forecasting task.

Exhibit 13 presents a comprehensive list of the features studies in the reviewed articles. Each feature is accompanied by a brief description and citations to the related published articles, providing a validated basis for their inclusion in our forecasting modeling.

Exhibit 13. Features in container traffic forecasting

No	Feature Type	Description	Source (Article)
1	Gross Domestic Product (GDP)	Measures the total value of all goods and services produced within a country's borders.	Gosasang et al. (2018), Tang et al. (2019), Shankar et al. (2021), Bernacki & Lis (2021), Van Meir et al. (2022), Matczak (2020), Kawasaki et al. (2022), Gołębiowski (2016)
2	Import Freight Volume	Volume of goods imported into a country, often measured in tons or TEUs (Twenty-foot Equivalent Units).	Gosasang et al. (2018), Tang et al. (2019), Shankar et al. (2021), Matczak (2020), Kawasaki et al. (2022), Caliskan & Karaöz (2019)
3	Export Freight Volume	Volume of goods exported from a country, often measured in tons or TEUs.	Gosasang et al. (2018), Tang et al. (2019), Shankar et al. (2021), Matczak (2020), Kawasaki et al. (2022), Caliskan & Karaöz (2019)
4	Labor Market Indicator	Demographic and labor market indicators, including total population, employment rate, and unemployment rate.	Gosasang et al. (2018), Tang et al. (2019), Shankar et al. (2021), Matczak (2020), Kawasaki et al. (2022)
5	Producer Price Index (PPI)	Measures the average change in selling prices received by domestic producers for their output.	Gosasang et al. (2018), Tang et al. (2019), Shankar et al. (2021), Van Meir et al. (2022), Kawasaki et al. (2022)
6	Rail Freight Volume	Volume of goods transported by rail, often measured in tons or TEUs.	Tang et al. (2019), Tufano et al. (2023), Gołębiowski (2016)
7	Truck Freight Volume	Volume of goods transported by truck, often measured in tons or TEUs.	Tang et al. (2019), Tufano et al. (2023), Gołębiowski (2016)
8	Exchange Rate of Currency	The value of one currency for the purpose of conversion to another.	Gosasang et al. (2018), Shankar et al. (2021), Van Meir et al. (2022), Caliskan & Karaöz (2019)
9	Consumer Price Index (CPI)	Measures the average change in prices paid by consumers for goods and services.	Gosasang et al. (2018), Tang et al. (2019), Shankar et al. (2021), Kawasaki et al. (2022)
10	Fuel Price	The cost of fuel, often measured per liter or gallon.	Shankar et al. (2021), Caliskan & Karaöz (2019)
11	Interest Rate	The cost of borrowing money, often expressed as a percentage.	Gosasang et al. (2018)
12	Water Level	The height of water in rivers or lakes, which can affect inland waterway transport.	Van Meir et al. (2022)

4.3 Data Preparation

We leverage available data to undertake an empirical case study focused on the European inland waterway transportation by gathering time series data for the twelve features identified in our literature review. These features are used to train various machine learning and deep learning models, aiming to predict CTV in the European COB transportation system. Additionally, we collect actual historical data pertaining to the EU's inland waterway CTV. This will enable us to compare our forecasted results with the actual historical container volumes, thus facilitating a comprehensive assessment of the implemented models and aid in the selection of the most effective approach.

We gathered quarterly data from 2007 to 2022 on the total CTV via European inland waterway transportation (https://ec.europa.eu/eurostat), ensuring there were no missing values. This data includes CTV from all European Union (EU) countries. Exhibit 14 describes the data collected for the twelve features identified in our literature review. We use abbreviations for each feature type to enhance conciseness and clarity in both documentation and subsequent coding processes.

For each feature, we selected the most relevant and readily available indicator. For instance, for GDP, we used the quarterly GDP data in Euros, as they are the most directly related and accessible data. In contrast, for the Labor Market Indicator, we opted to use the quarterly unemployment rate due to the unavailability of other potential indicators, such as total employment rate or time series data on working population changes. Following this rationale, we collected data for the twelve features (https://databank.worldbank.org/). As shown in Exhibit 14, our goal was to gather data for each feature with consistent seasonality, in this case, quarterly data. However, for features No.9 and No.12, only monthly data was available. Therefore, we calculated the average of three months' data within each quarter to convert the monthly data into a quarterly format for these two features. Consequently, the assembled dataset for training features is structured as 64 rows by 12 columns. With only three values missing, we employed the mean imputation method to fill these gaps.

Exhibit 14. Data collected for the twelve features.

No	Feature Type Identified	Abbreviation	Available Data Collected	Seasonality	Processing Method
1	Gross Domestic Product (GDP)	GDP	GDP in million EURO	Quarterly	N/A
2	Import Freight Volume	Inwards	Total Import of containers (TEU) in EU	Quarterly	N/A
3	Export Freight Volume	Outwards	Total export of containers (TEU) in EU	Quarterly	N/A
4	Labor Market Indicator	Unemployment	EU unemployment rate	Quarterly	N/A
5	Producer Price Index (PPI)	PPI	EU PPI	Quarterly	N/A
6	Rail Freight Volume	Rail	Rail freight volume by thousand tons	Quarterly	N/A
7	Truck Freight Volume	Road	Road freight volume by thousand tons	Quarterly	N/A
8	Exchange Rate of Currency	Exchange	EURO to USD exchange rate	Quarterly	N/A
9	Consumer Price Index (CPI)	CPI	EU CPI	Monthly	Take the average value of the three months
10	Fuel Price	Oil	Global price of average petroleum spot price	Quarterly	N/A
11	Interest Rate	Interest	The Economic and Monetary Union convergence criterion bond yields	Quarterly	N/A
12	Water Level	Water	Water level of the Rhine near Düsseldorf	Monthly	Take the average value of the three months

4.4 Methodology

From the literature review, several models exist that can perform forecasting without relying on the target's historical data. While it is apparently a standard approach to compare multiple models for forecasting CTV, to the best of our knowledge, ours is the first study that aims to forecast inland waterway transportation CTV without using historical traffic volume data. Although the models reviewed are generally reported to perform well in their specific contexts, it is worth noting that forecasting for inland waterway transportation may differ from forecasting for seaports due to limited data availability. Therefore, this research seeks to evaluate and compare these popular models to identify the most accurate approach to forecast inland waterway transportation container traffic. In this section, we describe the models, illustrate the implementation of these models, and introduce the metrics used for assessing their performance.

4.4.1 Prediction Models

Ridge Regression

Ridge regression (RR) (Pan, et al., 2021) is built on the foundation of linear regression. By incorporating a regularization component into the cost function, it is particularly useful for handling multicollinearity and preventing overfitting. As shown in equation (3), we have the linear regression model:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \epsilon_i \quad (3)$$

where y_i is the i^{th} observation of the target variable, x_{ij} is the value of the j^{th} feature for the i^{th} observation, β_j is the coefficient for the j^{th} feature, and ϵ_i is the random error term for the i^{th} observation. The objective function of the linear regression is written as following:

$$\hat{\beta} = argmin\,(\frac{1}{2n}\sum_{i=1}^{n}(y_i - (\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip}))^2) \quad (4)$$

where n is the number of observations. However, the cost function in RR is modified to include a regularization term as follows:

$$\widehat{\beta_{RR}} = argmin\,(\frac{1}{2n}\sum_{i=1}^{n}(y_i - (\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip}))^2 + \lambda\sum_{j=0}^{p}\beta_j^2) \quad (5)$$

where λ is the regularization parameter to control the strength of the regularization term, $\lambda \sum_{j=0}^{p} \beta_j^2$ serves as a penalty term to discourage the overly large coefficients. A larger λ provides stronger regularization which produces a simpler model while a lower λ leads to a similar model compared to the basic linear regression model. As a result, RR is a technique which addresses multicollinearity by regularizing the coefficient estimates towards zero which increases the interpretability and stability of the regression model.

Support Vector Regression

Support vector regression (SVM) (Fan et al., 2021) can also be used as a regression model. Given a set of training data $\{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$, where $x_i \in \mathbb{R}^d$, and $y_i \in \mathbb{R}$, the SVM works to find the following function f(x) to approximate y:

$$f(x) = < w, x > + b \tag{6}$$

where w is the weight vector, and b is the bias term. The objective of SVM is to minimize the following function with the subject to the associated constraints:

$$Min\ \frac{1}{2}\|w\|^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*) \tag{7}$$

$$subject\ to \begin{cases} y_i - < w, x_i > - b \ \leq \ \varepsilon + \xi_i \\ - y_i + < w, x_i > + b \ \leq \ \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{cases} \tag{8}$$

where $||w||^2$ is the square of the Euclidean norm of w, ε defines the width of the insensitive zone in which the predicted value has a zero loss, ξ_i and ξ_i^* are slack variables introduced for the infeasible cases where predicted values fall outside of the ε-tube, C is the regularization parameter which controls the trade-off between penalties on slack variables and the complexity of the model.

Long Short-Term Memory Neural Networks

Long short-term memory (LSTM) (Li et al., 2022) neural networks are one type of recurrent neural networks (RNN), specially designed for capturing long-range dependencies in time-series data and thus is popular used in time series forecasting (Yang et al., 2021). This makes the LSTM model effectively combat the vanishing gradient problem and capture both the long- and short-term dependencies in time series data. As a result, it is efficient to be implemented to understand the temporal characteristics and achieve high accuracy in time series forecasting.

CNN + LSTM

The Convolutional Neural Network (CNN) + LSTM model is proposed by Yang and Chang (2020) to forecast container throughput demand. The central concept of this hybrid model is to leverage the strengths of both CNN and LSTM architectures. While CNN excels at identifying crucial spatial features, it struggles with capturing long-term temporal dependencies. This limitation is precisely what LSTM can address. The combined model is particularly advantageous for time-series forecasting, where complex temporal sequences and spatial patterns frequently coexist.

Back-Propagation Neural Network

Back-propagation neural network (BPNN) (Tang et al., 2019; Ding et al., 2019) is a commonly utilized neural network architecture, often employed for comparative analysis against other methodologies or within hybrid models, particularly in the domain of time series forecasting like container forecasting and others. Characterized by its multilayer feedforward structure, the BPNN is distinguished by its training via the backpropagation algorithm, which facilitates iterative model refinement. This iterative process adjusts the model by comparing the predicted outputs to the actual inputs, enabling the network to learn from its errors.

Random Forest

The random forest (RF) algorithm (Kharfan et al., 2021) is the ensemble learning method based on the concept of decision trees. Each individual decision tree is trained on a random bootstrap sample with replacement. At each split, only a random subset of features is taken instead of considering all features in decision tree. The final prediction is made as follows:

$$\hat{y}_{RF}(X) = \frac{1}{n}\sum_{i=1}^{n} \hat{y}_{tree_i}(X) \tag{9}$$

Where $\hat{y}_{tree_i}(X)$ is the prediction made by the i^{th} tree. In addition, the Out-of-Bag Error (OOB) is used to estimate the model's performance. It is calculated by using the unincluded data points in the bootstrap samples of each tree. The equation below gives the calculation of OBB error:

$$OOB\ error = \frac{1}{n}\sum_{i=1}^{n} L(y_i, \hat{y}_{OOB_i}) \tag{10}$$

Where $\hat{y}_{OOB_i}$ is the aggregated prediction for the i^{th} data point using its OBB trees, y_i is the actual value, and L is the loss function. Typically, the loss function is Mean Square Error (MSE).

XGBoost eXtreme Gradient Boosting

eXtreme Gradient Boosting (XGBoost) (Jin et al., 2023) is another tree-based algorithm with the implementation of gradient boosting. It operates by building multiple individual trees in a sequential order where each tree corrects the errors made by its predecessor. Each tree in the model is a weaker learner, and it learns from the residuals of all previous trees, the final prediction of the model is the sum of results from all trees:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i) \tag{11}$$

Where f_k represents an individual tree, $f_k(x_i)$ is the prediction from tree k, $\hat{y}_i$ is the forecasted value of i^{th} instance x_i. The objective function of XGBoost is:

$$Obj(\Theta) = L(\Theta) + \Omega(\Theta) \tag{12}$$

Where $L(\Theta)$ is the loss function (like MSE), and $\Omega(\Theta)$ is the regularization term used to prevent overfitting of the model. The model is trained by iterations. In iteration t, $\hat{y}_{i(t)}$ is calculated below:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t(x_i) \tag{13}$$

In each iteration, XGBoost calculates the first and second-order derivatives (g_i, h_i) of the loss function with respect to the prediction $\hat{y}_i$ as follows:

$$\begin{cases} g_i = \partial_{\hat{y}_i} l(y_i, \hat{y}_i) \\ h_i = \partial_{\hat{y}_i}^2 l(y_i, \hat{y}_i) \end{cases} \tag{14}$$

By using a Taylor series up to the second order would give us the following approximation to minimize the objective function at iteration t as:

$$Obj^{(t)} \approx \sum_{i=1}^{n} \left[l\left(y_i, \hat{y}_i^{(t-1)}\right) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \Omega(f_t) \tag{15}$$

This approach uses both first and second order derivatives and the Taylor expansion enables XGBoost to generate the optimal trees efficiently in regression task.

4.4.2 Performance Metrics

In this study, we employ three widely recognized metrics to evaluate and compare the forecasting results. mean absolute percentage error (MAPE) is utilized to measure relative errors, offering a percentage-based, intuitive interpretation of the forecasting accuracy. The Mean Absolute Error (MAE) is applied to assess the average magnitude of forecasting errors, providing a direct measure of the error scale. Additionally, the Root Mean Squared Error (RMSE) is adopted, particularly for its effectiveness in highlighting large errors, which may be especially critical to avoid in CTV forecasting due to their significant impacts. The equations for these metrics are as follows:

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (16)$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i| \quad (17)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \quad (18)$$

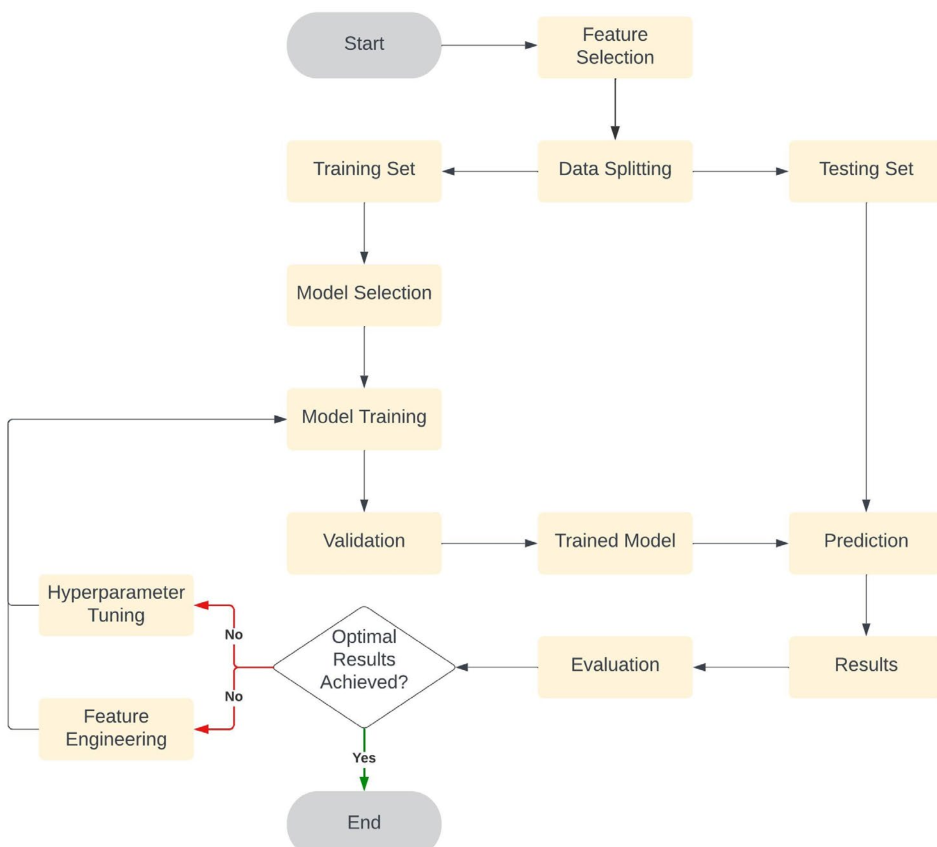
where y_i represents the actual value of i, $\hat{y}_i$ presents the predicted value of i, and n is the total number of observations.

4.4.3 Prediction Process

This study's forecasting methodologies are depicted in a flowchart presented in Exhibit 15. Initially, the models are trained, and predictions are made using all twelve features. However, given the potential data constraints in regions beyond the EU, an important phase of feature selection is undertaken. This phase assesses the models' efficiency when operating with a reduced feature set. This assessment is vital, particularly for stakeholders in regional inland waterway systems who may not have access to the complete set of twelve features but require accurate CTV forecasts. Through this exploration, the study aims to enhance the models' adaptability to various geographic and data contexts, a critical factor for their broader application in diverse environments.

In this study, we employ a combination of RF and Recursive Feature Elimination (RFE) for feature selection in each model. The choice of RF is driven by its robustness in handling complex, non-linear relationships among the twelve features, which are not straightforward in our case. RF's ensemble approach effectively reduces overfitting risks, thereby enhancing the feature selection process. Initially, RF is used to assess and rank the importance of features. Subsequently, RFE is applied to systematically eliminate the least important features, continuing this process until we reach the predetermined number of features for our analysis. Because of its robustness and versatility, this integrated RF-RFE strategy is applied consistently across all seven models in this study.

Exhibit 15. Flowchart of model implementation



Furthermore, we do not test every possible number of features from twelve down to one. Instead, subsets of seven and five features are selected to evaluate the models' performance, providing a representative and general assessment with a reduced number of input features. Feature selection was performed on the entire dataset prior to its division into training and testing sets. This method ensures that the testing data does not influence the feature selection process, maintaining strict adherence to the historical chronological order and ensuring that no future information impacts decisions made on past data. The training set consists of data from 56 quarters, spanning from 2007 to 2020. The testing set encompasses data from the following 8 quarters, covering the period from 2021 to 2022. We employ a 0.875:0.125 training-to-testing set ratio for short-term CTV forecasting. Given the limited amount of quarterly data available, this ratio allows the models to learn more stable patterns from historical data, thereby enhancing the accuracy of short-term predictions.

Next, as outlined in Exhibit 15, each model undergoes training and validation processes. Predictions are then made using the test data. The outcomes of these predictions are assessed using the previously mentioned metrics by comparing them with the actual historical CTV numbers. If necessary, an iterative refinement loop is initiated, focusing on enhancing hyperparameter tuning and data engineering to increase prediction accuracy. This cycle continues until each model reaches its optimal performance with the selected number of features. This iterative process is repeated for each of the seven models under study, ensuring a thorough exploration and optimization of all models.

We chose to code and run the seven models in Python 3.10 on Google Colab with the default computing resources provided by the free version. TPU (Tensor Processing Unit) has been chosen as the hardware accelerator for our Colab running environment. This setup is easily accessible, convenient, and efficient to conduct our forecasting study.

4.5 Application and Results

4.5.1 Prediction Results Using Twelve Features

Exhibits 16 and 17 present the forecasting results using all twelve features as predictors. The RR model demonstrated moderate accuracy with a MAPE of 2.97%. Although it provided a reasonable level of precision, its relatively higher RMSE (100,497) and MAE (77,592) indicated a susceptibility to larger errors in specific instances, which might be due to its inability to fully capture the complex interactions among the twelve features. In contrast, the SVM model underperformed compared to RR, with higher error values across all metrics (MAPE of 3.90%, RMSE of 137,435, and MAE of 104,300). This suggests that SVM's capacity to model the complexities inherent in the twelve features for accurately predicting TEU volume is somewhat limited.

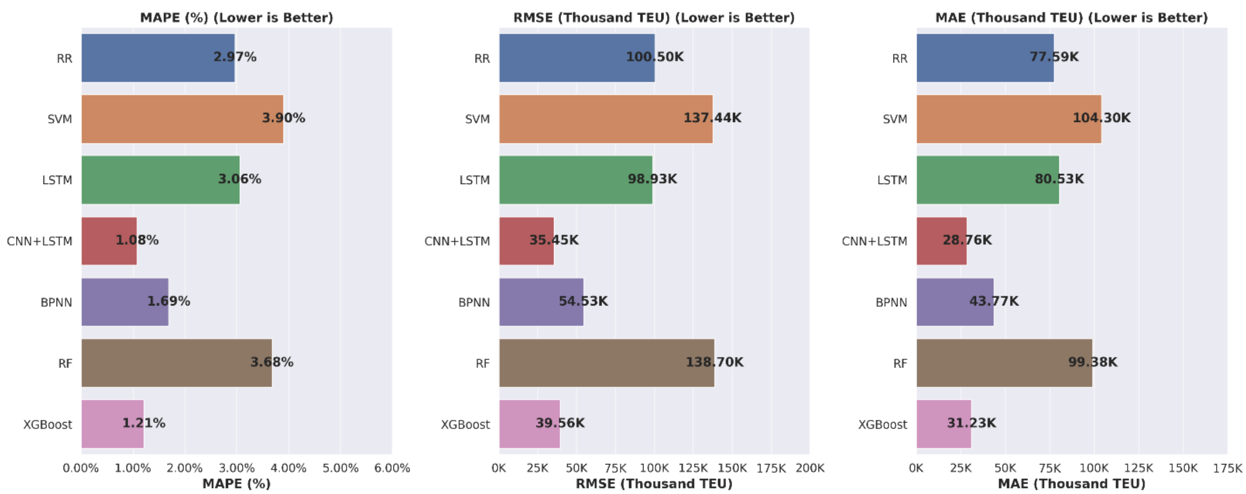
Notably, the LSTM network showed an improvement over RR in terms of RMSE (98,926), albeit with a slightly higher MAPE (3.06%) and MAE (80,534). This improvement signifies LSTM's enhanced ability in capturing temporal dependencies among the features, an essential aspect of CTV forecasting. The hybrid CNN+LSTM model emerged as the most accurate, significantly outperforming all other models. It achieved the lowest MAPE (1.08%), RMSE (35,451), and MAE (28,757), demonstrating exceptional proficiency in integrating and modeling both spatial and temporal aspects of the twelve-feature dataset. This suggests that the combination of convolutional and recurrent neural network architectures is particularly well-suited for this task while using the twelve features provided in this study. In addition, the BPNN showed promising results, with better accuracy than RR, SVM, and LSTM but not as high as CNN+LSTM. Its MAPE of 1.69%, RMSE of 54,529, and MAE of 43,772 indicate its capability as a viable alternative, especially in scenarios where the complexity of CNN+LSTM might be a limiting factor.

The performance of the RF model was comparatively lower, as indicated by its higher error metrics (MAPE of 3.68%, RMSE of 138,699, and MAE of 99,376). This performance suggests that the ensemble method, typically robust in various applications, may not be as effective in capturing the nuanced patterns present when utilizing all twelve features for inland waterway CTV forecasting. Finally, the XGBoost model demonstrated high accuracy, second only to the CNN+LSTM model. With a MAPE of 1.21%, RMSE of 39,560, and MAE of 31,227, XGBoost has proved to be highly effective, indicating its strong capability to handle the complexity and non-linearity associated with the twelve features. In summary, all tested models demonstrated notable accuracy, with each achieving MAPE scores below 4%. However, there was a significant variation in performance as evidenced by the range in RMSE (from 35,451 to 138,699) and MAE (from 28,757 to 104,300). Among these, the CNN+LSTM model stood out as the most proficient, distinctly outperforming the others across all three key metrics. Its superior performance underscores the model’s effectiveness and advanced capability in managing the complexities associated with the twelve features used, thereby providing highly accurate predictions.

Exhibit 16. Forecasting results using twelve features.

Model	MAPE	RMSE	MAE
RR	2.97%	100,497	77,592
SVM	3.90%	137,435	104,300
LSTM	3.06%	98,926	80,534
CNN+LSTM	1.08%	35,451	28,757
BPNN	1.69%	54,529	43,772
RF	3.68%	138,699	99,376
XGBoost	1.21%	39,560	31,227

Exhibit 17. Comparison of Forecasting Models Using Twelve Features



4.5.2 Prediction Results Using Seven Features

Exhibits 18 and 19 present the results when a reduced set of seven features are used to train the model and perform predictions. Exhibit 18 also presents the optimal features selection results. If a feature engineering approach is used, the associated method is also listed in Exhibit 18.

The RR model, utilizing features such as GDP, Inwards, Outwards, Unemployment, Road, Exchange, and Interest, recorded a MAPE of 4.50%, the highest among the tested models. This, combined with its RMSE of 130,621 and MAE of 118,851, suggested its limited capacity in effectively capturing the relationships within the reduced feature set, making RR the least favorable performer in this assessment. Conversely, the SVM model exhibited a substantial enhancement in performance, particularly noteworthy given its inclusion of a temporal feature extraction approach. By incorporating the year component alongside the seven selected features, the SVM achieved a MAPE of 2.27%, an RMSE of 89,975, and a MAE of 60,338. This marked improvement accentuates the pivotal role of temporal dynamics in CTV forecasting and SVM's proficiency in exploiting such additional information. The LSTM network, while not benefiting from any additional feature engineering, still showed commendable results. With a MAPE of 2.55%, RMSE of 88,163, and MAE of 65,747, LSTM's inherent strength in capturing temporal patterns was evident, albeit slightly overshadowed by the SVM's enhanced feature set.

Standing out was the CNN+LSTM model. Even without the aid of supplementary feature engineering, it registered the lowest MAPE (1.92%), RMSE (73,827), and MAE (50,158), distinctly outclassing its counterparts. This once again highlights the CNN+LSTM model's robust capability in seamlessly integrating and interpreting both spatial and temporal aspects of the seven features used. On the other hand, the BPNN also demonstrated a strong performance, albeit not as pronounced as the CNN+LSTM. With a MAPE of 2.09%, RMSE of 87,644, and MAE of 54,292, BPNN offered a balanced performance profile, positioning itself as a viable option in scenarios where the complexity of CNN+LSTM might be a constraint.

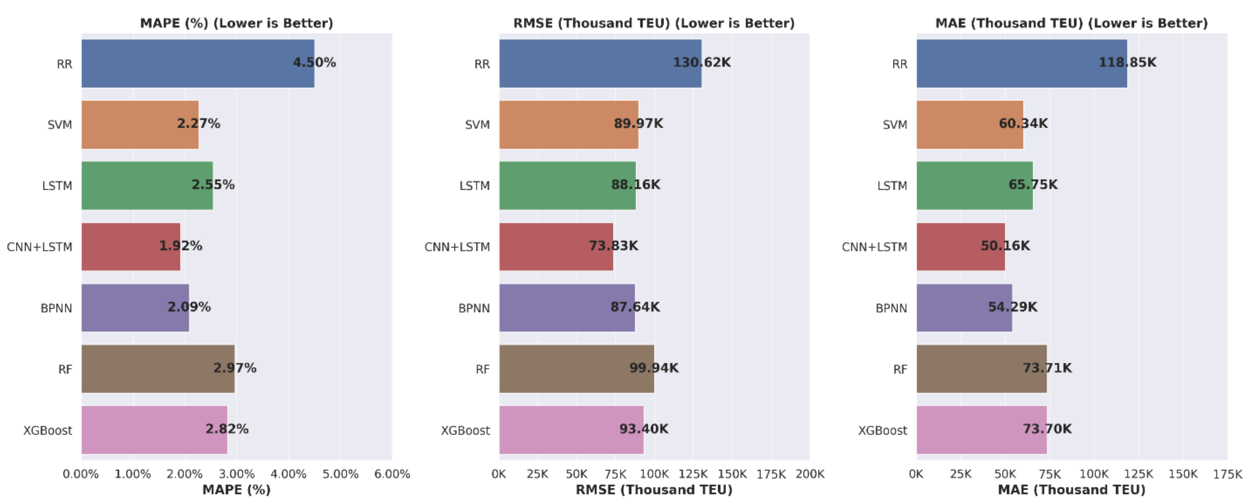
In contrast, the RF model, though robust in various applications, registered moderate performance in this context, indicated by a MAPE of 2.97%, RMSE of 99,943, and MAE of 73,713. This outcome suggests that RF's effectiveness is limited when features are reduced from twelve to seven. Lastly, the XGBoost model, while outperforming the RR and RF, did not quite reach the higher accuracy levels of other models. With a MAPE of 2.82%, RMSE of 93,399, and MAE of 73,698, it demonstrated reasonable proficiency but indicated potential limitations in harnessing the full predictive power of the seven-feature set.

In conclusion, the CNN+LSTM model's exceptional performance highlights its advanced capabilities in dealing with limited data sets. While the improvement seen in the SVM model with temporal feature extraction underscores the value of incorporating time-related elements in the forecasting process. Furthermore, only SVM benefited from feature engineering. This suggests that for most models, the information contained in the seven features is sufficient to produce predictions with relatively high accuracy.

Exhibit 18. Forecasting results using seven features.

Model	Feature Selected	Feature Engineering Approach	MAPE	RMSE	MAE
RR	GDP, Inwards, Outwards, Unemployment, Road, Exchange, Interest	N/A	4.50%	130,621	118,851
SVM	GDP, Inwards, Outwards, Unemployment, Road, Exchange, Interest	Temporal Feature Extraction Applied. The year component from datetime data is used in addition to the seven features.	2.27%	89,975	60,338
LSTM	GDP, Inwards, Outwards, Unemployment, Rail, Road, Interest	N/A	2.55%	88,163	65,747
CNN+LSTM	GDP, Inwards, Outwards, Unemployment, Rail, Road, Interest	N/A	1.92%	73,827	50,158
BPNN	GDP, Inwards, Outwards, Unemployment, Rail, Road, Interest	N/A	2.09%	87,644	54,292
RF	GDP, Inwards, Outwards, Unemployment, Rail, Road, Interest	N/A	2.97%	99,943	73,713
XGBoost	GDP, Inwards, Outwards, Unemployment, Rail, Road, Exchange	N/A	2.82%	93,399	73,698

Exhibit 19. Comparison of Forecasting Models Using Seven Features



4.5.2 Prediction Results Using Five Features

The results of using a further narrowed selection of five features are shown in Exhibits 20 and 21. The optimal selected features and the feature engineering approach are presented in Exhibit 20 for each model.

The RR model, utilizing GDP, Inwards, Outwards, Exchange, and Interest as features, recorded a MAPE of 4.85%, alongside an RMSE of 168,066 and an MAE of 118,878. This outcome indicates RR's limited capability in handling the further reduced feature set effectively. Interestingly, the SVM model, despite the incorporation of temporal feature extraction (specifically, the year component), did not show an improvement over RR. In fact, it registered a slightly higher MAPE of 5.17%, an RMSE of 174,479, and an MAE of 127,563. This suggests that the addition of temporal data in the SVM did not compensate for the challenges posed by only using five features for prediction. But without the feature engineering approach, the potential results would be worse.

The LSTM network, even without the benefit of additional feature engineering, demonstrated a significantly better performance. It achieved a MAPE of 2.50%, an RMSE of 99,474, and an MAE of 62,583. This highlights LSTM's inherent strength in extracting valuable insights from time-series data, even with this further reduced set of only five features. The CNN+LSTM model once again emerged as the top performer. With a MAPE of 1.91%, RMSE of 91,190, and MAE of 50,720, it outstripped all other models. This result reinforces the model's adeptness at handling both spatial and temporal dimensions in this specific task, even under the constraint of fewer features. In addition, the BPNN, using GDP, Inwards, Outwards, Unemployment, and Road as features, also showed a commendable performance with a MAPE of 2.53%, but with a notably lower RMSE of 64,935 and a higher MAE of 94,780. This indicates BPNN's effectiveness in certain aspects of the forecasting task, although it did not uniformly excel across all metrics.

The RF model exhibited the least favorable results, with the highest MAPE of 6.06%, an RMSE of 189,001, and an MAE of 161,757. This underscores the model's limitations in effectively dealing with a smaller set of features. Lastly, the XGBoost model, despite incorporating both temporal feature extraction and lag features, achieved a MAPE of 2.68%, an RMSE of 92,433, and an MAE of 69,553. While it performed better than RF, RR, and SVM, it did not reach the accuracy levels of LSTM or CNN+LSTM. This outcome suggests that while the additional features enhanced XGBoost's performance, there remains a gap in its ability to fully utilize the limited feature set as effectively as the LSTM or CNN+LSTM models.

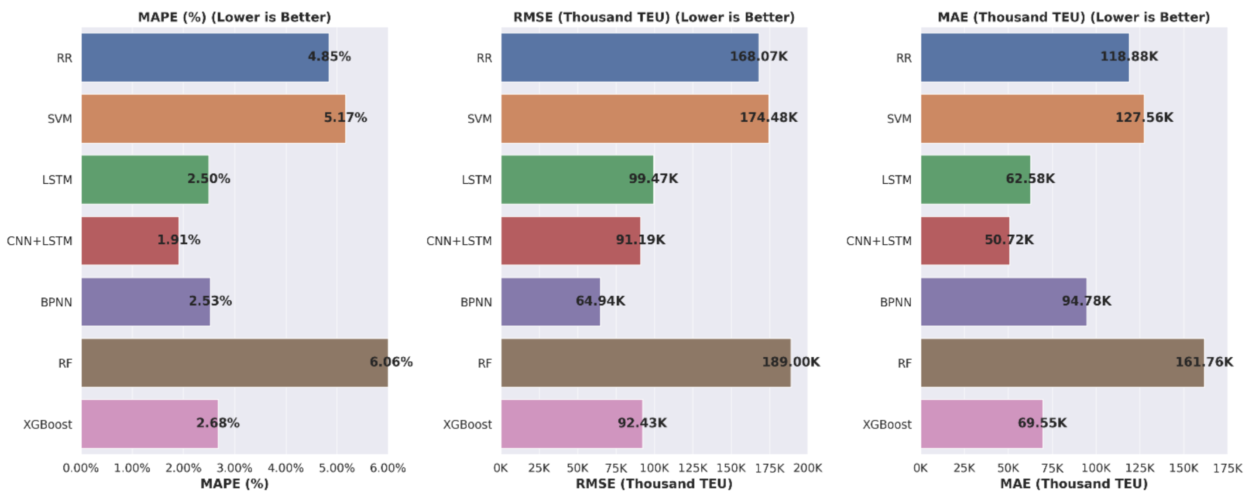
In conclusion, the results highlight the varying capabilities of different forecasting models when constrained by predicting only using five out of twelve features. The CNN+LSTM model's outstanding performance underscores its robustness and adaptability, confirming its suitability for complex forecasting tasks with limited data input. The LSTM model also showed significant potential in this context. In contrast, traditional models like RR and RF, and even advanced models like SVM and XGBoost, faced challenges in effectively leveraging this further reduced feature set for accurately produce the predictions.

Exhibit 20. Forecasting results using five features.

Model	**Feature Selected**	**Feature Engineering Approach**	**MAPE**	**RMSE**	**MAE**
RR	GDP, Inwards, Outwards, Exchange, Interest	N/A	4.85%	168,066	118,878
SVM	GDP, Inwards, Outwards, Exchange, Interest	Temporal Feature Extraction applied. The year component from datetime data is used.	5.17%	174,479	127,563
LSTM	GDP, Inwards, Outwards, Unemployment, Interest	N/A	2.50%	99,474	62,583
CNN+LSTM	GDP, Inwards, Outwards, Unemployment, Interest	N/A	1.91%	91,190	50,720
BPNN	GDP, Inwards, Outwards, Unemployment, Road	N/A	2.53%	64,935	94,780
RF	GDP, Inwards, Outwards, Unemployment, Road	N/A	6.06%	189,001	161,757

XGBoost	GDP, Inwards, Outwards, Unemployment, Road	Temporal Feature Extraction applied. The year component from datetime data is used. Lag Features are created. A Lag-4 feature is used.	2.68%	92,433	69,553

Exhibit 21. Comparison of Forecasting Models Using Five Features



4.5.2 Overall Prediction Results

As we understand, the availability of all twelve features may be limited in other regions where stakeholders also aim to forecast their COB volume in the near term. Therefore, it is essential to assess the impact on model performance when a reduced number of features are utilized. Investigating how model performance is sensitive to the number of features used can also highlight the importance of feature selection in predictive analytics. Exhibits 22, 23, and 24 individually illustrate the model performance across various models when a differing number of features are employed. We observe that the MAPE, RMSE, and MAE scores fluctuate across different models as the number of features is reduced from twelve to seven and then to five.

Exhibit 22. MAPE (%) by Model by Number of Features

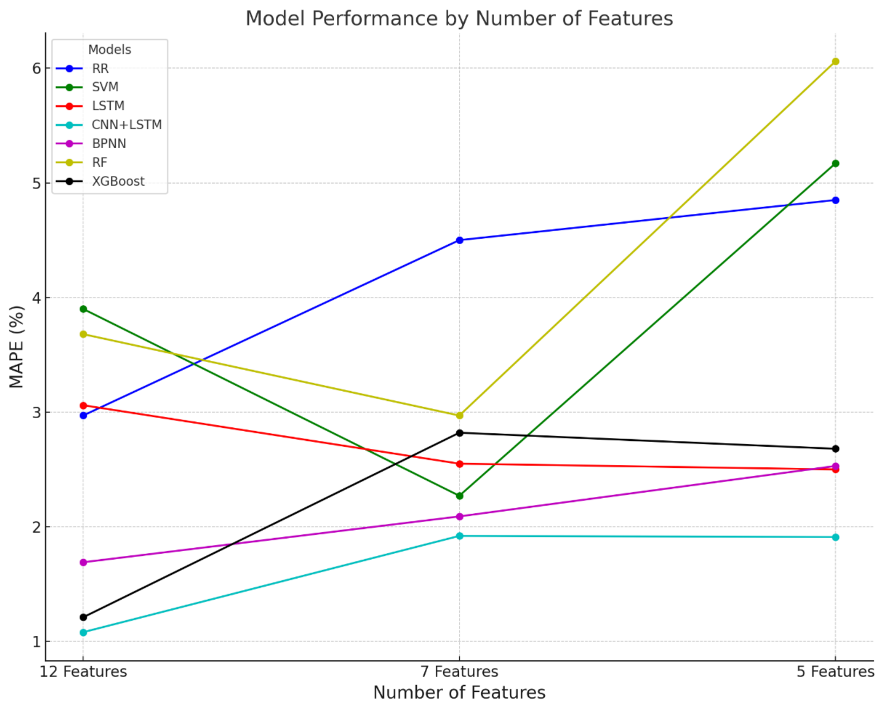


Exhibit 23. RMSE by Model by Number of Features

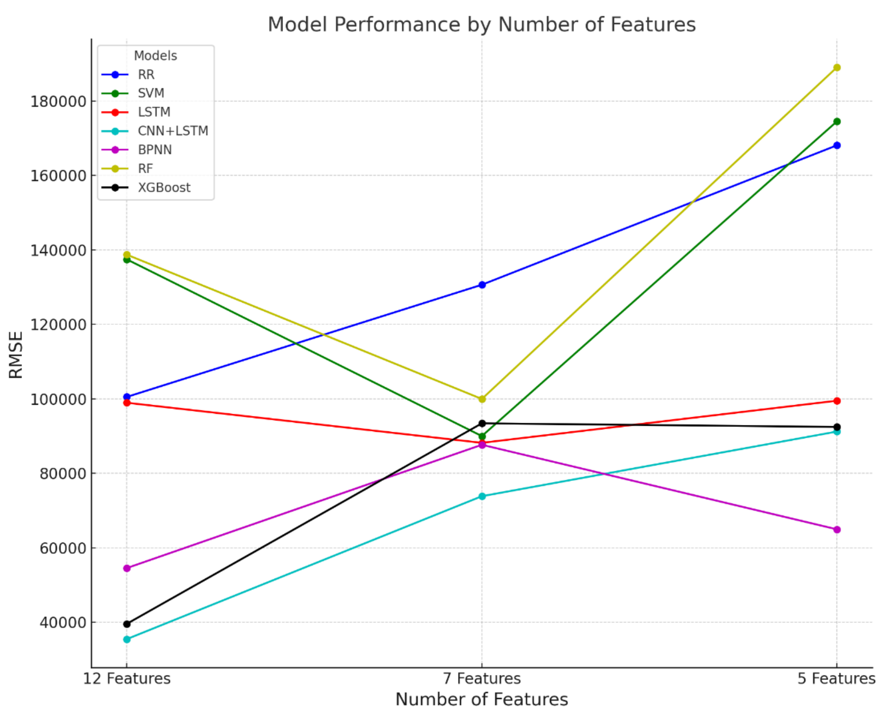
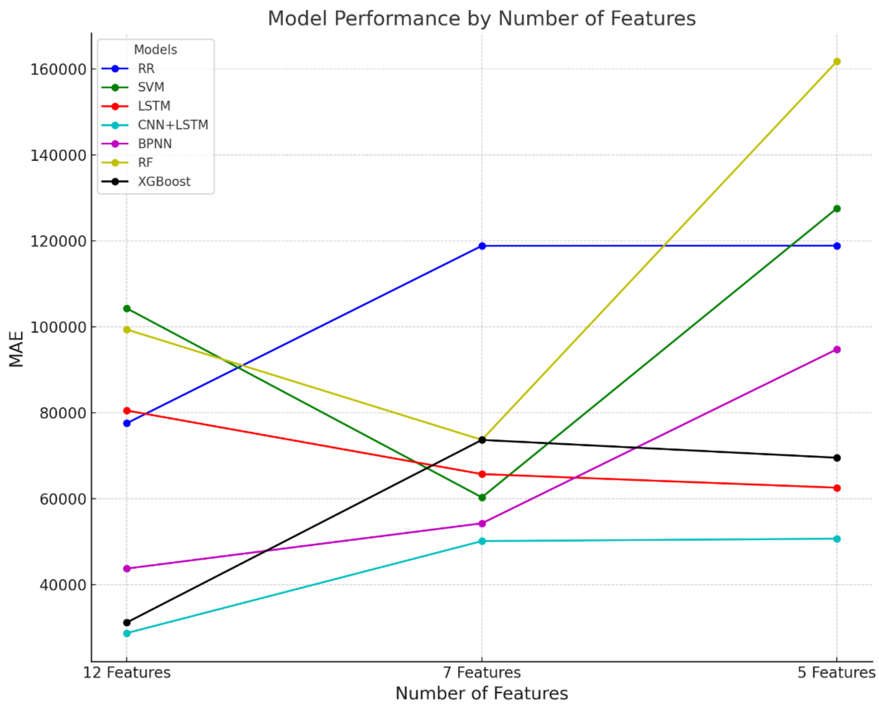


Exhibit 24. MAE by Model by Number of Features



4.6 Summary

This research provides a novel approach in predicting CTV in inland waterway transportation, with a distinct focus on leveraging economic indicators in the absence of historical CTV data for forecasting purposes. In this study, seven machine learning and deep learning models were employed and compared on their prediction ability, using sets of twelve, seven, and five features respectively. This comprehensive approach yielded promising results, with each model's performance offering valuable insights. Among these, the CNN+LSTM model emerged as the most effective, exhibiting superior performance across all feature sets. Its adeptness in integrating spatial and temporal data underscores its robustness in complex forecasting scenarios. Additionally, models such as BPNN and LSTM also delivered noteworthy outcomes, presenting themselves as practical alternatives in varying computational or data situations. It was observed that the number of features utilized plays a crucial role in optimizing the performance of different models. Thus, feature selection strategies should be customized when different models are chosen. The results proved that it is completely feasible to achieve high accuracy in inland waterway transportation CTV forecasting. From our study, the most effective strategy involves utilizing the CNN+LSTM model with all twelve features to optimize COB volume forecasting accuracy.

A key contribution of this study is the demonstration that highly accurate predictions of inland waterway transportation CTV are achievable using exclusively economic indicators, without relying on historical CTV data. This approach is particularly crucial for regions where COB transportation is in its early development stages or where historical data is unavailable. This breakthrough provides maritime and intermodal transportation stakeholders with a simplified, practical, yet effective method to forecast near-term COB volume based on economic indicators alone.

Consequently, the ability to forecast CTV with high accuracy greatly enriches the tool kit for inland waterway container volume predictive analytics. This advancement enables more strategic decision-making in areas such as port infrastructure investment, equipment procurement, and the strategic development of COB transportation. Its relevance is particularly pronounced in the realm of intermodal transportation and freight logistics, making a significant contribution to the advancement and strategic planning of these systems. As a result, our study could help countries across the world, such as the U.S., to acquire a fairly accurate CTV forecasting to aid them generating suitable COB development plans accordingly. We hope more freight logistics and intermodal transportation stakeholders in different regions of the globe can benefit from this practical predication method to generate suitable and competitive business strategies to ensure smooth COB development.

5.0 Conclusions

The outcomes of this research contribute to current COB transportation and maritime transportation literature, support maritime transportation decision-makers, assess the feasibility of launching COB transportation projects at an individual U.S. inland waterway port/terminal, and help form predictive port operation strategies and facility investment plans to respond to predicted COB throughput volume.

Our earlier work describes the status of COB research, summarizes information related to various aspects of COB research among different regions in the world, and provides a literature database for future COB information inquiry. The key findings, such as regions with the most developed COB transportation, success factors for developing COB, and top research topics, indicated a pattern could be learned from to develop successful COB transportation. This research helps lay a foundation and motivate future growth in both studying and developing COB transportation. This work was published in the journal of *Maritime Economics and Logistics* (Bu and Nachtmann, 2021).

The Value-Focused Thinking (Keeney, 1992) based COB Readiness Assessment (COBRA) scorecard provided a comprehensive and practical tool to enable maritime transportation stakeholders to evaluate the feasibility of developing COB transportation at an inland waterway port/terminal with available qualitative and quantitative input data. The COBRA guides the feasibility assessment process with a focus on decision-makers and stakeholders' value to enable decision-makers to understand intuitive and hidden aspects of COB development to identify more opportunities and limitations and to review port/terminal conditions in an all-inclusive point of view. This research would help stakeholders to generate well-prepared, fully considered COB development plans and strategies to obtain a better chance in developing successful COB transportation in the U.S. inland waterway system.

This project implemented machine learning algorithms to analyze existing COB transportation data from Northwestern Europe. The results of this research predict future COB traffic volume via major EU seaports to help connected inland waterway ports calculate upcoming container throughput volume. This can assist port decision-makers in developing their facility investment plans, layout designs, and operation strategies to cope with the upcoming COB traffic volume to increase operation efficiency, mitigate risk of defective equipment or inventory capacity, and reduce the total barge delay time at berth.

References

American Association of Port Authorities. (2017). Ports & World Trade. Retrieved from https://www.aapa-ports.org/unifying/landing.aspx?ItemNumber=21049&navItemNumber=20767

Awah, P. C., Nam, H., & Kim, S. (2021). Short term forecast of container throughput: New variables application for the Port of Douala. Journal of Marine Science and Engineering, 9(7), 720.

Bernacki, D., & Lis, C. (2021). Forecasting the cargo throughput for small and medium-sized ports: multi-stage approach with reference to the multi-port system.

Boudhoum, O., F. Oztanriseven, and H. Nachtmann. (2021). Value-focused inland waterway infrastructure investment decisions. Engineering Management Journal: 1-16.

Bu, F., & Nachtmann, H. (2021). Literature review and comparative analysis of inland waterways transport: "Container on Barge". Maritime Economics & Logistics, 1-34.

Caliskan, A., & Karaöz, B. (2019). Can market indicators forecast the port throughput?. International Journal of Data Mining, Modelling and Management, 11(1), 45-63.

Clott, C., Hartman, B. C., Ogard, E., & Gatto, A. (2015). Container repositioning and agricultural commodities: shipping soybeans by container from U.S. hinterland to overseas markets. Research in Transportation Business & Management, 14, 56-65.

Ding, M. J., Zhang, S. Z., Hai-dong, Z., Wu, Y. H., & Zhang, L. B. (2019). A prediction model of the sum of container based on combined BP neural network and SVM. Journal of Information Processing Systems, 15(2), 305-319.

Fan, G. F., Yu, M., Dong, S. Q., Yeh, Y. H., & Hong, W. C. (2021). Forecasting short-term electricity load using hybrid support vector regression with grey catastrophe and random forest modeling. Utilities Policy, 73, 101294.

Fazi, S., Fransoo, J. C., & Van Woensel, T. (2015). A decision support system tool for the transportation by barge of import containers: A case study. Decision Support Systems, 79, 33-45.

Gołębiowski, C. (2016). Inland water transport in Poland. Transportation Research Procedia, 14, 223-232.

Gosasang, V., Yip, T. L., & Chandraprakaikul, W. (2018). Long-term container throughput forecast and equipment planning: the case of Bangkok Port. Maritime Business Review, 3(1), 53-69.

Information Office of Shanghai Municipality. (2019). Population of Shanghai. Retrieved from http://www.shio.gov.cn/sh/xwb/n809/n814/n827/u1ai13631.html#:~:text=%E5%BC%80%E5%9F%A0%E6%97%B6%E4%BA%BA%E5%8F%A3%E4%B8%8D%E8%B6%B3,%E5%B8%B8%E4%BD%8F%E4%BA%BA%E5%8F%A3977.71%E4%B8%87%E4%BA%BA%E3%80%82

Jin, J., Ma, M., Jin, H., Cui, T., & Bai, R. (2023). Container terminal daily gate in and gate out forecasting using machine learning methods. Transport Policy, 132, 163-174.

Kawasaki, T., Matsuda, T., Lau, Y. Y., & Fu, X. (2022). The durability of economic indicators in container shipping demand: a case study of East Asia–US container transport. Maritime Business Review, 7(4), 288-304.

Kharfan, M., Chan, V. W. K., & Firdolas Efendigil, T. (2021). A data-driven forecasting approach for newly launched seasonal products by leveraging machine-learning approaches. Annals of Operations Research, 303(1-2), 159-174.

Keeney, R. L. (1992). Value focused thinking: a path to creative decision making. Cambridge, Mass: Harvard University Press.

Konings, R., van der Horst, M., Hutson, N., & Kruse, J. (2010). Comparative strategies for developing hinterland transport by container barge: analysis for Rotterdam and U.S. ports. Transportation Research Record, 2166(1), 82-89.

Li, Z., Gurgel, H., Xu, L., Yang, L., & Dong, J. (2022). Improving dengue forecasts by using geospatial big data analysis in google earth engine and the historical dengue information-aided long short term memory modeling. Biology, 11(2), 169.

Liu, X., Bai, Y., & Chen, J. (2017). An intermodal transportation geospatial network modeling for containerized soybean shipping. Journal of Ocean Engineering and Science, 2(2), 143-153.

Maritime Administration. (2020). US. Transportation Secretary Elaine L. Chao Announces $9.5 Million in Grants for America's Marine Highways. Retrieved from https://www.maritime.dot.gov/newsroom/press-releases/us-transportation-secretary-elaine-l-chao-announces-95-million-grants

Matczak, M. (2020). A simplified forecasting model for the estimation of container traffic in seaports at a national level–the case of Poland. TransNav: International Journal on Marine Navigation and Safety of Sea Transportation, 14(1), 153-158.

Merrick, Jason RW, and Margot W. Garcia. (2004). Using value-focused thinking to improve watersheds. Journal of the American Planning Association 70, no. 3: 313-327.

Nachtmann, H., & Pohl, E. A. (2013). Transportation readiness assessment and valuation for emergency logistics. International Journal of Emergency Management, 9(1), 18-36.

Notteboom, T., Yang, D., & Xu, H. (2020). Container barge network development in inland rivers: a comparison between the Yangtze River and the Rhine River. Transportation Research Part A: Policy and Practice, 132, 587-605.

Oklahoma Department of Transportation. (2017). Inland waterway fact sheet. Retrieved from https://www.odot.org/waterway/pdfs/ODOT_WW_FACT_SHEET.pdf

Pan, C., Wang, H., Guo, H., & Pan, H. (2021). How do the population structure changes of China affect carbon emissions? An empirical study based on ridge regression analysis. Sustainability, 13(6), 3319.

Parnell, G. S., Terry Bresnick, M. B. A., Tani, S. N., & Johnson, E. R. (2013). Handbook of decision analysis (Vol. 6). John Wiley & Sons.

Qiu, R., Liu, C., Cui, N., Gao, Y., Li, L., Wu, Z., ... & Hu, M. (2022). Generalized Extreme Gradient Boosting model for predicting daily global solar radiation for locations without historical data. Energy Conversion and Management, 258, 115488.

Shankar, S., Ilavarasan, P. V., Punia, S., & Singh, S. P. (2020). Forecasting container throughput with long short-term memory networks. Industrial management & data systems, 120(3), 425-441.

Shankar, S., Punia, S., & Ilavarasan, P. V. (2021). Deep learning-based container throughput forecasting: A triple bottom line approach. Industrial Management & Data Systems, 121(10), 2100-2117.

Shobayo, P., & Van Hassel, E. (2019). Container barge congestion and handling in large seaports: a theoretical agent-based modeling approach. Journal of Shipping and Trade, 4(1), 1-26.

Tang, S., Xu, S., & Gao, J. (2019). An optimal model based on multifactors for container throughput forecasting. KSCE Journal of Civil Engineering, 23(9), 4124-4131.

Tong, J., H. Nachtmann, and E. A. Pohl. (2015). Value-focused assessment of cargo value decreasing rates. Engineering Management Journal 27, no. 2: 73-84.

Tufano, A., Zuidwijk, R., & Van Dalen, J. (2023). The development of data-driven logistic platforms for barge transportation network under incomplete data. Omega, 114, 102746.

U.S. Army Corps of Engineers. (2021). USACE navigation portal. Retrieved from https://navigation.usace.army.mil/DIF/About.

U.S. Department of Transportation, Bureau of Transportation Statistics. (2021a), "U.S. Ton-Miles of Freight." Retrieved from https://www.nationalwaterwaysfoundation.org/file/27/Waterborne%20Competitiveness%20%20NWF%20Eno%20Center%20for%20Transportation%20Final%20Report.pdf.

U.S. Department of Transportation, Bureau of Transportation Statistics. (2021b) Freight facts and figures. Retrieved from https://www.bts.gov/topic/freight.

U.S. Department of Transportation, Bureau of Transportation Statistics. (2024) https://data.bts.gov/stories/s/Moving-Goods-in-the-United-States/bcyt-rqmu.

U.S. Department of Transportation, Bureau of Transportation Statistics. (2021) Transportation statistics annual report 2020. Retrieved from https://www.bts.gov/tsar

Van Meir, N., Rashed, Y., Storms, K., Sys, C., Vanelslander, T., & van Hassel, E. (2022). Forecasting the Future Demand for Containerized Inland Shipping on the Traditional Rhine.

Available at SSRN 4043354.

Yang, C. H., & Chang, P. Y. (2020). Forecasting the demand for container throughput using a mixed-precision neural architecture based on CNN–LSTM. Mathematics, 8(10), 1784.

Ypsilantis, P., & Zuidwijk, R. (2019). Collaborative fleet deployment and routing for sustainable transport. Sustainability, 11(20), 5666.

Zeng, Y. R., Zeng, Y., Choi, B., & Wang, L. (2017). Multifactor-influenced energy consumption forecasting using enhanced back-propagation

Zweers, B. G., Bhulai, S., & van der Mei, R. D. (2019). Optimizing barge utilization in hinterland container transportation. Naval Research Logistics (NRL), 66(3), 253-271.