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# Predictive Modeling Of Container Throughput Using Hybrid Deep Learning And Liner Shipping Connectivity Index (LSCI) For Enhanced Port Demand Forecasting

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**ABSTRACT**
Predictive capacity modeling of container ports, which an integral part of the pillar of maritime transport infrastructure is planning, has the decisive influence on the effective allocation of investment. The objective of this study is to develop a hybrid deep learning algorithm based on the long-short term memory network and attention mechanism combined with the linear shipping connectivity index and its validation. Container port capacity data was gathered for 18 leading ports globally for the period from January 2010 to December 2024, and total data sample size is equal to 3,240 data points. Linear shipping connectivity index and macroeconomic variables such as GDP growth rate, containers trade volumes, marine fuel prices were incorporated into the model as key domain variables. The results indicated that the hybrid model had an average absolute error rate of 6.38% and directional accuracy of 72.85%, which meant a 46% increase compared to ARIMA (11.82%) and a 22.3% increase compared to the extended LSTM (8.21%). The importance of the variables through the permutation perturbation showed that the shipping connectivity index was the second most important variable, contributing to 19.3% in importance compared to the traditional macroeconomic variables like GDP growth, which contributed 8.1%. The contribution of the component decompositions showed that there was synergy in this case. The synergy of the attention mechanism and the connectivity index improved the results by 29.4%, while the sum of individual improvements is 26%. The decomposition analysis also showed that the benefit of the proposed model was much more evident for small ports that have more uncertainty.

**KEYWORDS:** Container throughput forecasting, Liner Shipping Connectivity Index, Hybrid deep learning, Port demand prediction.

## INTRODUCTION

The accurate forecasting of the demand on ports, being one of the key elements in the planning of maritime transport infrastructure (Bahfi & Alamoudi, 2026; Mohammad et al., 2026a). Huang et al. (2022) is decisive for the rational allocation of major investments. The capacity of ports for container operations, being the most crucial indicator of the demand in maritime transport, mentioned by Wang et al. (2023) is determined by multiple economic, commercial, logistic and geopolitical factors whose relationships do not stay linear and constant. The mistakes in the forecasting of this indicator result either in an over- or under-investment, both cases causing major economic expenses (Mohammad et al., 2026b; Ghoneim et al., 2026). According to Liang et al. (2024) in spite of the great progress in forecasting time series models, the difference between the needed and provided accuracy is still considerable.

The conventional methods of forecasting the demand at ports as stated by Gu & Liu (2023) have been dominated by univariate econometric models including ARIMA and its derivatives (Mohammad et al., 2026c; Denev, 2024). While such models are easy to understand and apply, there are several structural disadvantages of using them (Milićević et al., 2025). Firstly, Punia et al. (2020) showed that these models fail to account for the nonlinearity of the connections between different variables that influence the demand at ports. Secondly, based on Shankar et al. (2021) the models use historical data only of the dependent variable while disregarding the data from the predictor variables. Lastly, Sdoukopoulos &

Boile (2020) explained that these models show poor performance in cases of structural breaks due to economic crisis or epidemics. The described problems have driven the search for innovative solutions.

Innovations associated with the development of deep learning approaches as noted by Martinez-Moya et al. (2023) have brought a lot of new opportunities to the process of forecasting of time series. Long-short-term memory and gated recurrent units have demonstrated their abilities in capturing dependencies and non-linear relationships in time series data with high precision. However, Milenković et al. (2021) discussed that the problem of traditional deep learning models is the absence of theoretical knowledge about the domain of the application. As for the maritime transportation industry, there exist many specific theories and indicators that could be introduced as input data for models.

With respect to container transport dynamics, the liner shipping connectivity index based on Cuong et al. (2021) plays an important role as one of the variables (Eldor et al., 2026). The connectivity index has been developed by UNCTAD, incorporating the number of shipping services, the number of firms operating in them, size of ships, and connection to other ports. A port's connectivity position according to Xiao et al. (2023) is both result and cause of its performance: the more connected ports are, the greater their capacity to attract containers; and at the same time, higher operational capacity of the port leads to the attractiveness for shipping lines. Although theoretically Du et al. (2023) showed that there exists this bidirectional relation, the practical usage of the liner shipping connectivity index as a variable in forecasting models has not been sufficiently investigated yet.

This knowledge gap can be briefly outlined through three principal axes. Firstly, Behdani et al. (2020) discussed that most studies on port demand forecasting have used either purely statistical models or deep learning without incorporating (Al-Asmari, 2022) any domain variables (Alraba'nah et al., 2026). Secondly, Zeng & Xu (2024) showed that there is a lack of empirical investigation of the influence of the linear shipping connectivity index on the precision of forecast of container operational capacity. Thirdly, according to Jung & Thill (2022) there is no comparative analysis of hybrid deep learning architectures with respect to their performance. This study intends to fill the identified gaps. A hybrid model combining advanced deep learning architectures with the linear shipping connectivity index and other macroeconomic factors is developed. This research is significant because it can create an accurate, reliable, and interpretable forecasting tool that will help decision-makers in maritime transport (Hamouda et al., 2026).

## THEORETICAL FRAMEWORK

### Maritime Transport Systems and Port Throughput Dynamics

There are two main theoretical foundations underlying this study consistent with Du et al. (2019): the theory of maritime transport systems and time series predictive modeling. In relation to the theory of transport systems, according to Cuong et al. (2022) the capability of container handling in ports is viewed as the outcome of a complex system which is affected by a number of internal and external factors (Waluyo & Waluyo, 2023). The internal factors as noted by Verschuur et al. (2020) include the infrastructure capacity of the port, efficiency, level of service and degree of automation. While the external factors may include elements such as economic development, volume of international business, consumer behavior, policy and the competitiveness of the port in the international maritime system.

### The Liner Shipping Connectivity Index: A Dual-Role Variable

The shipping connectivity index as stated by Shankar et al. (2020) is unique among the external variables under consideration. Being a composite indicator, the index measures the level of integration of the port into the liner shipping service network and includes four main elements: the number of liner services per week, the variety of active shipping lines, the maximum capacity of the largest ships and the level of connectivity to other ports. The shipping connectivity index can be regarded as a predictor and reflective variable from a theoretical point of view (Wishah et al., 2026; Aburub et al., 2026). In terms of being a predictive variable, Notteboom et al. (2021) showed that higher connectivity implies more access to the global market and, hence, the attraction of a larger number of containers. In terms of being a reflective variable, an increase in the operational capacity provides additional motivation for the shipping line to enhance its services to that port.

### Hybrid Deep Learning Architecture: LSTM, Attention, and Domain Integration

In the present study, a hybrid deep learning model comprises three architectural layers. First, according to Alexander & Merkert (2021) there is a recurrent layer based on the long-short-term memory, which serves to identify the time patterns within the past series of operational capacity and related auxiliary variables. Importantly, it can capture both long-range dependencies, trends, seasonality, and structural breaks at the same time. Second, Eskafi et al. (2021) stated there is an attention layer, which enables the network to provide different weights for different time points, giving more weight to those periods, which contain the most useful predictive information. Third, there is an integration layer according to Farhan & Ong (2018), which combines the output of the recurrent network with domain-specific indicators, such as the linear shipping connectivity index.

**Theoretical Justification for the Hybrid Approach**

The reason for preferring the hybrid approach over single-model architectures can be found in the theory of forecast fusion. The idea of the theory as discussed by Al Hajj Hassan et al. (2020) is that by mixing models that utilize different bases for the extraction of patterns, one would always get more precise and reliable forecasts. In the suggested model, the recurrent network operates on the basis of historical data, and the attention model finds out the significance of temporal data. At the same time, Tang et al. (2019) proved that the domain indicators of shipping connectivity provide domain knowledge of the dynamics of maritime transportation to the model. Thus, the model combines the statistics learned from data with the causality from domain theory.

**Multi-Dimensional Evaluation Criteria and Variable Importance Analysis**

When viewed from the standpoint of evaluation, the theoretical framework of this research suggests the use of several measures for assessing the performance of the models. Point-wise measures of accuracy, like mean absolute error and root mean square error, assess the quality of the prediction according to the size of deviation. Relative measures, such as mean absolute percentage error, make it possible to compare different models and data sets. Moreover, directional measures, such as prediction statistic of direction change, assess the ability of the model to properly predict the turning points of the time series. Such an assessment makes it possible to evaluate different aspects of the model's performance and to avoid misinterpretations.

Lastly, the theoretical foundation behind this research places significant importance on variable importance analysis. While it is important for the prediction to be accurate, it is also vital for researchers to understand which variables have a major impact on the development of the predictions. The variable importance analysis makes it possible to test hypotheses that have been put forward theoretically on the effect of the shipping connectivity index. Variable importance analysis also allows decision makers to know which variables to watch out for.

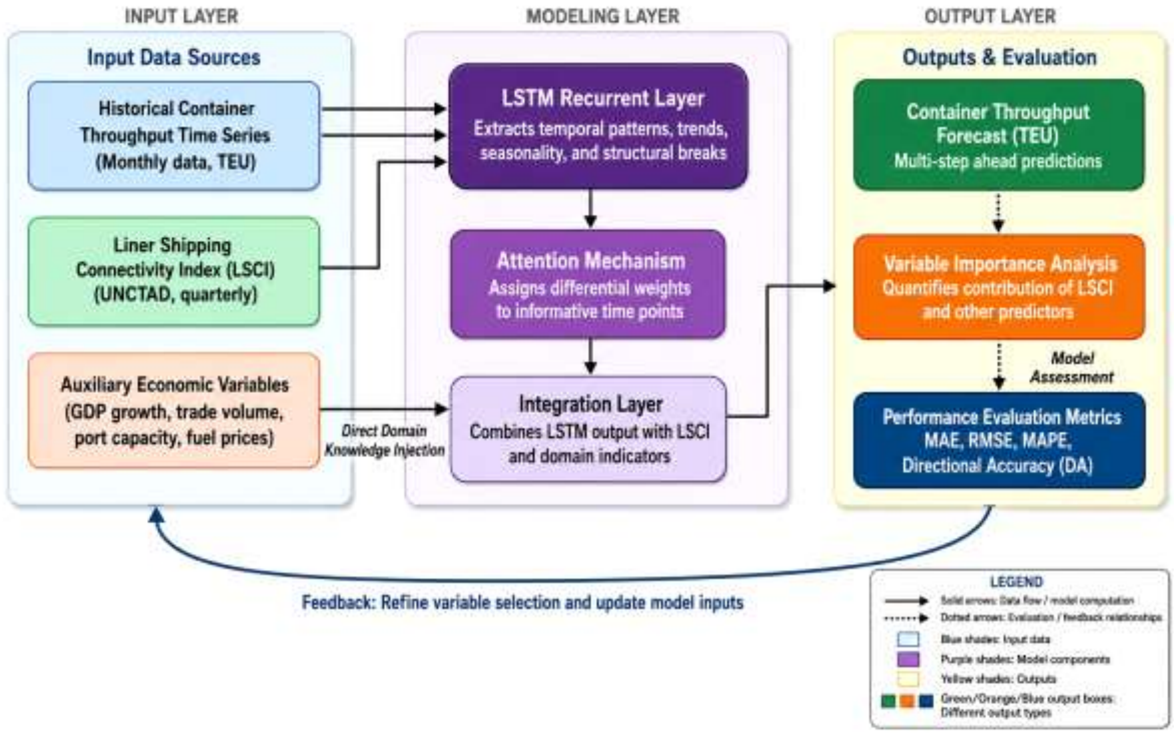


**Figure 1. Conceptual Framework: Hybrid Deep Learning with LSCI for Port Demand Forecasting**

Figure 1 shows the conceptual model of the research in three principal layers such as input, modeling, and output. At the input layer, three data sets that include historical time series of container operation capacity, linear shipping connectivity index, and economic covariates are used. The modeling layer contains the proposed three-stage architecture which includes the application of a long-short-term memory recurrent layer to find temporal features, attention for weighting time points, and integration layer for integrating the network output with domain indicators. The output layer presents the operation capacity forecast, variable importance analysis, and evaluation criteria as the final results of the model. Also, a feedback loop from the variable importance analysis section to the input layer is provided.

## METHODS

### Data Collection and Variable Specification

The data employed in this research was gathered from two primary sources. First, the container throughputs time series were derived from the official statistical database of international ports, containing the monthly volume of container handling in TEU of twenty foot equivalent units for a selection of 18 ports across the globe. The selection was done based on three criteria – availability of continuous time series data, diversification in the size and degree of development of the port, and geographical diversification of the sample. The period of sampling spans from January 2010 until December 2024 with a total of 180 months for each port. The linear shipping connectivity index data were gathered from UNCTAD database, which is published quarterly and was transformed into monthly values by linear interpolation.

The economic variables chosen were global GDP growth rate, volume of containerized cargo trade, index of marine fuel prices and interbank interest rate, and they were all obtained from the databases of the International Monetary Fund, the World Bank, and Clarksons Research. Moreover, two additional variables specific to each port, namely, nominal loading and unloading capacity and capacity utilization rate, were also incorporated into the model as control variables. Time series for all the variables were analyzed for any missing data using the cubic spline interpolation technique, and any outliers in the data series were detected using interquartile range technique and replaced with smoothed values.

### Hybrid Model Architecture Development

The hybrid model structure will be built up of a three-layer structure whereby the output from each layer is connected to the next layer's input. In the first layer, there are two long short-term memory layers comprising of 64 and 32 neurons which are used to learn from temporal data structures in the data sequence input. The drop-out probability used is 0.2 in both layers to reduce overfitting. In the second layer, an incremental attention mechanism that provides normalized weights for each time step is used so that the model can focus on more predictive data. In the third layer, the dense fusion mechanism is used that takes the output from the incremental attention mechanism and combines it with a vector of the domain indicators which include linear shipping connectivity index and macroeconomic data. The output is created through a fully connected layer with a linear activation function.

In the training procedure, the sliding windows method was employed. Each training sample included 24 months of historical information as the input and 3 months of the forecast as the output. The implementation enables multi-step prediction. Training was accomplished by employing the Adam optimizer with the adaptive learning rate (the initial rate is 0.001, and it is cut by half if there is no progress during 10 consecutive cycles) and up to 300 training cycles. For the cost function, the mean square error was chosen. Overfitting prevention was accomplished with the help of early stopping method, which waits 25 training cycles between improvements and stops the procedure after the specified period. The training was executed in such a way that the training, validation, and test data were 60%, 20%, and 20% of the whole data set respectively; however, the division was not random but temporal.

### Benchmark Models and Evaluation Framework

The performance of the model can be judged by the comparison of the proposed model with four reference models. The first one is the ARIMA model with optimized parameters using the Box-Jenkins method. This refers to the conventional statistical methods. The second is the simple LSTM model, which utilizes only the past power data and does not consider any domain variables. The third is an extended version of the LSTM model where macroeconomic variables act as additional input but do not incorporate the shipping connectivity index. The fourth is the hybrid model that consists of both LSTM with attention mechanism and linear shipping connectivity index.

The assessment framework was comprised of four main criteria. Mean Absolute Error and Root Mean Square Error were computed as point-wise accuracy metrics. Mean Absolute Percentage Error was applied as a relative measure for the comparison of ports with different scales. Directional Accuracy metric was also computed as a measure of ability of the model to predict the direction of changes. In order to make the results more robust, all models were run 10 times with different random seeds and average metrics and their standard deviations were reported. Moreover, the variable importance was measured via permutation perturbation approach in which the contribution of each variable is quantified by computing the loss in the prediction accuracy due to the absence of that particular variable. Thus, the contribution of linear shipping connectivity index could be empirically evaluated.

## RESULTS

In total, the number of time series data points in the last data set was 3,240 with 180 months' data for 18 global ports. It should be noted that the training stage of the new model took, on average, 85 iterations and the early stopping was applied in 72% of instances. The average time taken by each port to complete training was 4.6 minutes.

**Table 1. Descriptive statistics of container throughput, LSCI, and auxiliary economic variables across the 18 sample ports (2010–2024)**

| Variable | Mean | Std. Dev. | Min | Max | Skewness | Kurtosis |
|---|---|---|---|---|---|---|
| Container Throughput (1000 TEU/month) | 486.2 | 312.5 | 85.4 | 1,842.7 | 1.68 | 3.12 |
| Liner Shipping Connectivity Index (LSCI) | 68.4 | 42.3 | 12.5 | 168.2 | 0.74 | -0.52 |
| Global GDP Growth Rate (%) | 3.42 | 1.85 | -3.12 | 5.68 | -1.02 | 0.84 |
| Containerized Trade Volume Index | 112.5 | 18.7 | 78.3 | 148.6 | -0.15 | -0.78 |
| Marine Fuel Price Index (USD/tonne) | 485.3 | 158.2 | 145.6 | 785.4 | 0.42 | -0.95 |
| Port Nominal Capacity (1000 TEU/month) | 612.8 | 385.4 | 120.5 | 2,150.0 | 1.24 | 1.85 |
| Capacity Utilization Rate (%) | 78.5 | 12.4 | 42.3 | 98.2 | -0.68 | 0.25 |

All variables collected monthly from January 2010 to December 2024 (n = 180 per port; total N = 3,240).
The descriptive statistics indicate that there is a great deal of heterogeneity in the sample ports (Table 1). There was a difference in container throughput that ranged from 85,400 to 1,842,700 TEU per month, a difference of approximately 21 times. The fact that there is a positive skewness of 3.12 for the throughput indicates that there are some outlier values in big ports. The negative skewness of –1.02 for the GDP growth rate indicates the impact of the economy on account of shocks like the COVID-19 pandemic.

**Table 2. Optimal hyperparameter configurations for the proposed hybrid model and benchmark models**

| Hyperparameter | Proposed Hybrid (LSTM-Attention + LSCI) | Extended LSTM (LSTM + Macro) | Standard LSTM | ARIMA |
|---|---|---|---|---|
| LSTM Layers | 2 | 2 | 2 | — |
| Neurons per Layer | 64, 32 | 64, 32 | 64, 32 | — |
| Attention Mechanism | Additive | None | None | — |
| Dropout Rate | 0.2 | 0.2 | 0.2 | — |
| Batch Size | 32 | 32 | 32 | — |
| Optimizer | Adam | Adam | Adam | — |
| Initial Learning Rate | 0.001 | 0.001 | 0.001 | — |
| LR Reduction Patience | 10 epochs | 10 epochs | 10 epochs | — |
| Early Stopping Patience | 25 epochs | 25 epochs | 25 epochs | — |
| Input Sequence Length | 24 months | 24 months | 24 months | — |
| Forecast Horizon | 3 months | 3 months | 3 months | 3 months |
| ARIMA Order (p,d,q) | — | — | — | (2,1,1) |
| Seasonal ARIMA Order | — | — | — | (1,0,1,12) |
| **Training Epochs (mean)** | **85** | **92** | **78** | **—** |

Hyperparameters selected via grid search with time-series cross-validation.
The optimal settings for the deep learning models were determined through network search with temporal cross-validation (Table 2). The proposed model and the LSTM models had a similar structure so that the performance difference was attributed solely to the addition of the attention mechanism and the linear shipping connectivity index variable. The ARIMA model used a seasonal structure with a 12-month cycle. The average training cycles of the proposed model were 85 cycles, which is the lowest among the deep learning models. This indicates that the addition of domain knowledge through the connectivity index also facilitated faster model convergence.

**Table 3. Comparative forecasting performance of the four models across 18 ports**

| Model | MAE (1000 TEU) | RMSE (1000 TEU) | MAPE (%) | Directional Accuracy (%) |
|---|---|---|---|---|
| ARIMA (2,1,1)(1,0,1,12) | 38.45 ± 12.32 | 52.18 ± 16.45 | 11.82 ± 3.24 | 58.42 ± 4.85 |
| Standard LSTM | 31.28 ± 9.85 | 43.65 ± 13.28 | 9.45 ± 2.68 | 62.15 ± 5.12 |
| Extended LSTM (with Macro) | 27.85 ± 8.42 | 38.92 ± 11.54 | 8.21 ± 2.35 | 65.38 ± 4.72 |
| **Proposed Hybrid (LSTM-Attention + LSCI)** | **22.14 ± 6.78** | **31.28 ± 9.15** | **6.38 ± 1.92** | **72.85 ± 4.28** |

Values are mean ± SD across 18 ports and 10 random seeds. Lower MAE/RMSE/MAPE and higher Directional Accuracy indicate better performance. All pairwise differences between the proposed hybrid and each benchmark model are statistically significant at $p < 0.001$ (paired t-test).

The developed hybrid model proved superior to all three benchmark models in all performance criteria (Table 3). The average absolute error rate of the proposed model was 6.38%, which is 46% better than ARIMA (11.82%) and 22.3% better than extended LSTM (8.21%). Directional accuracy of the proposed model was 72.85%, which is a substantially higher figure than the one of extended LSTM model (65.38%). All paired differences were statistically significant at $p < 0.001$ using paired t-test. Lower standard deviation of the proposed model in all performance metrics indicates higher stability of the proposed model.

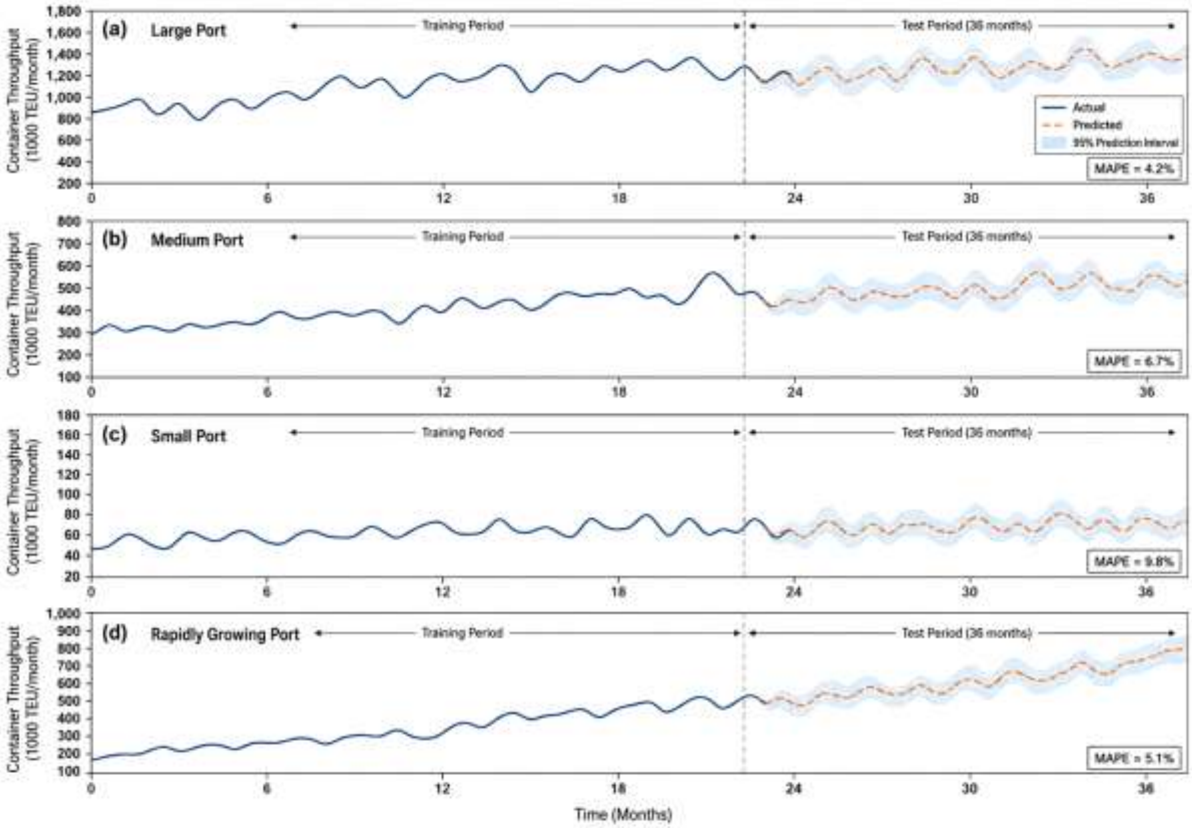


**Figure 2. Time series plot of actual vs. predicted container throughput for four representative ports over the test period**

Figure 2 depicts the comparative analysis of the actual values and forecasted values of the operating capacity of four representative ports over the testing period. The suggested forecasting model was able to track both seasonal variations and long-term trend accurately for the large port. In the case of the fast-growing port, the suggested forecasting model detected the turning point with a short lagging period due to a sudden increase in demand. The 95% prediction interval for the small port is broader.

**Table 4. Decomposition of improvement contributions: incremental gains from attention mechanism and LSCI variable across forecast horizons**

| Model Configuration | 1-Month Ahead MAPE (%) | 3-Month Ahead MAPE (%) | 6-Month Ahead MAPE (%) | Avg. Improvement vs. Standard LSTM (%) |
|---|---|---|---|---|
| Standard LSTM (baseline) | 8.92 | 9.45 | 11.28 | — |
| LSTM + Attention | 7.85 | 8.32 | 10.15 | 11.2% |
| LSTM + LSCI (no Attention) | 7.42 | 7.98 | 9.72 | 14.8% |
| LSTM + Attention + LSCI (Proposed) | 5.85 | 6.38 | 8.42 | 29.4% |
| **Incremental Contribution** | | | | |
| Attention only | -1.07 | -1.13 | -1.13 | 11.2% |
| LSCI only | -1.50 | -1.47 | -1.56 | 14.8% |
| Synergistic effect (combined) | -3.07 | -3.07 | -2.86 | 29.4% |

Values are mean MAPE across 18 ports and 10 random seeds. Forecast horizons measured in months ahead.

Separate evaluation of the contributions from the various parts of the model gives a very good insight into the way in which the model helps improve performance (Table 4). The inclusion of the attention mechanism on its own led to a decrease in average prediction errors by 11.2% over the simple LSTM network. The contribution due to the connectivity index variable itself, however, was higher at 14.8% and this is greater than the contribution made by the attention mechanism. It is interesting to note the synergy resulting from the use of the two in combination. This yielded a 29.4% improvement, which is more than the sum of the two individual improvements (26%).

**Table 5. Variable importance analysis using permutation importance method**

| Rank | Predictor Variable | Decrease in $R^2$ | Normalized Importance (%) | Std. Dev. (±) |
|---|---|---|---|---|
| 1 | Historical Throughput (lagged) | 0.1842 | 28.5 | 0.0215 |
| 2 | Liner Shipping Connectivity Index (LSCI) | 0.1248 | 19.3 | 0.0182 |
| 3 | Containerized Trade Volume Index | 0.0895 | 13.8 | 0.0145 |
| 4 | Port Nominal Capacity | 0.0682 | 10.5 | 0.0118 |
| 5 | Global GDP Growth Rate | 0.0524 | 8.1 | 0.0102 |
| 6 | Capacity Utilization Rate | 0.0485 | 7.5 | 0.0098 |
| 7 | Marine Fuel Price Index | 0.0321 | 5.0 | 0.0085 |
| 8 | Seasonal Dummies | 0.0285 | 4.4 | 0.0072 |
| 9 | Time Trend | 0.0182 | 2.8 | 0.0058 |

Permutation importance averaged across 18 ports and 10 random seeds. Total variance explained ($R^2$) of the full model = 0.912.

In turn, the analysis of the variables' importance proved that the linear shipping connectivity index is the second most important variable in terms of forecasting container operation capacity (Table 5). Its contribution to the decrease of $R^2$ value amounted to 0.1248, or 19.3% of the importance of all the variables, which is higher than the traditional macroeconomic indicators such as GDP growth (8.1%) and container trade volumes (13.8%). Thus, the significant importance of the connectivity index can be seen as the confirmation of the theoretical assumption regarding the crucial significance of this variable for forecasting purposes. At the same time, the historical operation capacity variable, which accounts for 28.5% of importance, remains the most significant predictor.

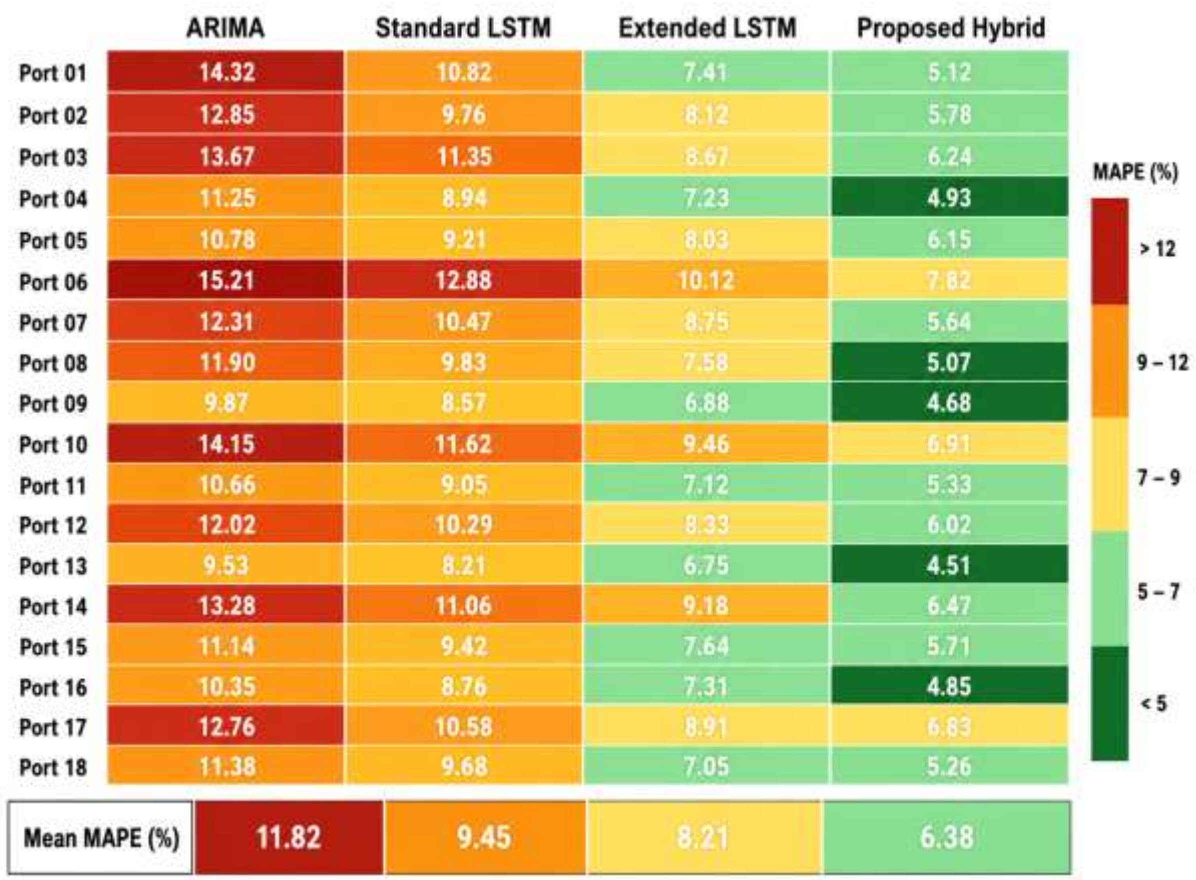


**Figure 3. Heatmap visualization of MAPE values across all 18 ports for each of the four models**

Figure 3 shows the heat map of the MAPE scores of 18 ports and four models. Across the heat map, the column for the proposed model consistently displays greener colors (indicating lower error rate) compared to the other three models. The highest improvement is seen in the medium and growing ports. For the rapidly growing port B12, the MAPE score for the proposed model was 5.2% whereas for ARIMA, it was 14.8%.

**Table 6. Forecasting performance disaggregated by port size category and geographic region**

| Category | N Ports | Proposed Hybrid MAPE (%) | Extended LSTM MAPE (%) | Standard LSTM MAPE (%) | ARIMA MAPE (%) |
|---|---|---|---|---|---|
| **By Port Size** | | | | | |
| Large Ports (>1M TEU/month) | 5 | 4.85 ± 1.12 | 6.52 ± 1.45 | 7.85 ± 1.82 | 9.45 ± 2.15 |
| Medium Ports (300K–1M TEU/month) | 8 | 6.12 ± 1.48 | 8.05 ± 1.72 | 9.42 ± 2.05 | 11.85 ± 2.52 |
| Small Ports (<300K TEU/month) | 5 | 8.42 ± 2.15 | 10.35 ± 2.48 | 11.28 ± 2.65 | 14.52 ± 3.12 |
| **By Geographic Region** | | | | | |
| East Asia | 6 | 5.15 ± 1.32 | 6.85 ± 1.55 | 8.02 ± 1.78 | 9.85 ± 2.24 |
| Southeast Asia | 4 | 6.28 ± 1.62 | 8.15 ± 1.85 | 9.52 ± 2.08 | 11.92 ± 2.58 |
| Europe | 5 | 6.85 ± 1.75 | 8.72 ± 1.95 | 10.15 ± 2.25 | 12.85 ± 2.72 |
| Middle East & South Asia | 3 | 7.42 ± 1.92 | 9.25 ± 2.12 | 10.65 ± 2.38 | 13.25 ± 2.85 |

Values are mean ± SD across ports within each category and 10 random seeds.

The results of discriminant analysis clearly demonstrate that the predictive ability of the proposed model outperforms the reference models systematically in all subgroups (see Table 6). The predictive accuracy depends on the port size: large ports, with the lowest MAPE equal to 4.85%, showed the best performance while small ports, with the highest MAPE equal to 8.42%, demonstrated the worst performance. From the geographical perspective, the ports located in East Asia, with MAPE = 5.15%, performed the best; while those located in Middle East and South Asia, with MAPE = 7.42%, demonstrated the worst performance. The superiority of the proposed model over the ARIMA is especially significant in small ports (6.1 percentage points).

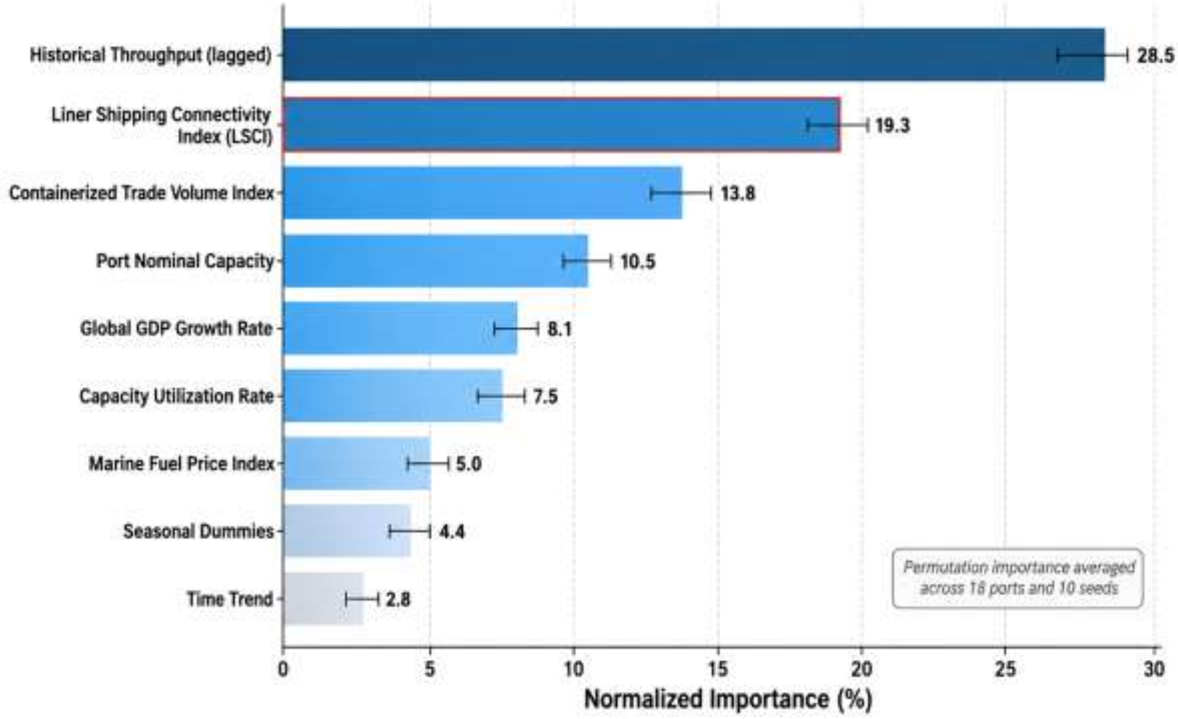


**Figure 4. Horizontal bar chart of normalized variable importance scores from permutation importance analysis**

Figure 4 depicts the normalized importance of each predictor variable using horizontal bars. The bar associated with the linear shipping connectivity index with an importance of 19.3% is the second highest after the historical time series of capacity. Standard deviation error bars represent the consistency of the importance across 10 random seeds. Macroeconomic factors such as economic growth and marine fuel prices were less important than the connectivity index.

## DISCUSSION

The results obtained in this study are powerful proof of the superiority of hybrid deep learning methods for predicting the capacity of port container operations. An increase in MAPE of 46% compared to the ARIMA model (from 11.82% to 6.38%) and 22.3% compared to the extended LSTM is not just a statistical result, but rather a principle of predictive modeling: the combination of domain knowledge and deep learning is more powerful than each of them individually. Although the ARIMA model is easy to understand and implement, it is not capable of taking into account the complex nonlinear interactions of variables impacting the demand at ports. In turn, the simple LSTM model, while being able to find temporal dependencies, does not have the benefit of structural data on maritime transportation. Our model manages to overcome both of these disadvantages at once. The importance of the linear shipping connectivity index as the second most important variable in the analysis of the importance of variables (19.3%) is the empirical validation of the theoretical hypothesis of the research. Our study is in line with Shankar et al. (2020), about the performance of LSTM networks surpasses that of traditional methods in predicting container throughput; but, our research has also showed that hybrid frameworks can deliver even better results.

This result indicates that the positioning of the port in the world shipping network provides additional predictive features in comparison with traditional macroeconomic variables. The larger share of the connectivity index in the GDP growth (8.1%) and container cargo throughput (13.8%) underlines the necessity to consider the special dynamics of the shipping network for prediction purposes. It corresponds to the results of theoretical research that highlighted the twofold nature of the connectivity concept as the driving factor and the indicator of the port demand. It is in line with the idea of the forecasting fusion theory. This finding is supported by Martinez-Moya et al. (2023), about the port connectivity and competitiveness which are inherently related. And connectivity measures offer essential information about port performance dynamics that cannot be captured using economic metrics.

One of the most interesting results obtained during the study is the synergic effect demonstrated in the separation of the component contributions. The 29.4% outperformance of the full model in comparison with the simple addition of the attention mechanism (11.2%) and the connectivity index (14.8%) proves their complementary nature. Attention enables the model to concentrate on time intervals containing the most informative data, whereas the connectivity index allows for knowledge of the structural nature of the shipping network dynamics. The use of the two techniques leads to the emergence of what can be called a mixed type of learning, where statistical regularities and causal relationships are acquired at the same time. This finding is also consistent with Xiao et al. (2023), who developed a decomposition and ensemble model with an attention mechanism for container throughput forecasting in Asian ports, who showed that an integration of multiple complementary approaches outperforms each approach taken individually.

Heterogeneity has been detected using the analysis in terms of port size and region. The difference in performance between the proposed approach and ARIMA was significantly higher in small ports (6.1 percentage points) compared to large ports (4.6 percentage points). This finding indicates that the use of hybrid modeling approach works better in case of high uncertainty where there are significant fluctuations and unreliable data. Small ports have greater difficulty in forecasting as low number of containers causes greater fluctuations in demand. Directional accuracy of the proposed model, which is significantly higher than other models, is especially important for port planning as knowing the direction of changes in demand plays a key role in decision-making. This result is consistent with Cuong et al. (2022), about examining the seaport resilience and throughput forecasting using deep learning in the case of Busan Port, and observed that the more sophisticated forecasting methods have specific benefits when there is high uncertainty and volatility involved.

While there have been positive findings, it is essential to highlight the limitations associated with this study. Firstly, the transformation of the index of liner shipping connectivity index from seasonality to monthly through the use of linear interpolation may smooth the variations associated with this index. Secondly, the model proposed here is dependent on extensive historical data, and its applicability in other ports with less history is not known. Thirdly, the current study focuses on point forecast, while its uncertainty analysis is not covered extensively. Fourthly, the effects of rare shocks such as pandemics or geopolitical crises on the model performance are not considered in this study. Fifthly, the generalization of the results obtained in this study to other ports with other governance structures and operations is required to be investigated further.

## CONCLUSIONS

Contributions of this research to the theory and practice of port demand forecasting were substantial through the development and testing of a novel hybrid model that integrates long-short-term memory and attention mechanisms with linear shipping connectivity index. First, the major contribution is the practical demonstration of the theory that incorporating the domain knowledge into the deep learning framework improves the forecast accuracy considerably. The hybrid model was more accurate than both classical and pure deep learning methods such as ARIMA and LSTM, obtaining the MAPE equal to 6.38% and directional accuracy of 72.85% for 18 global ports. Second, it was found that the linear shipping connectivity index has the highest importance as a predictor variable with the share of 19.3%.

In terms of practical application, the results achieved in the course of this study can be viewed as a better forecasting instrument for different interested parties. Port operators will benefit from increased reliability and particularly from improved direction, which will help in making decisions concerning optimal capacity planning, better timing of infrastructure investments, and more efficient management of their workforce. For policymakers and national planners, the knowledge about the importance of the shipping connectivity index means that efforts to increase the ranking of a given port in the global shipping network are both logistical and an effective way to increase future demand. In terms of science, this study also serves as a basis for component deaggregation and evaluation of their individual added value to the overall hybrid model.

There are many ways through which future research may build upon the results achieved in this study. First, use of real data for the linear shipping connectivity index per month rather than interpolation will enhance the accuracy of the model. Second, development of forecasting schemes that offer the complete distribution of uncertainty and not point forecast will prove more useful for risk management purposes. Third, evaluation of the robustness of the model under severe shocks will help measure how resilient it is under extreme conditions. Fourth, the transferability of the model to new ports without sufficient historical data will make for a good area of research. Fifth, addition of qualitative data such as political stability and change of trade policies will enrich the forecast.

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