

Forecasting Short-term Container Vessel Traffic Volume Using Hybrid ARIMA-NN Model

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ABSTRACT

A combination of linear and non-linear models results in a more accurate prediction in comparison with using linear or non-linear models individually to forecast time series data. This paper utilizes the linear autoregressive integrated moving average (ARIMA) model and non-linear artificial neural network (ANN) model to develop a new hybrid ARIMA-ANN model for prediction of container vessel traffic volume. The suggested hybrid method consists of an optimized feed-forward, back-propagation model with a hybrid training algorithm. The database of monthly traffic of Rajaei Port for thirteen years from 2005-2018 is taken into account. The performance of the developed model in forecasting short-term traffic volume is evaluated using various performance criteria such as correlation coefficient (R), mean absolute deviation (MAD), mean squared error (MSE) and mean absolute percentage error (MAPE). The developed model provides useful insights into container traffic behavior. Comparing the results with the real data-sets demonstrates the superior performance of the hybrid models than using models individually in forecasting traffic data.

1. Introduction

Forecasting short-term maritime traffic plays a pivotal role in port planning in terms of capacity planning and capacity management [1]. These forecasts enable logistics companies and port authorities to adopt appropriate policies to maintain their international competition by predicting transport lines and port operators. Predicting the throughput of the ports is usually the focus of marine traffic prediction studies. In contrast, there has been relatively little research on traffic prediction in terms of the number of vessels. Thus, a limited number of articles have used artificial neural networks (ANN) and hybrid methods in forecasting marine traffic [2]. Since 1969, many research efforts have been initiated in the field of developing forecasting models. Then, a wide range of approaches was tested to increase the accuracy of forecasting results such as ANNs, ARIMA, Box Jenkins, and so on. Evaluation of prediction results is usually assessed by comparing the forecasted values with real data [3].

In the maritime domain, ANNs are used in various fields such as traffic flow forecasting [4], predicting the impact of a wave on a vessel's diversion [5], and classifying vessels by dividing the vessel's routes [6]

into multiple groups based on automatic identification system (AIS) data. Furthermore, ANNs are used in the process of clustering, classifying, and detecting the irregular behavior of vessels [7]. Perera et al. [8] proposed an ANN for identifying and tracking multiple sea routes based on radar/laser tracking data. Abada [9] developed an artificially intelligent system capable of accurately predicting the rotation routes of vessels, in which the physical and operational information of a vessel was used as input to predict rotational maneuvers. In 2009, a study by Simsir et al. [10] aimed to predict the future coordinates of a manually controlled vessel using a trained ANN in which the neural network was trained using position and velocity data.

Predictive methods include qualitative prediction methods, such as visual prediction [11] and quantitative prediction methods, including time series prediction [12], gray prediction model [13], regression analysis [14], neural network model [9] and so on. The visual prediction model mainly relies on experience and comprehensive analysis and creates the judgment for future development, the main form of which is the Delphi method [11]. Primarily for the use of prediction in the absence of historical information and data, these

models were based on subjective judgment and expert analysis abilities.

Time series prediction includes moving average method, smooth development method, and trend prediction method. A limitation of these prediction models is that the prediction time cannot be more than one-third of the time for the data as prediction accuracy decreases over time. The regression analysis method shows causal rules between predicted values and their associated coefficients. However, in a complex system, there may be several factors that can affect the predicted values, and it is impossible to list the exact situation accurately [15]. The basic idea of gray prediction is to form a white module dynamically or non-dynamically with known data-sets in accordance with a particular rule and to solve future gray modules with a rule or algorithm [13].

In the maritime traffic domain, Du et al. [16] propose a hybrid deep learning framework for short-term traffic flow forecasting. According to the highly non-linear and non-stationary characteristics of traffic flow data, their framework consisted of Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs). Eslami et al. [17] developed a hybrid tanker freight rate (TFR) prediction model based on an artificial neural network (ANN) and an adaptive genetic algorithm (AGA). Stepwise regression of TFR variables selected three variables: crude oil price, fleet productivity, and bunker price. Wang et al. [18] proposed a hybrid model and integrating the advantages of ARIMA and ANNs. The hybrid model was tested on three sets of actual data, namely, Wolf's sunspot data, the Canadian lynx data, and the IBM stock price data.

In this article, short-term traffic at Rajaei port is predicted utilizing four models: ARIMA, ANN, Additive hybrid, and Multiplicative hybrid models, and their performance in short-term maritime traffic forecasting are evaluated based on available data-set. Our computational experience indicates the effectiveness of the new combinatorial model in obtaining more accurate forecasting results in comparison with existing models.

In the following, first, the utilized data are introduced. Then, the methodology is described, detailing the ARIMA model, ANN model, and hybrid models. Then, results are stated, and the relevant research implications are discussed. Finally, the results of this research are concluded.

2. Data

Traffic data from 2005-2018 consists of 100,139 observations of vessels referred to the Rajaei Port. In order to predict the number of vessels, the data-set is transformed into monthly data containing 156 rows (each point is the number of vessels referred to Rajaei port in one month). Forecasting performance of different models is assessed by dividing each data-set into two sub-sets, training set, and testing set. The

training set is used exclusively for model development, and then, the testing set is used to evaluate the proposed models. The input data, including the number of container vessels, are depicted in figure 1.

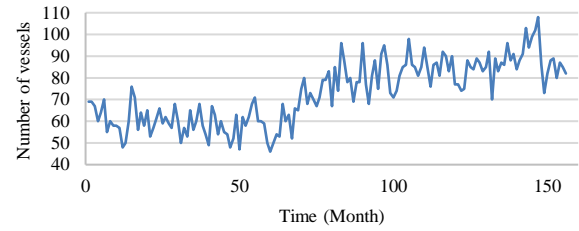


Figure 1. Number of container vessels

3. Materials and methods

In this section, for the sake of clarity, ARIMA and ANN models are discussed as preconditions for the construction of the hybrid model, with a focus on the two models' basic principles and modeling processes.

3.1. The ARIMA model

In an autoregressive integrated moving average (ARIMA) [19] model, the values of future variables are assumed to be a linear function of past observations and random errors; in other words, the basic process that produces the time series is as follows [20]:

$$y_t = \theta_0 + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \dots + \varphi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} \quad (1)$$

where y_t is the actual value, and ε_t are the random errors in the period t ; φ_i ($i = 1, 2, \dots, p$) and θ_j ($j = 1, 2, \dots, q$) are the model parameters. p and q are integers and are often referred to as the model order. Random errors, ε_t , are independent, with equal distribution, mean of zero, and constant variance of σ^2 . If $q = 0$, this equation becomes an autoregressive (AR) model of order p . When $p = 0$, the model is reduced to a moving average (MA) model of q order. The main role of the ARIMA model is to determine the appropriate pattern of the model with order (p, q) . Box and Jenkins [21] have developed a practical approach to construct the ARIMA model that has a practical impact on time series and forecasting analysis. The Box-Jenkins method [21] involves three iterative steps of model identification, parameter estimation, and error detection. The basic idea behind model identification is that if a time series is produced from an ARIMA process, it must have some theoretical correlation properties. Box and Jenkins [21] proposed using the samples' automatic correlation function as the main tool for evaluating the ARIMA model. In the identification phase, it is often necessary to convert the time series to static as stability is a prerequisite for building the ARIMA model. Once an experimental model is specified, estimating the model's parameters is simple. The parameters are estimated by minimizing the measurement errors with a non-linear optimization method. The final step in building a model is testing

error to know whether the model assumptions about the errors are appropriate or not.

3.2. The NN model

Based on the characteristics of the input data, the structure of ANN is determined. ANN can be classified into static and dynamic categories [22]. The static, or feed-forward network, is a network that does not involve either feedback elements or time delay. The output is computed from the inputs through feed-forward connections [23]. On the other hand, a dynamic network is a network in which output depends on network inputs, as well as on previous inputs and outputs [24].

A multilayer perceptron (MLP) model [25] can be used to model a feed-forward model with a single hidden layer. For a three-layer neural network, the relationship between outputs and inputs is given by the following mathematical formula [26]:

$$y_t = w_0 + \sum_{i=1}^Q w_{i,j} \cdot f(w_{0,j} + \sum_{i=1}^P w_{i,j} \cdot y_{t-i}) \quad (2)$$

Thus, $y_{t-i} (i = 1, 2, \dots, P)$ is the inputs and y_t is the output; $w_{i,j} (i = 0.1.2. \dots P; j = 1.2. \dots Q)$ and $w_j (j = 1.2. \dots Q)$ are the connection weights; P and Q are the numbers of input nodes and hidden nodes. f is a transfer function. The logical function is a common transfer function used in the hidden layer, as follows:

$$f(\xi) = \frac{1}{1 + e^{-\xi}} \quad (3)$$

Some other functions, such as hyperbolic, quadratic, Gaussian, and linear, are also used as neural network transfer functions. Hence, the ANN model practically creates a non-linear relationship between output and input:

$$y_t = F(y_{t-1}, \dots, y_{t-p}, w) \quad (4)$$

Where w is a vector of weights. F is a non-linear function determined by the structure and parameters of the network. Figure 2 shows the structure of a three-layered neural network.

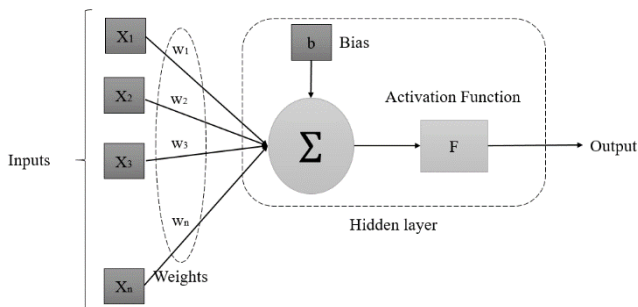


Figure 2. Three-layered Neural Network structure

In this research, the optimal hyper-parameters are found by grid-search method, which results in the most precise prediction [27], and a Network with 5 hidden

neurons is selected. The structure of the neural network is shown in Figure 3.

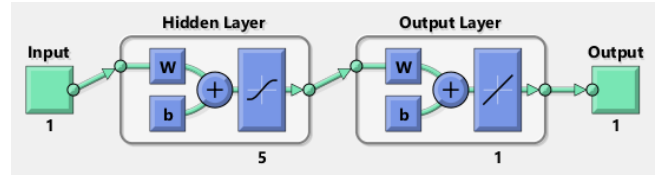


Figure 3. Neural Network structure

In a neural network, data-set are divided into three categories: Training data are used to build a network model, Validation data are used in the training phase to verify if the network capabilities of generalizing solutions are within acceptable levels, and Test data are used to test network performance after training. In this study, according to the recommendation by MATLAB software guide, 70% of the data-set was used as training data, 15% of the data was used as validation data, and 15% of the data was used as test data. Table 1 shows the sample composition for the ANN model. The selection of data is made randomly and automatically each time the program runs.

Table 1. Sample compositions in data-set

Sample size	Training set	Test set	Validation set
156	110	23	23

Training of an ANN model is a process of minimizing the global error function formed by weights. Among various training algorithms, Levenberg–Marquardt (LM) training algorithm is incorporated in this research [28]. The training process initiates with entering the training set into the input nodes. Then, the activation values are weighted and added at each hidden node. Finally, the total result is transformed into the output node’s activation value [29].

3.3. The hybrid model

The hybrid method [30] combines the ARIMA and ANN models to produce more accurate results. This process includes five steps, as follows:

- 1) Data are modeled using the ARIMA method.
- 2) The residual of the ARIMA method is used as the target variable of the neural network.
- 3) Two separate neural networks are trained with input and target data.
- 4) Two neural networks give two predictions in their output.
- 5) The sum of the average outputs of the neural network model and the ARIMA model is the final output.

The autocorrelation of the input data is modeled by the ARIMA model, and the non-linear relationship between the input and output data is modeled with the neural network. The block diagram of the neural network and ARIMA hybrid model is shown in Figure 4.

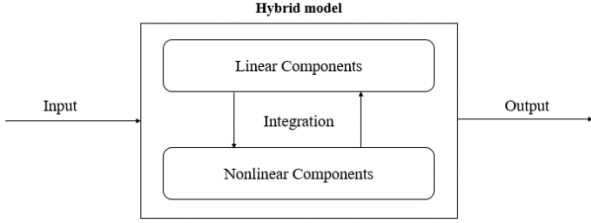


Figure 4. The block diagram of the neural network and ARIMA hybrid model

The precise description of the above operation is that in the first step, ARIMA is used to model the linear relationships in the original time series. $\{e_t\}$ represents the rest of the ARIMA model, respectively, in Additive and Multiplicative hybrid models:

$$e_t = x_t - \hat{x}_t \tag{5}$$

$$e_t = x_t / \hat{x}_t \tag{6}$$

where x_t is the real value and \hat{x}_t is the ARIMA model prediction value.

In the second step, the ANN model is used to model non-linear relationships in AIRMA models. $\{\hat{e}_t\}$ represents the values predicted by the ANN model. The last step combines the predicted values of the two steps above. Two models, additive hybrid model (Linear components + Non-linear components) and multiplicative hybrid model (Linear components \times Non-linear components), can be used for evaluating time series. For these two cases, the mathematical expressions are given in Equations (7) and (8):

$$\tilde{x}_t = \hat{x}_t + \hat{e}_t \tag{7}$$

$$\tilde{x}_t = \hat{x}_t \times \hat{e}_t \tag{8}$$

where \tilde{x}_t represents the predicted value of the hybrid model [18].

Artificial neural network models with hidden layers can capture non-linear patterns in time series. So, in time series forecasting, it is advantageous to combine ANN and ARIMA to deal with all interdependent components of the underlying patterns.

To sum up, there are two steps in the proposed hybrid model. An ARIMA model is initially defined, and the corresponding parameters are evaluated, i.e., an ARIMA model is built. As a result, this model is used to calculate the non-linear components. In the second phase, the non-linear components are managed by a neural network model [20].

4. Results and Discussion

Four ARIMA, ANN, additive, and multiplicative hybrid models are used to predict the container traffic of Rajaei port. The prediction accuracy [31] of the four models is investigated by examining the correlation coefficient of R, mean absolute deviation (MAD), mean squared error (MSE) and mean absolute percentage error (MAPE) since using a combination of

measures to evaluate the accuracy of the forecast is much better than using a single measure.

$$R = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n \sum x^2 - (\sum x)^2][n \sum y^2 - (\sum y)^2]}} \tag{9}$$

$$MAD = \frac{\sum |y_i - \bar{y}|}{n} \tag{10}$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \tag{11}$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \tag{12}$$

Table 2 shows a comparison of the performance of ARIMA, ANN, and hybrid models.

Table 2. Performance of ARIMA, NN, additive hybrid and multiplicative hybrid model

Method	R	MAD	MSE	MAPE
ARIMA	75.31	7.2128	8.9798	7.2128
ANN	77.50	3.5943	4.8015	3.5943
Additive	80.12	5.2236	6.6733	5.2236
Multiplicative	81.57	5.1636	6.9063	5.1636

Therefore, the results of ARIMA, ANN, Additive and multiplicative hybrid models for predicting the number of container vessels are presented in Figures 5 to 8 in which the values of the predicted vessels are compared with the actual values. Although the errors in the prediction of container traffic do not seem too different between Figs 5 to 8, the comparison of performance criteria (Table 2) indicates that hybrid models reduce the model uncertainty.

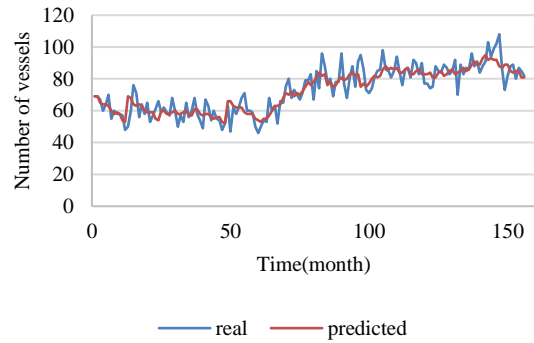


Figure 5. Comparison of the predicted total number of vessels with ARIMA model with real values of vessels' number

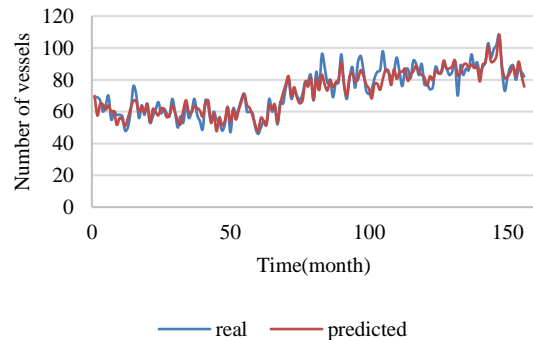


Figure 6. Comparison of the predicted total number of vessels with a NN model with real values of vessels' number

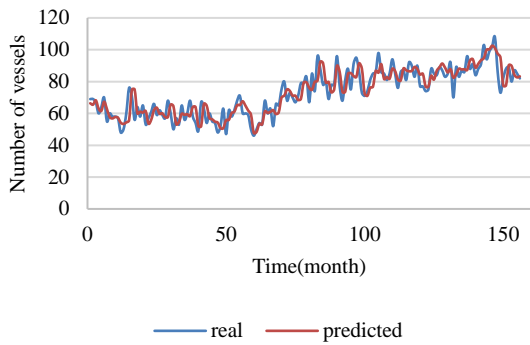


Figure 7. Comparison of the predicted total number of vessels with Additive hybrid model with real values of vessels' number

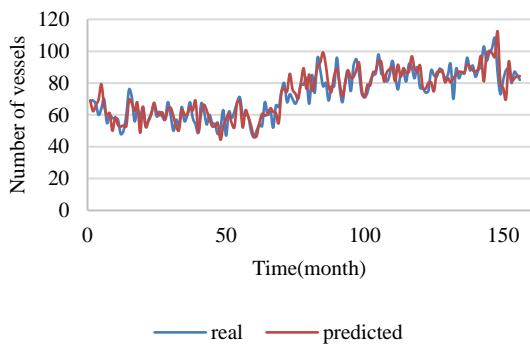


Figure 8. Comparison of the predicted total number of vessels with Multiplicative hybrid model with real values of vessels' number

Based on the results of the four models, the hybrid models provide better performance results for the prediction of the container vessels' number. Also, the comparison of predicted numbers and actual values confirms this result (Figure 5-8).

Figure 9 shows that the annual results of hybrid multiplicative models are closer to the actual data values.

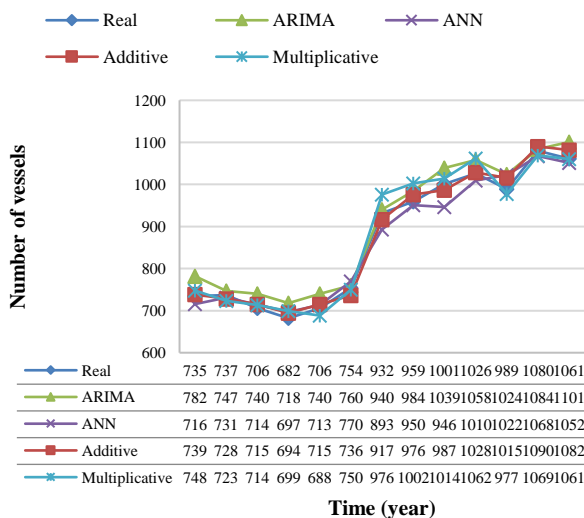


Figure 9. Results of four developed models to predict the number of container vessels

5. Conclusions

Over the past few decades, both ARIMA and ANNs have been widely used in time series analysis and forecasting due to their versatility and usefulness in modeling several issues. However, many researchers have found that none of them are wholly appropriate as a reliable forecasting model regardless of the situation's uniqueness. Some recent studies have focused on building hybrid models to enhance the accuracy and performance of time series forecasting. A hybrid model (additive and multiplicative model) is proposed in this paper, which merged the ARIMA model and the neural network to make predictions with the non-seasonal time series data of Rajae port.

Additionally, the linear ARIMA model and the non-linear ANNs model are used to capture the various patterns in time series. Throughout the linear and non-linear models, the hybrid model combines the flexibilities of ARIMA and ANNs, and it is an effective way to improve the reliability of forecasted data.

In this paper, we make the first attempt to predict container traffic volume in the Rajae Port, and the MSE, MAD, and MAPE accuracy tests are used as evaluation criteria. The lowest errors for the multiplicative hybrid model reveals that the introduced model is superior to the ARIMA model, the ANN model, and the additive hybrid model based on the data set of real traffic data. Moreover, indeed, the hybrid method gives more accurate predictions compared to ARIMA and ANN models.

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