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Artificial Bee Colony Optimized Recurrent Neural Network-Based Port Container Throughput Forecast

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Abstract*:* The Ports have become increasingly significant in the operation of international commercial activities as a result of the current economic globalisation. However, freight transportation planning for cargo movement through ports has become a big concern for the transportation sector over time and it is an essential duty for the country's economic progress. Therefore, determining the feasibility of a strategic port development necessitates assessing the port throughput. However, container throughput data is complicated and it frequently has multiple seasons, which makes precise forecasting difficult. To enhance the accuracy of container throughput forecast of port, an enhanced Artificial Bee Colony based Recurrent Neural Network (ABC-RNN) prediction model was proposed. Twenty-four sets of data are created to create an RNN prediction model, and the network output is the container throughput statistics (2015–2019) of the VOC port in Tuticorin. The thresholds and weights of Recurrent Neural Network (RNN) are optimised and they are finally established. The ESN is used with ABC optimized RNN to further enhance the dynamic process of learning and biological system modelling. The study also compares forecasted foreign trade container volume estimates from the RNN, ABC and combination technique of ABC optimized RNN for the cities of Cochin and VOC from 2015 to 2019. The results demonstrates that, the combined prediction model of ABC optimized RNN effectively improves prediction precision and produce more precise outcomes.

Keywords**:** *Ports, Cargo, Recurrent, Neural Network, Artificial Bee Colony, Forecasting*

1. Introduction

In the marine supply chain, seaports serve as common linkages between ships, importers, and exporters. The ships transport more cargo than any other kind of transportation. However, globalisation has recently spurred massive expansion in the shipping business. Cargo handling has provided a significant portion of the revenue for seaports. Profit maximisation is also an important business goal for policymakers and practitioners who are working to improve their transportation networks. Despite maintaining its existing market share, the port has faced intense rivalry and cargo volume variations which have an impact on its work strategy. In extremely competitive and dynamic business environment, the port industry faces significant issues such as accommodating larger vessels, container management, economic trends and so on. However, for the building, upgrade and day-to-day operational management of ports, precise projection of future throughput forecast is essential [1, 2].

The cargo handled by a port at a particular time is referred to as port throughput. The highest throughput in tonnes is denoted by TEU. Historical data is commonly used as an input in the forecasting process to develop informed predictions about future trends. When a large number of vessels are transported, the expectation of increased throughput of container is evident, especially it have a significant impact on development policies, investment, and port operations [3, 4]. However, when there is a paucity of previous data showing the same impact of port development, projecting the rise in port throughput that occurs as a result of infrastructure improvement is often difficult. As a result, establishing a reliable container throughput forecasting model has become a top priority [5, 6]. The short-term forecasting is essential in the port management system for scheduling and control. The analysts and policymakers has to be creative in constructing prediction models since ports have diverse characteristics [7]. Due to multiple influencing parameters, the traditional forecasting

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methodologies such as the Grey Model (GM), exponential smoothing, and regression analysis experience difficulties in delivering effective forecasts. Hence Artificial Intelligence are introduced for predicting the container throughput. The self-learning capabilities and non-linear approximation of AI based neural networks are exponential [8, 9]. Linear and nonlinear trends are present in a container throughput time series. To anticipate container traffic for international ports in Taiwan, six different approaches were used. However, the accuracy of the methods has to be further enhanced [10]. Using historical secondary data, the port's container is forecasted using six time series method. However, ANN a commonly used machine learning based technique possess poor performance than other techniques [11]. For container flow forecasting, a fuzzy neural network method is used and compared with ARIMA (Autoregressive Integrated Moving Average). Since flow of container are highly reliant on unknown variables, multivariate AI-based modelling techniques has to be developed [12]. Because persistent learning necessitates minuscule learning rates, Back Propagation (BP) neural networks typically learn at a modest rate. [13]. The container throughput is forecasted using the Dynamic Factor Analysis (DFA-ARIMAX) model. However, prediction accuracy of this model is somewhat limited and it has to be improved further [14, 15]. The size, position, and shape of the aperture affect how much coupling occurs between the feed line and patch. By separating Patch from the feed line, the ground plane reduces available to generate [16, 17]. A Multi-Layer Perception (MLP) Neural Network (NN) is used to handle control sway problem in containers, which shortens the computation time for the entire operation. [18, 19]. A time series forecasting was surveyed using various deep learning techniques. However, the prediction accuracy of this model is somewhat limited [20] and to increase the container throughput projection, a creative technique must be used.

This research proposes an enhanced ABC optimised RNN prediction model to improve port container throughput forecast accuracy. Based on the previous research results, port throughput, VOC 2015- 2019 GDP, volume of total international trade export and import are selected as network input. Twenty-four sets of data are created to create an RNN prediction model using the container throughput statistics (2015–2019) of the VOC port in Tuticorin as the network output.

2. Methodology of Forecasting Model

2.1. Artificial Bee Colony (ABC) optimized Recurrent Neural Network (RNN)

The RNN is a sort of artificial intelligence NN that utilizes a looped topology to allow continuous information about previous knowledge. In fact, machine learning algorithms are utilized in various conditions involving data with sequences like guessing the next word in a sentence. The choice of activation function type, number of hidden layer neurons, initial weights, learning rate and thresholds are the parameters that influence the estimation accuracy of RNN. Hence, an ABC algorithm is presented for optimising the RNN's initial thresholds and weights. The ABC algorithm is classified into four stages namely,

i. Initialization phase
ii. Employed bee phase
iii. Follow bee phase
iv. Scout bee phase

2.1.1. Initialization phase

In this phase, the honey source is represented by using the reconnaissance bee to modify all vectors $x_m(m = 1 \dots SN)$ and to set the control parameters. The size of population is represented as SN. Each honey source x_m comprises n variables($x_m, i = 1 \dots n$), because it is the solution vector of the issue to be optimised. The objective function is minimised by optimising these vectors. The following is the formula for randomly developing a viable solution:

$$x_{mi} = l_i + rand\ (0,1) * (u_i - l_i) \qquad (1)$$

Where, the upper and lower limit of x_{mi} is l_i and u_i respectively.

2.1.2. Employed bee phase

The employed bees finds the finest source of honey from nearby honey sources based on their memory position. When they identify a honey supply, they assess its suitability. To determine the new neighboring honey source v_{mi}, the following formula is utilized.

$$v_{mi} = x_{mi} + \phi_{mi}(x_{mi} - x_{ki}) \qquad (2)$$

Where, the randomly selected honey source is denoted as x_{ki}, the randomly selected position index is denoted as i and the random number between [-a, a] is denoted as ϕ_{mi}. According to greedy algorithm, the newly developed honey source v_{mi} analyses the fitness value and chooses between x_m and v_m. By using the following formula, the solution of fineness values are assessed:

$$fit_m(x_m) = \begin{Bmatrix} \frac{1}{1+f_m(x_m)}, & if\ f_m(x_m) \geq 0 \\ 1 + abs\big(f_m(x_m)\big), & if\ \&f_m(x_m) < 0 \end{Bmatrix} \qquad (3)$$

The value objective function for the issue x_m to be resolved is given by $f_m(x_m)$.

2.1.3. Follow bee phase

There are two sorts of bee groups in non-employed bees namely follower and scout bees. The honey source information is be shared by the employed bees. Following that, food source is selected by the bees at random based on the information. The following bees in the ABC algorithm choose honey source based on probability intended using a capability value given by an employed bees. As a result, a fitness based selection approach like roulette selection method is required. The following formula is used to evaluate the probability p_m that x_m will be chosen by the following bee:

$$P_m = \frac{fit_m(x_m)}{\sum_{m=1}^{SN} fit_m(x_m)} \tag{4}$$

When the next bee chooses honey source x_m, equation (2) generates a neighbouring honey source and its fitness value is determined. The greedy algorithm is used to choose between x_m and v_m when it comes to recruiting bees.

2.1.4. Scout bee phase

When the employed bee reaches the maximum number of iterations without improving the answer's quality, it is transformed into a scout bee and its solution is discarded. The algorithm is kept from sliding towards the local optimum as a result. Scout bee begins searching for new solutions at random after the conversion. If the x_m solution is abandoned. Hence, the $-^{ive}$ feedback characteristics are developed to counteract $+^{ive}$ feedback characteristics and honey sources that are poor in beginning or became poor because of the gathering are abandoned.

The optimization process of the ABC optimized RNN is represented in **Figure 1**.

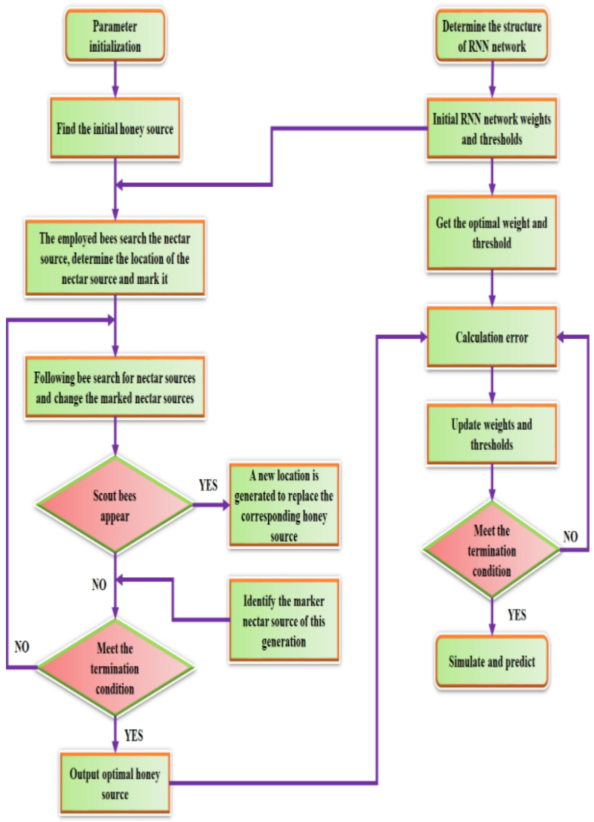

Fig. 1. Optimization process of the ABC optimized RNN

2.2. Echo State Network (ESN)

The Reservoir Computing (RC) method used by the ESN is comparable to the Liquid State Machine (LSM). The ESN are a part of the supervised machine learning idea and the RNN family. Hence, ESN is used with ABC optimized RNN to further enhance the dynamic process of learning and biological system modelling.

For a specific training input signals $\cup (n) \in \mathbb{R}^{N_u}$, ESNs are applied and the desired final output $Y^{target}(n) \in \mathbb{R}^{N_y}$, where discrete time is $n = 1, \dots, T$ and training datasets data points number is T. The goal is to create a model with an output of $y(n) \in \mathbb{R}^{N_y}$, where $y(n)$ closely fits the Y^{target} and generalises well to new data. **Figure 2** depicts the ESN model's fundamental structure.

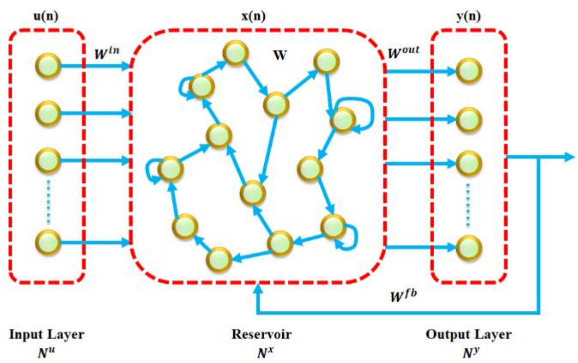

Fig. 2. ESN model structure

The ESN employs integrated discrete-time continuous value neurons with leaky. The type of reservoir state vector created by the nonlinear expansion with memory. The following time series kinds are used to update the reservoir state:

$$\hat{\times} = f(W_{in}(\cup (n)) + w \times (n-1) + W_{fb} y(n-1) \quad (7)$$

$$\times (n) = (1-a) \times (n-1) + a \, \hat{\times} (n) \quad (8)$$

Where, reservoir neuron activations vector is $X(n) \in \mathbb{R}^{N_\times}$ and its updated value is $\hat{\times}(n) \in \mathbb{R}^{N_\times}$ at a time step n, the recurrent and input weight matrices are W$\in \mathbb{R}^{N_\times \times N_\times}$ and $W_{in} \in \mathbb{R}^{N_\times \times (1+N_U)}$ respectively. The feedback weight from output to reservoir is $W_{fb} \in \mathbb{R}^{N_\times \times N_y}$ and leakage rate is $a \in (0;1]$. Neuron activation function, commonly the symmetric $\tanh(.)$ or positive logistic sigmoid is denoted by $f(.)$.Tanh, a vectorizer function that is implemented element by element, serves as the activation function in this study. The following describes the linear readout layer:

$$y(n) = W_{out} \times (n); \; W_{out} = YX^T(XX^T + \beta l)^{-1} \quad (9)$$

Where, the network output is $y(n) \in \mathbb{R}^{N_y}$, the output weight estimateds using Ridge regression is $W_{out} \in \mathbb{R}^{N_y \times (1+N_u+N_\times)}$, the identity matrix is denoted as l and vector's or matrix transpose is denoted as T. The regularisation constant (β) reduce the network's sensitivity to noise and overfitting. **Figure 3** depicts the ESN algorithm's flow diagram.

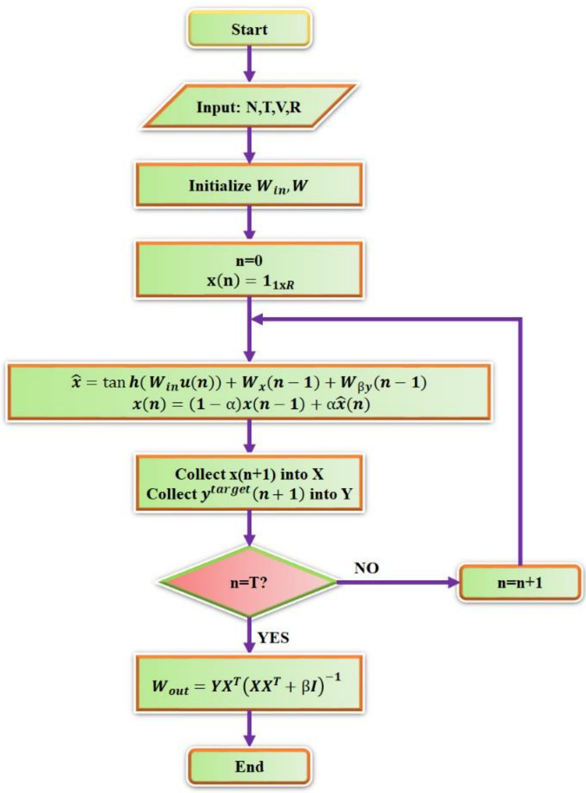

Fig. 3. Flow chart of ESN algorithm

The initial setup state input parameters are as follows: T, N and V, where N represents number of observations, T the length of time until training process is complete, and V the number of variables. Sizes of reservoir R, as well are the next parameters to choose. Furthermore, a random binomial distribution is used to generate the input weight $W_i \in \mathbb{R}^{N_\times \times N_\times}$. The reservoir weight $W \in {}^{N_\times \times N_\times}$ is then calculated using a uniform distribution that controls the sparsity level. The following stage is to use a nonlinear function (or $tanh$ function) to estimate and update the reservoir neuron activations. After obtaining $\times(n)$, collecting it in matrix X, as well as Y^{target} in matrix Y. Finally, equation (9) is utilised to determine the output weight and achieve the forecasted values $y(n)$.

3. Result and Discussion

The container throughput data is complicated and it frequently has multiple seasons, which makes precise forecasting difficult. To enhance the forecast of container throughput accuracy, an improved Artificial Bee Colony based Recurrent Neural Network (ABC-RNN) prediction model was proposed. The research utilises available results from existing research data and chooses port throughput, GDP, foreign trade import and export statistics from the VOC port during 2015 to 2019.

The study compares forecasted foreign trade container volume estimates from the RNN, ABC and combination technique of ABC optimized RNN for the cities of Cochin and VOC from 2015 to 2019. The actual values and values predicted using RNN, ABC and combined methods are represented in **Table 1**.

Table 1: Predicted results of different methods (TEU)

Region	Year	Actual value	RNN predicted value	ABC predicted value	Combined method prediction value
Cochin	2015	1144.79	1176.59	1162.74	1193.65
	2016	1267.72	1314.29	1288.15	1454.66
	2017	1337.24	1365.19	1349.96	1387.07
	2018	1417.17	1446.01	1392.65	1488.15
	2019	1563.38	1523.38	1604.54	1657.46
VOC	2015	9.85	9.91	9.73	9.98
	2016	20.43	13.43	14.78	23.56
	2017	13.17	13.65	14.44	15.37
	2018	14.30	14.44	14.18	16.98
	2019	14.89	15.37	15.37	15.55

From the table it is seen that, the amount of foreign trade containers in Cochin increased substantially from 2015 to 2019. In contrast to Cochin, the amount of foreign trade containers in VOC spikes in 2015 and 2016, then steadily drops over the next years. The forecasted values of containers in Cochin are represented in **Figure 4**.

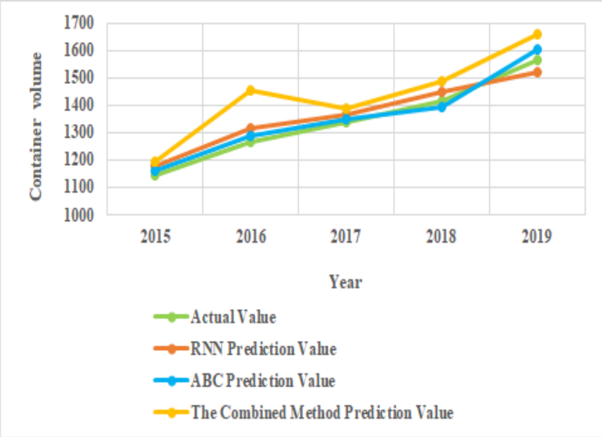

Fig. 4. Predicted values of containers in Cochin port

The forecasted values of containers in VOC are represented in **Figure 5**.

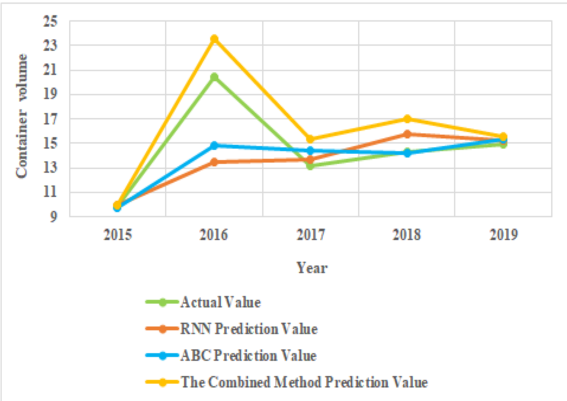

Fig. 5. Predicted values of containers in Cochin port

The container capacity values predicted by the ABC and the combined prediction model are more accurate than those predicted by the RNN technique. The combined prediction model of ABC optimized RNN effectively improves prediction precision and produce more precise outcomes. The statistical prediction approach's prediction accuracy is measured using the average absolute percentage error (MAPE), average absolute error, and root mean square error (RMSE) (MAE). The comparison of error statistics of different models are tabulated in **Table 2**.

Table 2: Error comparison statistics

Region	Year	Relative error of RNN prediction value	Relative error of ABC prediction value	Relative error of combined prediction value
Cochin	2015	3.14	1.58	1.06
	2016	3.48	1.64	1.03
	2017	2.25	0.85	0.79
	2018	2.19	1.38	1.21
	2019	2.65	2.61	1.57
VOC	2015	1.54	1.46	1.33
	2016	1.87	2.09	1.34
	2017	3.63	1.34	1.09
	2018	3.75	1.08	1.04
	2019	1.42	2.16	1.02

The error comparison of the predicted values for Cochin port is represented in **Figure 6**.

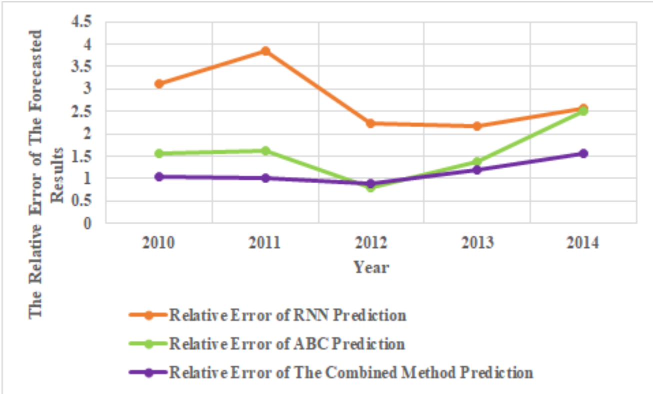

Fig. 6. Error comparison of the predicted values for Cochin port

Figure 7 illustrates the erroneous comparison of the estimated values for Cochin port.

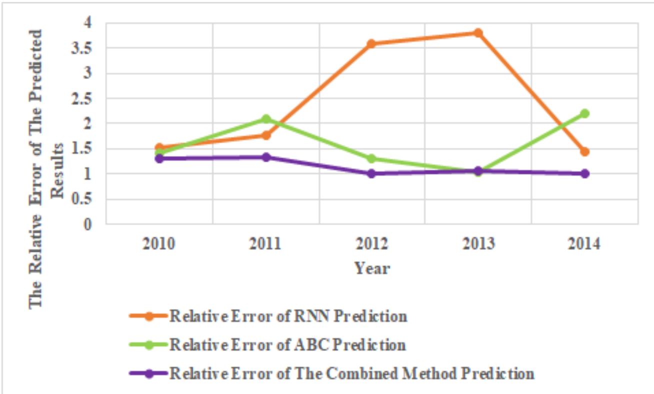

Fig. 7. Comparison of the predicted values' errors for the VOC port

Through comparison results, it is demonstrated that the relative error of RNN and ABC is comparatively high when compared with combined technique of ABC optimized RNN prediction results.

4. Conclusion

This paper suggests an enhanced ABC-RNN prediction model to increase container throughput forecasting accuracy .The creation of twenty-four data sets is necessary for the development of an RNN estimation method, of which the first twenty are used as the test dataset and the last four as the test set. This study also compares forecasted foreign trade container volume estimates from the RNN, ABC and combination technique of ABC optimized RNN for the cities of Cochin and VOC from 2015 to 2019. The result demonstrates that, the combined prediction model of ABC optimized RNN effectively improves prediction precision and produce more precise outcomes. Also, the error comparison results demonstrated that, the ABC optimized RNN has comparatively low error rate.

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