University of
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Forecasting Long-Term Container Port Throughput: The Case of Chittagong Port.

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Abstract

Objective: This study presents a long-term container throughput forecasting approach in the context of Chittagong Port Authority (CPA) for their future development of the container terminal.

Methodology: Time series data of 30 years (51 observations) from 1991-2019 is used. Data is taken from the different yearbooks of CPA, and World Bank Records for Bangladesh. Multivariate autoregressive modelling has been implemented to forecast future container throughout by applying the Vector Error Correction Model (VECM). To find out stationarity and the number of cointegration equations between variables, the Augmented Dickey-Fuller (ADF), and Johansen approach have been applied, respectively. Besides, to check the response to a shock of one variable to others, Impulse Response Function (IRF) is performed. Finally, three statistical techniques are applied to test the accuracy of the model.

Result: The result of the model predicts that container throughput may increase from 2.95 (million TEU) in 2020 to 8.73 (million TEU) in 2040 with the possibility of an average growth rate of 8.9% yearly over the two decades. GDP, Population, and Import are the most important factors and have an influence on the container throughput at CPA will be benefited in port operation and management.

Originality: While majority of the existing studies have forecasted short-term container throughput, this study focuses on long-term forecasting of container throughput. Whilst doing so, the major drivers of container throughout are identified. Further, implications of the long-term forecast for port development are discussed.

Research limitations: This study forecasts container throughput on using port level data. Use of terminal level data could be more useful as port development decision are often made on terminal level now-a-days. Further, a longer time series data for model estimation might improve robustness of the results, which was not possible to implement due to lack of data.

Keywords: Forecasting, Container throughput, Multivariate autoregressive, VECM.

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Abbreviations

ADF	Augmented Dickey-Fuller
APE	Absolute Percentage Error
CPA	Chittagong Port Authority
ECM	Error Correction Model
ECT	Error Correction Term
GDP	Gross Domestic Product
GNP	Gross National Product
IRF	Impulse Response Function
MAPE	Mean Absolute Percentage Error
RMSE	Root Mean Squared Error
TEU	Twenty Foot Equivalent Unit
UNCTAD	United Nations Conference on Trade and Development
VAR	Vector Autoregressive
VECM	Vector Error Correction Model

1. Introduction

1.1 Background

The exchange of goods across the world has increased by a world economy in globalization. Shipping is one of the most important parts of international trade. With the development of technology in shipping the world trade also has been accelerated. So, ports from every country will play an important role to cope with the growing world trade. Trade barriers are being decreased to enhance the trade flow and utilize products manufactured throughout the world. Maritime transportation and ports are one of the most important factors to generate economic growth, transportation cost is considered as the lowest in the shipping associated with other modes (G. UNCTAD, 2016). Around 132% of the gross domestic product of Thailand was distributed by trade in 2014 (World Bank, 2015). Consequently, using larger container vessels for shipments of cargo has become mandatory. In the long-distance, shipment by sea is more affordable than other means of transportation (Cenek et al., 2012). Therefore, the growth rate of container volume was the highest in number compared to other kinds of carriages from 2000 to 2019 (I. UNCTAD, 2019). So, the increasing capacity of vessels would help to reduce the voyage cost per TEU. By using large-sized vessels, the economics of scale can be generated. Thus, Sea trade dictates the whole shipping sector of international imported and exported commodities. “From Auckland to Dunedin, to transport a TEU container in every 1500 km, the ratio of the cost was the sea (1): rail (1.7): road (2.8)” (Kean et al., 2012). They mentioned sea transportation is the most cost-effective than other modes in the long distance.

Ports are mainly utilized to improve a country’s economy by importing and exporting cargoes. In the last few years, using large container ships has become apparent. So, the shipping companies aim at a single voyage cost per (TEU), the twenty-foot equivalent unit can be lowered by enhancing the capacity of the ships. Day by day the volume of container trade is increasing but the capacity of a port remains the same even though ports are directly related to load and unload containers at a specific time. Export containers are shipped to a terminal using hinterland connectivity of barges, rails, trucks, and then it is loaded on the vessel. On the other hand, for the import containers, the process is overturned. In both of the cases, the time spent by the containers at the terminal is lengthy and it creates instability for the consumers to carry away (Iannone, 2012). Hinterland connectivity of a port influences maritime transportation in a great deal, and the expansion of a country's economy has a significant effect on the utilization of the container terminal of a port (Wiese et al., 2011). As container growth is increasing substantially in the world, therefore, container terminals are being used highly in recent times. Also, a container terminal is used to load and unload containers directly from ships, for larger vessels it creates a problem on transhipment of cargoes in a short time at ports and port facilities, equipment is necessary to deal with the problem. To attract more ships calls ports must reduce congestion. If port congestion increases by 10% that leads to an increase of 0.7% of maritime transport cost (OECD,2015). Port congestion can be occurred due to many reasons, such as lack of technical facilities, area, and logistics services. To reduce the congestion at the port, a port expansion plan is needed. To identify the expansion size of a port with the estimated budget, the long-term container forecast is necessary to assist the decision-makers and government.

According to Statistical Yearbook-2018 of Chittagong Port Authority (CPA), the total container handled by the port was almost 2.8 Million TEUs. Further, a good number of external trades of the country is transported by sea. According to a record of OECD (2015), for each 10% of the increased port congestion conducts to increase 0.7% of transportation cost. To keep pace with the increased amount of container volume and to decrease the congestion, a port expansion is needed. In Bangladesh, because of the high utilization of the Chittagong Port container terminal, it creates congestion with regards to import and export container operations.

Therefore, the Chittagong Port Authority has created a master plan to develop the capacity of the container terminals. Terminal equipment and container yard layout are the key factors that influence a yard expansion, also to start the change, a long-run container throughput should be considered predicting the future consumption of the specific port (Gosasang et al., 2018a). Forecasting the container throughput has become the crucial input to plan and operate the Chittagong Port Authority, and government entities. Therefore, the objective of this research is to estimate long-term container throughput in the planning and port operation of CPA.

1.2 Significance of the Study

As there is a demand for containerized cargo for international trade, so, the rising trend of the volume of containers will be resumed for the economic development of a country. Besides, the high-level progress of the containerized cargo has enhanced the port operation of CPA and forced the construction of deep-sea Payra Port in Bangladesh. To develop or construct a new deep-sea port, the key element is long-run data about the container throughput of the specific port. To develop or plan a port strategy, forecasting of long-run container volume is a must for future prediction to generate revenue from a given project. Therefore, to operate a port efficiently, the long-term assessment of container throughput is mandatory for CPA. Unhappily, the author did not find any available research work about long-run container throughput forecasting in Bangladesh until 2021. In the circumstances stated above, this would be an interesting research work to resolve the problem.

1.3 Scope of the Dissertation

From the recommendation of (De Langen et al., 2012a), it is more appropriate to establish a method to fit with one type of cargo. As a result, the long-term forecast should be for a particular sort of cargo to reveal the most suitable model with no prejudice. The passage of containerized cargo at CPA is the highest in quantity linked to total cargo throughput correlated with other types of cargo volumes. Additionally, Chittagong Port Authority allocates nearly

80% of the total cargo throughput in Bangladesh (*Yearbook*, *2019*). Likewise, the research work concentrates on the container throughput at CPA by exploiting historic yearly data of the port from 1991-2019.

1.4 Research Questions

The research work aims to answer the following research questions given below.

- Can we forecast long-term container throughput?
- Do macroeconomic variables affect container throughput?

1.5 Structure of the Dissertation

The structure of the dissertation is designed as follows (figure 1).

Chapter 1 represents the introduction of the research paper. The chapter declares the background and significance of the study with the scope and research questions. Chapter 2 evaluates the important appropriate works of literature on containerization, container forecasting, and the relationship between macroeconomic variables with container throughput. Chapter 3 illustrates the research methodology and econometrics model. Chapter 4 shows the result and a discussion of the findings. Finally, chapter 5 provides the conclusion of the research work. In the study, all the assessment and data analysis are accomplished by EViews-11 (Student version) software.

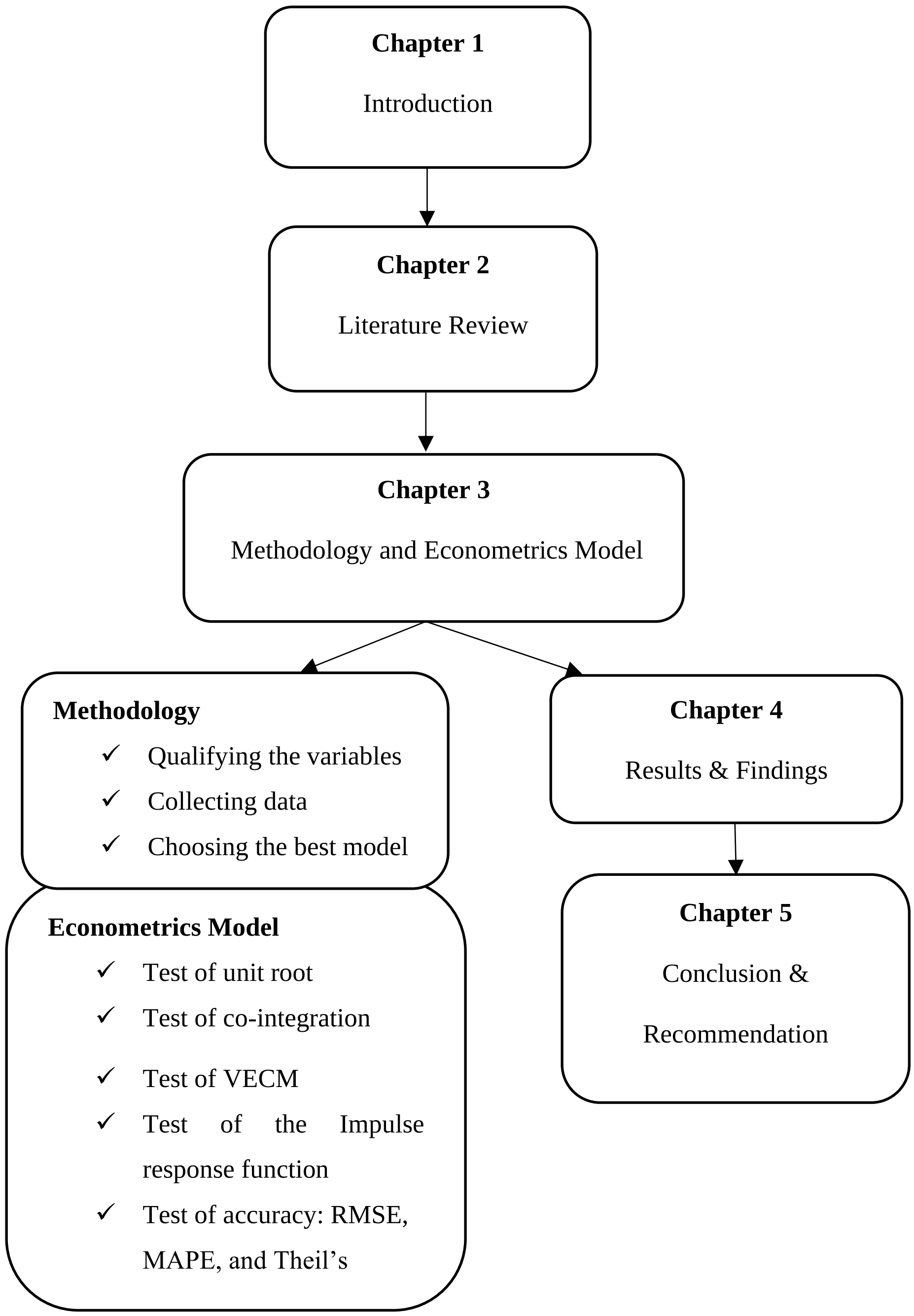


Figure 1: Structure of the dissertation

Source: Author

2. Review of Literature

The objective of this section is to deliver an enhancive report of the earlier research works and positioning current studies. Three different established online databases (i.e., Scopus, Oria, and Google Scholar) are used to find out the related articles and understanding the concept of containerization, container forecasting, and connection between economic variables and throughput of the container. Additionally, 15 examples from previous forecasting container/cargo throughput studies are shown below by using different forecasting models.

2.1 Containerization

Containerization was established in April 1956. A container was stuffed for the first time at the port of Newark, USA (Zangwa, 2018). Formerly, the objective of the container was to move goods with fewer conditions on physical handling, e.g., agricultural tools and textiles. Goods were transported in boxes; shipment became slow and expensive. Ships had to spend a long time while cargo was handled piece by piece. Trade-in container depends mainly on two major innovations. First is the mechanization, e.g. rail track, RTG, RMG, container cranes, trucks around the port area. This mechanization significantly reduced the labor unit cost and made larger ships viable. The second major innovation of containerization is universal standard advancement of container size, capacity, loading system, and holding mechanism. Because of these standard requirements, containers are used in different modes of transportation such as trucks, rail, ships, and throughout the country. Standardization of a container was implemented in the U.S. in early 1960. Therefore, the international requirement resulted in late 1960. Physical changes in containerization are needed to acquire economies of scale. Moreover, a large amount of land and less labor power is mandatory for a containerized port (Rua, 2014).

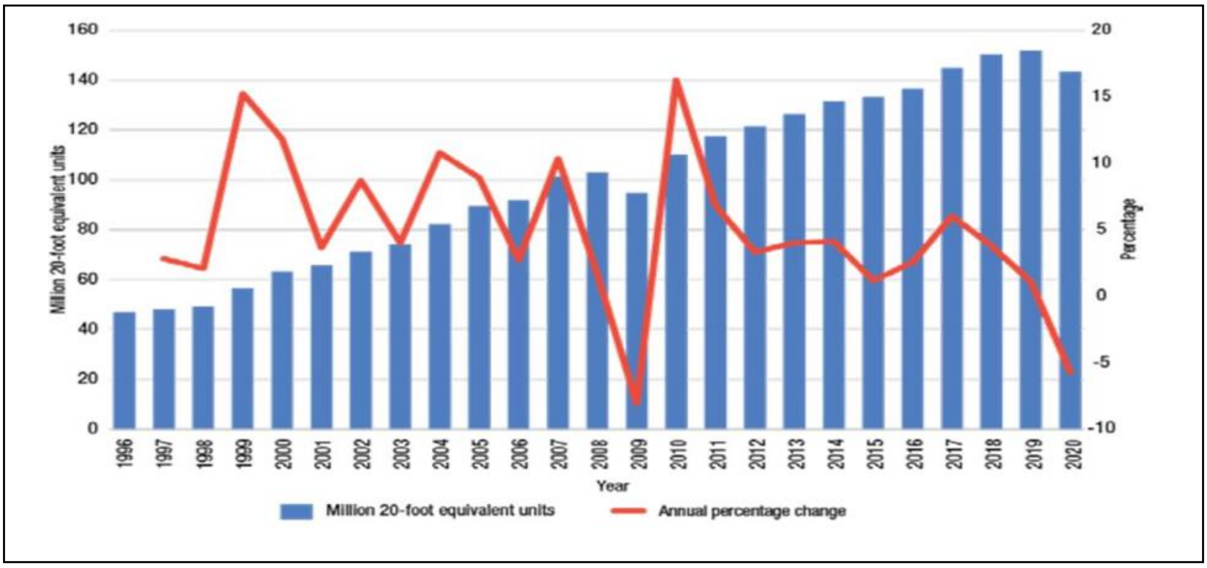


Figure 2: Trade of container globally in million TEU from 1996 to 2020 (I. UNCTAD, 2020)

In 2019, containerized trade has increased globally by 1.1%, knockdown from 3.8% in 2018 gradually total of 152 million TEUs. It has extended 0.4% in 2019. For specific trade, goods of automation are one of the most important (Shibasaki, 2021). For the time being, special containers are needed for specific requirements, e.g., tank containers, reefer containers also the cost of maritime transportation is lower than the other modes of shipments. For example, FloraHolland and Seagate have moved from air to sea to lower the transportation cost. Therefore, transportation cost in Europe was decreased by 40% (Vahabi, 2016).

2.2 Container Forecasting Technique

Most of the world commodities are transported via ships and ports has an important role to connect land and sea. According to UNCTAD (2020), in 2019, containerized trade increased globally by 1.1%, down from 3.8% in 2018 steadily total of 152 million TEUs. It has extended 0.4% in 2019 (figure 2). To invest in a port expansion project, long-term container throughputs are frequently used globally. Many related works show in one year of short-term container throughput forecasting provides better precision than a long-term forecast in a cyclic model. Nevertheless, to access the port financing for the future development of a port, a long-term forecast is widely used internationally (Milenković et al., 2019).

The container forecasting model is used to estimate the future characteristics of a business (M. Armstrong, 2001). In forecasting, the econometrics model is the most useful to identify the relationship between variables. If the relationship is known between them, there can be a big change among the variables over the forecast limit (J. S. Armstrong, 2001). Several techniques are applied to predict container volume throughput, such as neural network (Gosasang et al., 2011a), regression model (Chou et al., 2008a), grey forecasting model (Qiuhong, 2009), and vector error correction model (Rashed et al., 2013), etc. There is much research found in the aspect of container forecasting that indicates a correlation between macroeconomic variables and containers (Chou et al., 2008a). A vector error correction model (VECM) is used to change the situation from long-run to short-run. It can also identify the highest value of dependent variables after a change in the independent variables by applying the multiple time-series techniques. The vector error correction model is easy to apply to deal with multivariate time series data. The model is formed by mixing the limitations of a co-integration relationship into a VAR model (Xiaolin, 2012). Moreover, VECM was used in the Indonesian port to forecast the future need for container throughput (Syafi'i & Takebayashi, 2005). The correct implementation of the models ARIMA, VAR, and VECM are calculated by Xiaolin (2014). He also found the lowest error by applying the VECM model in forecasting. Therefore, it is said that this model is one of the most accurate. (Peng & Chu, 2009) recommended other forecasting techniques such as neural networks to forecast container throughput. From 1978 to 2006, a set of monthly data was used on container throughput in Taiwan by three major ports (Chen & Chen, 2010a). They proposed SARIMA, genetic programming, and decomposition model to forecast container throughput in the long term. Among the models, genetic programming delivered satisfactory results by offering a lesser MAPE. In the econometric models, VECM makes a greater accuracy point. In another study, a multivariate autoregressive model was used in Indonesia by (Syafi'i & Takebayashi, 2005). He applied augmented dickey-fuller analysis to check the stationarity of the data and Johansen's methodology to obtain the co-integration relationship among variables, which resulted in a satisfactory prediction of container throughput. Another study by (Fung, 2002) applied the VECM to calculate the container throughput handling for Hong Kong. Meanwhile, a unique method was utilized by (Hui et al., 2004) in Hong Kong's port to know the demand of container throughput by applying a VECM model. So, in this paper, a multivariate autoregressive model will be used to forecast long-term container throughput at Chittagong Port. We can apply an augmented dickey fuller (ADF) test to explain the exertion among variables, and a VECM to identify long-term and short-term connections among the variables. In most of the studies in the literature, many researchers have implemented VECM as the best model to forecast container volume demand of a country in a long run, in different ports internationally. Below, table 1 indicates some examples taken from previous studies on container and cargo forecasting by using different methods in different years.

Table 1: Summary of different studies on forecasting container and cargo throughput.

No	Object	Year	Author(s)	Ports Studied	Data Type	Sample	Forecast Methods	Accuracy Measures	Best Performing Method	Implications for literature
1	Container throughput	2018	Syafi'I, Katsuhiko Kuroda	Indonesia	Yearly (Long)	1982-2002	VECM, SARIMA	MAPE. MAE	VECM, SARIMA	VECM model is dependable than other models applied in the study. The authors also recommended more realistic forecasting models.
2	Container throughput	2018	Chan, Xu, and Qi	Ningbo	Yearly (Short)	2004-2015	(MA, MARS, ARIMA, GM, SVR and ANN)	Not reported	SVR	To measure forecast accuracy, the machine learning model performs better than traditional methods.
3	Container throughput	2018	Farhan and Ong	Top 20 international container ports	Monthly (Short)	1999-2007	SARIMA model	MAE, MAPE	SARIMA model	For different international ports, SARIMA delivers consistent throughput forecasts.
4	Container throughput	2016	Rashed, Meersman	Antwerp	Monthly (Short)	1995-2015	SARIMA model	MAPE	SARIMA	SARIMA performs better and because of the structural break of October 2008, container throughput continued to come back to its pre-crisis level.
5	Container throughput	2015	Xiao, Wang, Xiao, and Hu	Tianjin	Monthly (Short)	2001-2012	Regression neutral model	MAPE, RMSE, MAE	Regression Neutral	Neutral regression analysis can be utilized to forecast container throughput because of its satisfactory result.
6	Container throughput	2015	Rashed, Meersman, Sys	Hamburg-Le Havre Range	Yearly (Long)	1986-2014	VECM	Not applicable	VECM	VECM result reveals that after the financial crisis in 2008, economic activity was changed. Therefore, further study is recommended.
7	Cargo throughput	2013	Zhang and Zhao	Shanghai, Ningbo-Zhoushan	Yearly (Long)	2002-2011	VECM, combined	Mean square error (MSE)	Combined model	The combined model shows significant positive results when there is a lack of data information.

8	Container throughput	2013	Rashed, Meersman	Antwerp	Monthly (Long)	1995-2013	VECM	MAPE	VECM	VECM performs better for a short-term forecast for both port authority and in-port operation.
9	Cargo throughput	2012	de Langen, Meijeren	Hamburg-Le Havre Range	Yearly (Long)	1998-2008	A regression model with market research	Not applicable	Trend forecasts	The forecasting model adopted by the authors does not rely on trend forecast and trend-based model equally.
10	Container throughput	2011	Gosasang, Chan-draprakai	Bangkok Port	Monthly (Long)	1999-2010	Neural network, linear regression technique	RMSE, MAE	Neural network approach	Linear regression analysis predicts better results than the neural network model.
11	Container throughput	2010	Chen and Chen	Taiwan	Monthly (Short-Long)	1978-2006	GP, SARIMA	MAPE	GP	Among the models, GP achieves a better forecast than SARIMA and X-11. Also, valuable trends of container throughput are available at the port.
12	Container throughput	2009	Peng and Chu	Keelung, Taichung, and Kaohsiung	Monthly (Short)	2003-2006	Six univariate models	RMSE, MAE, MAPE	Classical decompositi on model	The classical decomposition model predicts better results than the seasonal dummy regression model.
13	Container throughput	2009	Qiuhong	Qinhuang-dao	Yearly (Short)	2002-2007	Grey model	Developm ent coefficient	Grey theory	Grey theory achieves a higher value of accuracy in practice for short-term forecast because of incomplete data of time series.
14	Container throughput	2008	Chou, Chu, and Liang	Taiwan	Yearly (Long)	1989-2001	Modified regression model	Total error	Traditional regression models,	The modified regression model shows a lower forecast error than the traditional regression model.
15	Cargo throughput	2004	Lam, Asce, Ng, Seabrooke	Hong-kong	Yearly (Short-Long)	1983-2003	Neural network approach	MAE	Neural network model	Neural network (NN) models are more accurate than regression analysis.

2.3 Container Throughput and Macroeconomic Variables

From the different studies on container and cargo throughput forecasting, it is found that authors have shown the connection between container throughput and macroeconomic variables such index of price, GDP, population, import, export, inflation rate, etc. GDP is one of the most popular macroeconomic variables to predict container volume at a port. In forecasting container throughput in port "every port should focus on different variables" (Jansen, 2014). Moreover, variables should emphasize the factors that are connected to the liner route than service level to forecast container throughput in a port. On the other hand, there should be more emphasis on the variables such as GDP, population, and investment in private and government sectors for a port like Chittagong. Hinterland connectivity is considered a crucial factor for developed and developing countries, but GDP and political strength are more necessary than this for Bangladesh as a developing country. The macroeconomic variables are used to forecast container throughput in the long-term for a gateway port must be associated with the demand of the specific country (Liu & Park, 2011). Table 2 shows the most important variables used in different forecasting studies.

Table 2: Different variables used in long-term container forecasting.

Variables	Sample	Topic	Source
Container throughput GDP Population Export, and import value	1982-2002	The demand of container throughput forecasting.	Takebayash et al., (2005)
Imported Container GDP	1989-2001	Modified regression model to forecast the throughput of import container.	Chou et al., (2008)
Container throughput GDP Exchange ratio Population number Interest value Inflation ratio	1999-2010	Comparison between traditional and NN forecasting models to forecast container throughput.	Gosasang et al., (2011)

3. Methodology and Econometrics Model

There are three (03) stages of forecasting methodology applied in the dissertation presented below.

Stage 1:

Identification of the variables: Different kinds of literature have been studied to find out the best fit macroeconomic variables such as Container throughput, GDP, Population, Import, and Export to forecast long-term container throughput at CPA.

Stage 2:

Data collection: The data collected for the dependent variable (container throughput) and independent variables (GDP, Population, Import, and Export) from the period of 1991 to 2019. The data covered 30 years (51 observations). The data for the dependent variable, Container throughput (TEU) were collected mainly from the Chittagong Port Authority website, different yearbooks of CPA, and the independent data were collected mainly from World Bank Records.

Stage 3:

Choosing the correct-fit model: Vector Autoregressive Model. We used the EViews-11 (Student version) software to get the best fit model for container forecasting because of its accuracy measures. To determine the connection between container throughput and macroeconomic factors is the goal of the model. VECM is applied to forecast container throughput at Chittagong Port in a long run.

To apply VECM as the forecasting model, the data must be primarily co-integrated and stationary. Augmented dickey fuller (ADF) is applied to test the data stationarity and Johansen co-integration test can be applied if the data is not stationary at the initial level. The approach is also used to know the relationship of co-integration among variables. Besides, to ascertain the shock of a variable on other variables, impulse response function (IRF) can be chosen. In this study, three accuracy measures are chosen to evaluate the forecasting model, VECM. They are Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Theil's Inequality Coefficient that are defined below in the econometrics model section.

3.1 Econometrics Model

3.1.1 Test of Unit Root (ADF)

Natural figures are every so often in non-stationary form and they have specific phases, trends, and seasonality. It means that variance and mean of the number are fluctuating on the period that may impinge on the dependability and uniformity of the time series data (Franses & McAleer, 1998). We can get stationary data from non-stationary natural figures by applying the augmented dickey-fuller test. The sequence of natural data will be examined if it must be stationary. The following equation is applied.

$$\Delta Z_t = \omega_1 + \omega_2 t + \beta Z_{y-1} + \alpha_m \sum_{m=1}^{n} \Delta Z_{y-1} + \mu_y$$

Below here, μ_y is an error term, moreover, ΔZ_{t-1}, ω_1, ω_2, β, and α_m are the parameters, y signifies the trend variable. We include the lag difference (n) in enough terms so that we can include error terms uncorrelated serially.

From the ADF t-test, we can assume the null hypothesis as shown below,

If, H_0: $\beta = 0$, (There is a unit root)

The alternative hypothesis can be explained below,

whether H_1: $\beta < 0$, (There is no unit root)

whether we do not want to reject null the hypothesis, the natural data must be in non-stationary form and therefore, we can conduct Johansen co-integration test. In contrast, we can only reject the null hypothesis if the natural data is stationary, and we analyse it by using the regression model in a time trend analysis.

3.1.2 Test of Co-Integration (Johansen Approach)

After checking the stationarity of the natural data, the Johansen approach of co-integration can be used to find out if the model shows any significant connections between macroeconomic variables by examining stationarity form over the non-stationarity variables (Sjö, 2008). The other methods to estimate long-term symmetry relationship have been planned by (King et al., 1987) proposed non-linear least squares (NLS). Johansen's approach is the best fit for the co-integration test is proposed by Engle & Granger (1991). This model performs better than other models and the test result is significantly reliable (Gonzalo, 1994). So, the author is interested to apply Johansen model to test co-integration between variables. This approach is mainly converted to a similar structure with different lagged variations from a vector autoregression approach (VAR). Regression analysis is done to obtain the absolute vector. In every equation is used by the Johansen model, there are error correction terms are originated from VECM. In the co-integration model, there can be found two types of ratio tests they are, the statistic of trace test and test statistics of lambda-max. The two equations of trace test and lambda-max are shown below.

Trace test statistics,

$$1.\ trace(p|q) = -A\sum_{m=p+1}^{q} \ln{(1-\alpha_i)}$$

λ_{max} statistics,

$$2.\ \lambda_{max} = -A\ln(1-\alpha_{p+1})$$

In the 1st equation, p reefers relationship of co-integrations, q denotes the variable quantity, A represents observations quantity, besides, α_i denotes the i^{th} solution which cannot be zero.

3.1.3 Vector Autoregressive Model (VAR)

There is much multivariate time series model, vector autoregressive model (VAR) is one of them. VAR denotes a general mathematical form of v dimension. If the co-integration between macroeconomic variables is found under a hypothesis, this VAR model can be described as a

VEC model that is a vector error correction model declared by Ganger Theorem. The equation of VECM is shown below.

$$\Delta Z_r = \sum_{m=1}^{k-1} \Pi_m \, \Delta Z_{r-1} + \Pi Z_{r-1} + \Phi D_r + \mu_y$$

In the above equation, Δ signifies an operative which is in 1st difference, co-efficient, error term, and order of the VAR is represented by Π_m, μ_y, and k, respectively. We considered D_r as a fixed seasonal dummy which is also a constant liner term. In this study, for the model we used, k = 5, Z_r = (Container, GDP, Population, Export, Import). We cannot find any linear pattern if, $\Pi = 0$, which means above mentioned variables are not co-integrated, likewise, there is a possibility of getting a linear pattern of stationarity if, If $\Pi > 0$. The vector error-correction model (VECM) lets variables adjust all together at various rates for short-run disequilibrium. This model provides decent estimation to find out the undetermined data-generating procedure as the theory is not sufficient to describe the vibrant adjustment procedure.

3.1.4 Test of Impulse Response Function (IRF)

In this study, we will try to find out a reaction of one specific variable over other macroeconomic variables to an impulse by applying (IRF). Whether the outcome response behaves as same it can be mentioned that the last variables contribute to the first one. By applying the model, we can observe the standard explanation of moving data system. How a dependent variable reacts over the period to any other independent variables can also be identified by this model. If we can operate infinite running standard analysis of k dimension from vector autoregressive model, impulse response function test would be significant (Lütkepohl, 2005). The equation of impulse response function is as follow:

$$Z_r = B_1 Z_{r-1} + \ldots \ldots B_i Z_{r-q} + \mu_y$$

$$\Phi_p(\Phi_{mk,p}) = \sum_{m}^{n} \Phi_{p-m} B_m$$

In the IRF equation, p denotes natural number (p= 1, 2, 3, 4……), when m > I, the value of $B_m = 0$, The mk ht represents the element of Φ_p in $\Phi_{mk,p}$ that describes the variable z_i in a response. It creates a shock to another variable k in a certain period. In the vector autoregressive model, Σ_u shows significantly positive results. To get a reasonable shock of a variable to other variables, we need some limitation requirements on the coefficient of the fundamental vector autoregression model, but it is exceptional whether the covariance format is transverse. The IRF model can identify a unique problem of the response function of time series data (Koop et al.,1996). On the other hand, the disadvantage of the IRF model is the data is used in the method is not sufficient. We have a limitation in this IRF analysis is orthogonalized response. In a VAR model, the IRF is one of the most important models to test the strength of identified calculation.

3.2 Accuracy Test of Model

There are different statistical tools are accessible to estimate the long-term and short-term forecasting performance of a model. There are many generally used forecast accuracy measures such as RMSE, MAPE, Theil's Inequality Coefficient, MAE, MSE, ME, etc (Wheelwright et al., 1998). In this paper, three techniques are chosen to implement in the research work they are Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Theil's Inequality Coefficient. To test the desired results, these accuracy measures are applied to a model but sometimes it does not show any changes if the sets of data run in equal trends.

3.2.1 RMSE

RMSE means Root Mean Squared Error. This is an accurate tool to test a model. This can be verified by the contemplation of square root by mean error absolute value, and it is used to identify the execution of a model named (GE) Gaussian Error (Chai & Draxler, 2014). The equation of RMSE is presented below.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}|\hat{Y}_t - Y_t|}{n}}$$

From the equation, the estimated, actual value, and period of data series are described by y_t, $\hat{y}_t$, and t, respectively. Since the measure would be positive, therefore, the smallest value of the measure would represent the best accuracy of the test.

3.2.2 MAPE

MAPE means Mean Absolute Percentage Error. This is also a statistical tool to measure the forecasting performance of a model. This measure is used especially in different levels to incorporate various forecasting data series (Frechtling, 2012). We can identify the accuracy of this measure by the insignificant result that means the estimated value must be close to zero to be more accurate. The equation of the MAPE is shown here.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{\hat{Y}_t - Y_t}{Y_t}\right| \times 100$$

From the equation, the estimated, actual value, and period of data series are described by y_t, $\hat{y}_t$, and t, respectively.

3.2.3 Theil's Inequality Coefficient

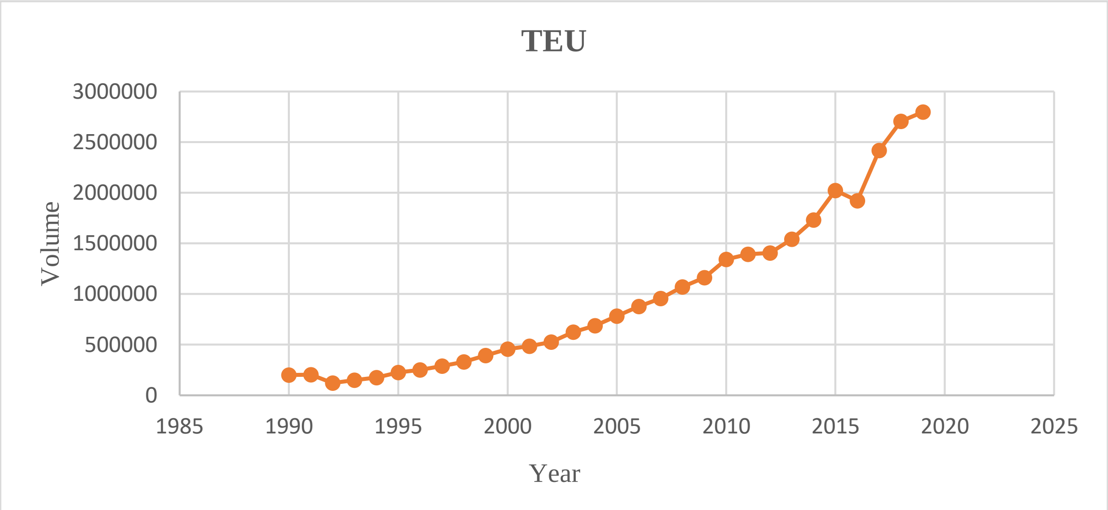
Theil's coefficient of inequity is also another statistical accuracy measure to identify the forecasting performance of a model.

$$U = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(\hat{Y}_t - Y_t)^2}}{\sqrt{\frac{1}{n}\sum_{t=1}^{n}Y_t^2} + \sqrt{\frac{1}{n}\sum_{t=1}^{n}\hat{Y}_t^2}}$$

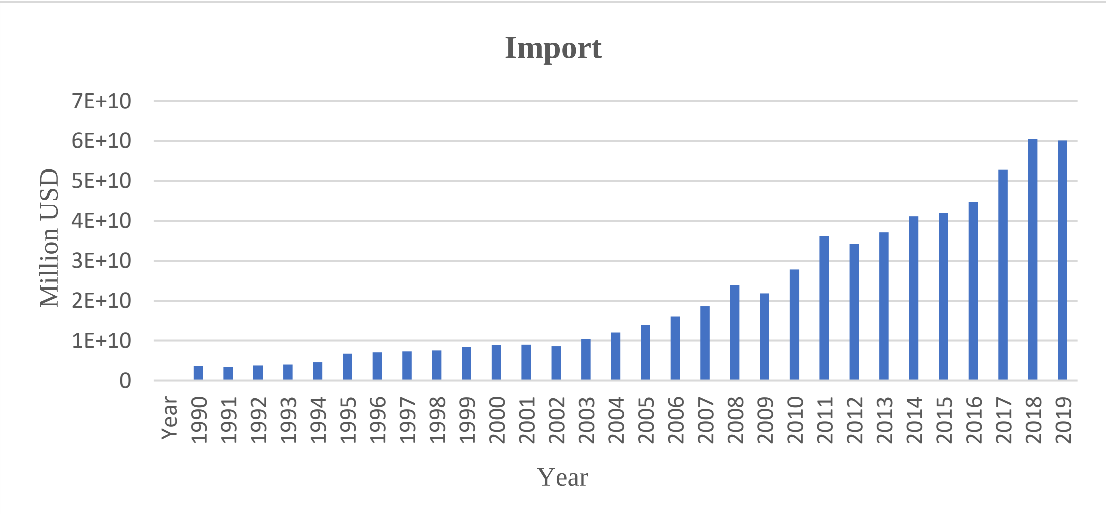
From the equation, it is shown that U is the coefficient of Theil. The estimated, actual value and period of the data series are described by y_t, $\hat{y}_t$, and t, respectively as well here. The value of U terminates from zero to one. If we want to get the best forecast value that signifies the actual value then the value of U must be zero, on the other hand, if the value is equal to one, that means the estimated value is completely different from the actual value (Udoumoh et al., 2016).

4. Empirical Result and Discussion

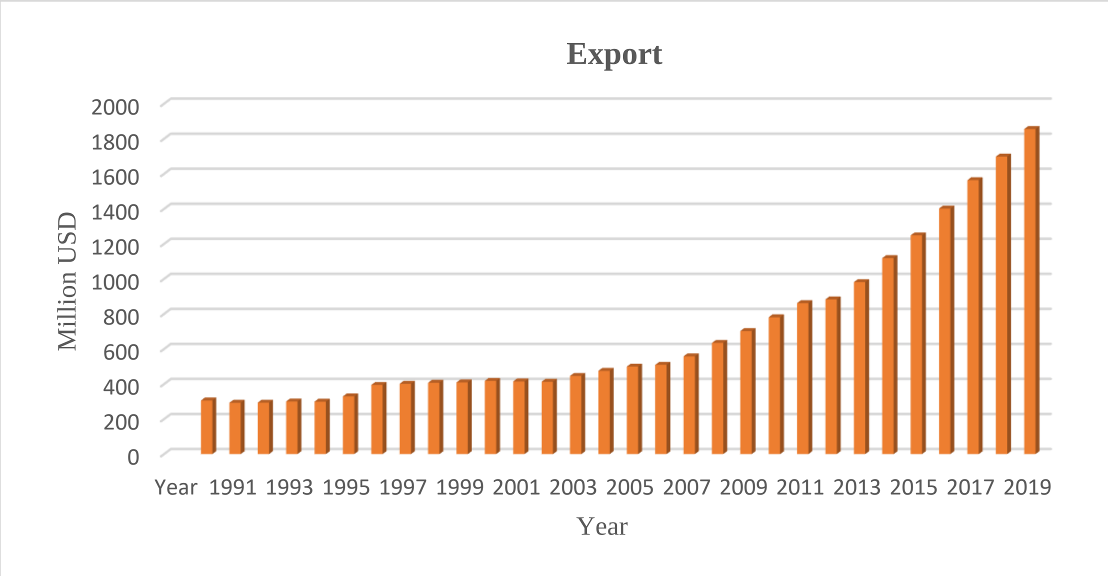
In this study, to forecast long-term container throughput five macroeconomic variables are used, they are container volume, GDP, population, import, and export. The time-series data were collected from 1990 to 2019. Before applying the data in the unit root test, the logarithmic of the original value is changed to get data series without heteroskedastic and more compatible. Data of container volume was achieved from the CPA website, and other data for GDP, population, import, and export was collected from world bank records for Bangladesh. Data of macroeconomic variables (TEU, Import, Export, GDP, and Population) are presented in figure 3 below.



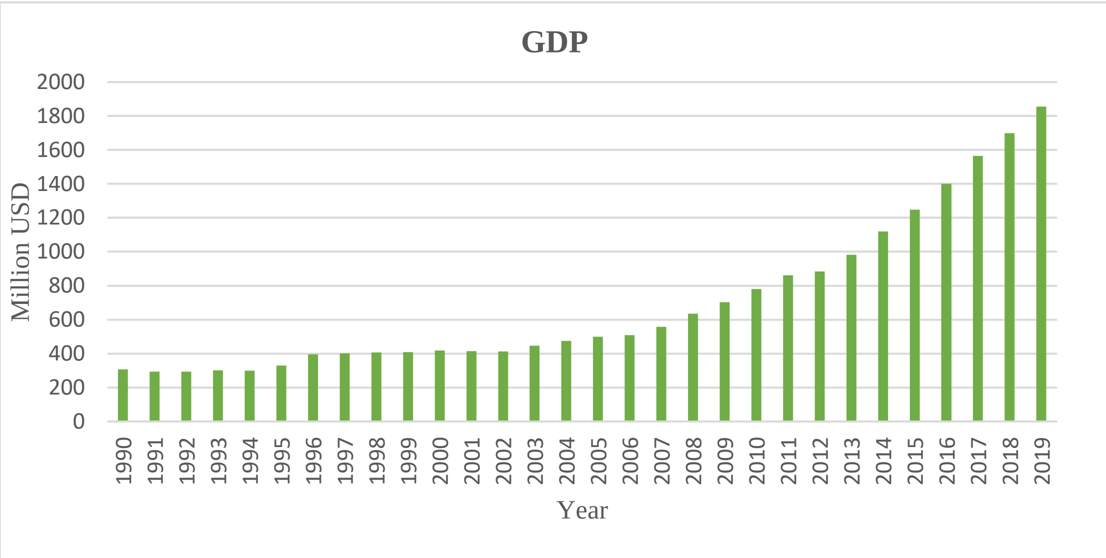
(I) Container in TEU (1990-2019)



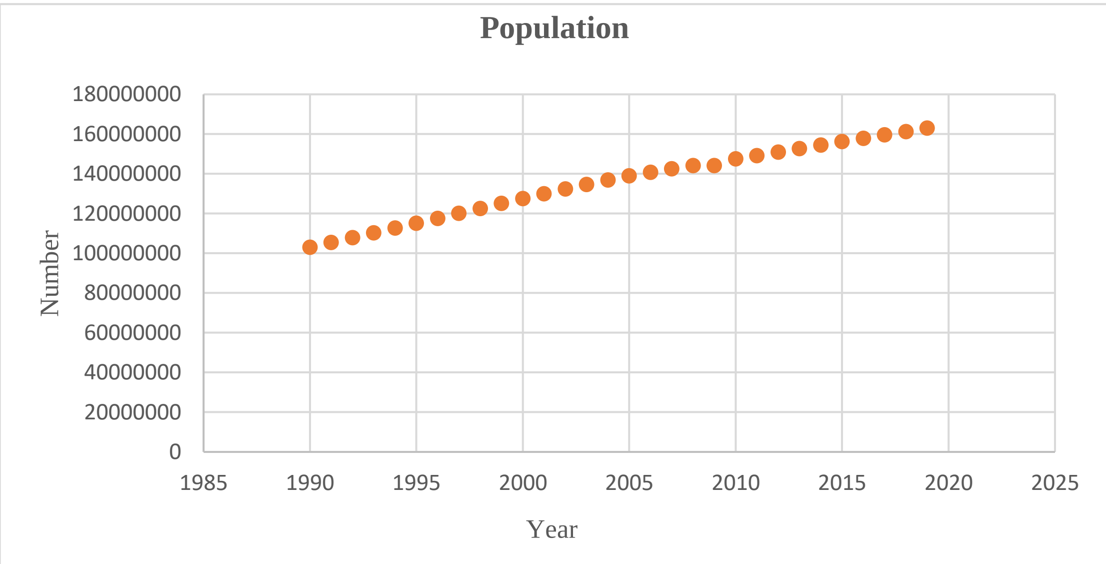
(II) Import in million USD (1990-2019)



(III) Export in million USD (1990-2019)



(IV) GDP in million USD (1990-2019)



(V) Population (1990-2019)

Note: Original value of each variables have been used. In the graph (II), 1E+10, 7E+10 refer 100 and 700 Million (USD) respectively.

Figure 3: Data of macroeconomic variables (1991-2019)

Source: Different Yearbooks of CPA and World Bank Records.

4.1 Result of ADF

As mentioned earlier, before applying to test the unit root of the time series data to make the data series more compatible logarithmic of the original value has been taken. By doing this we can also diminish the heteroskedastic of the data series and use it to best fit the model. We use the unit root test to identify the data series stationarity and if there are any integrated forms. We used the augmented dickey fuller (ADF) model to test the stationary of the data is shown in table 3 below. Data from 1990 to 2019 were considered to evaluate the order of integration on both level and 1st difference. The result showed there are 3 variables uncovered non-stationary at the level. These variables turned out to be stationary at 1st difference since the null hypothesis is rejected.

Table 3: Unit root test by ADF

Variables	**Augmented Dickey-Fuller (level)**			**Augmented Dickey-Fuller (1st difference)**		
	Value of test statistic	Critical value at 5%	Result	Value of test statistic	Critical value at 5%	Result
Container	0.080593	-2.967767	Non-St.	-5.396276	-2.971853	Stationary
GDP	4.796720	-2.976263	Stationary	…	…	…
Population	-7.275870	-2.967767	Stationary	…	…	…
Import	-0.195982	-2.967767	Non-St.	-5.794617	-2.971853	Stationary
Export	-1.563206	-2.967767	Non-St.	-5.250008	-2.971853	Stationary

Note: For the variables, logarithmic of the original values have been applied.

From table 3, it is seen that there are two variables stationary at the level named GDP and Population. Container volume, Import, and Export these variables become stationary at 1st difference. This means data should be converted to logarithmic form before applying it to the equation. Since the ADF consists of linear regression, therefore, we cannot reject the null hypothesis if the data series is non-stationary, but it is rejected only if the t-statistic value is greater than the critical value in the 5% level.

4.2 Result of Co-Integration

After getting the time series data in a stationary form, we applied Johansen co-integration approach to determine the cointegrated connections among the variables. Likewise, the resulting output comes with the trace statistic and maximum eigenvalue. we found a few con-integration connections among the variables that are established by p-value (probability) subsequently. All the ratio test results are achieved from the vector error correction model (VECM). We rejected the null hypothesis when there is no co-integration at (r = 0), at a 0.05 significance level. Therefore, the null hypothesis is not counted by the λ_{max}, and trace test results. On the contrary, we could not reject the null hypothesis in these criteria where r ≤ 3,4 compared to the alternative hypothesis with the value of r = 4,5 at 0.05 significance level.

Table 4: Test of co-integration by Johansen approach.

λ_{max} (Maximum Eigenvalue)				Value of Trace	
H_0 (Null)	H_1 (Alternative)	Max-Eigen Statistic	Critical Value at 5%	Trace Statistic	Critical Value at 5%
$c = 0$	$c = 1$	42.25875*	37.16359	117.6828*	79.34145
$c \leq 1$	$c = 2$	36.44842*	30.81507	75.42403*	55.24578
$c \leq 2$	$c = 3$	23.57624	24.25202	38.97561*	35.01090
$c \leq 3$	$c = 4$	13.04650	17.14769	15.39937	18.39771
$c \leq 4$	$c = 5$	2.352871	3.841465	2.352871	3.841465

In table 4, to notify co-integration relationship among variables 'c' is used and null hypothesis denotes there is not found any co-integration connections. If the value of max-Eigen is greater than the value of trace, then we can reject the hypothesis. If there are any (*) marks it means we rejected the null hypothesis at a 5% significance level for that specific value. we have chosen the value of optimal lag length and the optimal order of vector autoregressive model was 2 (system generated by AIC). By Johansen's approach result, we found that there are 2 cointegration equations shown at a 5% level at the Max-Eigen value results and 3 cointegration equations at the same level in the trace results. So, we opine that 3 identified cointegration relationships are measured in the Johansen approach among variables at a 5% significance level. This connection among the variables specifies the significant identification of a long-run relationship.

4.3 Result of VECM

In this work, the author is encouraged to apply the VECM forecasting model because it delivers accurate estimation of container forecast and it is also mentioned by many researchers in literature in the previous forecasting studies in different ports. In some different literature, it is found that many of the researchers have used cause and effect forecasting and vector autoregressive (VAR) model to forecast container volume (Gosasang et al., 2011a). From the findings, it is noticed that forecasting results by cause and effect does not conclude with significant relationships between variables and the calculation may be incorrect if the data is not stationary. Hence, for non-stationary data vector error correction model (VECM) is more appropriate also with the advantage of co-integration connections between different macroeconomic variables (Moniruzzaman et al., 2011). Therefore, the author has applied this model to forecast long-term container throughput in Chittagong port, Bangladesh. From the co-integration result by Johansen approach, it is revealed that variables are cointegrated and have a long-run relationship, consequently, we tested VECM. The calibration of the VECM model is carried out using the Johansen procedure for the estimation period from 1991 to 2019 with the time series data. VECM estimation result is presented in table 5 below. Note that the values in CoentEq1, the 1st value is coefficient C (1), values inside the first bracket (…) are standard error, and the third bracket […] is t-statistics. If the C (1) value is negative, then it has a long-run connection between variables. Moreover, the model can be considered as a fit if the F statistic value is more than 5% and the R-squared value is greater than 60% (Kavussanos & Visvikis, 2004).

Table 5: Vector error correction estimation

Error Correction	**(Container)** A_{r-1}	**(GDP)** B_{r-1}	**(Population)** C_{r-1}	**(Import)** D_{r-1}	**(Export)** E_{r-1}
CointEq1	-1.305 (0.093) [-13.930]	-0.668 (2.594) [-0.257]	-0.0007 (0.230) [-0.110]	-0.146 (0.230) [-0.637]	0.096 (0.189) [0.509]
(TEU (-1))	0.146 (0.072) [2.028]	0.467 (2.003) [0.233]	0.002 (0.005) [0.382]	0.114 (0.177) [0.644]	-0.089 (0.146) [-0.6148]
(GDP (-1))	-0.016 (0.009) [-1860]	-0.336 (0.251) [-1.338]	-0.003 (0.0006) [-4252]	0.015 (0.0222) [0.683]	-0.0057 (0.0183) [-0.312]
(Population (-1))	11.267 (2.183) [5.160]	8.113 (60.446) [0.134]	0.909 (0.1557) [5.840]	0.299 (5.3666) [0.0558]	3.395 (4.4112) [0.769]
(Import (-1))	-0.1744 (0.1252) [-1.392]	-2.555 (3.4866) [-0.7366]	-0.0116 (0.0089) [-1.2982]	-0.0296 (0.3079) [0.7728]	0.1334 (0.3134) [-0.5984]
Export (-1))	0.09831 (0.1551) [-0.6336]	-1.6741 (4.2952) [-0.3897]	0.0029 (0.0111) [0.2688]	-0.0296 (0.3813) [-0.0777]	-0.187 (0.3134) [-0.5984]
C	-0.094 (0.0381) [-24686]	0.2943 (1.055) [0.2363]	0.0016 (0.0027) [0.5805]	0.1146 (0.0936) [1.224]	0.0728 (0.0770) [0.9461]

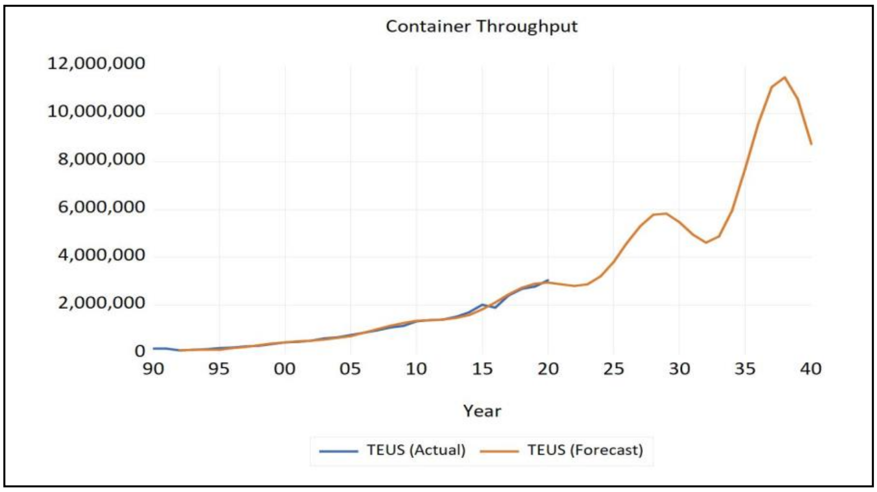
R-squared = 91.13%

F-statistic = 35.94

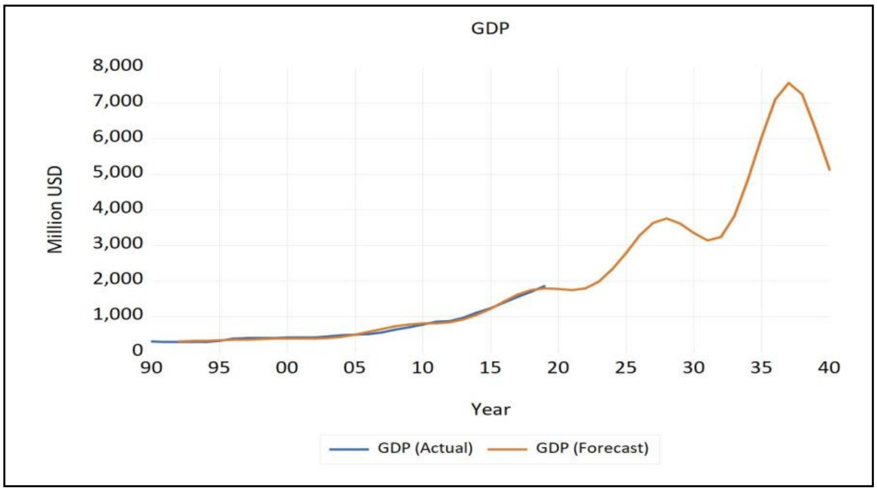
Note: In this table, A, B, C, D, and E represent Container, GDP, Population, Import, and Export. Besides, A_{r-1}, B_{r-1}, C_{r-1}, D_{r-1}, and E_{t-1} denote the coefficient matrix of lagged variables at level for the abovementioned variables, moreover, (TEU (-1)), (GDP (-1)), (Population (-1)), (Import (-1)), (Import (-1)), and Export (-1)) represent the coefficient matrix of lagged variables at 1st difference for those variables respectively. Before applying to VECM, the time series data of the logarithmic form is transferred again to its original form, the optimal lag length and optimal order of VAR was 4 that has been chosen by AIC of the VECM technique.

Source: Author

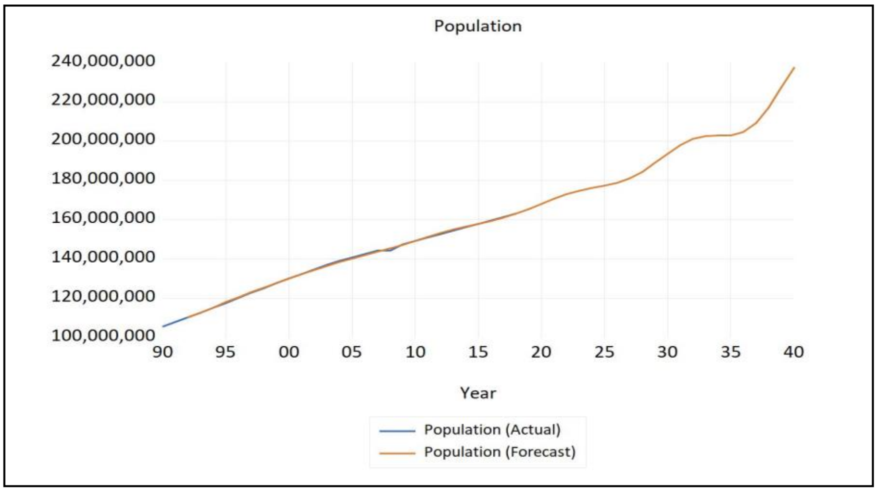
From the table 5**,** it is seen that the CoentEq1 value for C (1) is negative from Population (-0.0007), GDP (-0.668), and Import (-0.1476) to Container (-1.305), therefore we can say that Population, GDP, and Import has a long-run positive relationship to Container (TEU) than Export (0.096) to Container (TEU). On the other hand, it is observed from the estimation that the value for R-squared and F-statistic is 91.13% and 35.94 respectively which are significant therefore, these represent the VECM model as a great fit. In this model, most of the results show the long-term relationships of the real value very closely. Therefore, the forecast and actual value of the VECM model is presented below in graphs for each variable.



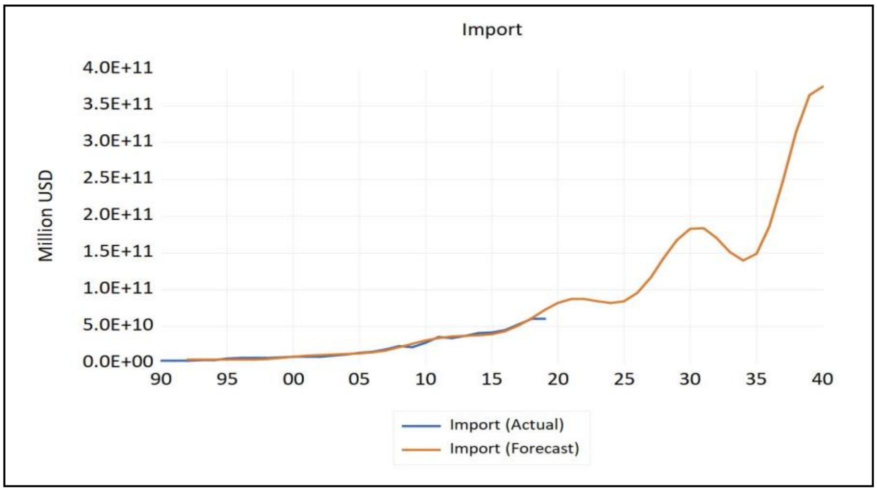
(I) Container volume in TEUs



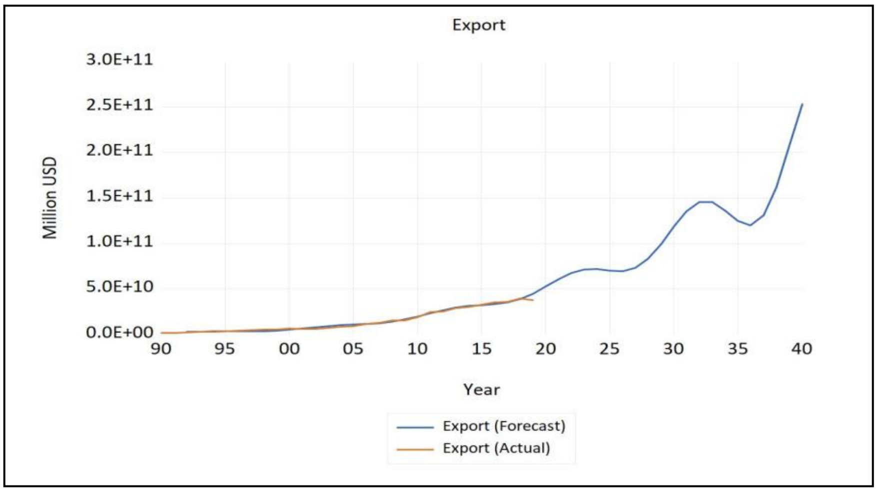
(II) GDP in Million USD



(III) Population



(IV) Import in Million USD



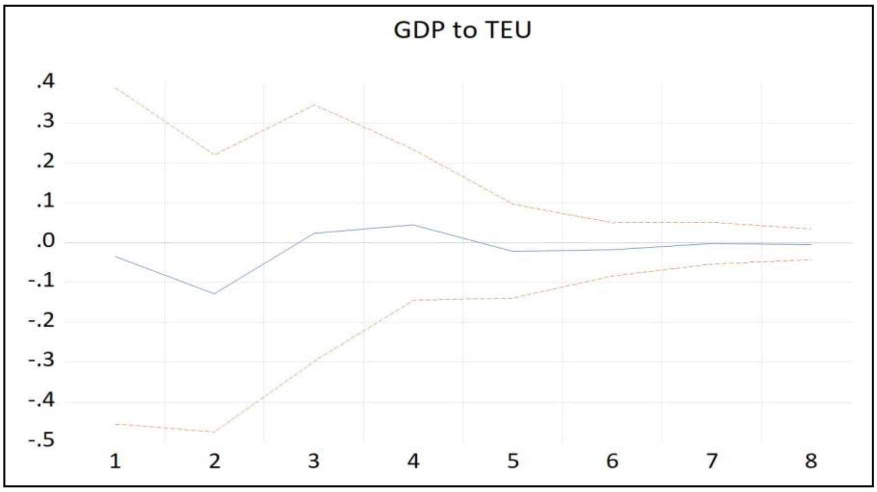
(V) Export in Million USD

Note: For the import value in the graph: 0.0E+00, 4.0E+11 refer 100 and 4000 Million (USD), on the other hand, for the export value in the graph: 0.0E+00 3.0E+11 refer 100 and 3000 Million (USD) respectively.

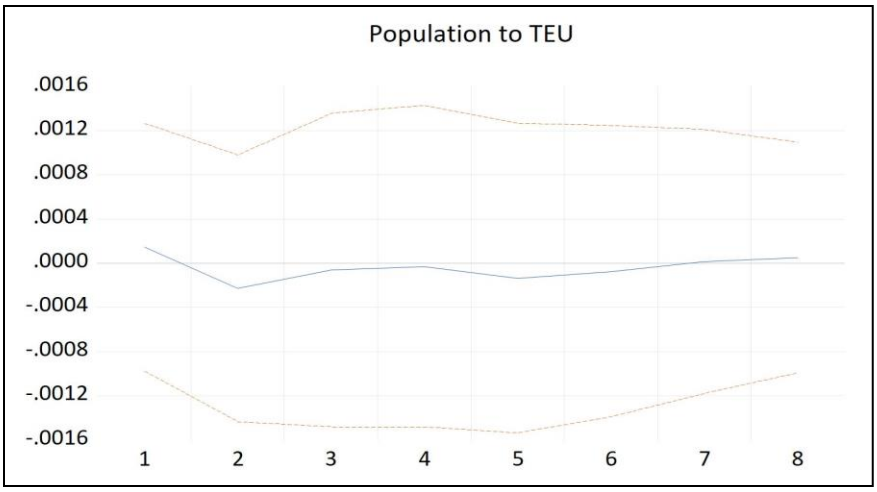
Figure 4: Forecast and actual data of the variables by VECM

4.4 Result of IRF

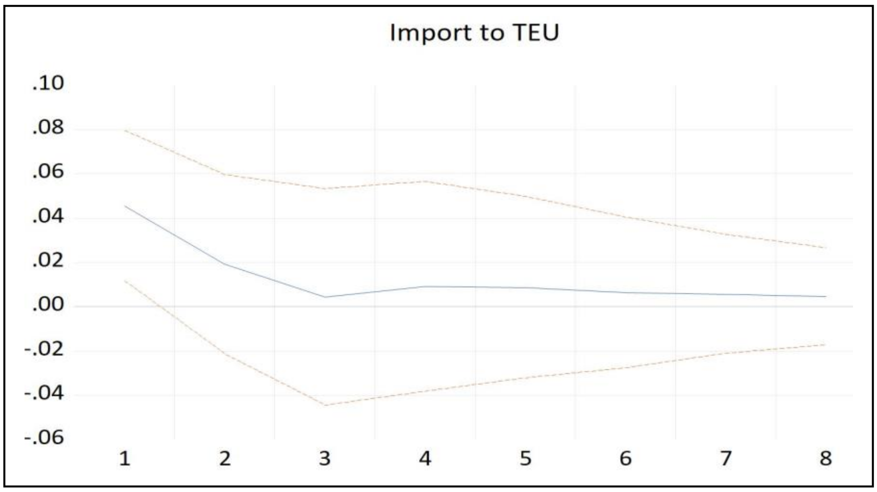
To identify a shock of one individual variable on other variables, we applied the Impulse response function (IRF) to notify if there is any response to one another. But whether there is no response to a shock of variables means the later cause the earlier. The outcome reveals that among the variables impulse response of shock exists to each other and becomes extinct after a specific period confirming the constancy of the estimated model. The figures below, it has shown the impulse response of containers (TEU) to other variables whereas the container volume shock has responded clearly to other variables with the long-run effects of 4-5 periods. From figure 5 (III) impulse response of import to TEU, and (IV) impulse response of export to TEU, it is observed that the value of import and export enacts clearly than the result of population and GDP that also denotes the increasing volume of container may have a significant impact on the outcome of import and export than other variables, population, and GDP. Additionally, it is also observed from figure 5 (I) impulse response of GDP to TEU that there is a shock of GDP to TEU that gives a clear response.



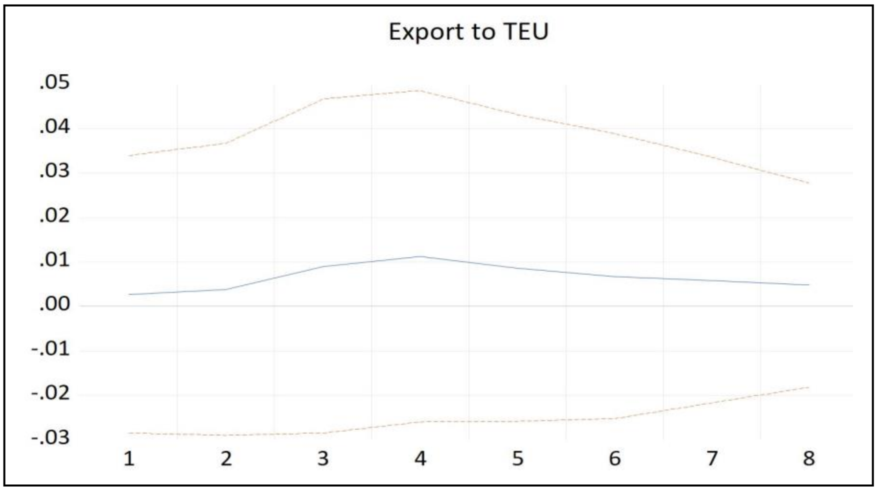
(I) Impulse response of GDP



(II) Impulse response of Population



(III) Impulse response of Import to TEU



(IV) Impulse response of Export to TEU

Note: Blue line presents the impulse response function, and the yellow lines refer to a 95% confidence interval.

Figure 5: IRF shock of variables to TEU

So, if the GDP increases in Bangladesh it may help to enhance the value of import and export that ultimately will help to raise the container throughput. From another figure 5 (II), it is seen that population growth is negative for the period of 2-5 and from 7-8, it started to increase again that refers the population growth may impact on the volume of import and export cargoes that is indirectly increasing container throughput. One of the most important indicators of economic growth is export value and in 2020, the export value for ready-made garments (RMG) in Bangladesh was 27.95 billion USD which is higher than last year (Singh, 2011). From figure 5 (IV), it is noticed that the export value of the country is always positive with significant growth so, it will help to increase the number of container throughput directly as most of the commodities are transported by Chittagong port. In a word, there will be a shock in export to have a positive response to TEU. Finally, from figure 5 (III) it is observed that import value is also always positive even though there was a slight decrease in the 1-3 periods, but it started to increase again 4-8 periods that implies the shock of import will react positively to TEU means there will be a significant impact on TEU with the increasing value of an import.

4.5 Result of Accuracy Test

We use parameters of the VECM model obtained in the previous section to forecast the container throughput. To evaluate forecasting performance, three forecast errors, MAPE, RMSE, and Theil's Inequality Coefficient are being used.

The forecasted accuracy of both RMSE, MAPE, and Theil's Inequality Coefficient is represented in table 6. The calculated accuracy result of RMSE for VECM is less than MAPE, which reveals that RMSE predicts a more accurate result. Besides, A forecast value and actual value will be a great fit if the result from Theil is close to zero (Udoumoh et al., 2016). ARIMA forecast performance becomes weak if the forecast limit rises, so the model is ineffective in identifying long-term relationships between variables (Simone, 2000). Consequently, to identify the best model SARIMA is compared with VECM as SARIMA is one of the most used models in container throughput forecast (Farhan & Ong, 2018). SARIMA performs better in long-term forecasting (Chen & Chen, 2010a). SARIMA predicts better forecasting result in cargo throughput (Rashed et al., 2018).

Table 6: Forecast evaluation

Test of variables (VECM)				**Comparison between models**		
Variables	**RMSE***	**MAPE**	**Theil**			
TEU	0.04572	0.23926	0.02910	TEU		
GDP	0.91334	2.67179	0.02877	**Criteria**	**VECM**	**SARIMA**
Population	0.00381	0.01598	0.00153	RMSE	0.04572*****	109960.5
Import	0.13459	0.45899	0.05227	MAPE	0.23926*****	9.463640
Export	0.11641	0.41700	0.04178	Theil	0.02910*****	0.043069

Note: Data series is taken in the natural form of the logarithm. (*) indicates the value is more accurate. The accuracy test of SARIMA is also presented in appendix (E).

Source: Author

From the forecast evaluation, it is found that the Theil value is equivalent to zero, therefore, it indicates that the forecast value for TEU, GDP, Population, Import, and Export are almost close to the actual values and it identifies the model as a perfect one for long-term container forecasting. In a nutshell, the VECM model performs better in long-run forecasting of container throughput at Chittagong Port.

4.6 Result of Forecasted Container Throughput

In this study, we only showed container forecasting throughput from 2020 to 2040 to achieve the objective of the long-term forecast of container volume at CPA by using a vector error correction model, and from the result, a few statements are pointed out. Macroeconomic variables are considered for the study are Container, GDP, Import, and Export values. In this research, we applied the same process to forecast and generate time series data throughout a specific period of 2020 to 2040. We have identified the last time-series data as the beginning value to get the result of the forecasting value, ΔZ_{r+1}. Moreover, Z_{r+1}, and (r+1) represent the model estimation and forecasting year, respectively. The forecasting result is shown in figure 6 and from this graph it is seen that container throughput increases from 2.95 Million TEU in 2020 to 8.73 TEU in 2040 and the regular growth rate is observed 8.9% every year.

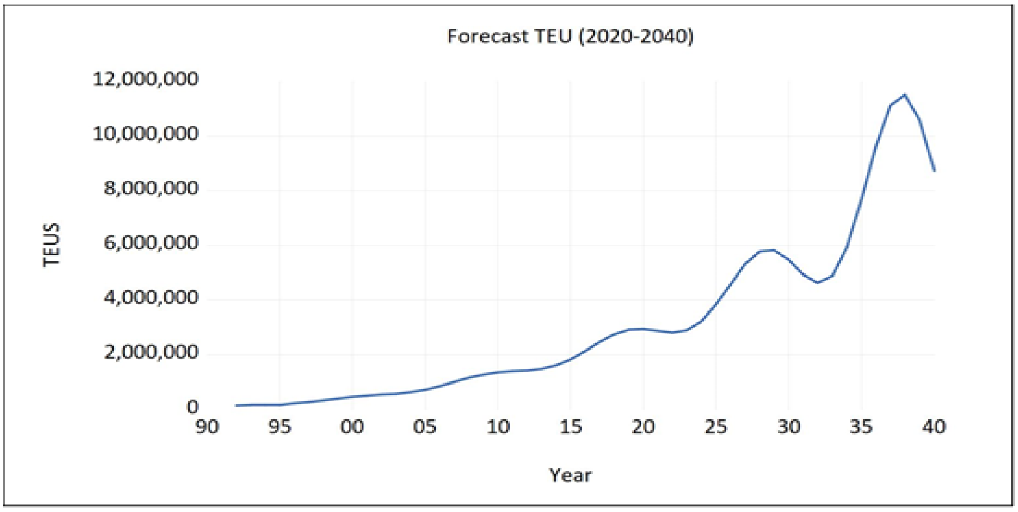


Figure 6: Forecasting of TEU at CPA (2020-2040)

On the contrary, the average growth rate was 13.16% annually from 1991 to 2019 considering the actual value. Thus, in the first two decades, the growth rate 13.16%, and last two decades 8.9% growth rates are close to each other to notify the forecasting result acceptable.

5. Conclusion and Recommendation

5.1 Summary of Research Findings

The potential growth of containerized cargo in Bangladesh has forced Chittagong Port Authority (CPA) to improve their performance and technical facilities, and the construction of new deep-sea Payra port. But at first, we need to consider the volume of container demand at CPA for the future before applying a new expansion strategic plan. To generate revenue from a future project long-term forecasting of container volume is a must in the development of a port. Therefore, this research will sort out the demand for container throughput in the next 20 years till 2040 at CPA. Vector Error Correction Model (VECM) is used to do the research work, meanwhile, to find out the stationarity of the time series data Augmented Dickey-Fuller (ADF) test is applied. Besides, we had to apply the Johansen approach to identify the number of cointegrations between dependent and independent variables. Lately, we used the Impulse Response Function (IRF) to see if there is any shock in the response of one variable to other variables. It is observed through potential forecasting results that pragmatic assessment reveals the best fit of the model by developing the long-term advancement of the actual data series close to each other. There is another example of the constancy of the forecasted results is the (IRF) test. We found the response of shock of independent variables to TEU and disappears after a while. Additionally, forecasting container throughput at CPA generated by VECM indicated a satisfactory result, and three accuracy measures were considered to test the accuracy of the model. In 2020, we estimated container throughput is 2.95 Million TEU which is equal to KC consultants with their study projection in 2013.

Finally, in 2040, our forecasted container volume is 8.73 Million TEU with an average annual growth of 8.9%. Therefore, Chittagong Port Authority can execute the best strategy by expanding or managing the port container terminal as it cannot handle such a huge container demand with its existing facilities.

5.2. Implication for Port Capacity

Development of port capacity is a crucial strategy for the improvement of a new port with the existing ones, whereas both operate the same hinterland connectivity with various competitive situations (Luo et al., 2012). In many cases, the port exposed capacity may not be a limitation of the production system and container throughput may be greater than the capacity design (Luo et al., 2012). Besides, if a port handles container volume to its capacity, it invites congestion cost that requires port capacity expansion mandatory (Olivier & Slack, 2006). In a previous study, from an informal assessment of few efficient ports revealed that because of active investment in either port infrastructure or equipment, ports become inefficient (Lagoudis et al., 2017). Even though Chittagong port is technically an efficient port in short-term without investing actively in port resource but in the long-term it suffers in terms of service level (Ziaul Haque Munim, 2020). So, the strategic decision should be based on both technical efficiency scores and service level, respectively. Besides, the port capacity in Chittagong port has become so important to meet the present demand of (20000-25000TEU per day) that the port infrastructure construction should be developed in advance. Therefore, port authority should focus on long-term forecast of container throughput and modify port extension projects yearly. CPA also can cooperate with highly efficient neighbouring ports as well as to improve the efficiency scale, various terminals can adopt a group of logistics services between efficient and inefficient terminals based on their existing returns to scale (Ziaul Haque Munim et al., 2019).

5.3 Implication for Port Governance Policy

The government and major stakeholders are responsible to decide over major port development projects (Luo et al., 2012). However, while Bangladesh government organizes the discussion and give permission for the development proposal, therefore, CPA invests heavily in the infrastructure development and invites other terminal operators at different jetties for the operation. The operation at different jetties is made by the private operators themselves.

Though Terminal Handling Charges (THC) are publicized against shippers, the main allegations between carriers and terminal operators are kept in secret. So, even though actual charges of port and terminal do not exist, it is sure that each terminal are run in a system that boosts its profit margin. Besides, at CPA, another key point for the port authority is that a private operator should not take over both NCT (New Mooring Container Terminal) and CCT (Chittagong Container Terminal), or even if they are taken by two different parties should not collaborate otherwise it will generate lower surplus (Ziaul Haque Munim et al., 2019). So, to increase the total surplus, autocratic price fixing policy must be avoided. At CPA, By Annual Development Plan (ADP) to implement a project five-year plan is taken into consideration. Besides, it takes on an average of 3 years to approve a project by the government. It is said that at least 33 signatures are needed to release an import container from CPA (Begum, 2003). This is one of the main reasons for the long dwell time and congestion of import containers in the port. This poor governance policy hampers effective communication in the port operation. So, CPA should implement a transparent governance policy for their port users and stakeholders.

5.4 Implication for Port Pricing

When a monopoly firm confronts a different player in the market as per the economic theory, it can adopt a pricing strategy or extend capacity to protect its market status (D. C. Wilson, 1992). In a duopoly market for the price competition, how different assumptions on demand, cost, and product diversity lead to various Nash equilibrium price is discussed by (Baye & Kovenock, 2008). They mentioned having various products and linear demand, each firm can charge different prices and gain a linear-sloped positive profit. Same result is also shown by (Cheng & Holyoak, 1985). At CPA, a cheap and good pricing system should be developed and operated. The billing of port services should be transparent for the port users. Besides, a tariff structure must be clear, simple, and easily understandable so that port users can assess the different types of service modules also mitigate the uncertainty in long-term business planning.

From the supplier's point of view, it is mentioned that any good pricing system allows a proper re-allocation of benefits (Frechtling, 2012). Agency theory with game theory can give new perceptions in port pricing and concessions studies (Z. H. Munim & Saeed, 2016). Therefore, CPA also can apply a comparative static analysis to analyse the changes in throughput, price, and profit with respect to capacity, demand, and pricing sensitivity.

5.5 Further Study Scopes

Since this study was done only considering container volume at CPA from 1990-2019, therefore, it would be an interesting research work if any researcher incorporates the bulk cargo volume and forecast for future demand. There could be another fascinating study if anyone includes other ports, such as Mongla Port with CPA, and forecast long-term cargo/container throughput for Bangladesh as a whole.

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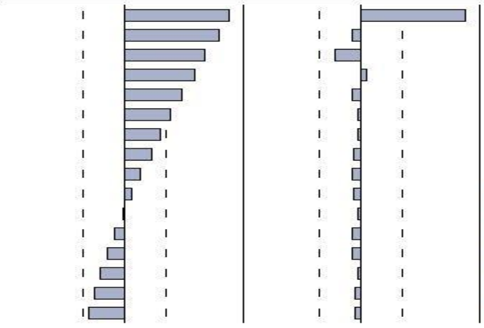
Appendices

Appendix A

Auto and partial co-relation among variables

Date: 01/24/21 Time: 17:56
Sample: 1990 2019
Included observations: 30



	AC	PAC	Q-Stat	Prob
1	0.917	0.917	27.847	0.000
2	0.829	-0.079	51.387	0.000
3	0.711	-0.229	69.378	0.000
4	0.610	0.047	83.132	0.000
5	0.503	-0.081	92.842	0.000
6	0.408	-0.023	99.500	0.000
7	0.317	-0.025	103.69	0.000
8	0.231	-0.063	106.03	0.000
9	0.146	-0.069	107.00	0.000
10	0.063	-0.063	107.19	0.000
11	-0.013	-0.026	107.20	0.000
12	-0.086	-0.066	107.59	0.000
13	-0.155	-0.069	108.95	0.000
14	-0.215	-0.021	111.71	0.000
15	-0.268	-0.052	116.32	0.000
16	-0.314	-0.044	123.07	0.000

Appendix B

Co-integration test result in EViews application

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.790941	117.6828	79.34145	0.0000
At most 1 *	0.740745	75.42403	55.24578	0.0003
At most 2 *	0.582384	38.97561	35.01090	0.0179
At most 3	0.383196	15.39937	18.39771	0.1251
At most 4	0.083454	2.352871	3.841465	0.1251

Trace test indicates 3 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.790941	42.25875	37.16359	0.0120
At most 1 *	0.740745	36.44842	30.81507	0.0092
At most 2	0.582384	23.57624	24.25202	0.0613
At most 3	0.383196	13.04650	17.14769	0.1794
At most 4	0.083454	2.352871	3.841465	0.1251

Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Appendix C

VECM output in EViews Application

Vector Error Correction Estimates
Date: 01/28/21 Time: 14:35
Sample (adjusted): 1984 2002
Included observations: 19 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
EXPORT(-1)	1.000000
GDP(-1)	-0.639175 (0.04265) [-14.9853]
IMPORT(-1)	2.020740 (0.21234) [9.51662]
POPULATION(-1)	8.73E-05 (0.00012) [0.75469]
TEU(-1)	-0.004784 (0.00112) [-4.27420]
C	3017.077

Error Correction:	D(EXPORT)	D(GDP)	D(IMPORT)	D(POPULA...	D(TEU)
CointEq1	-0.055906 (0.07316) [-0.76421]	3.840656 (0.53938) [7.12053]	-0.006399 (0.10313) [-0.06205]	0.717677 (14.2236) [0.05046]	11.29705 (5.08066) [2.22354]
D(EXPORT(-1))	-0.144387 (0.25157) [-0.57394]	0.173667 (1.85484) [0.09363]	0.016716 (0.35465) [0.04713]	-3.580856 (48.9128) [-0.07321]	-1.215166 (17.4716) [-0.06955]
D(GDP(-1))	0.041723 (0.03487) [1.19638]	1.416692 (0.25713) [5.50962]	0.126371 (0.04916) [2.57040]	-1.306666 (6.78063) [-0.19271]	12.20508 (2.42204) [5.03918]
D(IMPORT(-1))	0.051562 (0.16043) [0.32141]	-0.796136 (1.18281) [-0.67309]	0.075668 (0.22616) [0.33458]	-2.506184 (31.1912) [-0.08035]	-53.13886 (11.1415) [-4.76946]
D(POPULATION(-1))	-0.000486 (0.00148) [-0.32720]	0.072513 (0.01095) [6.62425]	0.001809 (0.00209) [0.86415]	0.748307 (0.28866) [2.59231]	-0.306170 (0.10311) [-2.96934]
D(TEU(-1))	0.003111 (0.00125) [2.49663]	0.019888 (0.00919) [2.16503]	0.003032 (0.00176) [1.72648]	-0.015683 (0.24224) [-0.06474]	-0.488737 (0.08653) [-5.64830]
C	3047.062 (4589.25) [0.66396]	-209746.4 (33836.5) [-6.19883]	-5527.149 (6469.62) [-0.85432]	730302.2 (892281.) [0.81847]	1204872. (318722.) [3.78032]
R-squared	0.706766	0.837344	0.774883	0.539998	0.934209
Adj. R-squared	0.560149	0.756017	0.662325	0.309997	0.901313
Sum sq. resids	42806077	2.33E+09	85070574	1.62E+12	2.06E+11
S.E. equation	1888.696	13925.33	2662.558	367216.5	131169.5
F-statistic	4.820493	10.29592	6.884280	2.347809	28.39915
Log likelihood	-165.9235	-203.8821	-172.4481	-266.0547	-246.4949
Akaike AIC	18.20247	22.19812	18.88927	28.74260	26.68368
Schwarz SC	18.55042	22.54607	19.23722	29.09055	27.03163
Mean dependent	2107.421	5371.579	660.8421	2857944.	226658.2
S.D. dependent	2847.799	28191.96	4581.942	442075.9	417544.6

Determinant resid covariance (dof adj.)	4.65E+41
Determinant resid covariance	4.67E+40
Log likelihood	-1024.426
Akaike information criterion	112.0449
Schwarz criterion	114.0332
Number of coefficients	40

Appendix D

The accuracy test result of the model (VECM) in EViews

Forecast Evaluation
Date: 01/30/21 Time: 23:48
Sample: 1990 2040
Included observations: 51

Variable	Inc. obs.	RMSE	MAE	MAPE	Theil
EXPORT	30	1.68E+09	1.14E+09	12.38519	0.041775
GDP	29	49.13930	42.28253	6.817621	0.028772
IMPORT	30	3.03E+09	2.02E+09	13.57861	0.052273
POPULATION	30	426770.3	335873.4	0.241685	0.001527
TEUS	30	75726.51	52666.40	6.462108	0.029100

RMSE: Root Mean Square Error
MAE: Mean Absolute Error
MAPE: Mean Absolute Percentage Error
Theil: Theil inequality coefficient

Appendix E

The accuracy test result of the model (SARIMA)