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Handling Short Run Disequilibrium in Freight Demand Forecasting at Major Indian Ports Using Error Correction Approach

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Abstract

The freight movements through Indian ports in the last decade have been significant; however, scientific investigations in estimating future freight traffic at these ports have been missing in the existing literature. This paper forecasts freight flow at major ports in India by estimating cointegrated error correction model. This approach is simple, yet comprehensive, which considers the short run disequilibrium in freight movements, while forecasting the future demand. The models are estimated by using annual port freight data from years1980–81 to 2013–14. Sensitivity analysis is carried out for three possible growth scenarios: high, low and baseline growth. The comparison between the model forecast and Ministry of Shipping, India projections showed that, lower error is associated with the proposed model. The model is used to predict the freight volume for 11 major ports in India till the year 2025–26. This study has important implications towards infrastructural requirement decisions of the Indian major ports such as construction of new terminals, providing better road access to ports, etc. The study will be also beneficial to shipping companies to build their investment scenarios.

Keywords: Indian major ports, error correction model, demand forecast, freight volume

1. Introduction

There are 13 major ports in India and the coastline is spanning about 7516 Kilometres along east and west coast. The major ports are Kolkata, Paradip, Visakhapatnam, Chennai, Tuticorin, Cochin, New Mangalore, Mormugao, Mumbai, JNPT, Ennore, Kandla, and Port Blair. The major ports in India play a crucial role in overall development of national economy as the Indian marine transport carries almost 95% by volume of the country's international trade. The Government of India through its 'Maritime Agenda 2010-2020" (MA10-20) program is focusing more on port development, specifically for their operation and status in the international domain. Because the freight throughput could reflect the status of a port (port systems) comprehensively,

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analyzing economic factors with freight movements and developing an appropriate demand model for future demand is indeed necessary for port planning. Through MA10-20 program, the Government has planned for future developments in Indian port sector to raise the port performance at par with global standards (Dynamic Role of Government must for Port Development 2014). The future port facility developments for Indian port sector require large and irreversible investments and given the scale of investment, accurate estimation of freight flow is the central theme for such investments.

Accurate projections of freight movements will not only help in allocating such investment systematically for the expansion of Indian port infrastructure, but also further help in operational improvements. The Ministry of Shipping (MoS)published the forecasts volume till 2019–20 for all the major ports in India to ensure the port facilities to be developed for meeting the future freight demand(Maritime Agenda: 2010–2020 2011). The Transport Research Wing (TRW) of MoS used the standard regression analysis to project the freight volume till 2020. However, the forecast errors associated for the recent years are significant. For example, the actual freight movement through Kolkata port was 41.39 million tons, whereas the MA10–20 forecast was 63.72 million tons (53.9% overestimated) for the year 2013–14. Similarly, for Paradip port the projected value (79.4 million tons) was over estimated by 16.8%, while the actual freight value was 68 million tons during 2013–14. Another port Cochin's freight volume was overestimated by 62.5% for the same year. Consequently, an improved estimation approach is needed to produce freight forecast at Indian ports. Additionally, port policy makers in India require accurate cargo forecast to make decisions on overall port planning process, terminal construction, berth location selection, port operation strategies, and etc. Interestingly, scientific study on freight movements for Indian ports has been missing in the available sample of literature. In addition to the MA10-20, the only studies available on freight demand estimation are Sahu and Patil 2013; Sahu and Patil 2014; Patil and Sahu, 2015. Some of the past studies on Indian ports (Haralambides and Gujar 2012; Panigrahi and Pradhan 2012; Raghuram and Shukla 2014; Sahu, Sharma, and Patil 2014) restricted the analysis to historical, social, port classification, and maritime policy aspects.

The forecast of port freight influences investment policies of the Government, shipping companies, and terminal operators. Port throughput has a strong effect on regional economy development (Seabrooke, et al. 2003). Therefore, freight movement pattern is of great interest to Government, agencies, institutions, and researchers. Developing accurate freight prediction models are important to port and port users because of two primary reasons. The two reasons are: (1) positive growth of freight flow in the future years will enable the port to achieve higher profit. It will also give an insight to shipping companies for investment expansion in order to maintain their market share; (2) slower growth in freight movements will help the shipping companies to implement conservative investment scenarios so to minimize the operational cost.

Although, scientific review of literature reported several forecast models for port throughput, most of the models are not robust to produce accurate forecast when certain short term irregular event occurs. This paper discusses about freight movement projections for Indian major ports with cointegrated error correction modelling mechanism (ECM). The ECM approach minimizes the short run disequilibrium error associated with demand estimation. The present study is limited to 11 major ports excluding Ennore and 'Port Blair' ports due to data unavailability.

The remaining of the article is structured in seven sections out of which this is the first. The related past research is presented in section 2. In section 3, a concise description of the study data is provided. The model specification is discussed in section 4. The model estimation and validation are covered in section 5. This section is followed by section 6, where sensitivity analysis is discussed along with long term freight flow projections. Eventually, section 7 concludes the article.

2. Background

The classical regression analysis is the most popular method (Woo, et al. 2011) used in port freight forecasting; which analyzes and quantifies causal relationship between variables (e.g., freight flow with GDP). Coto-Mill'an, Baños-Pino, and Castro (2005) explained the determinants of marine exports and imports using such models. Seabrooke, et al. (2003) predicted the Hong Kong port freight movement using regression models. They used macro-economic parameters to project the future freight. Dorsser, Wolters, and Wee (2012) forecasted the freight flow based on a combination of system dynamic modeling, judgment, and causal relations at Le-Havre port, France. They developed log linear regression models to forecast the seaborne freight. Peng and Chu(2009) developed six univariate forecasting models (SARIMA model, grey model, trigonometric regression model, hybrid grey model, regression model with seasonal dummy variables, and classical decomposition model) to predict container volumes at three major ports in Taiwan. They compared the results from all six models and concluded the classical decomposition model is producing more accurate forecasts in their case.

Chou, Chu, and Lian (2008) utilized a modified regression approach to predict container volumes for Taiwan's import. This approach was used to modify the errors resulted from the non-stationary contribution coefficient in the prediction model. They concluded that the total forecast error is lower in the case of modified regression model. Some other researchers focused on trend extrapolation of historic time series such as autoregressive integrated moving average (ARIMA) models (Klein 1996), vector autoregressive models (Veenstra and Haralambides 2001), grey models (Guo, Song and Ye 2005), and neural networks (Weiqun and Nuo 2003; Chen and Chen 2010). Al-Deek et al. (2000) predicted seasonal variations in freight movement at Miami port with the use of ARIMA models. Chou, Lee, and Lin (2003) analyzed container volumes at Kaohsiung harbour by means of time series models (SARIMA). Schulze and Prinz (2009) forecasted container shipment in Germany using ARIMA model.

Artificial neural network (ANN) and multiple regression analysis are utilized to develop freight prediction models for Miami, Jacksonville, and Florida ports in the United States (Al-Deek, et al. 2000; Klodzinski and Al-Deek 2003). The models are then used to estimate daily inbound (outbound) truck trips for these ports. Klodzinski and Al-Deek (2003) concluded that ANN is more flexible and accurate tool for predicting truck trips resulting from seaport freight movement. Liang and Chou(2003) suggested a new fuzzy regression model by combining regression analysis and traditional fuzzy set theory to forecast the export/import freight volume at Taiwan's ports. In another study, Lam, et al. (2004) forecasted 37 different freight movements using neural network at Hong Kong port.

Liu, et al. (2007) studied Shanghai port container throughput using 'radial basis function neural network (RBFNN)' by combining a cubic polynomial curve model, and a grey model. The RBFNN forecast method produced more accurate results than both the individual model. Chen and Chen (2010) used genetic programming (GP) for predicting the container throughput at three Taiwan ports: Kaohsiung Port, Keelung Port, and Taichung Port. They compared the results from GP model with X-11 (a time series decomposition model) and SARIMA model. Although, all models predictions values are good, the GP model offered the lowest error (35% lower than the other models). They concluded GP is the optimal approach for container volume projection in Taiwan.

On Indian port freight movements, only few recent studies conducted by the same authors are found in the literature. In a study on Mumbai port, Sahu and Patil (2013, 2015) developed univariate and multivariate regression models to predict annual freight volume at Mumbai port based on national macroeconomic indicators. Annual inbound and outbound data from 1950–51 to 2013–14 were used for estimating the models. They found multivariate linear regression models are producing more accurate forecasts. They used the models to forecast the cargo volume at Mumbai ports till the year 2017–18. In another study (Sahu and Patil 2014) on Indian ports, they used eleven years monthly time series freight flow data to estimate monthly projections. Ministry of Shipping, India also uses classical regression to forecast port freight volume for Indian ports.

Although, literature supports the use of regression models for port freight forecast, the standard regression model fails to give accurate projections, when there is a change in 1) port operation policy, 2) global market conditions, 3) infrastructure, and etc. For example, Mormugao port in India experienced sudden sharp reduction in freight activities from the year 2011–12 because of the change in Government's policy on iron ore exports. In other words, in case of short run disequilibrium of the freight flow, it is needed to adopt certain alternative approaches for more precise prediction. In such situations, an appropriate model structure needs to incorporate the short run disequilibrium and predict the future cargo demand with lowest error. The error correction models (Engle and Granger 1987; Hui, Seabrooke, and Wong 2004; K. Fung 2001; M. K. Fung 2002; Sargan 1984) are found to be useful in the short run disturbance situation. This modeling mechanism is adopted for the present study.

3. Data

The most recent annual freight flow data for the 11 major ports are available to us from the fiscal years 1980–81 to 2013–14. Figure 1 shows the freight growth at all the study ports. There is continuous growth for almost all the ports. However, there is reduction in freight volume for Mormugao (M), Kolkata (K), and Chennai (C) in the last 2–3 years. There is sharp decline in Mormugao volume due the Government's restriction for iron ore export. Although this policy has affected Kolkata and Chennai's freight tonnage, the impact is not that significant as in case of Mormugao. The annual freight flow can be related to India's macroeconomic conditions based on the assumption that these conditions are the primary determinants for port freight forecast. Data related to macroeconomic variables like national GDP, foreign trade, export, import, etc. were obtained from reserve bank of India, centre for monitoring Indian economy data bases.

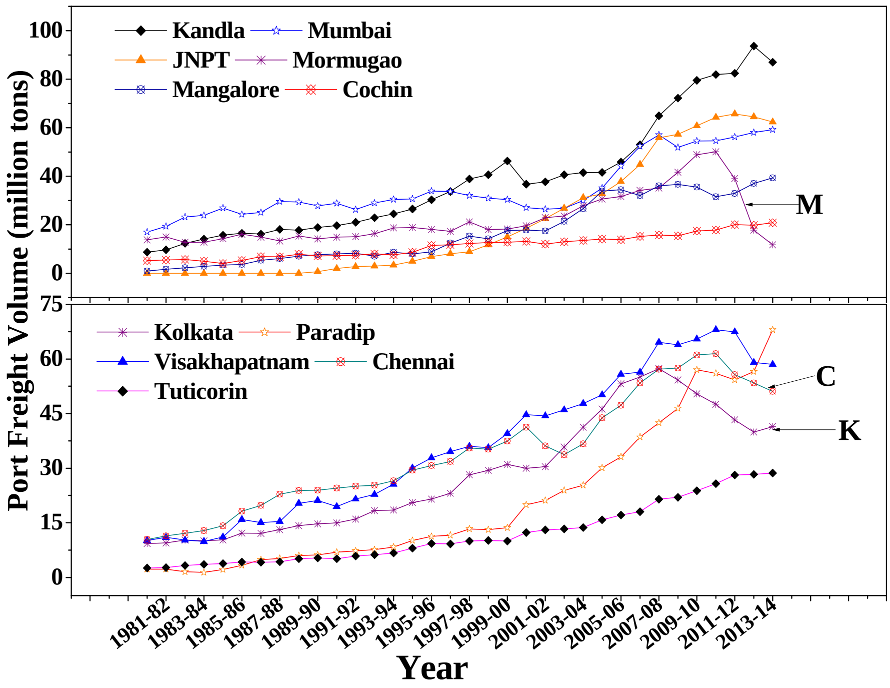

Figure – 1: Freight growth at major ports during the study period

The above mentioned sets of explanatory variables are tested for multicollinearity using Pearson's correlation coefficient test in MinTab16.0.The test results are presented in Table 1. The values within brackets are p-values. Test results show that all the variables are highly collinear. Further, it is found that freight flow at any port has stronger association with GDP as compared to the remaining variables. Therefore, GDP is considered as the independent variable for forecasting the port freight. Figure 2 clear shows the linear relationship between GDP and port volume.

Table – 1: Pearson's correlation test

	GDP	Foreign Trade	Export	Import
GDP	1.000 (0.000)	0.949 (0.000)	0.952 (0.000)	0.946 (0.000)
Foreign Trade		1.000 (0.000)	0.999 (0.000)	0.999 (0.000)
Export			1.000 (0.000)	0.997 (0.000)
Import				1.000 (0.000)

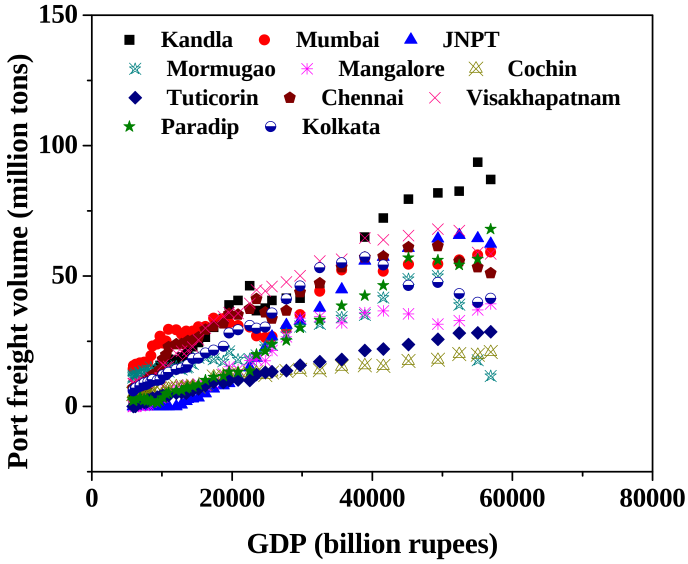

Figure – 2: Association of port volume with GDP

4. Error correction model

Classical regression explains the association between a set of variables and this approach is valid in case of a stationary data set. In situations, where the data set are non-stationary, classical regression fails to produce accurate predictions. The possible reason for this is that, the independent variables create illusion of causal relationships under the common trend of all the variables, while they are included in the model. This is referred as spurious regression, where estimation is done with unrelated variables.

In such situations, where the data set is non-stationary, the commonly adopted approach is to use the first differenced data set instead of using the original series. In the estimation process, the changed value from a particular period to the next period enters into the model. But, the error term might experience serial correlation with such modified model specification. In addition, the modified model only considers the short term adjustments describing the correlation between the changes of a variable with the change of other variable. It ignores the long term relationship between the non-differenced actual data, and in this process there is a high probability of losing vital information present in the original data. To overcome such problems, researchers in the past have suggested alternate approaches. One such approach known as cointegration was proposed by Engle and Granger (Engle and Granger 1987). In cointegrated models, although each individual variable is nonstationary; the linear combination of all the variables is stationary (I(0)). Statistically, two or more variables with stochastic trend will be cointegrated, if they have long-term or equilibrium relationship. Although, the cointegrated model represents the long term relationship, there may be disequilibrium in short-run. Therefore, the equilibrium errors need to be treated further and this error term can be corrected for short run behaviour prediction using Error Correction Mechanism (ECM). ECM was first used by Sargan (Sargan 1984) and later popularized by Engle and Granger (1987) as short run disequilibrium correction. The model specification used for the present research is discussed in the subsequent sub-section.

4.1 Error correction model specification

The long term cointegrated relationship between a set of variables measured at time *t* for space *i* can be given as shown in Eq.1.

$$[Y_{t,i}] = [A_i] + [B_i][X_{t,i}] + [\epsilon_{t,i}] \qquad (1)$$

Where, A_i = Regression intercept; B_i = Regression coefficient; $\varepsilon_i \sim N(0,\sigma_\varepsilon^2)$

The error correction model specification for short run relationship for the above long run model takes the following form as in Eq.2.

$$[\Delta Y_{t,i}] = [A'_i] + [B_{0,i}][\Delta Y_{t-p,i}] + [B'_i][\Delta X_{t,i}] + \alpha[\epsilon_{t-1,i}] + u_{t,i}z \qquad (2)$$

Where, $\Delta Y_{t,i} = Y_t - Y_{t-1}$; $\Delta X_{t,i} = X_t - X_{t-1}$. It may be noted that this short run model represent the lag 1 differenced variations of the long run model. Additionally, the error associated at lag 1of the dependent variable is used as another explanatory variable in this model form. The differenced specification helps in removing the trending component of the variables to show how changes of the explanatory variables are related to the response variable.

4.2. Model diagnostics

As already discussed in section 3, it was found that the linear association between port freight and national GDP is very high. Therefore, the following model form is proposed through model M1.

Model M1:

$$\widehat{PPF}_{p,yr} = a_0 + \beta_1 GDP_{yr} + \varepsilon_p \qquad (3)$$

Where, $\widehat{PPF}_{p,yr}$= Projected port freight in million tons for port *p* in the year *yr*.
GDP_{yr} is the national gross domestic product in billion rupees for the year *yr*.

4.2.1 Model specification test

Ramsey(1969) suggested a statistical test to check the correct functional form of the regression equation. This test is known as Ramsey's regression equation specification error test (RESET) (refer Gujarati and Sangeetha 2010 for more details).This test is conducted for the proposed model form for the present study. The test results are reported in Table 2.

Table – 2: RESET results for model M1

Port	Variable	Coefficient	*t*-stat.	*p*-value	Implication
Kolkata	$\widehat{PPF_p}^2$	-0.059	-10.28	0.000	Misspecification
Paradip		-0.003	-0.21	0.838	No Misspecification
Visakhapatnam		-0.027	-15.51	0.000	Misspecification
Chennai		-0.028	-6.12	0.000	Misspecification
Tuticorin		-0.007	-3.51	0.002	Misspecification
Cochin		-0.043	-3.42	0.002	Misspecification
New Mangalore		-0.032	-5.86	0.000	Misspecification
Mormugao		0.004	0.57	0.577	No Misspecification
Mumbai		-0.002	-0.29	0.776	No Misspecification
JNPT		-0.005	1.19	0.248	No Misspecification
Kandla		-0.003	-0.18	0.862	No Misspecification

The above test results suggest that the proposed model is correctly specified for five ports such as: Paradip, Mormugao, Mumbai, JNPT, and Kandla. For the remaining ports, the model specification appeared to be wrongly specified. Therefore, a log-linear model specification M2 is considered for the ports: Kolkata, Visakhapatnam, Chennai, Tuticorin, Cochin, and New Mangalore. The model is presented below.

Model M2:

$$\widehat{lnPPF}_{p,yr} = a_0 + \beta_1 lnGDP_{yr} + \varepsilon_p \qquad (4)$$

RESET is carried out for M2 and the test results are presented in Table 3. The results confirmed model M2 specification is correct for the earlier mentioned ports.

Table – 3: RESET results for model M2

Port	Variable	Coefficient	*t*-stat.	*p*-value
Kolkata	$\widehat{lnPPF_p}^2$	-0.464	-1.49	0.216
Visakhapatnam		-0.454	-1.14	0.492
Chennai		-0.442	-1.26	0.258
Tuticorin		-0.128	-1.24	0.234
Cochin		-0.462	-1.03	0.428
New Mangalore		-0.318	-1.04	0.356

4.2.2 Test for cointegration

The Augmented Dickey-Fuller (ADF) test (Gujarati and Sangeetha 2010) is used for checking the order of integration. The ADF test is carried out using SAS9.2 for each port freight flow and national GDP. The summary of the ADF test statistics are given in Table 4.

Table – 4: ADF test statistics for testing cointegration

Variables	ρ	τ-stat	p-value	Integration order
$\widehat{PPF}_p$	(-62.52,-20.27)*	(-6.48,-3.62)	(0.001,0.043)	I (3)
$\widehat{lnPPF}_p$	(-110.92,-14.661)	(-5.21,-3.75)	(0.001,0.045)	I (2)
GDP	-23.19	-7.45	0.008	I (3)
$lnGDP$	-19.82	-4.53	0.012	I (2)

**The values within brackets are the values within which the test statistics for all ports lies. ρ is the lagged correlation between freight flows for a particular port. τ test statistics is the equivalent t-test statistics. For more details on ADF test, refer to Gujarati and Sangeetha, 2010.*

The test results confirmed that the model forms are cointegrated. Therefore, M1 can be used as long run model for Paradip, Mormugao, Mumbai, JNPT, and Kandla. Similarly, M2 can be used long run model for Kolkata, Visakhapatnam, Chennai, Tuticorin, Cochin, and New Mangalore. The short run model specification for M1 and M2 can be written as follows as presented in M3 and M4.

Model M3:

$$\widehat{\Delta PPF}_{p,yr} = a_0 + \beta_0 \Delta PF_{p,yr-p} + \beta_1 \Delta GDP_{yr} + \alpha\varepsilon_{p,yr-1} + u_{yr} \qquad (5)$$

Model M4:

$$\Delta \widehat{lnPP}F_{p,yr} = a_0 + \beta_0 \Delta PF_{p,yr-p} + \beta_1 \Delta lnGDP_{yr} + \alpha\varepsilon_{p-1} + u_{yr} \qquad (6)$$

5. Model estimation and validation

The proposed long-run models (M1, M2) and short run models (M3, M4) are estimated in SAS9.2. The models are estimated using the annual data from 1980–81 to 2011–12. The data for the latest two years, i.e. 2012–13 and 2013–14 are used to validate the models.

5.1 Model estimation

The long-run model estimation results are presented in Table 5 and short-run in Table 6. The model performances are measured through R^2, *Adj.*R^2, *F-value*, and *Durbin-Watson (D-W)* statistics. The R^2values varied from 0.859 to 0.988, which confirmed remarkable performance of the proposed model structures for each port. The adjusted R^2 values suggested that more than 85% of the Indian port freight movement variations can be explained by the national *GDP*. The *GDP* (*lnGDP*) coefficients are statistically significant at 95% confidence level. The *F-value* for each port is also statistically significant at 95% confidence level. The positive sign of *GDP* coefficient indicates that the port throughput will increase with increase of *GDP*. However, the lower values (maximum value being 1.139 for Tuticorin) of *Durbin-Watson* statistics indicated the presence of serial correlation.

Although the cointegrated model M3 can be used for long term forecast, there will chances of high forecast error associations during short term disequilibrium. For example, the MA10–20 forecast tonnage value during the year 2013–14 was 53.64 for Mormugao port, whereas, the actual volume was 11.74 million tons. This disequilibrium (sharp decline) was happened due to the Government's policy to ban iron ore exports during 2011–12. In such cases the long run model prediction may be significantly different than the actual values. Error correction model (ECM) is required to correct this short run disequilibrium to give better projections. ECM considers both short term and long term effects of the data. The model results can be used for making decisions on operational planning for the infrastructure. In other word, forecast with error correction mechanism helps in reducing operational cost of the infrastructure and allocating various resources optimally.

The results for short run models showed a lower R^2 value as expected for all the cases (Table 6). The reduction occurred due to the removal of trend component with first difference of the long run model. The coefficient of the error term at lag 1 has negative sign, which confirms the equilibrium restoration. The remaining variables are statistically significant at 5% level except $\Delta PF_{t-p}(\Delta lnPF_{t-p})$, for Visakhapatnam and New Mangalore. In all the cases the error term is the most significant variable. The *Durbin-Watson* value is found to be more than 1.838 for all the ports. This higher value indeed confirmed the absence of serial correlation.

Table – 5: Long run model estimation results

Port	*Variable*	*Constant*	*Coefficient*	R^2	*Adj.*R^2	*F-stat*	*p*	*D-W*
Kolkata	*lnGDP*	-5.5 (-8.01)	0.884 (12.81)	0.859	0.854	164.20	0.000	0.181
Paradip	*GDP*	-11.5 (-10.70)	0.0014 (37.80)	0.981	0.981	1428.69	0.000	1.191
Visakhapatnam	*lnGDP*	-5.22 (-10.56)	0.861 (17.87)	0.922	0.919	319.34	0.000	0.302
Chennai		-2.79 (-8.96)	0.633 (19.77)	0.935	0.933	390.90	0.000	0.549
Tuticorin		-9.32 (-37.55)	1.17 (47.28)	0.988	0.988	2235.68	0.000	1.321
Cochin		-4.41 (-12.39)	0.682 (19.29)	0.932	0.930	372.06	0.000	0.721
New Mangalore		-10.02 (-14.07)	1.250 (17.88)	0.922	0.919	319.73	0.000	0.453
Mormugao	*GDP*	0.580 (3.00)	0.001 (20.40)	0.945	0.943	416.14	0.000	0.716
Mumbai		8.830 (12.53)	0.0009 (17.58)	0.920	0.917	309.02	0.000	0.558
JNPT		9.211 (5.13)	0.001 (18.38)	0.936	0.933	337.89	0.000	0.409
Kandla		0.266 (2.16)	0.0016 (29.65)	0.970	0.969	878.84	0.000	0.877

The values shown in brackets are the t-statistics for the corresponding coefficients.

Table – 6: Short run model estimation results

Port	*Variable*	*Constant*	*Coefficient*	R^2	*Adj.* R^2	*F-stat*	*D-W*
Kolkata	$\Delta lnPF_{t-1}$ $\Delta lnGDP$ ε_{t-1}	0.028(1.65)	0.370(2.82) 0.021(2.56) -0.225(-5.32)	0.163	0.128	7.35	2.134
Paradip	ΔPF_{t-1} ΔGDP ε_{t-1}	-0.422(-1.43)	0.483(2.42) 0.001(2.62) -0.845(-3.63)	0.421	0.345	5.57	2.238
Visakhapatnam	$\Delta lnPF_{t-2}$ $\Delta lnGDP$ ε_{t-1}	-0.039(-1.79)	0.097(1.14) 1.415(2.79) -0.167(-4.14)	0.178	0.132	3.19	1.838
Chennai	$\Delta lnPF_{t-1}$ $\Delta lnGDP$ ε_{t-1}	-0.036(-1.48)	0.537(3.10) 0.928(2.99) -0.534(-4.48)	0.348	0.333	4.74	1.975
Tuticorin	$\Delta lnPF_{t-2}$ $\Delta lnGDP$ ε_{t-1}	0.053(2.14)	-0.277(-2.49) 0.682(2.36) -0.408(-4.03)	0.289	0.192	4.98	1.971
Cochin	$\Delta lnPF_{t-2}$ $\Delta lnGDP$ ε_{t-1}	-0.009(-2.19)	0.139(2.84) 0.758(2.97) -0.337(-3.28)	0.216	0.182	5.29	1.948
New Mangalore	$\Delta lnPF_{t-2}$ $\Delta lnGDP$ ε_{t-1}	0.015(1.63)	0.187(1.91) 0.756(2.56) -0.213(-3.36)	0.134	0.117	3.54	2.012
Mormugao	ΔPF_{t-1} ΔGDP ε_{t-1}	-0.427(-1.70)	0.287(2.54) 0.001(2.19) -0.489(-5.46)	0.386	0.332	5.19	1.976
Mumbai	ΔPF_{t-1} ΔGDP ε_{t-1}	-0.777(-1.86)	0.356(2.84) 0.001(2.17) -0.430(-3.78)	0.355	0.271	4.22	2.205
JNPT	ΔPF_{t-1} ΔGDP ε_{t-1}	-1.129(-2.14)	0.407(2.93) 0.001(2.11) -0.294(-3.10)	0.474	0.391	5.72	1.911
Kandla	ΔPF_{t-2} ΔGDP ε_{t-1}	-0.014(-1.09)	0.366(2.39) 0.001(2.32) -0.863(-3.80)	0.409	0.328	9.14	2.112

The values shown in the brackets are the t-statistics for the corresponding coefficients.

5.2 Model Validation

The short run model validation is done using the latest two years of data i.e. 2012–13 and 2013–14. The validation results suggested significant reduction in forecast errors, while using the ECM approach for short run modeling. For example, the actual freight flows for Kolkata port during 2012–13 and 2013–14 were 39.93 and 41.39 million tons respectfully. The corresponding years forecasts by Maritime agenda 2010-2020 (MA10-20) were 54.19 (35.71% over estimation) by and 63.72 (53.95% over estimation) million tons. Our model forecasts for the same years are 45.86 (14.85% over estimation) and 43.75 (5.70% over estimation) million tons. Essentially, the ECM approach lowered down the forecast error significantly. Similarly, for Tuticorin port, the actual freight values were 28.26 and 28.64 million tons for the above indicated years. The corresponding MA10-20 projected values were 34.09 (20.63% over estimation) and 39.91 (39.35% over estimation); where as our mode forecasts are 30.29 (7.20% over estimation) and 30.69 (7.16% over estimation) million tons. Similar, results are found for the remaining ports. The comparisons between the actual freight value, MA10-20 projections and our model predictions for the year 2013–14 are presented in Figure 3. It can be noticed that the observed values are very much closer to our model forecast values. The forecast error comparison for the year 2013–14 is shown in Figure 4. It may be observed from the error comparison plot that radical reduction in forecast error using the error correction model for Mormugao port. The forecast error associated with MA10–20 projection is about 357% (point E). But, the ECM prediction error is about 9.54% (point Erd). The proposed modeling mechanism improves on the absolute error associated with the forecast and error percentage decline over time. Therefore, it is suggested that ECM approached may be used to revise the long term projections when short run disequilibrium appears in port throughput.

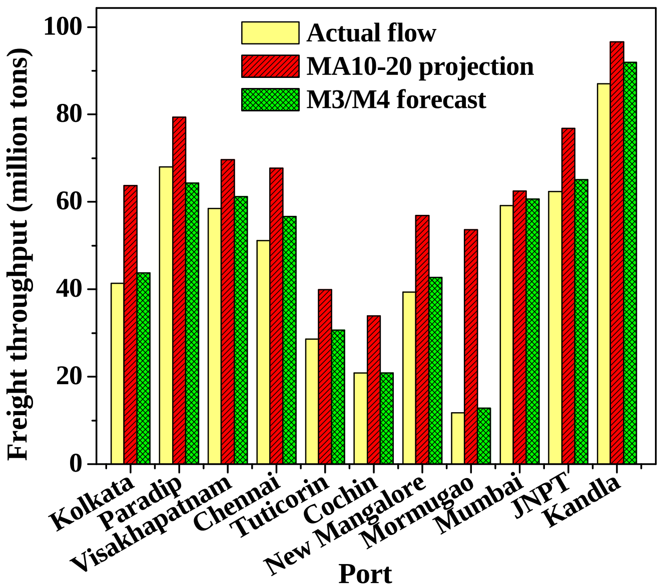

Figure – 3: Comparison of projections for 2013-14

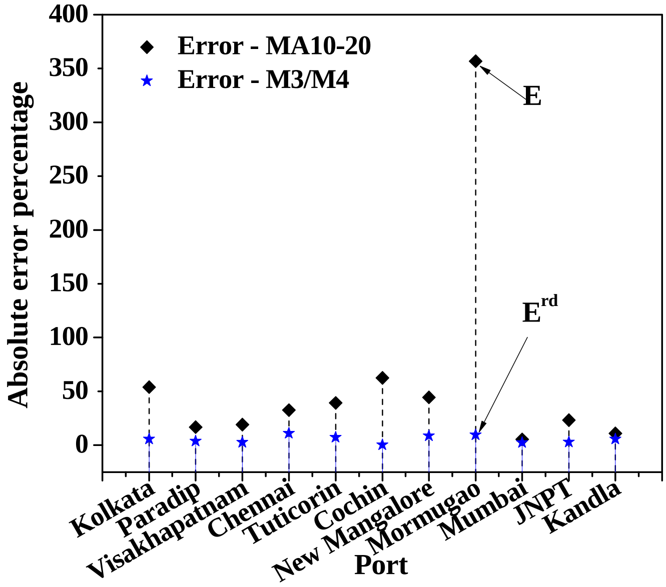

Figure – 4: Prediction errors for 2013-14

6. Sensitivity analysis and forecast results

Port freight throughput sensitivity analysis is carried out for three different scenarios: baseline, low growth and high growth assumptions of national GDP. We used the growth assumptions by reviewing two reports: 1) World economic outlook April–2014 by International monetary fund (IMF)(IMF 2014); 2) China and India, 2025, A comparative assessment by RAND Corporation, USA(RAND 2011). In IMF economic outlook, the growth rates were available till 2019–2020 and RAND Corporation provided values from 2020–2021to 2025–26. The growth rate assumptions for national GDP are reported in Table 7. The calibrated models are used to forecast the freight movements year by year for the different growth rates.

Table – 7: Growth rate (%) scenarios

	Year	2014-15	2015-16	2016-17	2017-18	2018-19	2019-20
IMF	Low growth	4.40	4.50	4.60	4.80	5.00	5.10
	Baseline	5.42	6.35	6.48	6.65	6.73	6.80
	High growth	6.20	6.80	6.90	7.10	7.30	7.40
	Year	**2020-21**	**2021-22**	**2022-23**	**2023-24**	**2024-25**	**2025-26**
RAND	Low growth	5.20	5.40	5.40	5.40	5.40	5.40
	Baseline	6.82	6.30	6.30	6.30	6.30	6.30
	High growth	7.50	8.40	8.40	8.40	8.40	8.40

The model forecasts and the MA10–20 projected freight tonnage values are presented through Figures 5 and 6. By comparison, it may be observed that for ports like Visakhapatnam, Mumbai and Mormugao, the MA10–20 projections are closer towards the model forecast. It may be noted that the MA10–20 projection are available till 2019–20. MA10–20 forecast for Visakhapatnam port is marginally overestimated till 2019–20, while for Mormugao port; the MA10–20 projections are very close to model baseline forecast from the year 2017–18 to 2019–20. The base line forecast from the model is lower than the MA10–20 projection during this period for

Mormugao port, while the high growth condition projects higher volume than MA10–20 throughput. Similarly, for Mumbai port, our model forecast is lower than the MA10–20 forecast till the year 2017–18 and then it gradually surpasses the MA10–20 projections. In this case, even the base line forecast is more optimistic than the MA10–20 prediction for the year 2019–20. For JNPT port, interestingly, MA10–20 reported that there will be no cargo growth between the years 2016–17 to 2019–20, whereas, our model forecast shows there will be continuous growth of freight activities during the forecast period. MA10–20 projections are highly overestimated for the remaining ports. The three economic scenarios shown in Table 7 suggests that the freight movements will grow continuously till 2020–21 and then the growth will be at an average of 5.40% (baseline) till 2025–26.

7. Conclusions and closing remarks

In India, Ministry of Shipping (MoS) has been using standard regression modeling approach to forecast freight throughput for the major ports. The MoS projections have been used for port facility planning and associated infrastructure development till date. In January, 2011 MoS published the freight volume projections till 2020 in MA10–20 for all the major ports. However, it is found that MoS projections are associated with high errors for the recent years, when compared with the actual freight movement at some ports. The associated errors drastically increase when there is disequilibrium in freight flow. Therefore, in reply to there is a need for a scientific and systematic forecast model for Indian ports, this paper analyzes the past freight volume systematically and produces projections with the use of a conitegrated model structure. This paper addressed the short run disequilibrium issue involved in the simple regression mode by using error correction technique. The estimated models are used to carry out a sensitivity analysis on freight growth variations at all the ports for the next 12 years. The comparison between the sensitivity analysis results and MA10–20 forecasts suggested that the new conitegrated modelstructure provides more accurate forecast with higher confidence level.

Although the new cointegrated model provides higher prediction accuracy, there are still further scopes for future research on Indian port freight demand estimation. In the model formulation, other explanatory factors like economic activities of port surrounding areas may be considered. Inclusion of neighborhood activities in the model structure may result in more accurate and representative results. The present study used annual data on freight movements. Further, quarterly or monthly data may be collected and tested with such other forecasting methods as artificial intelligence, neural networks, and or advanced data mining techniques to predict port freight movements in India.

Additionally, with large data, use of nonparametricregression may be thought to produce freight forecast. A reliable forecast model is essential since, it helps to the port operators for making strategies and decisions on port planning, renovating building structures, and various port facilities. The present modeling results may be helpful to transport planners, policy, and strategy makers, while making decisions on hinterland connectivity, freight rate, and other supporting infrastructure development like rail and road connectivity. In addition, this study will also be helpful in allocating funds for the Indian port system developments for the future years.

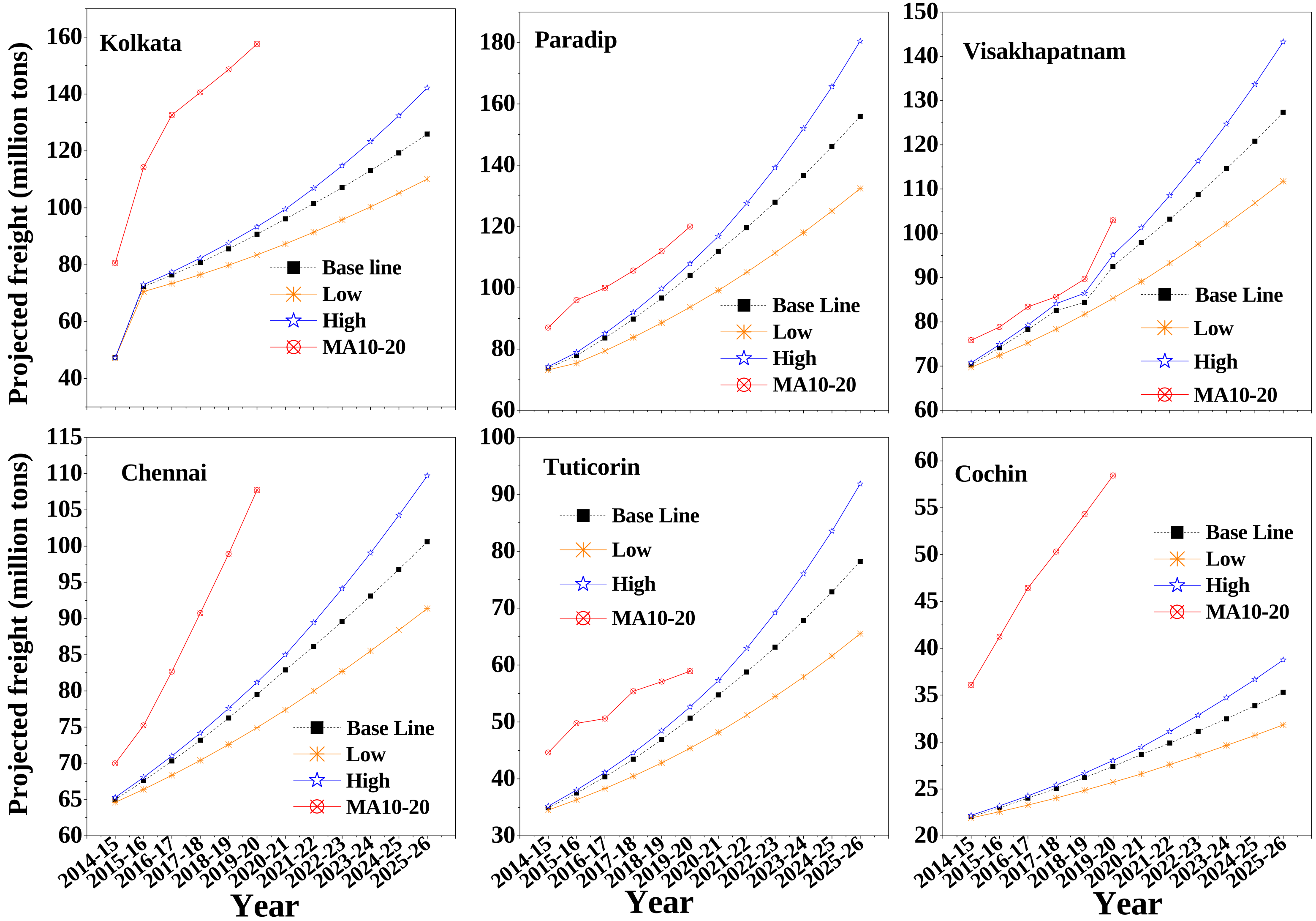

Figure –5: Freight forecast for Kolkata, , Paradip, Visakhapatnam, Chennai, Tuticorin, and Cochin

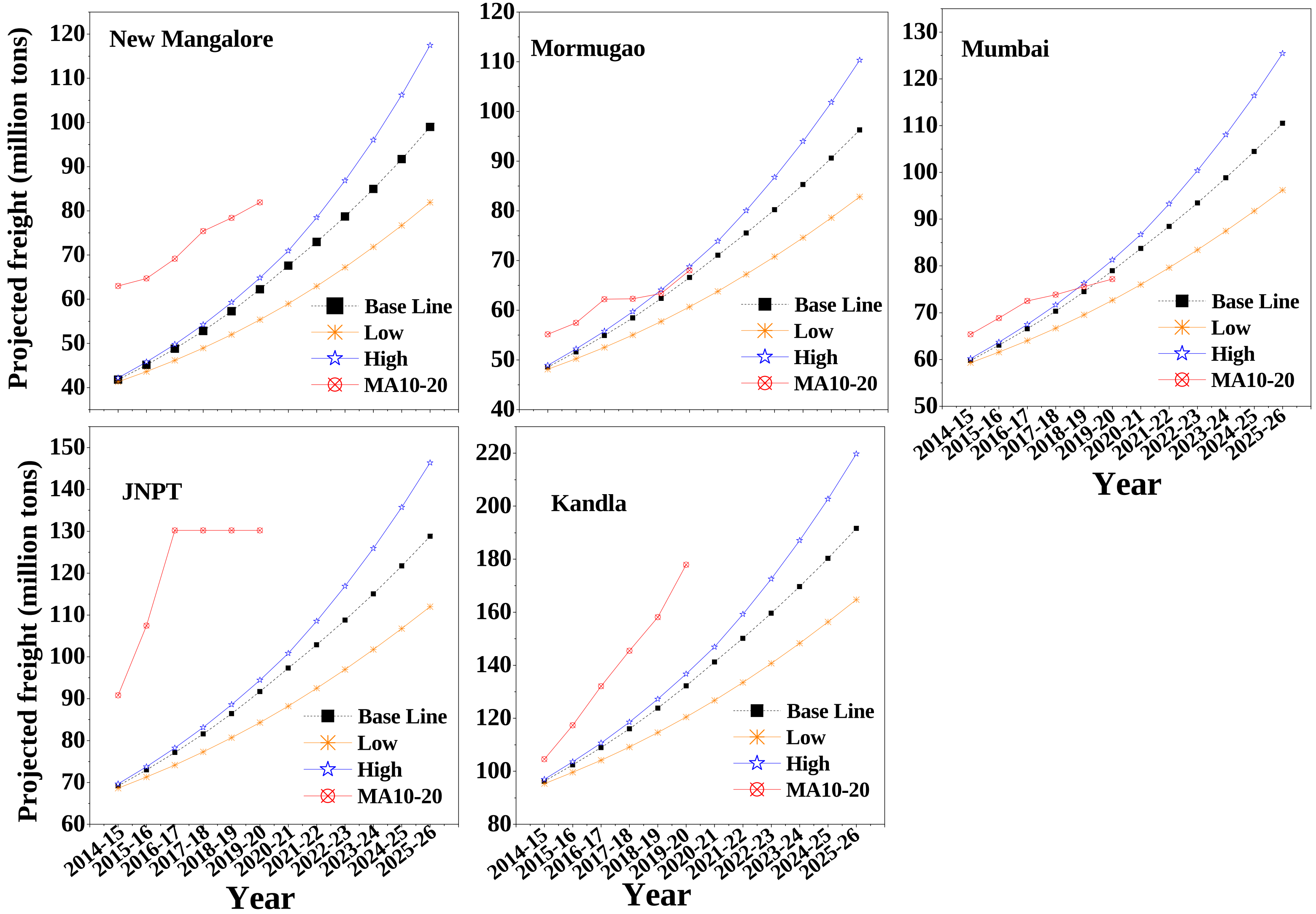

Figure – 6: Freight forecast for New Mangalore, Mormugao, Mumbai, JNPT, and Kandla

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