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FORECASTING THE DEMAND OF CONTAINER THROUGHPUT IN INDONESIA

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ABSTRACT

This paper forecasts the demand of container throughput in Indonesia. The analysis was done in multivariate autoregressive model. ADF test was used to check the stationarity of data and order of integration. To find the existence and the number of cointegration relationship, Johansen approach was used. The number of cointegration relations was established by a sequential likelihood ratio test on the rank of an estimated parameter matrix from VEC model and Impulse response function (IRF) was performed to know response to a shock of a variable of other variables. The empirical analysis demonstrated that the estimation model provides indication of goodness-of-fit and of the forecasting potential of the model. Most of the model estimation result follows the long-term development of the actual data series closely. The impulse response of a shock of a variable to itself and other variables die out after certain period. This verified the stability of all the estimated models. The forecast of container throughput in Indonesia generated by VECM indicated the reasonable result.

1. INTRODUCTION

As the biggest archipelago country in the world with over 17,000 islands, the existence of sea transportation in Indonesia play important role as the engine of growth, trade and development. According to Statistical Yearbook of Indonesia[1], from 1977 to 2002, the average annual growth of export accounted for 7.96% and 8.47% for import. Approximately 90% of those Indonesia's external trade is transported via sea. It indicates the growth of external trade will continue to increase and the importance of sea transportation. As the rising trend of containerized cargo in the world, Indonesian containerized cargo also show the same pattern with average annual growth of 14.7% (from 1990 to 2002). In 2002, total container handled in Indonesian container port was 4,539,884 TEU, with the rank position of 15 from the world container traffic (Containerisation International Yearbook, 2004)[2]. The increasing trend will continue to the future year due to the economic development and rising share of containerized cargo for foreign and domestic trade.

The high growth of containerized cargo in Indonesia has compelled the improvement port performance and facility, and the construction of new port. One of the key issues for developing port facilities and construction of new port is information about the demand of container throughput. In port planning and development, forecasting of container throughput demand is a necessary step in predicting future revenues for a proposed development project. Hence, analysis of container throughput demand is very important for port management. Moreover, it also will be useful for the future liner shipping strategy in determining services network. Unfortunately, up to now, there is almost no published paper dealt with forecasting the demand of container throughput in Indonesia. In light of the above consideration, this paper attempts to solve the problem.

The approaches in estimating demand of trade market are often associated with time series data. The standard classical methods such as the ordinary least squares (OLS) and hypotheses testing are based on the assumption that the time series are stationary. Broadly, a series is stationary if its means and variance are constant over time and the value of the covariance between the two time periods depends only on the distance or gap or lag between the two time periods and not the actual time at which the covariance is computed (Gujarati, 2003)[3]. A non-stationary series is said to be integrated of order d or I(d) if it must be differenced d times to make it stationary. Since the distribution theory in non-stationary series is different from the standard Gaussian asymptotic theory, application of classical estimation methods such as OLS for estimating relationships between non-stationary variables may cause to spurious regressions which means the regression yields "look good" with high R^2 , but have no meaning. The problems with estimation of single equation framework with integrated or non-stationary variables are: non-standard distribution of coefficient estimates, error process not being stationary, explanatory variables generated by processes that display autocorrelation, existence of more than one cointegrating vector and failure of weak exogeneity (Banerjee et al. 1986)[4].

To solve the problem of integrated variables, we can use cointegration test and estimation of vector error correction model (VECM) to distinguish between short run and long run relationship. The existence of cointegration can prevent the errors in the long run relationship from becoming larger and larger. This is modeled through the popular econometrics specification of error correction model which integrates the long-run equilibrium analysis and short-run dynamic adjustment by including in the short-run dynamic models a measure of disequilibrium in the last period.

The aim of this paper is to forecast the demand of container throughput in Indonesia by presenting multivariate autoregressive model. The rest of this paper is organized as follows. Section 2 describes data collection. Section 3 describes econometrics model and methodology. Section 4 provides empirical results and discussion. Finally, conclusion is given in section 5. All calculation concerning data analysis and model estimation was performed through TSP software.

2. DATA

In forecasting the demand of container throughput, some variables are included, namely, container throughput (TEU), GDP (million US $), population, export (million US $), and import (million US $) with time series data from 1982 to 2002. Since the container port characteristic and management policy time series data is difficult to find, the model does not consider the port characteristic and management policy. Container throughput data was taken from Containerisation International Yearbook, while Statistical Yearbook of Indonesia provides GDP, population, export, and import data. The time series data of the above variables is shown in Table 1.

Table 1 Container throughput, GDP, population, export and import in Indonesia

Year	Cont. (TEU)	GDP (Million US $)	Population	Export (Million US $)	Import (Million US $)
1982	158,352	90,218	154,307,298	3,929	13,314
1983	233,379	78,092	157,702,058	5,005	12,207
1984	219,093	83,692	161,171,503	5,870	11,185
1985	228,619	87,472	164,629,618	5,869	8,984
1986	364,008	67,457	167,930,442	6,528	9,632
1987	393,131	77,958	170,986,776	8,580	11,302
1988	588,267	86,306	173,722,564	11,537	12,340
1989	862,256	99,949	176,502,125	13,480	15,164
1990	923,663	110,924	179,379,000	14,604	19,917
1991	1,156,265	125,486	182,320,816	18,248	23,559
1992	1,329,365	136,952	185,329,109	23,296	25,165
1993	1,600,539	156,292	188,387,039	27,077	26,157
1994	1,912,160	173,736	191,514,264	30,360	29,616
1995	2,048,130	196,930	194,755,000	34,954	37,718
1996	1,764,392	223,486	196,916,781	38,093	39,333
1997	2,478,674	134,988	199,082,865	41,821	37,756
1998	2,000,484	119,097	201,312,593	40,976	24,683
1999	3,551,868	155,219	203,587,425	38,873	20,322
2000	3,797,948	131,831	205,843,000	47,757	27,495
2001	3,901,761	139,365	208,724,802	43,685	25,490
2002	4,539,884	180,152	212,003,000	45,046	24,763

Source : Containerisation International Yearbook and Statistical Yearbook of Indonesia, various years

3. ECONOMETRICS MODEL AND METHODOLOGY

3.1 Unit root test

Before estimating cointegration space and determination of cointegration rank, it is important to test the order of integration of each variable or to check the existence of unit roots, which make the series non-stationary. Testing for unit roots has become a standard tool in modern econometrics data analysis. Conventional statistical analysis assumes that the time series at hand are stationary, and a unit root implies non-stationary (Mills, 1990)[5]. Testing for unit roots enables direct inference on the degree of non-stationary and subsequent degree of differencing to transform a time series to stationarity. Several test are available in the literature. In this paper, we restrict to the augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979)[6]. The basic equation of ADF tests is as follows:

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \alpha_i \sum_{i=1}^{m} \Delta Y_{t-1} + \varepsilon_t \tag{1}$$

where ε_t is a pure white noise error term and $\Delta Y_{t-1} = (Y_{t-1} - Y_{t-2})$, $\Delta Y_{t-2} = (Y_{t-2} - Y_{t-3})$, etc. β_1, β_2, δ, α_i are parameters and t is the time or trend variable. The number of lagged difference (m) terms to include is often determined empirically, the idea being to include enough terms so that the error term is serially uncorrelated. The null of non-stationarity is equivalent to testing the significance of $\delta = 0$; that is, there is a unit root - the time series is nonstationary. The alternative hypothesis is that δ is less than zero; that is, the time series is stationary.

3.2 Cointegration

Having established unit root test, to find the existence and the number of cointegration relationship, we can perform cointegration test. The fundamental idea of cointegration is that although two series or more are non-stationary, or integrated, such that first difference are required to obtain stationarity, a liner combination of these series can be stationary. This linear combination is known as cointegrating vector or cointegrating relationship. The cointegrating relationship may, therefore, be thought of, as a long-run steady state of dynamic relationship though there can be finite short-run variations around the long-run relationship. The variables comprising the cointegrating relationship would not drift too far apart relative to each other owing to equilibrating forces that tend to keep them together. Therefore, this idea of cointegation is in intuitive consonance with the observed co-movement of number of economic variables.

The concept of cointegration was introduced by Engle and Granger, 1987[7] provided the issue of integrating short-run dynamics with long-run equilibria. Although widely used in empirical research, the Engle-Granger (EG) method has several shortcomings such as the size distortion, non-unique sample properties depending on the variable used for normalization and its inability to identify multiple cointegrating vectors (Banerjee et al., 1993)[8]. The others methods for estimation of long-run equilibrium relationship have been proposed by Stock (1987)[9] which suggested non-linear least squares (NLS), Engle and Yoo (1991)[10] suggested three steps procedure, maximum likelihood model was proposed Johansen (1988,1991)[11),12] and Johansen and Julius (1990,1994)[13),14]. Gonzalo (1994)[15] has shown that Johansen approach has better properties than other estimators and their finite sample properties are consistent with asymptotic results. In this paper we concern to the Johansen and Julius (1990,1994) procedure. The Johansen technique proceeds by transforming a vector autoregressive model in levels into an equivalent differenced form, including lagged differences and an implied set of cointegrating vectors as the right hand explanatory variables. The differenced form is then estimated by using maximum likelihood methods. The implied vector cointegrating vectors are extracted using reduced rank regression technique. By Johansen approach, VECM can be estimated in which error correction term is included in each equation. Two types of likelihood ratio test statistics can be derived from Johansen procedure, namely, the trace test statistics,

$$trace(r \mid k) = -T \sum_{i=r+1}^{k} \ln(1 - \lambda_i) \tag{2}$$

and max-lamda test statistics,

$$\lambda_{\max} = -T \ln(1 - \lambda_{r+1}) \tag{3}$$

where r is cointegration relationship, k is number of variables, T is number of observations, and λ_i is the i-th eigenvalue. If trace test statistics ($r|k$) and $\lambda_{\max}$ greater than c_k, critical value, then reject H(r). H(r) denotes the hypothesis that the rank of Π (see equation 4 for term Π) in H(k) is $\leq$ r; for example, H(0) states the rank of Π is 0, H(1) states the rank of Π is 0 or 1.

3.3 Vector autoregressive model

A vector autoregressive (VAR) model is a multivariate time series model whose general mathematical form with K-dimensional is given by the following formulation:

$$Y_t = \Pi_1 Y_{t-1} + ... + \Pi_k Y_{t-k} + \Phi D_t + \varepsilon_t \quad (4)$$

where $Y_t = (y_{1t}, ..., y_{KT})$, Π_i are K x K coefficient matrix, k is the order of the VAR, ε_t is residual error-term, and $\varepsilon_t \sim N(O,\Sigma)$ (where Σ is a K x K positive definite matrix). The deterministic term D_t can contain a constant, a liner term, seasonal dummies, intervention dummies, or other regressors that we consider fixed and non-stochastic. The Granger representation theorem states, under the hypothesis of cointegration, the VAR can be written as a vector error correction (VEC) model as the following formulation.

$$\Delta Y_t = \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \Pi Y_{t-1} + \Phi D_t + \varepsilon_t \quad (5)$$

The K x K matrix Π can be expressed as $\Pi = \alpha\beta'$ where both α and β' are K x r matrix of full rank. For the model used in this study, K = 5, Y_t = (Container, GDP, Population, Export, Import). β' is a matrix representing cointegration relation such that $\beta' Y_t$ is stationary and is interpreted as long run equilibrium relationship between the jointly determined variables. It is important to emphasize that one can not estimate the individual coefficient of β unless one specifies a normalization or identification. There may be stochastic shocks forcing to the system during the short-run, however, with the existence of cointegration relationship, there will be forcing variables which cause the system converge to the long-run relationship. The deviation from equilibrium relations $\beta' Y_t$ form a stationary process and α is the speed of adjustment coefficient for the equation. Under the reduced rank hypothesis of the Π matrix, the maximum eigenvalue and the trace statistics are employed to ascertain the number of cointegrating vector. If Π has zero rank, no stationary linear combination can be identified, i.e. the variables in Y_t are not cointegrated. If the rank r of Π is greater than zero, there exist r possible stationary linear combinations. The short-run models are estimated consistently after taking into account parametric restrictions implied by long-run relationships. The vector error-correction model (VECM) allows a number of variables to adjust simultaneously at different rates in response to short run disequilibrium. The approach provides a good approximation to the unknown data-generating process since the theory is often not adequate for describing the dynamic adjustment process.

3.4 Impulse response function

In applied work, it is often interest to find the response of one variable to an impulse in another variable in a system that involves a number of variables as well. If there is a reaction of one variable to an impulse in another variable we may call the latter causal for the former. The impulse response function (IRF) trace out the moving average representation of the system and describes how the variable responds over time to a single surprise increase in itself or in any other variables. The variance decomposition tells us how much of the average squared forecast error variance of one variable at the k-th step ahead is associated with surprise movements in each variable of the model. Both the innovation accounting tools can be used to make inferences regarding the nature of dynamic interactions between variables and variable exogeneity and Granger non-causality. For, example, if the variance of a particular variable is explained primarily by its own innovations then the variable is weakly exogenous to the system. The impulse responses or dynamic multipliers can be obtained from infinite moving average representation of a K-dimensional VAR model (Lutkepohl, 1991)[16) as follows:

$$Y_t = A_1 Y_{t-1} + ... + A_p Y_{t-p} + u_t \quad (6)$$

$$\Phi_n(\varphi_{ik,n}) = \sum_{j=1}^{n} \Phi_{n-j} A_j \quad (7)$$

where n =1,2, ….., ∞, $\Phi_0 = I_K$, $A_j = 0$ for $j > p$ and $\varphi_{ik,n}$ (the ik-th element of Φ_n) represents the response of variable y_i to a shock in variable k, n periods ago. Since the covariance matrix of a VAR, Σ_u, is positive definite, it is essential to transform the innovation of the system into a contemporaneously uncorrelated form. If disturbance across equations are correlated, an innovation in one of the equations will describe its dynamic response to a complex combination of several economically interpretable shocks. In order to have economically interpretable shocks, the orthogonalisation requires imposition of restrictions on contemporaneous coefficients of underlying structural VAR and hence imposing a particular causal order on the relationship.

The orthogonalised impulse responses proposes by Sims (1980)[17), which derived from the Choleski decomposition of the variance-covariance matrix of the VAR, are not in general unique since they depend on the particular orderings of the variables in the VAR. They are unique only if the variance-covariance matrix is diagonal. However, orthogonalized impulse responses have advantages since different orthogonalised ordering give rich additional information about the dynamic of the model as some variables might consistently across different orderings. The generalised impulse responses proposed by Koop et al (1996)[18)] overcome the non-uniqueness problem of the orthogonalised impulse responses. The generalized impulse responses have advantage that they take into account the properties of the data generating process. However, the generalized impulse responses have disadvantage since they are derived solely from data. On this study, we restrict the analysis through the orthogonalised impulse responses. The impulse responses, in the context of vector autoregression, are an efficient tool to determine the stability of the estimated equation. The stability is indicated by the convergence of the impulse response to zero.

4. EMPIRICAL RESULT AND DISCUSSION

4.1 Unit root test

Prior to perform unit root tests, the logarithmic of the original series have been used in order to reduce the possibility of heteroskedasticity and to make the series more comparable. As previously mentioned, the unit root test is intended to find the stationarity of data and integrated order. The results of unit root tests by augmented Dickey-Fuller (ADF) are presented in Table 2. ADF tests were performed on the full sample for the period 1982-2002 both on levels as well as differenced forms to find the order of integration. All the variables are found to be non-stationary at their levels. A non-stationary series can be made stationary by differencing. The variables become stationary at first difference, or integrated order 1 or $I(1)$ since the null of unit root is rejected at first difference.

Table 2 Unit root test by Augmented Dickey-Fuller (ADF)

Series	Level	First difference	Integrated order
log(Container)	-3.065	-5.386*	I(1)
log(GDP)	-2.169	-4.102*	I(1)
log(Population)	-2.801	-3.714*	I(1)
log(Export)	-1.322	-3.831*	I(1)
log(Import)	-2.042	-6.098*	I(1)

Notes: The Dickey-Fuller regressions include an intercept and a linear trend term (random walk with deterministic trend). The null hypothesis is that the series is non-stationary. This hypothesis is rejected if the test statistics is larger in absolute value than the critical value. Critical value for ADF test at 5% level of significance is -3.617. * denotes rejection of the null hypothesis of non-stationary at the 5% significance level.

4.2 Cointegration test

To find the existence and the number of cointegration relationship, we compute the maximum eigen values (λ_{max}) and the trace statistics by applying Johansen procedure. The number of cointegration relations is established by a sequential likelihood ratio test on the rank of an estimated parameter matrix from VEC model. Results of these tests with 95% critical values are reported in Table 3. The λ_{max} and trace test reject the null hypothesis of no cointegration (r = 0) at a 5% significance level. However, neither of the criteria can reject the null hypothesis of $r \leq 4$ against the alternative hypothesis of r = 5 at 5% significance level. We, therefore, can conclude there exist four cointegration relationship at 5% significance level, and there exist considerable evidence of the existence of long-run relationship.

Table 3 Cointegration test by Johansen procedure

λ_{max}				Trace test	
Ho Null	H1 (alternative)	Test statistic	95% Critical value	Test statistic	95% Critical value
r = 0	r = 1	69.54*	33.26	148.06*	69.98
$r \leq 1$	r = 2	38.6*	27.34	78.51*	48.82
$r \leq 2$	r = 3	24.3*	21.28	39.91*	31.26
$r \leq 3$	r = 4	15.43*	14.6	15.6	17.84
$r \leq 4$	r = 5	0.17	8.08	0.17	8.08

Note: 'r' indicates the number of cointegration relationships. The null hypothesis is if there is no cointegration. This hypothesis is rejected if λ_{max} and trace test statistics is larger than the critical value. * denote rejection of null at 5% significance level. The optimal lag length of VAR was selected by AIC. Optimal order of VAR was 2.

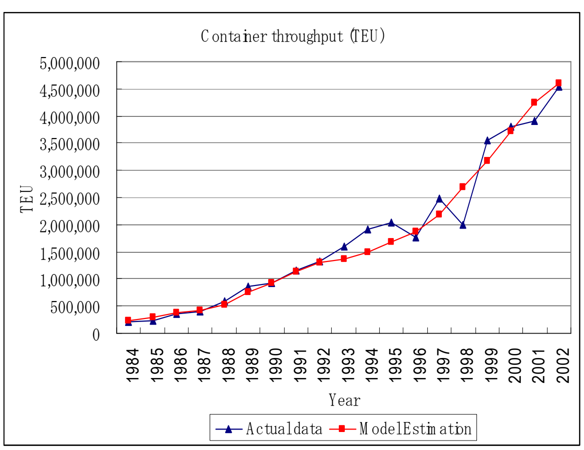
4.3 Vector error correction model (VECM)

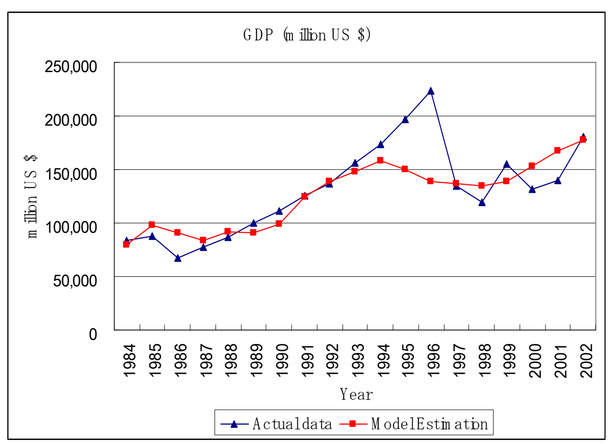
As stated earlier that under the hypothesis of cointegration, the VAR can be written as a vector error correction model (VECM). In this section we show the regression result of vector error correction model based on the Johansen procedure. Coefficient matrix of VECM is given in Table 4. To evaluate the accuracy of the model, we generate a series over a sample period and observe how well this estimation series match with the actual data. The process is straightforward; the first and second data in the sample are fed in the model as starting values for the calculation of ΔY_t as given in equation 5. Adding the later to the starting value provides the model estimation Y_t for the third year in the sample. The process is repeated for each year in the sample period. The estimation series (in logarithmic) is transformed again to the original value (level). Comparison of the model estimation Y_t with the actual data is shown in Figure 1. The figure provides indication of goodness-of-fit and of the forecasting potential of the model. Most of the model estimation result follows the long-term development of the actual data series rather closely. Since there was a shock of GDP due to the economic crisis in 1997, the estimation result of GDP and import around 1997 are significantly different with the actual data.

Table 4 Coefficient matrix of vector error correction model

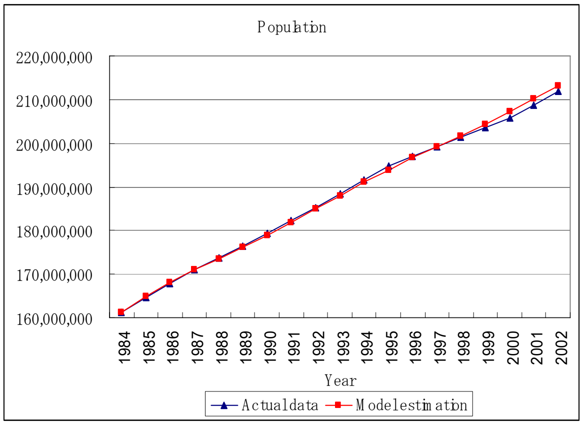
	Coef. matrix of the lagged variable in difference					Coef. matrix of the lagged variable in levels						
	Δ Y	Δ X	Δ Z	Δ E	Δ I	Yt-1	Xt-1	Zt-1	Et-1	It-1	Constant	
Δ Y	-0.309	0.568	-31.768	0.042	-0.112	-0.429	-0.244	1.122	0.442	-0.254	-5.618	coef.
	0.409	0.474	30.485	0.807	0.391	0.591	0.659	6.556	0.920	0.560	49.812	std.error
	-0.755	1.198	-1.042	0.051	-0.287	-0.725	-0.370	0.171	0.481	-0.453	-0.113	t value
Δ X	0.116	0.746	84.498	-0.424	0.092	-0.075	-1.859	-3.530	1.173	0.544	32.010	coef.
	0.220	0.255	16.419	0.435	0.211	0.318	0.355	3.531	0.495	0.301	26.828	std.error
	0.526	2.919	5.146	-0.975	0.437	-0.237	-5.241	-1.000	2.367	1.804	1.193	t value
Δ Z	-0.012	-0.010	0.267	0.008	-0.006	0.020	0.011	-0.136	-0.010	-0.010	1.092	coef.
	0.003	0.004	0.231	0.006	0.003	0.004	0.005	0.050	0.007	0.004	0.378	std.error
	-3.992	-2.799	1.156	1.364	-2.025	4.366	2.186	-2.731	-1.450	-2.281	2.892	t value
Δ E	0.490	0.614	2.527	0.112	0.036	-0.379	-0.395	7.706	-0.609	0.643	-57.409	coef.
	0.214	0.248	15.956	0.422	0.205	0.309	0.345	3.431	0.481	0.293	26.072	std.error
	2.285	2.471	0.158	0.265	0.176	-1.223	-1.147	2.246	-1.266	2.195	-2.202	t value
Δ I	0.383	0.519	5.816	-0.654	0.542	-0.105	0.133	-2.839	0.628	-0.485	21.136	coef.
	0.286	0.331	21.269	0.563	0.273	0.413	0.459	4.574	0.642	0.391	34.753	std.error
	1.341	1.569	0.273	-1.161	1.986	-0.254	0.290	-0.621	0.979	-1.242	0.608	t value

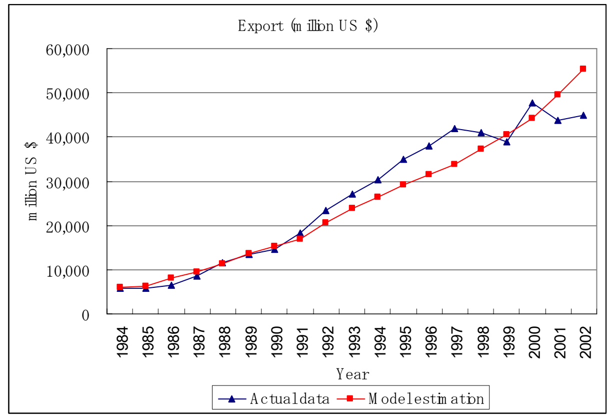
Note:
Y = Container, X = GDP, Z = Population, E = Export, I= import.



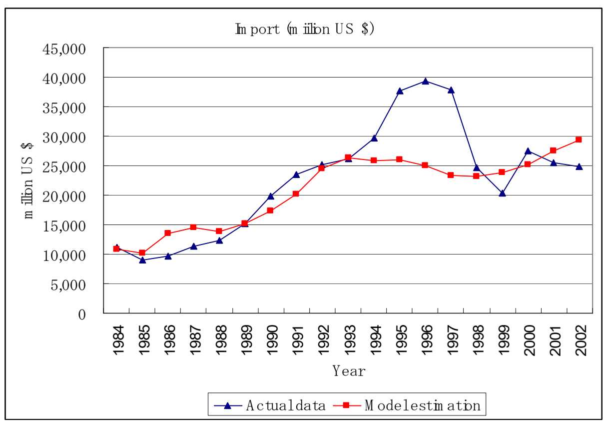


(a) (b)





(c) (d)



(e)

Fig. 1 Comparison between actual data and model estimation (a) Container throughput, (b) GDP, (c) Population, (d) Export, (e) Import

4.4 Impulse response function

Impulse response function was performed to know response to a shock of a variable of other variables. If a variable does react to the shock of another variable, it is said that the latter causes former. We found the impulse response of a shock of each variable to it self and other variables die out after certain period as depicted in Figure 2. This verifies the stability of all the estimated models. Figures 2 (a) plot the IRF of container throughput to itself and others variables. A shock of container throughput is responded positively to itself and other variables as well; the effects last for 5-6 periods. The important thing from the figure is GDP and export reacts more positively than import and population. It can be interpreted as increasing of container throughput will give more significant impact on GDP and export volume than population and import. This illustration also matches with Figure 2 (a) and (c).

A shock of GDP provides positive responses to itself and other variables as shown in Figure 2 (b); it is easy to understand, increasing in GDP will increase export and import which in turn increasing total container throughput. The growth of population will directly impact on export and import cargo which in turn increasing container throughput, this condition is also reflected in Figure 2 (c). As the indicator of economic development, the growth of export will cause rising in GDP and others factors as depicted in Figure 2 (d) which shows a shock in export give positive responds to itself and other variables. Figure 2 (e) shows that a shock of import is responded positively to itself and all variables except export, and container throughput is responded more positively than other variables. It means the rising of import will give more significant impact on the increasing of container throughput than other variables.

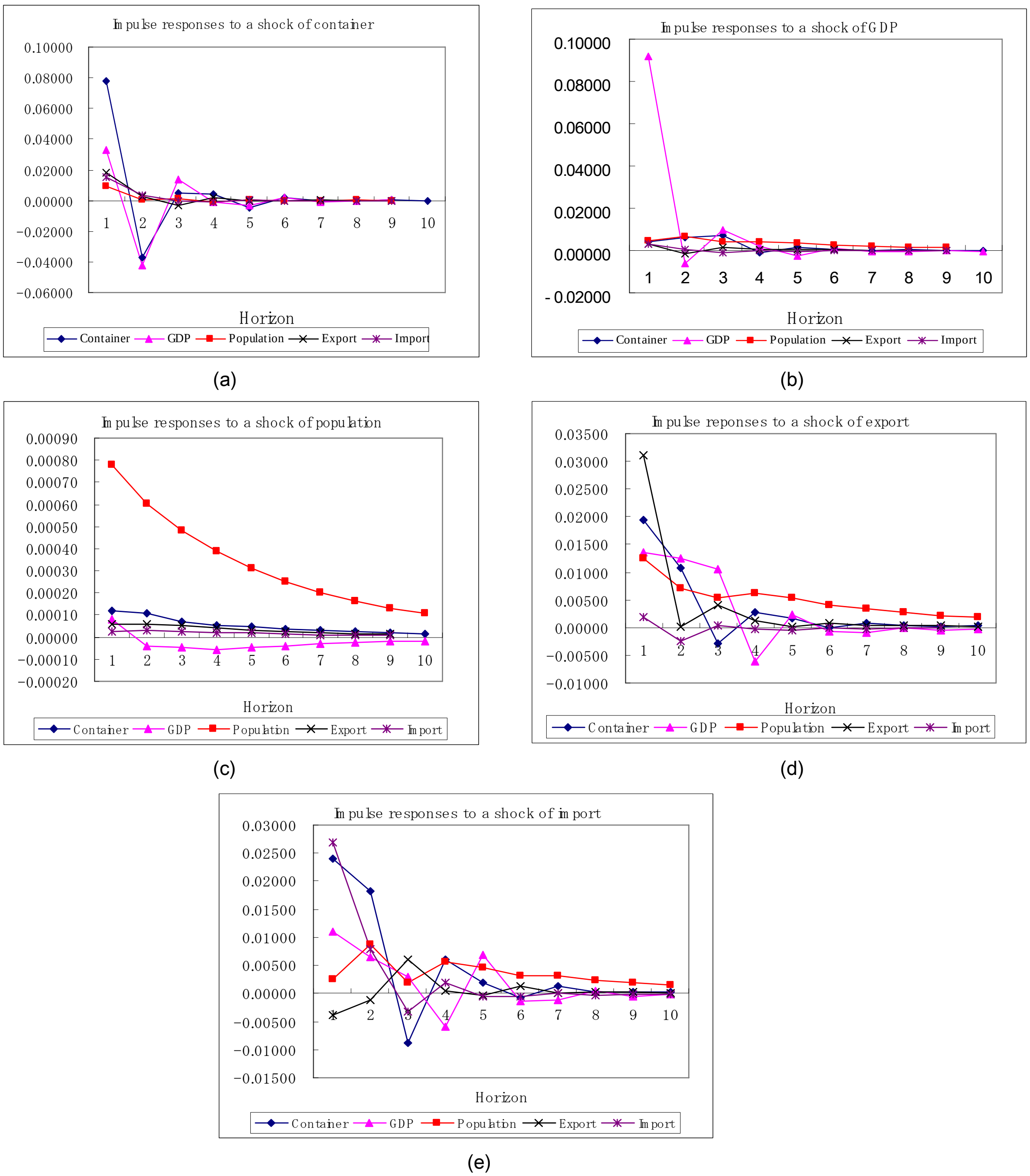


Fig. 2 Impulse responses of a shock of (a) container throughput, (b) GDP, (c) Population, (d) Export, (e) Import

4.5 Forecasting of container throughput

Since the objective of this study is to forecast the container throughput, we only show forecasting of container throughput from 2003 to 2015. In forecasting the model, we adopt the following assumptions:

- Variables included in the model are container throughput, GDP, population, export and import.
- Statistical structure of the model will not change substantially in the future.
- Port management policy is not included in the model.
- There is no significant change in liner shipping network.

The procedure for forecasting is the same with the procedure to generate a series over a sample period as mentioned earlier. The last known value of time series is used as starting value for the calculation of ΔY_{t+1}. Adding the later to the starting value provides the model estimation Y_{t+1} for the $t+1$ in the forecasting year. The process is repeated for each year up to 2015. The forecasting result is shown in Figure 3. The figure indicates container throughput increases from 4,982,755 TEU in 2003 to 18,712,042 TEU in 2015 with the average annual growth 11.69%. If we compare with the actual data from 1982 to 2002 with the average annual growth of container throughput was 20.72%, the forecasting result seems to be reasonable. Moreover, the proportion of goods traded internationally in container is expected to increase, as traditional bulk cargo such as coal, grain and salt are increasingly being shipped in container. With this huge potential demand of container throughput, Indonesian port authorities should implement the best strategy for developing the future container port in order to provide better quality services for shippers and liner shipping companies. Beside that, in order to meet the future demand, the construction of new ports are inevitably due to the current container ports capacity can not handle such huge container demand.

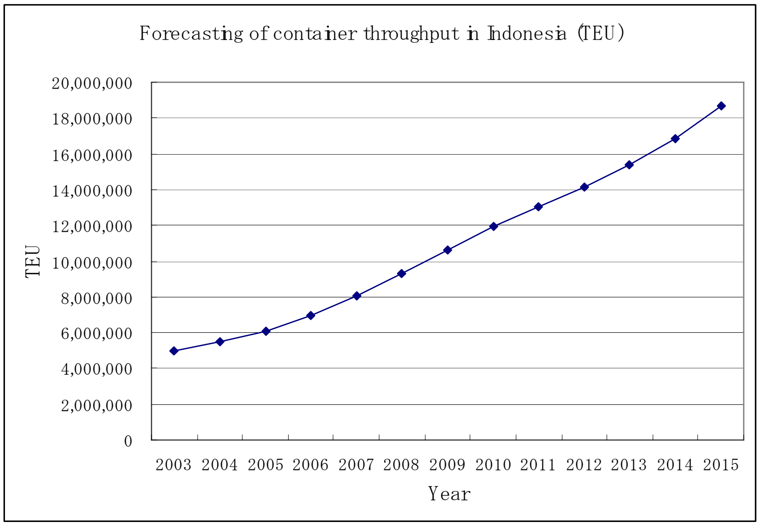


Fig. 3 Forecasting of container throughput in Indonesia

5. CONCLUSION

The high growth of containerized cargo in Indonesia has compelled the improvement port performance and facility, and the construction of new port. One of the key issues for developing port facilities and construction of new port is information about the demand of container throughput. In port planning and development, forecasting of container throughput demand is a necessary step in predicting future revenues for a proposed development project. Hence, analysis of container throughput demand is very important for port management. This paper presented forecasting demand of container throughput in Indonesia. The analysis was done in multivariate autoregressive model. ADF test was used to check the stationarity of data and order of integration. Johansen approach was used to find the existence and the number of cointegration relationship. The number of cointegration relations was established by a sequential likelihood ratio test on the rank of an estimated parameter matrix from VEC model. Impulse response function (IRF) was performed to know response to a shock of a variable of other variables.

The empirical analysis demonstrated that the estimation model provides indication of goodness-of-fit and of the forecasting potential of the model. Most of the model estimation result follows the long-term development of the actual data series rather closely. The impulse response of a shock of a variable to itself and other variables die out after certain period. This verified the stability of all the estimated models. The forecast of container throughput in Indonesia generated by VECM indicated the reasonable result. In 2015, we estimated container throughput is 18,712,042 TEU with the average annual growth 11.69%. With this huge potential demand of container throughput, Indonesian port authorities should implement the best strategy for developing the future container port in order to provide better quality services for shippers and liner shipping companies. Beside that, in order to meet the future demand, the construction of new ports are inevitably due to the current container ports capacity can not handle such huge container demand.

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