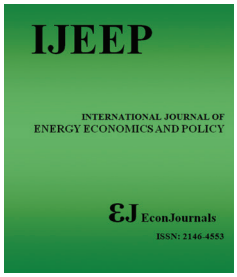

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State-space Implementation in Forecasting Carbon and Gas Prices in Commodity Markets

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ABSTRACT

Carbon is a waste that becomes a new economic commodity. It has been traded like stock prices in commodity markets. Owing to its new status, research on carbon price movements as a new economic commodity linked to gas has gained a considerable amount of interest. A deeper observation of the future of world gas prices can also be an indicator of the stability of this commodity. We use the state-space model as a statistical basis for modeling the daily movement of carbon values and gas prices. As a result, as we have calculated, the state-space model is able to predict and provide in-depth observational information on the relationship between carbon and gas. The economic implications show that carbon is not only good for the environment; its trading in the stock exchange also indicates that it can be a new stable and sustainable economic commodity.

Keywords: Commodity Markets, Forecasting, State Space Model, Carbon, Natural Gas
JEL Classifications: C1, C3, G17, Q4, Q47

1. INTRODUCTION

Climate change is currently a worldwide concern due to its negative impact. One of the reasons of extreme climate changes is the amount of carbon released into the environment. The 2020 Annual Climate Report of the NOAAs stated that temperatures have increased at an average rate of 0.08°C per decade since 1880, with an average increase of 0.18°C since 1981. Therefore, to solve problems generated by climate change, wise and responsible carbon management is necessary. Several management procedures have been recommended, including reforestation and intensification of farm management, provided that all efforts are carefully monitored to ensure that the costs of carbon management are not burdensome (Sinnott-Armstrong and Howarth, 2005). Continuously spurred economic growth has resulted in faster growth in emissions, especially carbon; thus, even greater efforts are needed to tackle it (Garnaut et al., 2008).

The world's economists are also involved in thinking and contributing to the reduction of the impact and amount of carbon. Carbon is currently used as an economic commodity, with the scheme of each entity having a share of carbon release, resulting in a demand for excess carbon from other entities; thus, carbon becomes a new economic commodity (NEC) that is traded. One of the alternative policies that can be recommended to restrain the growth of carbon emissions is to develop a carbon energy market, in addition to increasing the efficiency of regulations with regard to energy (Setyawan et al., 2020). Carbon emission pricing and trading has been a key feature of the worldwide regulatory response to climate change through the European Union Emissions Trading Scheme (EU ETS) since 2005. It is a cap-and-trade scheme

whereby companies must submit one emission allowance for every metric ton of emitted carbon dioxide (Batten et al., 2021). Therefore, consumers and producers in the ETS market should consider changes in the volatility of carbon prices affected by shocks arising from energy price changes.

In ensuring the sustainability of the market for carbon commodities, the methods of observing volatility and predicting future carbon values can be the basis for consideration. In this study, we compare the daily price of carbon with the daily price of natural gas to determine whether the price of carbon can also be influenced by external factors. Some previous studies forecasting the energy prices have been widely conducted, such as that of Hendrawaty et al. (2021), who forecasted crude oil prices, and Ambya et al. (2020), who estimated natural future gas. Moreover, carbon prices are a complex data that is typical of economic systems; they exhibit uncertainty, nonlinearity, mutation, and instability caused by interactions among many factors and their heterogeneous external environment (Chevallier, 2011).

One method that can be used in forecasting is the state-space method. State space is an approach of jointly modeling and predicting several interconnected time series data, and have dynamic interactions (Aoki and Havenner, 1991). State-space model is an approach used to simultaneously model and predict several interconnected time series data, whose variables have dynamic interactions and are in unobserved time series data (state vector).

2. STATISTICAL METHODS

State-space model was first introduced by Kalman (1960). It is used to jointly model and predict several interconnected time series data, and have dynamic interactions (Wei, 2006). State-space model describes a multivariate through additional variables (state vector). State vector contains a summary of all information from the previous value and the present value of a time series relevant to the prediction of future values (Chuang and Wei, 1991). According to Chuang and Wei (1991) and Akaike (1970), the state space represents a stochastic process from a stationary. This model is defined as the state transition equation

$$z_{t+1}=Fz_t+Ge_{t+1} \quad (1)$$

$t=1,2,\ldots T$

and the output equation

$$x_t=Hz_t \text{ or } x_t=[I_r,0]\, z_t \quad (2)$$

where
x: observation vector with dimension r×1
z_t: state vector with dimension s×1,s≥r, where r is x_t

and s-r is the last element required for forecasting x_t future
F: a coefficient matrix of size s-s called the transition matrix, which determines the dynamic properties of the model
G: a coefficient matrix of size s×r called the input matrix, which determines the variance structure of the transition equation

For model identification, the r rows and G columns are arranged into an identity matrix (I_r) of size r×r

H: Coefficient matrix measuring r×s, which is called the observation matrix

ei: Random residual vector, which is normally distributed with dimension r with mean 0 and covariance matrix e-e.

The equations of state are also known as system or transition equation. The output equation is also called the measurement or the observation equation. The random error e_t is also called the innovation or shock vector. The observation equation in the SAS procedure is as follows:

$$X_t=[I_r,0]\, Z_t \quad (3)$$

where I_r denotes the identity matrix r×r. SAS will extract X_t from Z_t without being presented in the measurement equation.

2.1. Information Criteria (IC)

Information criteria are used as a reference in selecting the best model. In the state-space model, the best model selection criteria used is the Akaike information criterion (AIC). The best model is the model that has the smallest AIC value (Akaike, 1970). The AIC for the VAR model uses the maximum log-likelihood approach as follows:

$$\mathrm{Ln}(L)-\frac{n}{2}\mathrm{lnln}\left(\left|\hat{p}_{\_}\right|\right) \quad (4)$$

Then, the AIC for the p can be calculated using the following equation:

$$AIC_p=\mathrm{nlnln}\left|\hat{p}_{\_}\right|+\mathrm{pr}^2 \quad (5)$$

where
n: number of observations
r: dimension of the process vector x_t

$\left|\widehat{\text{covariance}}_p\right|$: Determinant of matrix, which is white noise in AR modeling (p).

2.2. Canonical Correlation Analysis

The types of correlation often known in the case of univariate are simple, partial, and multiple correlations. In the case of multivariate correlation, the correlation analysis is better known as canonical correlation analysis. Canonical correlation analysis is employed to simultaneously identify and quantify the relationship between two groups of variables. Canonical correlation analysis is not as easy as the simple, partial, and multiple correlations. Therefore, in the canonical correlation analysis, the correlation between the independent cluster and the dependent is not only the correlation between the independent variable and dependent (Tsay, 2014).

Determination of the state vector elements is through a series of canonical correlation analysis of the sample autocovariance matrix. In the state space, variables with significant correlations are included in the state vector, but variables that are not real are excluded (Lutkepohl, 2013). Chuang and Wei (1991) stated that state vectors are uniquely determined through canonical correlation analysis between a set of values for the current and past observations (x_n, x_{n-1},x_{np}) and a set of observed values for the current and future events (x_n, $x_{n+1|n}$,$x_{n+p|n}$), where P_n is a vector of the values of the current and past events relevant to the prediction of x_{n+1} and predictor space $f_n=(x_n, x_{n+1|n},x_{n+p|n})$ and f_n is a vector of the current and future events.

In the canonical correlation analysis, the submatrix is determined from the covariance matrix based on the block Hankel matrix:

$$\Gamma = \begin{bmatrix} \Gamma(0) & \Gamma(1) & \Gamma(2) & \cdots & \Gamma(p) \\ \Gamma(1) & \Gamma(2) & \Gamma(3) & \cdots & \Gamma(p+1) \\ \vdots & \vdots & \vdots & & \vdots \\ \Gamma(p) & \Gamma(p+1) & \Gamma(p+2) & \cdots & \Gamma(2p) \end{bmatrix}$$

P-value refers to the VAR model with the smallest AIC value. The canonical correlation analyst refers to the block Hankel matrix of the sample covariance matrix as follows:

$$\hat{\Gamma} = \begin{bmatrix} \hat{\Gamma}(0) & \hat{\Gamma}(1) & \hat{\Gamma}(2) & \cdots & \hat{\Gamma}(p) \\ \hat{\Gamma}(1) & \hat{\Gamma}(2) & \hat{\Gamma}(3) & \cdots & \hat{\Gamma}(p+1) \\ \vdots & \vdots & \vdots & & \vdots \\ \hat{\Gamma}(p) & \hat{\Gamma}(p+1) & \hat{\Gamma}(p+2) & \cdots & \hat{\Gamma}(2p) \end{bmatrix}$$

where $\hat{\Gamma}(j), j = 0,1,\cdots,$ 2p is the sample covariance matrix.

The components of a predictive vector $x_{n+i|n}$ allow for a non-independent linear relationship. Thus, canonical correlation analysis is conducted on all components of the data space

$$P_n=[x_{1,n}, x_{2,n},x_{r,n},x_{1,n-1},x_{2,n-1},x_{r,n-1},x_{1,np},x_{2,np},\cdots,x_{r,np}]$$

and the components of the predictor space

$$f_n=[x_{1,n},x_{2,n},x_{r,n},x_{1,n+1|n},x_{2,n+1|n},x_{r,n+1|n},x_{1,n+p|n},x_{2,n+p|n},\cdots,x_{r,n+p|n}]$$

Canonical correlation analysis forms a series state vector, z_n^j. To calculate the canonical correlation value, a series f_n^j of subvectors f_n is examined and forms a submatrix consisting of rows and columns of corresponding to the component f_n^j. The smallest canonical correlation of will be used in the selection of state vector (SAS Institute Inc. 2003).

2.3. Selection of State Vector Components

According to (Chuang and Wei, 1991), the canonical correlation between $x_n=[x_{1,n},x_{2,n},\cdots,x_{r,n}]'$ and p_n is 1,…, 1, 0. State vector is then pooled to x_n and the first subset on a series f_n^1 collected into $[x_{1,n},x_{2,n},\cdots,x_{r,n},x_{1,n+1|n}]'$. The smallest canonical correlation of $\hat{\Gamma}^1$ is seen, whether it is greater than or equal to 0. If >0, $x_{1,n+k|n}$ is entered into the state vector. If it is equal to 0, then the linear combination of f_n^j is not correlated with p_n. Thus, the $x_{1,n+1|n}$ component and some $x_{1,n+k|n}$ are removed from the state vector. The selection of the state vector is complete when there are no more elements from f_n to be added to or removed from the state vector. For each run of a series of canonical correlation analyses, the smallest significant canonical correlation is calculated based on the AIC (Wei, 2006).

$$C=-n\ln \ln (1-\rho_{min}^2)-2[r(p+1)-q+1] \quad (6)$$

where
q: Dimension of f_t^j in the current period or process
r: The order of the state vector
p: The order of the VAR process.

If $C < 0$ and ρ_{min} is equal to 0 or $\rho_{min} > 0$. If $\rho_{min} > 0$, $x_{1,n+1|n}$ is then added to the state vectors.

To test the significance of the canonical correlation,, one approach that can be used is the Chi-squared (χ^2) test with the following hypotheses:
H_0: =0
$H_{1:}$ 0

If $\chi_{hit}^2>\chi_{(db)}^2$, then H_0 is rejected, which means correlation canonical significance.

2.4. Parameter Estimation

According to (Wei, 2006), after the state space is identified, one of the state spaces uses the maximum-likelihood approach. This procedure is conducted iteratively, and the estimates are obtained from canonical analysis and used to obtain efficient estimators for F and G. In this estimation process, one of the elements in F and G must have a constant value, such as 0 or 1.

For a series of n observations x_1,x_2,x_n because $x_t=(I-FB)^{-1}$ Ge_t, B as backshift operator, we get $x_t=H(I-FB)^{-1}$ e_t and $Ge_t=[H(I-FB)^{-1})$ $G]^{-1}$ x that the log likelihood function is obtained as follows:

$$\ln L(F,G,\sum|x_1,x_2,x_n)-(n/2)\ln|\sum|-(1/2)tr-1^S(F,G) \quad (7)$$

where

$$S(F,G)=\sum_{t=1}^{n} e_t e_t'$$

2.5. Kalman Filtering

Kalman filtering is the most common approach for statistical estimation. This has been demonstrated by (Harrison and Stevens, 1976), who stated that all forecasting methods are special cases of Kalman filtering. In this case, Kalman filtering can handle changes in the model, parameters, and variance or diversity. Kalman filtering consists of two independent estimates to form a weighted estimate. Estimates can be based on past knowledge

or new information (data). Kalman filtering aims to combine the two information to obtain improved estimates. This is similar to the Bayesian approach, which combines "prior" and "sampling" information to obtain a posterior distribution (Makridakis, 1999).

According to Chuang and Wei (1991), Kalman filtering is a recursive procedure used to perform from state vectors. Kalman filtering is a recursive updating procedure that involves forming an initial estimate of the state and then revising the estimate by adding corrections to the initial estimate. The magnitude of the correction is determined by how well the initial guess predicts the new observation.

Forecasting accuracy $\hat{x}_t(l)$ depends on the quality of the estimate $\hat{z}_t$ from the state vector z_t. When a new information is available, the state vector, the same is done for the forecast theorem approach. We get: $p(x_{t-1})\ p(z_{t-1},x_t)p(y_{t-1})|x_t)$ posterior distribution $p(x_t)$ becomes the prior distribution to find out the new posterior distribution, namely, $p(x_{t+1})$, where the observation x_{t+1} is available. In this case, assume that the posterior distribution of the state vector z_t at time t, i.e., $p(x_t)$ follows the normal distribution with the mean z_t and the covariance matrix $\Gamma_t p(x_t) \sim N(\hat{z}_t, \Gamma_t)$.

At time t + 1, when the observation x_{t+1} is available, the state vector can be updated, and a new posterior distribution $p(x_{t+1})$. x_{t+1} is equivalent to the forecasting error$_{t+1}$, so to get $p(x_{t+1})$, you only need to find the posterior distribution of (e_{t+1},x_t), namely, $p(e_{t+1},\ x_t) \sim N(\hat{z}_{t+1},\Gamma_{t+1})$,

where

$$z_{t+1} = F\hat{x}_t + R_{t+1}H'\left(\Omega + HR_{t+1}H'\right)^{-1} e_{t+1} \quad (8)$$

$$= F\hat{x}_t + K_{t+1}(x_{t+1} - \hat{x}_t(1))$$

$$\Gamma_{t+1} = R_{t+1} - R_{t+1}H'\left(\Omega + HR_{t+1}H^{'}\right)^{-1} HR_{t+1} \quad (9)$$

$$= R_{t+1} - K_{t+1}HR_{t+1}$$

$$= \left(I - K_{t+1}H\right)\left(F\Gamma_t F^{'}G\sum G\right)$$

Where:
$K_{t+1} = R_{t+1}H'\left(\Omega + HR_{t+1}H^{'}\right)^{-1}$ and $R_{t+1} = F\Gamma_t F^{'} + G\sum G'$.

Equations (8) and (9) are basic recursive formulas used to update the mean and covariance matrix as well as the distribution of the state vector z_{t+1} after the new observation that is x_{t+1} is available. The guess of state is $\hat{z}_{t+1}$ is the sum of $F\hat{z}_{t+1}$, which is the assumption from the observation to the t forecasting error 1 step forward that is $e_{t+1} = x_{t+1} - \hat{x}_t(l)$. Matrix K_{t+1} is also called the Kalman-gain, which determines the weight for forecasting error.

3. RESULTS AND ANALYSIS

3.1. Description of Research Data

In the initial process, the research process generally describes the data used. The data in this study consists of daily gas prices (with the symbol "GP") and carbon (with the symbol "CO_2"), and both are time series data. Table 1 shows that the amount of data that we observed was 90, with mean values of 2901 and 18.61 for GP and CO_2, respectively. The daily gas data is at a minimum of 1640 and a maximum of 5867, whereas the carbon data is at a minimum of 4.41 and a maximum of 75.26.

In the next step, we tested the correlation between variables. This is commonly carried out in economics research to ensure that the variables are related at an early stage, so that more difficult processes in research can be predicted to succeed. The following correlation test results are presented in more detail:

Table 2 demonstrates that the daily gas and carbon price variables have a positive and perfect relationship by looking at Pearson's correlation coefficients of 1.0. Furthermore, we have to ensure daily data on stationary gas and carbon. In this process, we perform differencing. Considering the importance of information about the differencing data, we present descriptive statistics after the process is conducted.

Table 3 shows that the amount of final data that we observed was 89, with mean values of 1.191011 and 0.780337 for GP and CO_2, respectively. Furthermore, the two variables have reached the level of stationarity, which is the main requirement in forecasting with state-space models. In the level 1 differencing, the gas and carbon variables are stationary. So, if it is assumed that X_t and Y_t are the observed values of GP and CO_2, let x_t and y_t be the values of GP and CO_2, respectively, after differencing and subtracting the mean difference. The series of NECs are modeled as follows:

NEC=[xt yt]=[(1–B) Xt–1.191011 (1–B) Yt–0.780337]

where B is the backshift operator.

In the next step, we analyze the value of the AIC on the autoregressive model according to the series. Of course, we consider the smallest AIC value; at lag 3, we get a value of 1260.117. The smallest AIC value presented in Table 4 determines the number of autocovariance matrices; the results will be used in performing the canonical correlations.

Table 1: Descriptive statistics

Variable	*n*	Mean	SD	Sum	Minimum	Maximum
GP	90	2901	765.98146	261061	1640	5867
CO_2	90	18.61500	15.83186	1675	4.41000	75.26000

GP: Gas price, CO_2: Carbon, SD: Standard deviation

Table 2: Correlation test

Pearson correlation coefficients Correlation Test, *n*=90 Prob > |r|under H0: Rho=0		
	GP	CO_2
GP	1.0000	0.31241 0.0027
CO_2	0.31241 0.0027	1.0000

GP: Gas price, CO_2: Carbon

Table 3: Descriptive data after differencing

Variable	Mean	SE	Number of observations	Differenced status
GP	1.191011	417.8008	89	Has been differenced. With period (s)=1
CO_2	0.780337	2.872792	89	Has been differenced. With period (s)=1

GP: Gas price, CO_2: Carbon, SE: Standard error

Table 4: Information criterion for autoregressive models

Lag=0	Lag=1	Lag=2	Lag=3	Lag=4	Lag=5	Lag=6	Lag=7	Lag=8	Lag=9	Lag=10
1261.399	1267.653	1265.104	1260.117	1263.018	1270.147	1277.759	1278.214	1281.789	1282.111	1288.931

Analysis of the schematic representation of partial autocorrelations will be shown on Table 5. This stage will provide information on which elements of the autocorrelation matrix at different lags are significantly greater than or less than 0. More details are presented in Table 5.

Table 6 presents the third-order autoregressive model identified with the confirmed AIC statistic as plausible, because the partial autocorrelation for lags greater than 2 is not significant. Furthermore, the Yule–Walker estimates for the autoregressive model are performed to give the coefficient matrix output of the autoregressive vector model at each lag as follows:

or can be expressed as follows:

$[x_i\ y_i]=[a_{10}\ a_{20}]+[-0.14399-8.5133-0.000003-0.11178][x_{t-1}\ y_{t-1}]+[-0.05267\ 28,7089\ 0.00206\ 0.05011\ ][x_{t-2}\ y_{t-2}]+0.03931[\_\ 28,67226\ 0.00099\ 0.26602\ ][x_{t-3}\ y_{t-3}]$

3.2. Determination of State Vector

In performing correlation analysis on vectors, we used canonic correlation of order 3 to explore the relationship between two multivariate variables (vectors) in the study, all measured in the same set. The canonic correlation can be seen from the third-order autocovariance matrix, which has been previously analyzed. The criterion is that if the value of the information criterion is negative or not real, it will be removed from the state vector, whereas the information criterion is entered into the state vector. Table 7 provides information on test values from the canonic correlation analysis.

In Table 7, the output above indicates that the IC value of the canonical correlation y(T + 1|T) is positive of 3.79242. To fulfill our belief in the correct state vector of the chi-squared test value in Table 7, the results are significant using chi-squared (X^2) we get X^2hits = 5.368963 $<X_{0.05(5)}{}^2$= 11.070. This means that the canonical correlation is not significant; thus, the component is not included in the state vector.

Therefore, from the testing of the significance of canonical correlation analysis, the real components obtained are x_t, y_t, and $y_{t+1|t}$. This component becomes the final state vector component as follows:

From the form of notation in Table 8, we write the following equation:

$z_t=[x_t\ y_t\ y_{t+1|t}]$

Table 5: Schematic representation of partial autocorrelations

Name/Lag	1	2	3	4	5	6	7	8	9	10
Price	.	.	.	.	.	.	.	.	.	.
CO_2	.	+	+	.	.	.	.	.	…	.

+ is>2*SE, − is < −2*SE, s between. SE: Standard error

Table 6: Yule–Walker estimates for minimum akaike information criterion

	Lag=1		Lag=2		Lag=3	
	Price	CO_2	Price	CO_2	Price	CO_2
Price	−0.14399	−8.5133	−0.05267	28.7089	0.039315	28.67226
CO_2	−0.0003	−0.11178	0.002068	0.05011	0.00099	0.266026

CO_2: Carbon

Table 7: Canonical correlation analysis

Price (T; T)	CO_2 (T; T)	CO_2 (T+1;T)		Information criterion	χ^2	DF
1	1	0.403226		3.79242	15.26009	6
Price (T; T)	CO_2 (T; T)	CO_2 (T+1;T)	CO_2 (T+2;T)	Information criterion	χ^2	DF
1	1	0.446482	0.24532	−4.47587	5.368963	5

Table 8: Selected state-space form and preliminary estimates

State vector		
Price (T; T)	CO_2 (T; T)	CO_2 (T+1;T)

After these steps, the information generated canonical correlation analysis and initial autoregression as the basis for forming the initial estimate of the state space.

3.3. State-Space Model

The information obtained from the stage of selecting the VAR order and determining the state vector through a series of canonical correlation analyses is used to generate an initial estimate of the state-space model parameters. The initial value of the parameter estimation process iteratively is efficient estimators for F and G obtained using five iterations, after which the following is obtained:

$$\hat{F} = \left[-0.11089\ -8,164050001\ 0.001478\ 0.192451\ 0.629868\right]$$

$$\hat{G} = \left[1\ 0\ 0.000162\ -0.17686\right]$$

$$\widehat{172057.5} = \left[\_\ -115.04\ -115.04\ 6.967175\right]$$

Table 9: Iterative fitting: Maximum-likelihood estimation

Iter	Half	Determinant	Lambda	F (1,1)	F (1,2)	F (3,1)	F (3,2)	F (3,3)	G (3,1)	G (3,2)	Sigma (1,1)	Sigma (2,1)	Sigma (2,2)
0	0	1,244,641	0.1	−0.1106818	−8.1615483	0.00183097	0.07331542	0.50732314	−0.0000262	−0.1117793	172057.47	−85.670787	7.2765257
1	0	1,196,731	0.01	−0.1132163	−8.1616396	0.00168506	0.18724611	0.56237362	0.00016664	−0.1320808	172058.591	−127.84242	7.05035925
2	0	1,185,696	0.001	−0.1106462	−8.1624433	0.00148297	0.18812187	0.63434248	0.0001618	−0.1798188	172057.47	−111.66337	6.96374557
3	1	1,185,540	0.01	−0.1109252	−8.1641153	0.00147827	0.19386652	0.62805642	0.00016287	−0.1760402	172057.48	−116.06706	6.96867025
4	2	1,185,520	0.1	−0.1108862	−8.1640478	0.00147802	0.19246823	0.62984734	0.00016206	−0.1768416	172057.477	−115.05649	6.96719754
5	8	1,185,520	1	−0.1108856	−8.1640476	0.00147804	0.19245104	0.62986761	0.00016204	−0.1768613	172057.477	−115.04001	6.96717543

Furthermore, the iterative fitting and maximum likelihood estimation shown in the output in Table 9:

Finally, we can achieve the goal of modeling daily gas and carbon price forecasting data with state space. The Table 10 shows estimates with maximum likelihood, not initial estimates.

The main equation of the state-space forecasting model for gas and carbon data is as follows:

$$z_{t+1}=Fz_t+Ge_{t+1}$$

$$\begin{bmatrix} x_t \\ y_t \\ y_{t+2|t+1} \end{bmatrix} = F \begin{bmatrix} -0,11089 & -8,16405 & 0 \\ 0 & 0 & 1 \\ 0,001478 & 0,192451 & 0,629868 \end{bmatrix}$$

$$\begin{bmatrix} x_t \\ y_t \\ y_{t+l|t} \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0,000162 & -0,17686 \end{bmatrix} \begin{bmatrix} e_{1.t+1} \\ e_{2.t+!} \end{bmatrix}$$

and

$$\text{var}\,[e_{1.t+1}]=[172057.5\text{–}115.04\text{–}115.04\ 6.967175]$$

Table 10: Selected state-space form and fitted model

State vector		
Price (T;T)	**CO_2 (T;T)**	**CO_2 (T + 1;T)**
Estimate of transition matrix		
−0.11089	−8.16405	0
0	0	1
0.001478	0.192451	0.629868
Input matrix for innovation		
1	0	
0	1	
0.000162	−0.17686	
Variance matrix for innovation		
172057.5	−115.04	
−115.04	6.967175	

Figure 1: Forecasting of gas

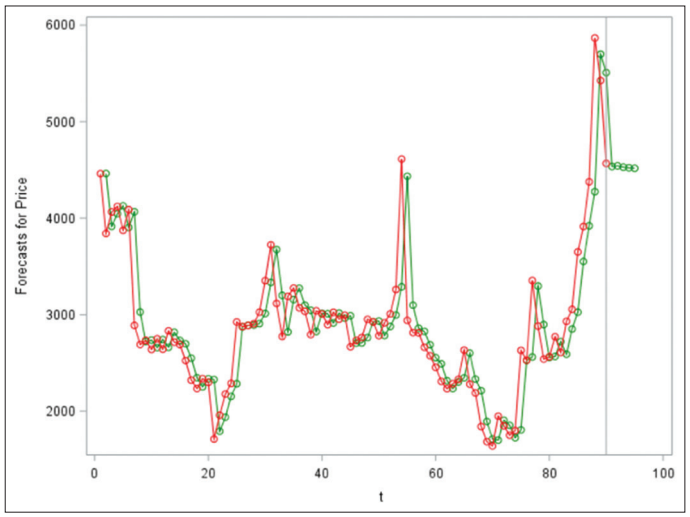
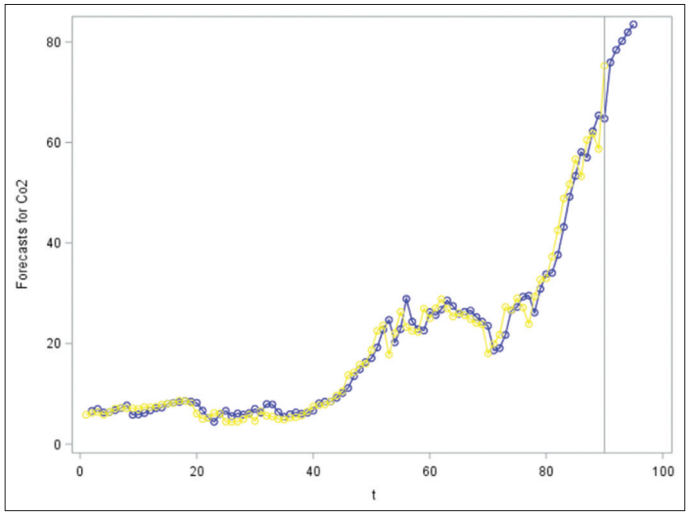


Figure 2: Forecasting of carbon



The above equation can be described as follows:

$x_{t+1}=x_{t+1|t}+e_{1,t+1}$

$y_{t+1}=y_{t+1|t}+e_{2,t+!}$

$y_{t+2|t+1}=0.001478x_t+0.192451y_t+0.629868y_{t+1|t}+0.000162\ e_{1,t+1}-0.17686\ e_{2,t+!}$

The forecasting of gas and carbon based on the Kalman filtering is presented in the following figures:

Figures 1 and 2 present the results of the forecasting of gas and carbon, which exhibit an increasing trend. As can be seen from the figures, the volatility of gas data tends to be more aggressive than the carbon data, which increases at an even slower rate. Gas and carbon data have jointly increased in recent times. This indicates a condition where there is an interrelationship between gas and carbon.

4. CONCLUSION

Overall, this study aimed to observe the daily price of gas and carbon, which is suspected to have a relationship. Carbon has become a NEC that demonstrates a positive movement. As a result, the daily prices of gas and carbon are stationary in the second- and first-level differentiation, respectively. Furthermore, there is a unidirectional causality relationship between the daily prices of gas and carbon. More importantly, with carbon being an economically valuable commodity, it is hoped that it will reduce the amount of carbon released so that extreme climate change can be avoided, and green energy can be started.

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