Master's Thesis

Forecasting Korean LNG import price using ARIMAX, VECM, LSTM and hybrid models

SUNG HYUN SEO

Graduate School of Technology and Innovation Management

Ulsan National Institute of Science and Technology

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Abstract

In this paper, an optimal forecasting model for the South Korean LNG import price was explored by combining an econometric model, a machine learning model, and a hybrid model. The autoregressive moving average model with extrinsic inputs model (ARIMAX) and VECM were the econometric models, and LSTM was the selected machine learning model. ARIMAX-LSTM and VECM-LSTM were used as hybrid models. Various independent variables, such as the Dubai oil price, European gas price, Australian Newcastle coal price, US natural gas price, Japanese liquified natural gas price and system marginal price in Korea were used for forecasting models. As it was proved that granger causality of each independent variables toward South Korean LNG import price is stronger in the order of the Dubai oil price, European gas price, Australian Newcastle coal price, US natural gas price, Japanese liquified natural gas price and SMP, the variables used for forecasting were added one by one in the order of strong granger causality. Optimal lags were derived from VECM analysis for each variable combination and these were used for VECM and LSTM prediction.

As a result of forecasting, 6 LSTM models, 4 VECM-LSTM were ranked in the top 10 forecasting models out of the total 90 models. Single econometric models were not included in the list. The best forecasting model was the LSTM with Dubai oil price, European gas price, Australian Newcastle coal price, US natural gas price, and Japanese liquified natural gas price with lag of 6, and its mean absolute percentage error (MAPE) was 3.5209. In addition, because LNG price forecasting is more important when price fluctuation is high, forecasting models were employed for 11 months with high fluctuation among the test periods. Seven hybrid models, one LSTM models, and two ARIMAX models were ranked in the top 10 forecasting models. VECM-LSTM using Dubai oil price with lag of 5 was derived as the best model with a MAPE of 4.9360. As a result of two forecasting analyses for both the whole and high fluctuation periods, we found that LSTM using Dubai oil price, European gas price, Australian Newcastle coal price, US natural gas price, and Japanese liquified natural gas price with a lag of 6 and VECM-LSTM using Dubai oil price, European gas price with a lag of 5 were ranked within the third best for both tests. Of the two models, the VECM-LSTM is in particular considered as the optimal model in that it has both high forecast accuracy and interpretability.

Keywords : LNG, ARIMAX, VECM, LSTM, ARIMAX-LSTM, VECM-LSTM

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Explanation of terms and abbreviations

Adam Adaptive with moment

ADF Augmented Dickey–Fuller

AIC Akaike Information Criterion

ANN Artificial Neural Networks

ARMA Auto Regressive Moving Average

ARIMAX Auto Regressive Moving Average with Extrinsic input model

ECT Error Correction Term

FPE Final Prediction Error

HQC Hannah-Quinn Information Criterion

IGU International Gas Union

IMO International Maritime Organization

JCC Japan Crude Cocktail

JKM Japan and South Korean Marker

KOGAS Korea Gas Corporation

LNG Liquified Natural Gas

LSTM Long Short-Term Memory

MAPE Mean Absolute Percentage Error

MOTIE Ministry of Trade, industry and Energy

ML Machine Learning

NBP National Balancing Point

NN Neural Network

PP Phillips–Perron

RMSProp Root Mean-Squared Prop

SC Schwarz Information Criterion

SMP System Marginal Price

TTF Netherlands Title Transfer Facility

VAR Vector Auto Regressive

VECM Vector Error Correction Model

ZEE Zeebrugge Hub

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1. Introduction

South Korea was the world's third-largest importer of liquefied natural gas (LNG) after Japan (76.9 million tons, 22%) and China (61.7 million tons, 17%) in 2019 at 40.1 million tons (11%) of global LNG imports (IGU 2020). In addition, in line with the South Korean government's energy conversion policy, the demand for LNG is expected to increase further in the future, and South Korea's role and status in the global market is expected to be expanded. According to the South Korea’s Third Basic Energy Plan, in 2017, the share of coal and LNG in the total energy demand was 35.2% and 19.3%, respectively, but in 2040, the share of coal is expected to decrease to 30.5%, and the share of LNG will increase significantly to 25.4%. In addition, the proportion of renewable energy will reach 14.1% by 2040 from 6.1% in 2017. Under this policy, the power industry is also trying to reduce coal-fired power and increase the proportion of combined-cycle power plants fueled by LNG. In the power industry, the construction of new coal-fired power plants has been prohibited, and old coal power plants are being abolished or converted to LNG power plant. In addition, all future power plants will be combined-cycle power plants fueled by LNG. Therefore, LNG is expected to take up a greater share of the South Korean power industry. Actually, for the working group for the Ninth Basic Plan for power supply and demand announced by the South Korean government in May 2020, out of a total of 60 coal generators, 30 units (15.3 GW) will be abolished, and 24 of them (12.7 GW) will be converted to LNG. Accordingly, the capacity of LNG power plants is expected to increase from 41.3 GW in 2020 to 60.6 GW in 2034.

As the proportion of LNG used grows, stakeholders' attention to LNG prices is expected to increase, especially those in the electricity market. The South Korean electricity market has adopted a cost-based pricing system, so power plants are operated in the order of the lowest fuel cost, and they are mainly operated in the order of nuclear, coal-fired, and LNG power plants due to each source fuel’s price characteristics. At this time, when the power plant is operated in the order of low fuel cost according to the electricity demand for each hour, the fuel cost of the last power plant becomes the system marginal price (SMP). However, considering the South Korean power demand and supply capacity, LNG power plants usually determine SMP. In 2017, 81.7% of the SMP was determined by the LNG power plant. Accordingly, some of the more than 50 LNG-fueled power plants in South Korea were operated, and some were not. However, previously, all LNG power plants were supplied with natural gas at the same price from the South Korean state-run gas company, Korea Gas Corporation (KOGAS), so the order was decided mainly due to factors other than fuel price such as facility efficiency. However, some power plants directly import LNG, and these direct importers of LNG have different fuel costs as power plants are supplied with natural gas from the KOGAS, which leads to competition in LNG costs between the KOGAS and LNG direct importers. As a result, LNG prices have become an important factor that decides whether to operate a power plant, and attention to

LNG price has increased.

In addition, LNG price is a major factor that determines the risk of the renewable energy business. According to Moon and Jung (2020), the long-run positive relationship between the import price of LNG and the SMP in South Korea demonstrates that the fluctuations in global fuel price are likely to increase uncertainties in renewable investments. Therefore, LNG price prediction can contribute to the mitigation of business risks and the encouragement in investments in new and renewable energies by enabling more accurate economic evaluations of new and renewable energies. In addition, the International Maritime Organization (IMO) is implementing regulations starting in 2020 that limit the sulfur content of ship fuel oil from 3.5% m/m(mass/mass) to less than 0.5% m/m on all routes (Lee et al., 2020) Accordingly, the shipping industry is replacing fuel with low sulfur fuel oil or LNG to meet the IMO's sulfur standards, and in response to this demand, the LNG bunkering business has also expanded. LNG prices have an important impact on the economics of these shipping companies and bunkering operators. furthermore, many other stakeholders, such as the manufacturing industry, hydrogen-related business, and others, are involved in LNG. Therefore, LNG price forecasting is very important for many stakeholders across various industries.

2. Literature Review

Ghoddusi et al. (2019) reviewed more than 130 articles about the energy economics/finance applications of machine learning (ML) published between 2005 and 2018. According to this review, support vector machines (SVMs), artificial neural networks (ANNs), and genetic algorithms (GAs) are among the most popular techniques used in energy economics papers, and most of these papers mainly used either individual ML techniques or hybrid ML/statistical econometrics techniques. Energy commodity price series typically demonstrate complex features such as non-linearity, lag-dependence, non-stationarity, and volatility clustering which make the use of simple traditional models challenging (Cheng et al., 2018b). ML methods may provide superior forecasting performance because they have higher flexibility in handling complex internal dynamics. Papers dealing with forecasting crude oil prices are predominantly based on advanced and hybrid versions of ANNs and in less degree of SVM models. Also, combining multiple methods (ensemble approach) has become more common in recent years. Among recent papers evaluating the predictive accuracy of methods, Safari and Davallou (2018) is a particular case. According to Safari and Davallou (2018), among various models, such as the exponential smoothing model (ESM), auto-regressive integrated moving average (ARIMA), nonlinear autoregressive (NAR), EWH (hybrid of ESM, ARIMA, and NAR with time-varying weights using the Kalman filter), GWH (hybrid of ESM, ARIMA, and NAR with constant weights using GA), PHM (hybrid of ESM, ARIMA, and NAR with equal weights), and the

ZHM hybrid model (ARIMA-ANN), PHM showed the best performance with a mean absolute percentage error (MAPE) of 2.44%. NAR's and GWH's MAPEs were the second best at 2.86%, and others were greater than 3%.

However, a vast majority of papers focusing on price predictions either considered only crude oil or power price prediction. Predictions of natural gas price have occurred much less frequently (Ghoddusi et al., 2019). Nevertheless, research on LNG price prediction has also been conducted in many studies, although this is less frequent than oil price prediction. According to Wang et al. (2020), forecasting studies can be categorized into two types of models, i.e., structure- and data-based models. Structure-based models refer to models that forecast natural gas by considering other factors such as oil price, gas production, gas consumption, gas imports, etc. Data-based models predict using only historical gas price data. As for structure-based model, Nguyen and Nabney (2010) combined the Wavelet transformation with MLP, RBF, LR, GARCH, and Kalman or particle filters to predict the UK's electricity demand and monthly gas price. It was confirmed that the forecasting performance of the adaptive GARCH model was the best, and its MAPE was 1.8%. Viacaba et al. (2012) predicted US natural gas prices using the support vector regression (SVR) and selective SVR (SelSVR) models, and the price of electricity, storage, pipeline imports, LNG, natural gas consumption, gross production, marketed production, renewable consumption, renewable production, and weather were used as independent variables. The forecasting performance was 0.0991 for RMLSE. Ceperic et al. (2017). analyzed the Henry Hub spot price using a classic time series model such as ARIMA and strategic seasonality-adjusted support vector regression machines (SSA-SVR). The dependent variables used were natural gas price differences, heating oil prices, heating oil price differences, WTI oil prices, WTI oil price differences, coal prices in the Appalachian Mountains, coal price differences, Baker Hughes US Natural Gas Rotary Rig count, total US natural gas marketed production, and NG imports from Canada. Among these variables, the optimal combination of variables was selected for each analysis model through the feature selection algorithm.

As for the data-based models, Lin and Wesseh (2013) applied the Markov-switching volatility model to predict the natural gas index, which was equal dollar weighted and based on 18 highly capitalized companies in the natural gas industry. The forecasting performance was 0.0625–0.086 MSE. Naderi et al. (2019) used four analysis methods: the least square support vector machine (LSSVM), genetic programming (GP), ANN, and ARIMA to determine oil and gas prices. The optimal integrated equation was derived by combining the above four methodologies through the meta-heuristic bat algorithm (BA), and its MAPE was 1.49%. Su et al. (2019) predicted the monthly Henry Hub natural gas spot price by using ANNs, SVMs, gradient boosting machines, and Gaussian process regression models, and it was confirmed that ANN has superior performance compared to other models as its MAPE 11.2–13.7%. Independent variables include crude oil price (WTI), heating oil price, natural gas, rotary rigs, heating degree days, cooling degree days, natural gas marketed production, natural gas total consumption, natural gas underground storage volume, and natural gas imports. However, Su et al. (2019) predicted daily, weekly, and monthly Henry Hub spot prices using linear regression, linear SVMs, quadratic SVM, cubic SVM, and a least squares regression boosting algorithm model. The performance of the least squares regression boosting algorithm model was the best with an MSE of 0.4376. Wang et al. (2020) described support vector regression and long- and short-term memory networks and a modified data-driven model, i.e., the improved pattern sequence similarity search (IPSS) and a weighted hybrid based on three models. The forecasting performance of IPSS model was the best.

Several features can be found in the existing literature. First, ML models' performances were better than the econometric models, and the hybrid model's forecasting performance was better than a single model. Time series were rarely pure linear or nonlinear. They often contained both linear and nonlinear patterns. However, it is difficult for a single model to fully explain and forecast the time series. For example, the conventional econometric model cannot deal with nonlinear relationships, and the ML model alone is not able to handle both linear and nonlinear patterns equally well. In this situation, combining different models can increase the chance of capturing different patterns in the data and improving forecasting performance (Zhang, 2003). Accordingly, in this study, not only single econometric, machine learning models, but also hybrid model will be used for analysis.

However, although several hybrid models were used in the above-mentioned papers, there is a limitation that they are mainly focused on only improving the forecast accuracy. There are several criteria in addition to the forecasting accuracy in relation to the evaluation of the prediction models. Murphy (1993) suggested three criteria for this specific evaluation: (1) consistency during the forecasting process, (2) the quality or the correspondence between the forecasts and the target values, and (3) the value or the profit that the forecast provides to decision makers. Only a few studies were dedicated to criterion (3), while the greatest part of the literature focuses on criterion (2). This phenomenon is also applicable to natural gas price forecasting. Most of the papers evaluated the performance of the model using only forecast accuracy. The structure-based models mentioned above focused on which variables and parameters were applied to have the best forecast accuracy and, in most cases,, it was not described how the independent variables relate to the natural gas price, which is a dependent variable. However, for forecasting models to be effectively utilized in practice, criterion (3) is also important. Usually, statistical econometric models can provide good theoretical interpretability with a clear calculation construction while ML models use a "black box" approach and often lack a good interpretation of the model, compared to econometric models. (Jiang et al., 2016). Accordingly, when the econometric and ML models are combined, it is expected that there is a sufficient possibility that a hybrid model that combines the interpretability of an econometric model and the forecast accuracy of an ML model to be derived. Therefore, in this paper, not only were single econometric models and ML models but also a hybrid model combining both models used, and this hybrid model is expected to enhance the value or the profit that the forecast provides to decision makers. ARIMA and vector autoregressive (VAR) (or the vector error correction model [VECM] in the case cointegration exists] are used as econometric models. Multivariate ARIMA and VAR models are the other most popular forecasting econometric models that generalize the univariate ARIMA models and univariate autoregressive (AR) model by allowing for more than one evolving variable (Siami-Namini et al., 2018). In addition, long short-term memory (LSTM) will be used as an ML model. Neural network-based methodologies can clearly extract nonlinear features that cannot be captured by an econometric model in volatility predictions, and these have demonstrated outstanding performance, particularly in the financial time-series model. The LSTM, a special type of RNN, is superior to the feedforward neural network model as a financial time-series model (Kim & Won, 2018)

In order to establish a model with high interpretability, a structure-based model is used among data-based and structure-based models. When building a forecasting model probably the most important step is the selection of model input variables (Ceperic et al., 2017). However, in most of the existing literature, there were no specific explanations for the reasons for selecting intendent variables, and variables related to supply and demand such as temperature, production, and inventory were used as independent variables. In this paper, many literature studies were involved to select potential optimal variables. In addition, oil price, coal price, electricity price, and natural gas prices in other regions were used as independent variables rather than the variables related to supply and demand that were used mainly in the existing papers. The study of these variables is expected to help identify the dynamics of LNG prices with other energy commodity prices and provide useful insights for price prediction in LNG importing countries. Besides, as mentioned above, there are relatively few previous studies on LNG price forecasting compared to other commodity price forecasting, such as oil price, but most of the studies on natural gas price forecasting were limited to the US and European markets. However, considering that Asia accounts for more than 60% of the global LNG imports as of 2019, a lot of research on the prediction of LNG prices in Asia is required. Therefore, it is meaningful that this study investigates LNG import prices in South Korea, one of Asia's major LNG importers.

Therefore, in this paper, South Korean LNG import price is going to be predicted through the autoregressive moving average model with extrinsic inputs model (ARIMAX), VECM, LSTM, and hybrid models by using the prices of other energy commodities as explanatory variables. This is expected to contribute in (1) verifying whether the hybrid models such as ARIMAX-LSTM, VECM-LSTM have better forecasting performance than the single econometric and machine learning model, (2) identifying dynamics between South Korean LNG import price and other energy commodity prices, and enhancing interpretability of model, (3) studying LNG price in South Korea where has not

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been treated though it is the third-largest LNG import country.

This study is organized as follows. Section 3 introduces the methodology and data description used in this research. In section 4, empirical study is conducted, and section 5 covers conclusion.

3. Methodology and Data

To forecast the monthly LNG import price in South Korea, we analyzed it through a traditional econometric model, an ML model, and a hybrid model combining both a traditional econometric model and an ML model. Traditional econometric and ML models each have their own strengths and weaknesses. In general, traditional econometric models provide a better explanation than ML models. Traditional econometric models not only predict price but also provide insights into the target variable by identifying the relationship between independent and dependent variables. ML models have a better forecasting performance compared to the economic models. However, there is a disadvantage in that it is not possible to identify the dynamics between the independent and dependent variables in ML models. Accordingly, the attempt to derive an optimal hybrid model that combines both econometric and ML models will be meaningful in that it should be able to encompasses the strengths of both. Therefore, in this study, econometrics models, an ML model, and a hybrid model are all used. ARIMAX and VECM will be the econometric models, and LSTM will be the ML model.

3.1. ARIMAX

The ARIMAX model consists of four parts: the AR, integrated (I), moving average (MA), and exogenous variable. The model has the following details.

1. AR: The general characteristics of AR of order p are as follows:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} + \varepsilon_t \tag{1}$$

where $\beta_1 \ldots \beta_2$ $are\ parameters, \alpha\ is\ content, and\ \varepsilon_t\ is\ the\ random\ variable\ (white\ noise)$

2. I is the difference of variables. It is necessary to find the differences because the ARIMA is nonstationary, so it must be converted to be stationary by differences in the p order.

3. MA uses the error term from forecasting to calculate the differences between variables that really happen (Y Actual) with the dependent variables (Y Forecast) or $\varepsilon_t = Y_{at} - Y_{ft}$ in the past to help with forecasting the variables needed in the future in the following manner:

$$Y_t = \delta + \varepsilon_t - \gamma_1 \varepsilon_{t-1} - \gamma_2 \varepsilon_{t-2} - \cdots - \gamma_q \varepsilon_{t-q} \tag{2}$$

where the MA of order q or MA(q) by q means the last order of error value used. The form of model development ARIMA is ARIMA (p,d,q); that is, the order of AR=p, of I=d, and of MA=q, respectively. (Sutthichaimethee & Ariyasajjakorn, 2017)

In general, ARIMA models do not include independent variables, so it is difficult to determine the relationship with specific independent variables and to have excellent long-term forecasting performance in combination with various independent variables, which is a concern in traditional regression analysis. The ARIMAX model was devised to further consider exogenous variables to improve ARIMA's limitations. In this study, both ARIMA and ARIMAX were used.

3.2. VECM

The VAR model is used to show the simultaneous interactions among a group of variables through a system of equations that considers that sets of explanatory variables for each equation as being formed by the lags in each of the model's endogenous variables in addition to its deterministic or exogenous variables and their respective lags. In general, a VAR model of order n with a Gaussian error can be expressed in matrix form as

$$y_t = \sum_{s=1}^{n} A_s y_{t-s} + Bx_t + e_t \qquad t = 1, \dots, T \tag{3}$$

where y_t is a k × 1 column vector of the k endogenous variables in time t, A_s is the k × 1 matrices of the coefficients of each endogenous variable with lag s, y_{t-s} is a k × 1 column vector of the k endogenous variables with lag s, x_t is a p × 1 column vector of the p exogenous variables in time t, B is a k × p matrix of the coefficients of each exogenous variable, and e_t is a k × 1 column vector of the random errors of each endogenous variable in time t, distributed Gaussian, without autocorrelation, with mean equal to zero and a constant variance. This study used cointegration analysis introduced by Granger (1981) and developed later by Engle and Granger (1987), Johansen (1988), and Johansen and Juselius (1990). Granger's theorem establishes the existence of an error-correction model of x_t, assuming Δx_t and $\beta' x_t$ have stationary and invertible VARMA representations for the cointegration vector β′ (Engle & Granger, 1987). The cointegration vectors, β, have the property of making β′x stationary, although x is non-stationary (Johansen & Juselius, 1990). Considering the VAR model of equation 1, the error correction representation (VECM) applied according to Johansen and Juselius (1990) corresponds to:

$$y_{t=} \sum_{s=1}^{n-1} \Gamma_s y_{t-s} + \Pi Y_{t-n} + Bx_t + e_t \quad t=1,\dots,T \tag{4}$$

where the terms and dimensions of the VAR model are maintained; the matrix $\Gamma_s = -I + \sum_{i=1}^{s} A_i$,

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where I is the identity matrix; and $\Pi = -I + \sum_{i=1}^{n} A_i$, which scores the long-term information between the variables. Cointegration verifies the existence of a stochastic tendency in common within a set of variables. The Johansen & Juselius test (1990) is used to evaluate the existence of cointegration through two different tests: The trace test and the maximum eigenvalue test. In the Trace test, the null hypothesis assumes that there are at most r cointegration vectors, which is tested against the alternative hypothesis that there is exactly r ± 1. In the maximum eigenvalue test, the null hypothesis corresponding to exactly r cointegration vectors is contrasted against the existence of r ± 1 cointegration vectors (Parot et al., 2019).

3.3. LSTM

LSTMs are a special type of RNN designed to learn long-term dependencies. They were first developed by Hochreiter and Schmidhuber (1997). The LSTM a complex structure called the LSTM unit in the hidden layer it contains. A simple representation of this structure is given in Figure 1. Since they work very well on a wide variety of problems, they are widely used today.

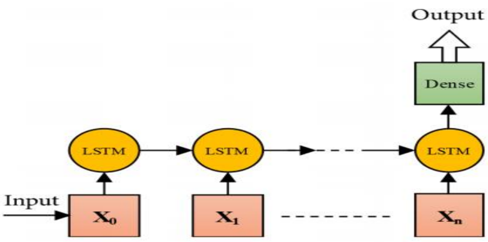

Figure 1. LSTM architecture(Atienza, posted on 2017)

As a rough description, in an LSTM structure, there is also a memory along with the RNN cell. Thanks to this memory, information from the previous time can be retrieved and transmitted to the next one. The model decides which information to take using training. Remembering information for a long time is in practice the default behavior of these networks and not something they try to learn. The structure of an LSTM unit is shown in Figure 2.

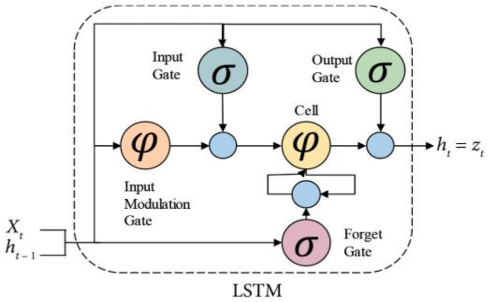

Figure 2. LSTM structure (Kang, 2018)

In Figure 2 X_t represents the input data at the t time step and the output of the previous unit. h_t is hidden units output, while h_{t-1} is their previous output. For the LSTM unit, input gate i_t^j (5) forget gate f_t^j (6) and output gate σ_t^jj (7) equations may be used:

$$i_t^j = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i)^j \ ; \tag{5}$$
$$f_t^j = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + b_f\right)^j \ ; \tag{6}$$
$$\sigma_t^j = \sigma(W_{x\sigma}x_t + W_{h\sigma}h_{t-1} + b_\sigma)^j \ , \tag{7}$$

where σ is sigmoid function, *w* terms are weight matrices and *b* terms are voltage vectors. Unlike the traditional epoch unit, each *j* LSTM unit preserves its memory at *t* time with (c_t^j). Here, the equation whose memory cell is given is updated via equation (8).

$$c_t^j = f_t^j c_{t-1}^j + i_t^j c_t^{\sim j} \tag{8}$$

The new memory content is updated with equation (9), and the output for the LSTM unit is calculated by equation (9).

$$f_t^j = \tanh(W_{xc}x_t + W_{\hbar c}\hbar_{t-1} + b_c)^j \ ; \tag{9}$$
$$\hbar_t^j = \sigma_t^j \tanh(c_t^j) \tag{10}$$

As in other ANNs, training is carried out on LSTM networks by epoch. An epoch specifies the total number of iterations of a given set of data used for training purposes in the calculation of network weight values (w). An epoch refers to the case that an entire data set has passed forward and then back on the network. It is sensible to update weights to optimize models of a deep learning algorithm by transmitting the entire data set over a single network many times to obtain a better and more accurate prediction model. However, it is not clear how many epoch numbers will be needed to achieve optimal weights and to train a model with the same data set. Different sets of data exhibit different behaviors, so a different number of epochs may be needed to best train networks (Temür et al., 2019).

3.4. Hybrid model

In an ARIMA model, the future value of a variable is assumed to be a linear function of several past observations and random errors. Random errors are assumed to be independently and identically distributed with a mean of zero and a constant variance of σ_2. However, by modeling residuals using ANNs, nonlinear relationships can be discovered (Zhang, 2003). Accordingly, the proposed methodology of the hybrid system consists of two steps. In the first step, an ARIMAX or VECM model is used to analyze the linear part of the problem. In the second step, an LSTM model is developed to model the residuals from the ARIMAX or VECM model. Since the ARIMAX and VECM model cannot capture the nonlinear structure of the data, the residuals of the linear model will contain information about the nonlinearity (Zhang, 2003).

3.5. Performance evaluation

In this study, mean absolute percentage error (MAPE) is used as a loss function to evaluate the performance of forecasting models; MAPE is a scale-independent measurement of the difference between real and predicted values, expressed as a percentage, and can intuitively explain the relative errors. It considers not only the deviation of prediction value and actual value, but also the ratio between them. It is given by

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \times 100 \qquad (11)$$

where n is the number of the instances of monthly data and denotes the observed and predicted values at time t.

3.6. Data Description

This study aims to predict the average monthly import price of LNG in South Korea. This target variable will be expressed as KORNG, and the unit is U$/MT. The explanatory variables are Dubai oil price, Australian Newcastle coal FOB price, Dutch ownership transfer facility, Henry Hub spot price, Japanese LNG import price, and South Korean system marginal price (SMP). Dubai oil price, Australian Newcastle coal FOB price, Netherlands TTF (Title Transfer Facility), Henry Hub price, and Japanese LNG import price refer to the World Bank Commodity Price Data (The Pink Sheet) published by the World Bank, and SMP is collected from the South Korea Electric Power Exchange. Lastly, the dependent variable, average monthly import price of LNG in South Korea, is based on data from the South Korea International Trade Association. All of the data used in this study were public data, which will facilitate easy use of the forecasting model. For convenience, Dubai oil price will be denoted as DUBAI, Australian Newcastle coal FOB price as COAL, Netherlands TTF (Title Transfer Facility) as EUNG, Henry Hub spot price as USNG, Japanese LNG import price as JPNG, and South Korean system marginal price as SMP.

Table 1
Data description

Variables	Abbreviation	Reference
South Korea LNG import price(U$/MT)	KORNG	South Korea International Trade Association
Dubai oil price	DUBAI	World Bank commodity price data (Pink sheet)
Netherlands Title Transfer Facility (TTF)	EUNG	
Newcastle coal FOB price	COAL	
Henry Hub spot price	USNG	
Japan LNG import price	JPNG	
South Korean System Marginal Price(land)	SMP	South Korean Power Exchange

As the reason for the choice of explanatory variables, first in the case of DUBAI, it was selected based on the fact that LNG import prices for South Korea and Japan in term contracts are usually linked with crude oil prices (Choi and Heo, 2017). Among the three major international oil prices, Western Texas Oil, Brent Oil, and Dubai Oil, Dubai oil was used, as it not only showed the highest correlation between South Korean LNG import prices but also has a high correlation with Japan Crude Cocktail (JCC), which is mainly used as an oil price index in the Asian LNG contract. In many cases, JCC is the average monthly price (US$/bbl) of 10 crude oil products imported into Japan, compiled by the Japan Customs Service and published by the Customs Association, and has a high correlation with the Dubai spot oil price one month before (Cho and Han, 2015). On the other hand, since JCC has a time difference from international oil prices, this study uses Dubai oil prices to quickly grasp LNG price trends. In addition, South Korean LNG imports are partially procured in spot as well as long-term contracts. The fluctuation of S&P Platts' Japan and South Korean Marker (JKM) index, which is used as a reference for LNG spot price in Northeast Asia, reflects the inter-fuel competition in the Asian markets, particularly with coal (Alim et al., 2018). Therefore, it is assumed that coal price can be a significant variable in predicting South Korean LNG import price. In addition, European markets are, for the most part, cointegrated with the JKM as well (Chinappini et al., 2019) As for LNG, a significant amount of LNG is exported from Asia, such as from Qatar (22%), Malaysia (7%) and Indonesia (4%), and Australia (21%) (IGU 2020). It is located between Northeast Asia and Europe, supplying LNG to Europe or Northeast Asia depending on market conditions, which serves to balance European gas prices with Northeast Asian spot prices. The TTF used as the European gas price index in this study could sufficiently represent European gas prices considering that European gas prices exhibit very similar characteristics, particularly German (Gaspool), Belgium (ZEE), Dutch (TTF) and British (NBP) natural gas prices (Chinappini et al., 2019). In the case of Henry Hub price, since there is a LNG Sales and Purchase Agreement (SPA) in which the Henry Hub price and the contract price are linked in South Korea, it is thought that there will be an effect on the domestic LNG import price. Japanese gas price is also used in this study. Japan and South Korea have similar geopolitical locations, similar LNG long-term contract price structures, and share the same spot price index, JKM. Accordingly, Japanese gas price is highly likely to be a valid variable for predicting South Korean gas prices. The last variable included is the SMP of the South Korean electricity market. SMP refers to the marginal price used to produce 1kwh of electricity. The South Korean power market adopts cost-based pricing and in order to meet the power demand for the time period, the power plants are started in the order of the lowest fuel cost among power plants in the country. At this time, the variable cost of the most recently started power plant becomes SMP. Fuel cost contributes to the determination of SMP, and SMP affects demand for fuel, which in turn may affect price, so SMP was added as a variable in this study to investigate the interaction between LNG and the electricity market.

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The data used is in the form of monthly period data from January 2002 to September 2020. The start point was determined in consideration of the fact that SMP data existed from 2002; September 2020, which was the most recent data at the time of this study, was set as the end point. This can be seen that this data collection period covers most of available period, considering that the South Korean monthly LNG import price data, which is the target variable of this study, was published from 1998.

4. Empirical Study

4.1. Analysis Period

From the data collection period (January 2002 to September 2020) the data from January 2002 to December 2016 were used as a training set, and the test period was set from January 2017 to September 2020. There are two major peculiarities during the test period. The first is that the proportion of direct imports in South Korea started to increase significantly to over 10%. The proportion of direct imports of LNG increased sharply from about 6% in 2015 and 2016 to 12% in 2017, followed by 14% in 2018 and 18% in 2019. In South Korea, KOGAS has the status of an exclusive wholesale business that imports and supplies most of the country's LNG demand. Therefore, before the proportion of direct imports increased, most of South Korea's LNG, which accounts for about 95%, was imported and supplied by KOGAS, and the import price of KOGAS became the price of South Korea's LNG imports.

Table 2
LNG direct import trend in South Korea

Year	2015	2016	2017	2018	2019
LNG Direct import(%)	5.6%	6.3%	12.3%	13.9%	17.8%

However, as the proportion of direct LNG importers increased significantly from 2017, a major change occurred in the South Korean LNG import structure. It is hard to still claim that KOGAS' LNG import price is South Korean LNG import price. It is rather a price that reflects the import price of several direct LNG importers including KOGAS. Therefore, uncertainty over the South Korean LNG import price has increased. In addition, as many companies are currently promoting direct import of LNG, the proportion of direct import of LNG is expected to increase furthermore in South Korea. Meanwhile, the KOGAS promoted an individual tariffs system to respond to the increase in direct importation of LNG, and the Ministry of Trade, Industry and Energy in South Korea approved it in January 2020. Unlike the average tariffs system, in which the same LNG price is applied to all power plants on the basis of the KOGAS' average import costs, in the individual tariffs system, separate prices are charged on the basis of separate contracts for each power plant. Therefore, in the future, the contract will be differentiated by power plant or portfolio, and LNG will be imported based on a number of these diverse contracts. This phenomenon will increase uncertainty in the import price of LNG in South Korea, making it difficult to forecast LNG price precisely. Accordingly, by predicting the price of South Korean LNG imports from January 2017 to September 2020, when direct imports increased significantly, past the 10% range, we intend to seek an optimal model with high predictive performance despite uncertainty in the future LNG import price.

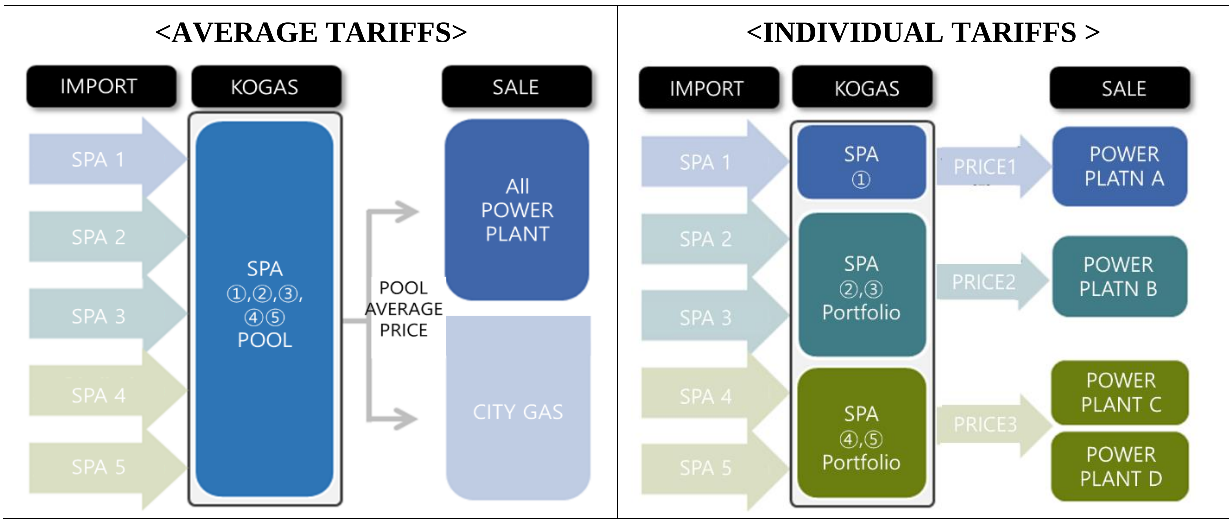

Figure 3. Individual Tariffs Conceptual Framework (MOTIE of South Korea)

Meanwhile, in 2020, the prices of various commodities plummeted due to the coronavirus, and LNG experienced a sharp decline as well. South Korean LNG import price, which was about U$479/MT in April 2020, recorded about U$262/MT in September 2020 as plunging by more than 45% in a few months. Risks to products increase during such a sharp fluctuation period; therefore, it is more important for risk management to accurately predict the LNG price during a period of a sharper-than-usual fluctuation. From this point of view, this forecasting period includes the period of corona virus, which has seen a historically sharp decline, so it is expected that it will be able to contribute to investigate which analysis model can most accurately predict South Korean LNG import prices in the event of an unexpected event.

The analysis was conducted using R program for econometric models such as ARIMAX and VECM, and Python for ML model, LSTM.

4.2. ARIMAX Modeling

First, ARIMAX was used to analyze South Korean LNG import prices. In order to apply ARIMAX, the data must be stationary. If the time series variable is not stationary, a phenomenon in which the effect of unexpected shocks lasts infinitely may occur, or a phenomenon in which there no correlation is found although there is a correlation. However, original time series of all variables are non-stationary, which means unit root exists (Figure 4).

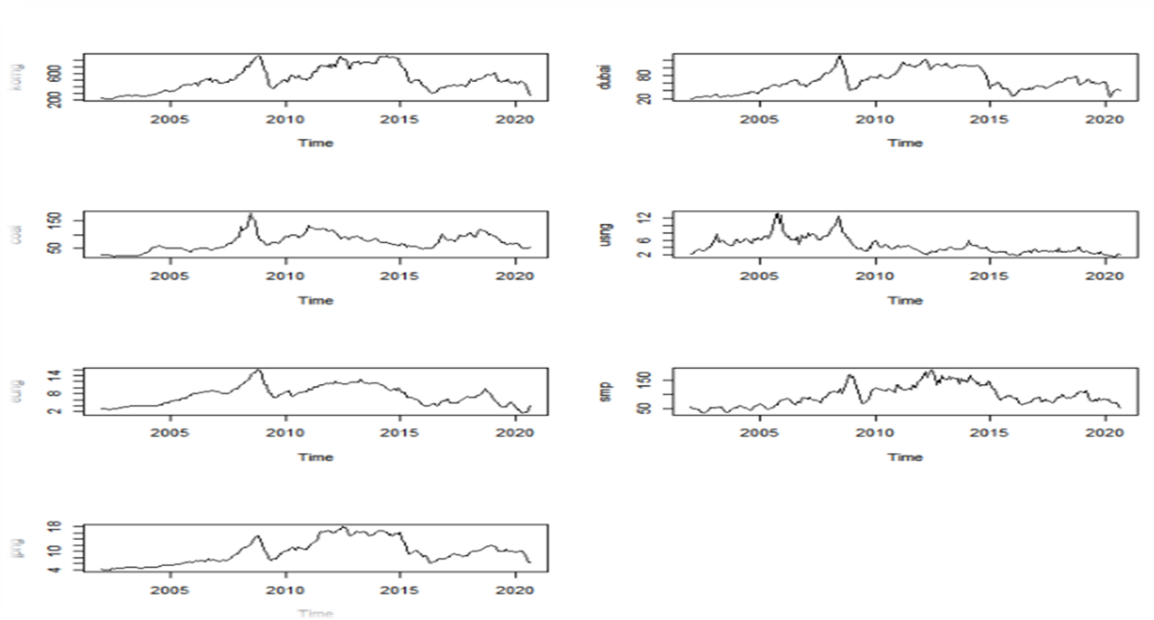

Figure 4. Plots of variables

As a result of conducting the augmented Dickey Fuller (ADF) test for a more accurate check of the stationarity, the P-value of all variables except the USNG exceeded 0.1, so the null hypothesis that a unit root exists was not rejected. Accordingly, log transformation was performed to secure the stationarity of these non-stationary time series. As logarithmic transformation not only has the effect of converting to a stationary time series, but also has the effect of adjusting the scale between variables, log transformation was applied to all variables, including USNG, for which stationarity was proved in the original time series. As a result, although the P-value of the ADF was partially reduced, which had an effect of improvement, all variables except for USNG were still non-stationary. Therefore, the differencing was performed. The differencing lag was set to 12, and as a result, the P-value of all variables was derived to be less than 0.1, and DUBAI, EUNG, USNG, and SMP each showed less than 0.01, indicating that it was converted into a stationary time series.

Table 3
ADF test results

Data form	KORNG	DUBAI	COAL	EUNG	USNG	JPNG	SMP
Original data	0.7290	0.6960	0.3554	0.5714	0.01	0.8393	0.8789
Log transformation	0.8704	0.7037	0.3917	0.7073	0.01	0.9164	0.9121
Differencing of log transformation	0.03675	0.01	0.01	0.01	0.01	0.03187	0.01

As time series of all variables are proved to be stationary, ARIMAX analysis was conducted. Originally, the total data was from January 2002 to September 2020, but currently there are data from January 2003 to September 2020 by differencing with lag 12. Accordingly, the training period became from January 2003 to December 2016, while the test period is still from January 2017 to September 2020. In consideration of the fact that the independent variables at the same time point in the future to be predicted cannot be known in advance, the independent variables data one month before the time point to be predicted was used. This will be applied equally to VECM and LSTM, which will be covered in the future. As a result of conducting ARIMAX analysis through the autoarima function of R based on the data from January 2003 to December 2016, the order was derived as (1,0,2).

4.3. VECM Modeling

One of the models commonly used to identify the dynamic relationships of multivariate time series variables is the vector autoregressive (VAR). When there is a cointegration relationship in which the non-stationary time series have a common probabilistic trend, a vector error correction model (VECM) that is able to analyze the long-term equilibrium relationship and short-term fluctuations of the corresponding time series variables may be considered. The stationarity of the data was proved in ARIMAX analysis, and a cointegration test was performed to implement the VAR or VECM analysis method.

Table 4
ARIMAX results

Variable	Estimate	Std. Error	Pr(>|z|)
Ar1	0.966968	0.024155	< 2.2e-16 ***
Ma1	-0.480006	0.083129	7.732e-09 ***
Ma2	-0.278232	0.077416	0.0003257 ***
Dubai	0.161872	0.035178	4.194e-06 ***
COAL	-0.028114	0.029213	0.3358637
EUNG	0.011749	0.052841	0.8240501
USNG	0.019816	0.023126	0.3915268
SMP	0.152921	0.044342	0.0005633 ***
JPNG	0.809326	0.068230	< 2.2e-16 ***

Granger (1987) states that even if an individual economic time series is a non-stationary time series, if there is a linear combination that allows these time series to have a stable long-term equilibrium relationship, the linear combination becomes a stationary series, and these time series are in a cointegration relationship. The Johansen test was used for the cointegration test. In order to perform the Johansen test, firstly it is required to determine an optimal lag. As a result of analyzing optimal lag in the range of max lag 12 using the VARselect function in R, the value of AIC and FPE were 12, HQ was 3, and SC was 1. Although lag 12 was derived by AIC and PFE, considering that the max lag was 12, lag 12 was excluded from the optimal lag. As for the remaining time lag, as 1 is too short and considering that many long-term South Korean LNG contracts are usually linked with JCC with a time difference of about three or more months, we set the time lag 3 derived from HQ to proceed with the analysis. Trace and Eigen statistics were used for Johansen test, respectively.

Table 5
VARselect results

Criteria	AIC	HQ	SC	FPE
lag	12	3	1	12

As a result of the Johansen test using trace and eigen statistics, when r=0, the statistic is greater than the 1% significance level, thus rejecting the null hypothesis that there is no co-integral relationship under the 1% significance level. In the trace statistic test, from r<=4 the 1% significance level is satisfied, and in the case of an eigen statistic test, from r<=2 the it is estimated to be significant with 1% level, so it can be proved that at least two cointegrations exist. As it is turned out that the cointegration exists, vector error correction model will be conducted.

Table 6
Johansen test results

Test for the cointegration(trace)				
No. of cointegration	Test	10%	5%	1%
r <= 6	7.29	7.52	9.24	12.97
r <= 5	20.14	17.85	19.96	24.60
r <= 4	35.77	32.00	32.91	41.07
r <= 3	63.11	49.65	53.12	60.16
r <= 2	93.33	71.86	76.07	84.45
r <= 1	142.05	97.18	102.14	111.01
r <= 0	310.80	126.58	131.70	143.09
Test for the cointegration(eigen)				
No. of cointegration	Test	10%	5%	1%
r <= 6	7.29	7.52	9.24	12.97
r <= 5	12.85	13.75	15.67	20.20
r <= 4	15.63	19.77	22.00	26.81
r <= 3	27.34	25.56	28.14	33.24
r <= 2	30.22	31.66	34.40	39.79
r <= 1	48.72	37.45	40.30	46.82
r <= 0	168.74	43.25	46.45	51.91

Before VECM is conducted, causality between the dependent variable, KORNG, and independent variables was investigated through a granger causality test. The null hypothesis that lagged x-values do not explain the variation in y of granger causality is rejected when the p-value is less than the significance level, and X is judged to be granger-cause to Y. Granger causality was analyzed through the Granger test function in R, and as a result, it was found that DUBAI has Granger causality at a significance level less than 0.1% of KORNG, but KORNG lacked Granger causality to DUBAI. This seems to reflect the fact that most long-term South Korean LNG contracts are linked to oil prices. It was analyzed that EUNG has Granger causality toward KORNG at a significance level of 0.1%, and that KORNG has Granger causality at 1% significance to EUNG. COAL was found to have Granger causality to the KORNG at a level of 0.1% significance level, while the KORNG granger causes toward COAL with the 5% significance level. It was found that the USNG and the KORNG granger cause at a significance level of 5% each other. The p-value of JPNG is 0.0006474, which means a Granger causality of 0.1% significance to KORNG, while KORNG has a much stronger granger causality to JPNG, at p-value of $3.377e^{-14}$. Lastly, it was analyzed that the SMP does not have Granger causality to the KORNG, but rather, the KORNG has very strongly granger causality to SMP ,with a significant level of 0.1% and P-value of $1.489e^{-13}$.

As a result of the granger causality test between KORNG and explanatory variables, it was found that DUBAI had the largest and most obvious causal effect toward KORNG, and EUNG also strongly influenced KORNG. It was proved that COAL also has a strong granger causality to KORNG, and USNG also has some effects on KORNG. On the other hand, although it was found that JPNG had a significant effect on KORNG than USNG, it was proved that KORNG had a much greater effect on JPNG. SMP did not have a significant effect on the KORNG, while KORNG had a strong causal effect on SMP. Accordingly, it is estimated that the independent variables granger causalities to KORNG were in the order of DUBAI, EUNG, COAL, USNG, JPNG and SMP. Although the SMP itself was not able to verify significant granger causality toward the KORNG, it was determined that there was a long-term relationship between all independent variable data sets, including SMP with KORNG, in the Johansen test. Therefore, it is judged that it is possible to conduct the VECM analysis including SMP.

Table 7
Granger causality test results

Causality	p-value	Causality	p-value
DUBAI → KORNG	2.2E-16 ***	KORNG → DUBAI	0.6437
EUNG → KORNG	9.283E-06 ***	KORNG → EUNG	0.001711 **
COAL → KORNG	0.0002567 ***	KORNG → COAL	0.02324 *
USNG → KORNG	0.04364 *	KORNG → USNG	0.03023 *
JPNG → KORNG	0.0006474 ***	KORNG → JPNG	3.377e-14 ***
SMP → KORNG	0.4345	KORNG → SMP	1.489e-13 ***

* 5%, ** 1% ***0.1%

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As a result of VECM analysis, it was found to be significant in the range from 0.1% to 1% in dubai-1, coal-1, dubai-2, coal-2, eung-2, usng-2, korng-3, dubai-3, and jpng-3. DUBAI was found to be significant at 0.1% significance level in all three lags, COAL showed 5% significance level at lag 1 and 2, and EUNG was significant at 5% level at lag 2. KORNG and JPNG appear to be significant at the level of 1% at a time lag 3.

Table 8.
VECM test results

ECT	-0.3649(0.0333)***			Intercept	-0.0041(0.0037)	
korng-1	dubai-1	**coal-1**	eung-1	usng-1	jpng-1	smp-1
-0.0529 (0.0630)	-0.3485 (0.0460)***	0.1112 (0.0428)*	0.0390 (0.0464)	0.0105 (0.0220)	-0.0178 (0.0412)	-0.0562 (0.0971)
korng-2	dubai-2	coal-2	eung-2	usng-2	jpng-2	smp-2
0.014 1(0.0690)	-0.3174 (0.0463)***	-0.0980 (0.0433)*	0.0910 (0.0450)*	-0.0360 (0.0215).	0.0158 (0.0426)	0.0605 (0.0896)
korng-3	dubai-3	coal-3	eung-3	usng-3	jpng-3	smp-3
0.1353 (0.0714).	-0.1805 (0.0515)***	0.0372 (0.0425)	-0.0459 (0.0466)	0.0117 (0.0219)	-0.1114 (0.0406)**	-0.1010 (0.0812)

Based on the derived VECM model above, the relationship between each independent variable and KORNG was investigated through the impulse response function (IRF). First, in the case of the effects of independent variable on KORNG, it is identified that KORNG responds in a positive direction to the shock of DUBAI and COAL and that the response becomes stronger over time and continues to be affected in the long term. EUNG gives a short shock to KORNG at the beginning and it weakens. the weakened shock persists in the long term. KORNG does not seem to show any special response to the shock of USNG. As for JPNG and SMP, it is estimated that KORNG is affected in a negative direction, and the effect of SMP is greater than that of JPNG. On the other hand, in the case of the effect of KORNG on explanatory variables, it was proved that KORNG had little effect on DUBAI and USNG, and had a slight effect on EUNG in the positive direction and negative direction on COAL in the long term. In addition, it was found that KORNG slightly affected JPNG and SMP in the positive direction in the early stage, and significantly in the negative direction in the long-term. The composition of KORNG by lags was also examined through variance decomposition. It is identified that approximately 83% of KORNG is made up of historical data of itself until lag3, but from lag4 the proportion of DUBAI increase to 30%, and after lag7, it accounts for more than 80%. In addition, it is worth noting that although COAL is small in the long term, it steadily occupies the 2nd largest portion after DUBAI.

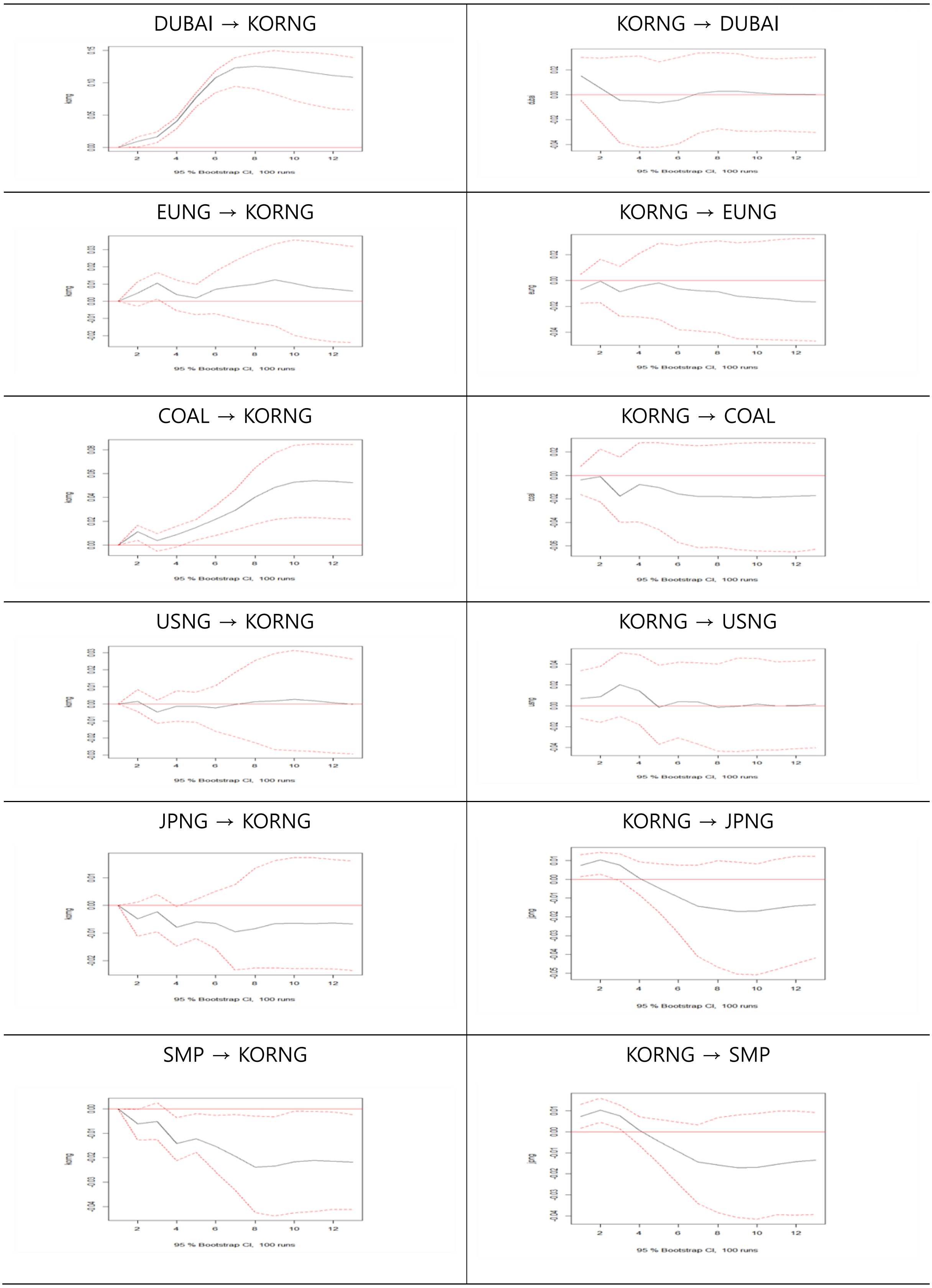

Figure 5. Impulse Response Function

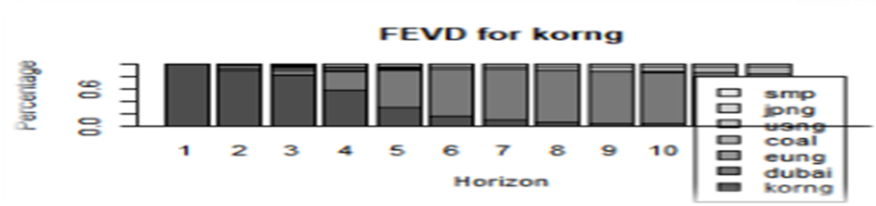

Figure 6. Variable Decomposition

Table 9
Variable Decomposition

Lag	KORNG	DUBAI	EUNG	COAL	USNG	JPNG	SMP
1	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
2	91.49%	2.56%	0.64%	3.51%	0.06%	0.67%	1.07%
3	82.73%	8.26%	3.12%	3.20%	0.56%	0.66%	1.48%
4	58.36%	30.33%	2.28%	3.24%	0.40%	1.38%	4.01%
5	30.34%	60.82%	1.18%	3.32%	0.22%	0.97%	3.15%
6	15.61%	76.74%	0.79%	3.54%	0.13%	0.66%	2.53%
7	9.48%	82.58%	0.66%	4.16%	0.08%	0.61%	2.43%
8	6.63%	83.88%	0.63%	5.60%	0.06%	0.55%	2.65%
9	5.08%	83.71%	0.68%	7.28%	0.05%	0.47%	2.72%
10	4.14%	83.17%	0.67%	8.84%	0.05%	0.43%	2.71%
11	3.54%	82.59%	0.63%	10.10%	0.04%	0.40%	2.70%
12	3.11%	82.06%	0.59%	11.09%	0.04%	0.38%	2.73%

4.4. LSTM Modeling

LSTM network has achieved acceptable performance when applied on sequence data (Reimers & Gurevych, 2017). However, obtaining good performance with LSTM networks is not a simple task, as it involves the optimization of multiple hyperparameters (Reimers & Gurevych, 2017). For time series forecasting problems, the important hyperparameters are the lag size (i.e. number of past observations), the batch size, the number of neurons in the layer, the epochs size, the optimization algorithm, the number of hidden layers, and others. Hyperparameter selection improves the model performance (Reimers & Gurevych, 2017).

The lag size parameter has a significant impact on the performance of time series forecasting (Ribeiro et al., 2011). Therefore, it is crucial to test the performance of a model using different lag sizes. In this study, all lags except for 1 derived in VECM were used for each variable combination. Adjusting batch size is another factor in determining the performance of the LSTM model. Hence, it is significant to find an optimal batch size (Shi et al., 2019). The batch size was analyzed in units of 10 in the range of 10 to 30. Selecting the optimal number of neurons for the layer in the LSTM network is likewise not a straightforward task. If the number of neurons is very small, the LSTM will not able to memorize all necessary information to perform prediction optimally. Also, if the number of neurons is very high, the LSTM will overfit on the training set and will not demonstrate suitable generalization to accurately forecast test set (Reimers & Gurevych, 2017). In order to find the optimal number of neurons, it was analyzed in units of 10 in the range of 10 to 200. One training epoch is considered a single iteration over all training instances (Reimers & Gurevych, 2017). If the number of training epochs is too small, the model will not capture the patterns of training set. Also, if the epoch number is too large, the model will suffer from overfitting. Therefore, finding a suitable epoch number is vital in achieving a model with high performance. Epoch numbers were analyzed in units of 100 in the range of 100 to 1000. In the case of optimization algorithm, adam was used. Adam is an efficient stochastic optimization algorithm that only requires first-order gradients with little memory requirement (Kingma & Ba., 2014), it has combined the advantages of two popular methods: AdaGrad (Duchi, et al., 2011), which works well with sparse gradients, and RMSProp (Tieleman & Hinton, 2012), which has an excellent performance in non-line and non-stationary settings (Chang et al., 2019). Default values built in the model was used for other parameters in this study. As a result of exploring the parameters of the independent variable set of KORNG, DUBAI, EUNG, COAL, USNG, JPNG, SMP, the batch size, number of neurons, and number of epochs were derived as 10, 150, and 800, respectively. For the lag size, lag 3 derived from VECM analysis was used. On the other hand, as a result of LSTM analysis by adding KORNG(t-1) to the independent variables, it was confirmed that the parameter was optimal when the batch size was 10, the number of neurons was 150, and the number of epochs was 500 with sequence lag 3.

4.5. Hybrid Modeling

The hybrid model is conducted by combining LSTM with ARIMAX and VECM. LSTM is implemented with residuals produced from forecasting result of ARIMAX or VECM. After that, the forecasting values of LSTM with residuals of ARIMAX or VECM are combined with the original forecasting values of ARIMAX or VECM. When modeling with LSTM, the batch size was searched in the range of 10 to 30 in units of 10, the number of neurons in the range of 10 to 100 in units of 10, and epochs in the range of 100 to 1000 in units of 100. In the case of the lag size, 12 lags were used for LSTM with residuals of ARIMAX in consideration of the yearly seasonality of the monthly time series; for the residuals of VECM, the lag size derived from VECM analysis was used.

4.6 Empirical Study Results

In this chapter, a forecasting model for South Korean LNG import price will be implemented based on ARIMAX, VECM, LSTM and hybrid models discussed above. In order to enhance a reliability of forecasting models, the sliding window technique was used. Figure 7 depicts the sliding window mechanism. Since the forecasting is one step ahead (hence, the term "one-step ahead forecasting"), the forecast horizon is 1. In the first validation, the working window includes p historical observations

(x_1,x_2, …, x_p), which are used to forecast the next value x_{p+1}. In the second validation, the oldest value x_1 is removed from the window and the latest value x_{p+1} is added, keeping the length of the sliding window constant at p. The next forecasting value will be x_{p+2}. The window continues to slide until the end of the dataset is reached. If the number of observations is N, then the total number of validations is (N–p). The sliding window test in time-series forecasting is useful because it reflects a progressive reduction in the impact of historical data by not using all datasets for model training. In addition, a sliding window test consists of sequential data divided into windows with multiple overlapping periods that repeat training and testing (Chou et al., 2018). In this paper, data from January 2002 to December 2016 are set as the first window, and then sequentially predicted from January 2017 to September 2020 through the sliding window method. The window size was fixed to be 180 months, and it is predicted for 45 months in future.

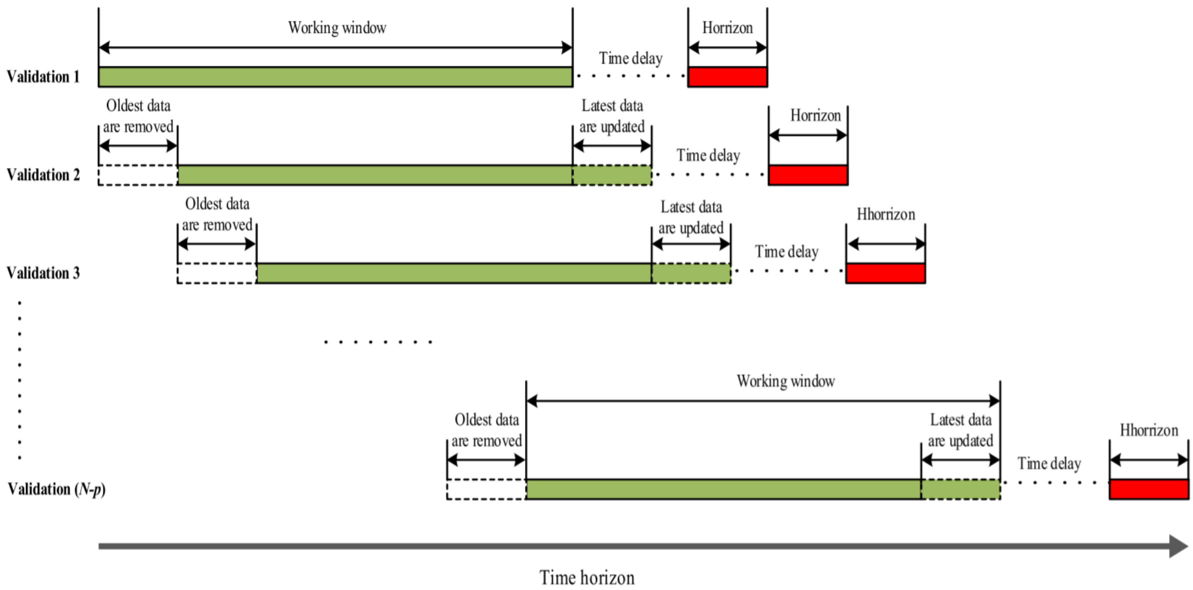

Figure 7. Sliding window conceptual diagram(Chou et al., 2018)

At the first time, independent variable set of DUBAI, COAL, EUNG, USNG, JPNG, and SMP is used. After that, it is predicted by removing independent variables one by one in the order of granger causality. As a result of the granger causality test, strong and clear granger causality is considered in the order of DUBAI, EUNG, COAL, USNG, JPNG, and SMP. As the different set of variables is used for the forecasting, the optimal parameters of forecasting model also change. Accordingly, in the case of ARIMAX, the optimal order is derived and applied by autoarima function at each forecasting model of each independent variable set. In the case of VECM and LSTM, the optimal lag was derived and used each time through the VARselect function in R according to the different composition of variables.

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Table 10
Top 10 Forecasting models (whole period)

Rank	Model	Variables	Lag	MAPE
1	LSTM	DUBAI, COAL, EUNG, USNG, JPNG	6	3.5209
2	VECM-LSTM	DUBAI, EUNG	5	3.6003
3	VECM-LSTM	DUBAI	3	3.8825
4	LSTM	KORNG, DUBAI, COAL, EUNG, USNG	6	4.2074
5	VECM-LSTM	DUBAI	5	4.2372
6	LSTM	KORNG, DUBAI, COAL, EUNG, USNG	3	4.2389
7	LSTM	KORNG, DUBAI, COAL, EUNG, USNG, JPNG	3	4.2574
8	LSTM	DUBAI, EUNG	5	4.2934
9	LSTM	KORNG, DUBAI, EUNG	5	4.3186
10	VECM-LSTM	DUBAI, EUNG	3	4.3301

The forecasting performance of the forecasting models was determined by MAPE and the top 10 models were summarized at table 10. 6 LSTM models, 4 VECM-LSTM were ranked and LSTM with DUBAI, COAL, EUNG, USNG, JPNG with lag 6 showed the lowest MAPE. Single econometric model was not included in the top 10 models at all and only the single ML model and the hybrid model were listed up. Accordingly, it is proved that ML or hybrid model are better than single econometric model. In addition, hybrid model, especially VECM-LSTM showed high forecasting performance as much as ML model. Therefore, it is found that VECM-LSTM model provides not only explanations between relationship of variables but also high forecasting performance about South Korean LNG import price. As for independent variables, a smaller number of variables are usually used for hybrid model and in the case of LSTM, with a larger number of variables was better.

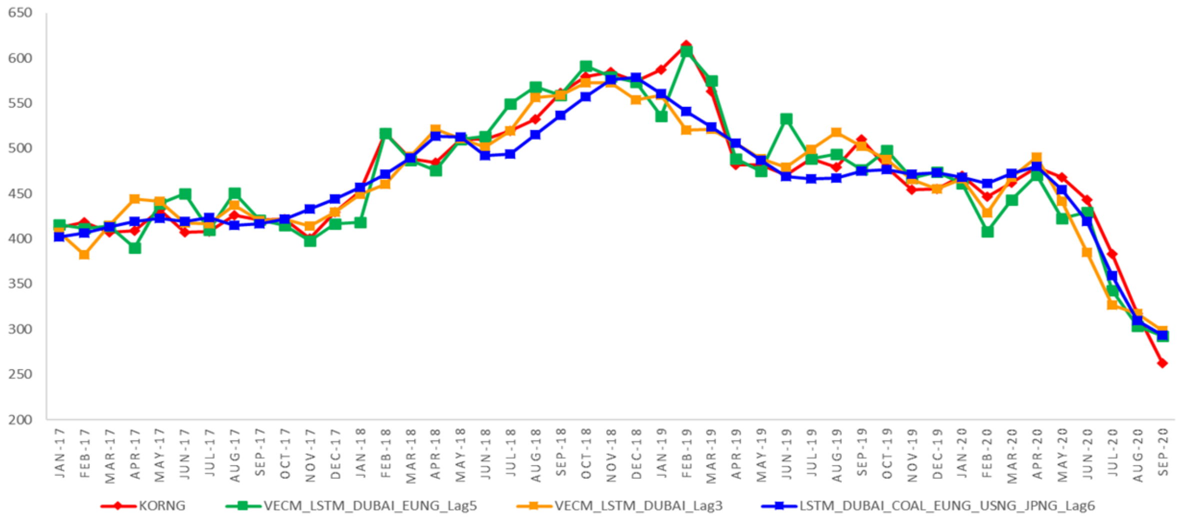
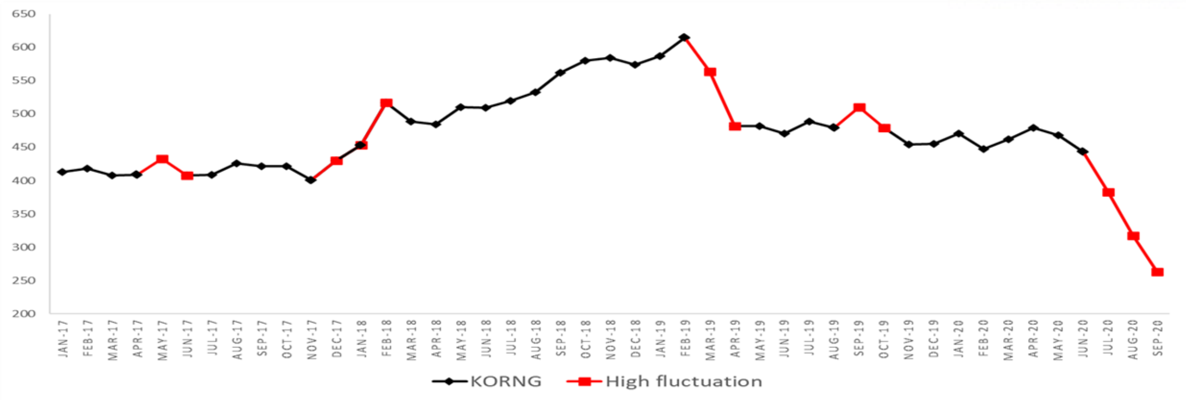


Figure 8. Top 3 Forecasting models

Table 11
All Forecasting models (whole period)

Model	Variables	Unit/Batch/Epoch	Lag	MAPE	Rank
ARIMAX	KORNG, DUBAI, EUNG, COAL, USNG, JPNG, SMP	-	-	5.69	50
	KORNG, DUBAI, EUNG, COAL, USNG, JPNG	-	-	5.79	54
	KORNG, DUBAI, EUNG, COAL, USNG	-	-	8.84	80
	KORNG, DUBAI, EUNG, COAL	-	-	9.19	82
	KORNG, DUBAI, EUNG	-	-	9.25	84
	KORNG, DUBAI	-	-	9.24	83
	KORNG	-	-	9.82	87
ARIMAX -LSTM	KORNG, DUBAI, EUNG, COAL, USNG, JPNG, SMP	30 / 70 / 200	12	5.92	55
	KORNG, DUBAI, EUNG, COAL, USNG, JPNG	40 / 100 / 300	12	5.37	42
	KORNG,DUBAI,EUNG, COAL,USNG	20 / 20 / 800	12	7.48	69
	KORNG, DUBAI, EUNG, COAL	10 / 30 / 500	12	6.31	58
	KORNG, DUBAI, EUNG	20 / 40 / 700	12	5.61	49
	KORNG, DUBAI	20 / 10 / 1000	12	8.30	78
	KORNG	30 / 10/ 400	12	4.67	19
VECM	DUBAI, EUNG, COAL, USNG, JPNG, SMP	-	3	5.21	34
		-	12	8.45	79
	DUBAI, EUNG, COAL, USNG, JPNG	-	3	5.21	33
		-	6	8.88	81
		-	12	7.53	70
	DUBAI, EUNG, COAL, USNG	-	3	5.14	31
		-	6	7.61	72
		-	9	7.43	68
	DUBAI, EUNG, COAL	-	2	5.76	51
		-	3	4.89	25
		-	9	7.60	71
		-	12	9.27	85
	DUBAI, EUNG	-	3	4.97	27
		-	5	7.07	65
		-	9	7.81	77
	DUBAI	-	3	5.49	45
		-	5	6.75	63
		-	6	6.75	62
VECM -LSTM	DUBAI, EUNG, COAL, USNG, JPNG, SMP	30 / 30 / 700	3	5.78	52
		10 / 60 / 1000	12	11.26	88
	DUBAI, EUNG, COAL, USNG, JPNG	10 / 60 / 800	3	6.00	56
		30 / 40 /200	6	6.30	57
		30 / 50 / 1000	12	14.65	89
	DUBAI, EUNG,COAL, USNG	30 / 30 / 700	3	5.78	52
		30 / 40 / 500	6	5.27	37
		40 / 10 /100	9	7.74	74
	DUBAI, EUNG, COAL	10 / 10 / 800	2	4.48	15
		10 / 30 / 1000	3	5.14	32
		10 / 90 / 600	9	15.39	90
		20 / 90 / 100	12	7.77	76
	DUBAI, EUNG	10 / 20 / 100	3	4.33	10

Model	Variables	Lag	Unit/Batch/Epoch	MAPE	Rank
VECM -LSTM	DUBAI, EUNG	5	10 / 50 / 400	3.60	2
		9	10 / 20 / 300	7.35	67
	DUBAI	3	30 / 30 / 600	3.88	3
		5	10 / 60 / 700	4.24	5
		6	40 / 100 / 800	4.50	16
LSTM	KORNG,DUBAI, EUNG, COAL, USNG, JPNG, SMP	3	10 / 150 / 500	4.42	13
		12	10 / 190 / 800	5.00	28
	KORNG,DUBAI, EUNG, COAL, USNG, JPNG	3	10 / 140 / 900	4.26	7
		6	10 / 150 / 800	4.80	21
		12	10 / 190 / 700	5.60	48
	KORNG,DUBAI, EUNG, COAL, USNG	3	20 / 170 / 800	4.24	6
		6	10 / 100 / 700	4.21	4
		9	10 / 180 / 400	5.42	44
	KORNG,DUBAI, EUNG, COAL	2	10 / 130 / 800	4.34	11
		3	20 / 150 / 900	5.22	35
		9	10 / 190/ 400	5.28	38
		12	20 / 180 / 800	5.50	46
	KORNG,DUBAI, EUNG,	3	10 / 170 / 900	4.97	26
		5	20 / 150 / 900	4.32	9
		9	10 / 160 / 500	5.42	43
	KORNG,DUBAI	3	30 / 180 / 1000	4.72	20
		5	20 / 170 / 1000	4.48	14
		6	20 / 150 / 1000	4.41	12
	KORNG	3	10 / 120 / 1000	4.85	22
		6	10 / 100 / 800	4.86	24
		9	10 / 160 / 600	5.34	40
		12	10 / 160 / 1000	5.24	36
	DUBAI, EUNG, COAL, USNG, JPNG, SMP	3	10 / 90 / 900	6.38	59
		12	10 / 150 / 800	5.59	47
	DUBAI, EUNG, COAL, USNG, JPNG	3	20 / 150 / 700	4.51	17
		6	10 / 140 / 1000	3.52	1
		12	10 / 160 / 700	5.30	39
	DUBAI, EUNG, COAL, USNG	3	10 / 150 / 700	7.15	66
		6	10 / 150 / 300	6.43	60
		9	10 / 120 / 300	5.36	41
	DUBAI, EUNG, COAL	2	10 / 150 / 500	9.41	86
		3	10 / 200 / 300	6.84	64
		9	30 / 190 / 900	5.13	30
		12	10 / 170 / 200	7.75	75
	DUBAI, EUNG	3	10 / 140 / 300	7.72	73
		5	10 / 120 / 900	4.29	8
		9	10 / 200 / 200	5.01	29
	DUBAI	3	30 / 170 / 600	6.53	61
		5	20 / 150 / 600	4.60	18
		6	20 / 100 / 1000	4.85	23



Month	KORNG	Change%	Month	KORNG	Change%	Month	KORNG	Change%
May-17	432.42	5.74%	Mar-19	563.32	-8.32%	Jul-20	383.12	-13.58%
Jun-17	407.61	-5.74%	Apr-19	481.91	-14.45%	Aug-20	317.19	-17.21%
Dec-17	429.93	7.36%	Sep-19	509.98	6.39%	Sep-20	262.78	-17.15%
Feb-18	517.22	14.15%	Oct-19	479.05	-6.06%			

Figure 9. High fluctuation month

In fact, however, LNG price forecasting is more important when price fluctuation is high. In order to check the forecast accuracy during the high fluctuation period, 11 months with a higher price change rate compared to the previous month were selected out of the 44-month test period. As a result of evaluating forecasting performance for top 11 months, seven hybrid models, one LSTM models, and two ARIMAX models were ranked among the top 10 forecasting models. During high fluctuation periods, hybrid model's forecasting performance was better than LSTM. VECM-LSTM using DUBAI with lag 5 was derived as the best model with MAPE 4.9360. As a result of two analysis for all period and high fluctuation periods, it is found that LSTM using DUBAI, EUNG, COAL, USNG, and JPNG with 6 lag and VECM-LSTM using DUBAI and EUNG with lag 5 were ranked within 3rd rank at both of tests.

Table 12
Top 10 Forecasting model (High fluctuation period)

Rank	Model	Variables	Lag	MAPE
1	VECM-LSTM	DUBAI	5	4.9360
2	VECM-LSTM	DUBAI, EUNG	5	5.0592
3	LSTM	DUBAI, EUNG, COAL, USNG, JPNG	6	5.2854
4	ARIMAX	DUBAI, EUNG, COAL, USNG, JPNG	-	5.5577
5	ARIMAX-LSTM	DUBAI, EUNG, COAL, USNG, JPNG	-	5.6801
6	ARIMAX	DUBAI, EUNG	-	5.7281
7	ARIMAX-LSTM	DUBAI, EUNG, COAL, USNG, JPNG, SMP	-	5.9271
8	VECM-LSTM	DUBAI	6	5.9979
9	VECM-LSTM	DUBAI, EUNG, COAL, USNG, JPNG	6	6.0447
10	ARIMAX-LSTM	KORNG	-	6.0462

Table 13
All forecasting models (High fluctuation period)

Model	Variables	Unit/Batch/Epoch	Lag	MAPE	Rank
ARIMAX	KORNG, DUBAI, EUNG, COAL, USNG, JPNG, SMP	-	-	6.14	14
	KORNG, DUBAI, EUNG, COAL, USNG, JPNG	-	-	5.56	4
	KORNG, DUBAI, EUNG, COAL, USNG	-	-	12.53	87
	KORNG, DUBAI, EUNG, COAL	-	-	12.37	86
	KORNG, DUBAI, EUNG	-	-	11.82	84
	KORNG, DUBAI	-	-	11.59	83
	KORNG	-	-	12.16	85
ARIMAX -LSTM	KORNG, DUBAI, EUNG, COAL, USNG, JPNG, SMP	30 / 70 / 200	12	5.93	7
	KORNG, DUBAI, EUNG, COAL, USNG, JPNG	40 / 100 / 300	12	5.68	5
	KORNG,DUBAI,EUNG, COAL,USNG	20 / 20 / 800	12	7.09	31
	KORNG, DUBAI, EUNG, COAL	10 / 30 / 500	12	7.16	32
	KORNG, DUBAI, EUNG	20 / 40 / 700	12	5.73	6
	KORNG, DUBAI	20 / 10 / 1000	12	8.16	49
	KORNG	30 / 10/ 400	12	6.05	10
VECM	DUBAI, EUNG, COAL, USNG, JPNG, SMP	-	3	7.06	30
		-	12	9.37	62
	DUBAI, EUNG, COAL, USNG, JPNG	-	3	6.56	22
		-	6	10.55	77
		-	12	9.56	65
	DUBAI, EUNG, COAL, USNG	-	3	7.34	36
		-	6	9.66	66
		-	9	9.30	60
	DUBAI, EUNG, COAL	-	2	9.31	61
		-	3	6.94	28
		-	9	7.82	43
		-	12	10.74	79
	DUBAI, EUNG	-	3	6.75	24
		-	5	9.23	57
		-	9	9.43	63
	DUBAI	-	3	6.64	23
		-	5	7.94	46
		-	6	8.54	50
VECM -LSTM	DUBAI, EUNG, COAL, USNG, JPNG, SMP	30 / 30 / 700	3	6.84	26
		10 / 60 / 1000	12	9.74	67
	DUBAI, EUNG, COAL, USNG, JPNG	10 / 60 / 800	3	7.49	39
		30 / 40 /200	6	6.04	9
		30 / 50 / 1000	12	12.56	88
	DUBAI, EUNG,COAL, USNG	30 / 30 / 700	3	6.88	27
		30 / 40 / 500	6	7.22	34
		40 / 10 /100	9	10.34	75
	DUBAI, EUNG, COAL	10 / 10 / 800	2	6.84	25
		10 / 30 / 1000	3	7.02	29
		10 / 90 / 600	9	19.92	90
		20 / 90 / 100	12	8.81	55
	DUBAI, EUNG	10 / 20 / 100	3	6.55	21

Model	Variables	Lag	Unit/Batch/Epoch	MAPE	Rank
VECM -LSTM	DUBAI, EUNG	5	10 / 50 / 400	5.06	2
		9	10 / 20 / 300	7.42	37
	DUBAI	3	30 / 30 / 600	6.06	11
		5	10 / 60 / 700	4.94	1
		6	40 / 100 / 800	6.00	8
LSTM	KORNG,DUBAI, EUNG, COAL, USNG, JPNG, SMP	3	10 / 150 / 500	6.48	18
		12	10 / 190 / 800	10.79	80
	KORNG,DUBAI, EUNG, COAL, USNG, JPNG	3	10 / 140 / 900	6.49	20
		6	10 / 150 / 800	6.40	16
		12	10 / 190 / 700	8.65	52
	KORNG,DUBAI, EUNG, COAL, USNG	3	20 / 170 / 800	7.59	40
		6	10 / 100 / 700	6.45	17
		9	10 / 180 / 400	11.00	82
	KORNG,DUBAI, EUNG, COAL	2	10 / 130 / 800	7.16	32
		3	20 / 150 / 900	7.70	41
		9	10 / 190/ 400	9.80	68
		12	20 / 180 / 800	10.79	81
	KORNG,DUBAI, EUNG,	3	10 / 170 / 900	8.13	48
		5	20 / 150 / 900	6.09	12
		9	10 / 160 / 500	10.10	70
	KORNG,DUBAI	3	30 / 180 / 1000	7.83	44
		5	20 / 170 / 1000	6.49	19
		6	20 / 150 / 1000	7.91	45
	KORNG	3	10 / 120 / 1000	9.27	59
		6	10 / 100 / 800	9.47	64
		9	10 / 160 / 600	10.14	71
		12	10 / 160 / 1000	10.24	73
	DUBAI, EUNG, COAL, USNG, JPNG, SMP	3	10 / 90 / 900	7.28	35
		12	10 / 150 / 800	8.65	51
	DUBAI, EUNG, COAL, USNG, JPNG	3	20 / 150 / 700	6.11	13
		6	10 / 140 / 1000	5.29	3
		12	10 / 160 / 700	10.18	72
	DUBAI, EUNG, COAL, USNG	3	10 / 150 / 700	8.66	53
		6	10 / 150 / 300	8.73	54
		9	10 / 120 / 300	9.24	58
	DUBAI, EUNG, COAL	2	10 / 150 / 500	10.45	76
		3	10 / 200 / 300	9.80	69
		9	30 / 190 / 900	8.09	47
		12	10 / 170 / 200	13.75	89
	DUBAI, EUNG	3	10 / 140 / 300	10.30	74
		5	10 / 120 / 900	7.76	42
		9	10 / 200 / 200	9.20	56
	DUBAI	3	30 / 170 / 600	10.66	78
		5	20 / 150 / 600	6.31	15
		6	20 / 100 / 1000	7.49	38

5. Conclusion

This study sought to identify an optimal forecasting model for the South Korean LNG import price by using econometric models, an ML model, and a hybrid model. ARIMAX and VECM were used as econometric models, and LSTM was selected as an ML model. Various independent variables such as Australian Newcastle coal price, US natural gas price, Japanese LNG price, and SMP in South Korea were applied for forecasting models.

As for the dynamics of South Korean LNG import price, it was found that independent variables granger cause toward South Korean LNG import price in the order of Dubai oil price, European natural gas price, Australian Newcastle coal price, US natural gas price, Japanese LNG price and SMP. In addition, South Korean LNG import price showed a positive response from the shocks of Dubai oil price, European gas price, Australian Newcastle coal price and a negative response from the Japanese LNG price and SMP. Also, from the variable decomposition, it was identified that approximately 83% of South Korean LNG import price is made up of historical data of itself until lag 3, but from lag 4 the proportion of Dubai oil price increase to 30%, and after lag 7, it accounts for more than 80%.

In the empirical study, 6 LSTM models, 4 VECM-LSTM were ranked on top 10 forecasting models and single econometric models were not included. Therefore, it is found that ML or hybrid models are better than single econometric models. The best forecasting model was the LSTM with Dubai oil price, European natural gas price, Australian Newcastle coal price, US natural gas price, and Japanese LNG price, with lag 6 and MAPE was 3.5209. In addition, as LNG price forecasting is more important when price fluctuation is high, forecasting models were conducted on 11 months with high fluctuation among 44-months, test periods. Seven hybrid models, one LSTM model, and two ARIMAX models were ranked among the top 10 forecasting models. VECM-LSTM using Dubai oil price with lag 5 was derived as the best model with MAPE 4.9360. Hybrid models, especially VECM-LSTM, showed better forecasting performance than others. Two analyses for whole test period and high fluctuation periods showed that LSTM using Dubai oil price, European natural gas price, Australian Newcastle coal price, US natural gas price, and Japanese LNG price with lag 6 and VECM-LSTM using Dubai oil price and European natural gas price with lag 5 were ranked within 3rd rank in both of tests. This proves that the ML and hybrid models showed a better forecasting performance. Therefore, it is inferred that hybrid models, especially VECM-LSTM, showed forecast accuracy as high as LSTM and that during high-volatility periods the forecasting performance of VECM-LSTM was even better than LSTM models. This is meaningful as it shows that the hybrid model between econometric models and ML model not only forecasts the future price of LNG, but also clarifies how independent variables interact with each other and affect the price of LNG. This high interpretability of hybrid model will contribute to stakeholder's decision making rather than ML models that only derive future price of LNG. Therefore, the VECM-LSTM model can be regarded as superior to a single LSTM

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model for forecasting South Korean LNG import price.

Nevertheless, there are some limitations to this study. First, the policy factor should be studied carefully. This is because the country's energy mix is usually determined by energy policies, and related policy factors are likely to have a significant impact on the commodity demand and prices. In addition, it is necessary to study the effects of variables other than the six independents variables used in this study. In particular, shipping cost is expected to contribute to commodity prices forecasting as a major cost incurred in trade transactions of energy commodity. On the other hand, although this study tried to reflect recent changes in the South Korean LNG market such as the recent increase in direct LNG imports, there should be continuing attention to research on optimal LNG price forecasting models, as South Korean LNG market structure is likely to change continuously in the future.

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