



Original Article

Statistical model for forecasting uranium prices to estimate the nuclear fuel cycle cost

Sungki Kim^a, Wonil Ko^a, Hyoon Nam^a, Chulmin Kim^b, Yanghon Chung^c,
Sungsig Bang^{c,*}^a Nuclear Fuel Cycle Analysis, Korea Atomic Energy Research Institute, 1045 Daedeokdaero, Yuseong-gu, Daejeon 305–353, Republic of Korea^b Department of Nuclear and Quantum Engineering, Korea Advanced Institute of Science and Technology, 291 Daehak-ro, Yuseong-gu, Daejeon 305–701, Republic of Korea^c Department of Business and Technology Management, Korea Advanced Institute of Science and Technology, 291 Daehak-ro, Yuseong-gu, Daejeon 305–701, Republic of Korea

ARTICLE INFO

Article history:

Received 21 February 2017

Received in revised form

30 March 2017

Accepted 1 May 2017

Available online 17 June 2017

Keywords:

ARIMA Model

Cost Driver

Forecasting

Nuclear Fuel Cycle Cost

Uranium Price

ABSTRACT

This paper presents a method for forecasting future uranium prices that is used as input data to calculate the uranium cost, which is a rational key cost driver of the nuclear fuel cycle cost. In other words, the statistical autoregressive integrated moving average (ARIMA) model and existing engineering cost estimation method, the so-called escalation rate model, were subjected to a comparative analysis. When the uranium price was forecasted in 2015, the margin of error of the ARIMA model forecasting was calculated and found to be 5.4%, whereas the escalation rate model was found to have a margin of error of 7.32%. Thus, it was verified that the ARIMA model is more suitable than the escalation rate model at decreasing uncertainty in nuclear fuel cycle cost calculation.

© 2017 Korean Nuclear Society, Published by Elsevier Korea LLC. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

1. Introduction

In the case of nuclear fuel cycle cost, the uranium cost takes up a significant portion of approximately 26–30% [1]. Accordingly, it is necessary to forecast the future uranium price even more accurately in order to decrease the uncertainty of the nuclear fuel cycle cost.

Uranium recorded its highest price in 2007 at approximately 140 US\$/poundU (Uranium). Since then, the price has decreased and is now at approximately 40 US\$/poundU (March 2015). The reason why the price of uranium soared in 2007 is that there was an imbalance between uranium demand and supply. Uranium prices can change owing to various external factors, in addition to the above mentioned imbalance of demand and supply. For example, since the Fukushima nuclear accident that took place in Japan, the share of nuclear power generation as part of total electricity generation of nuclear power generating nations in the European Union (EU), including Germany, has decreased. As such, the demand for

uranium decreased until May 2014. Moreover, uranium demand may decrease, because nuclear power generation has decreased owing to shale gas development and decreases in oil prices [2]. However, shale gas distribution is currently vast, and significant cost is expected to be incurred in developing the infrastructure required for gas development [3,4]. Thus, shale has yet to significantly affect the share of nuclear power generation. Moreover, it is expected that uranium prices will not decrease in the long-term because oil price decreases are limited over time as well.

Germany, the representative nation in the EU in terms of decreased nuclear power generation, has increased its share of electricity generated from new and renewable sources. As such, its generation costs have increased significantly. Accordingly, electricity consumers in Germany are experiencing significant difficulty owing to the increase in electricity prices. In the end, advanced EU nations that are lowering their share of nuclear power generation have yet to find an alternative energy source that can effectively replace nuclear power generation. For example, neither solar heat nor wind power can produce a sufficient amount of electricity to replace nuclear power. Moreover, new and renewable energy sources cannot produce electricity stably during weather changes. Thus, they are considered unfit as a power supply base.

* Corresponding author.

E-mail address: ssbang@kaist.ac.kr (S. Bang).

One of the key reasons why uranium prices have increased is that rising nations such as China are continuing to construct many nuclear power plants in order to cope actively with climate change, and to sufficiently supply the electricity needed for their economic advancement. China plans to construct approximately 100 nuclear power plants on its eastern coast. Accordingly, the construction of China's nuclear power field is expected to significantly affect future uranium prices around the world, and will increase uranium prices.

If it is possible to forecast uranium prices relatively accurately, it will be possible to identify the right time for purchasing needed uranium at a low price, and to secure a necessary uranium inventory. Moreover, this study will contribute significantly to an assessment of the economics of the nuclear fuel cycle because it will be possible to increase the accuracy of uranium cost prediction, which is a key cost driver for nuclear fuel cycle costs [5,6]. Accordingly, this paper utilizes a time-series analysis method, which is a statistical method that uses past data to forecast future uranium prices. In other words, future uranium prices are forecasted by utilizing the autoregressive integrated moving average (ARIMA) model according to the procedure shown in Fig. 1.

2. Uranium price forecasting model

A nuclear fuel cycle economic analysis that uses a dynamic model involves an engineering cost calculation method. In other words, the uranium price at each year in the future is calculated by factoring in the escalation rate with the uranium price of the base point. This uranium price is used as the input data for the nuclear fuel cycle cost calculation. Accordingly, the nuclear fuel cycle cost's uncertainty decreases when the future uranium price is accurate [7]. However, a significant price trend difference was found between the actual uranium price and uranium price values that were forecasted using the escalation rate model, as shown in Fig. 2. Accordingly, the value for calculating the sum of the uranium cost for each year according to the current value is bound to yield a significant difference.

Thus, in order to decrease the nuclear fuel cycle cost, calculation of the uranium price per year in the future needs to use a scientific estimation method that can come up with a figure that is close to the actual price, without uncertainty, because the uranium cost is a key cost driver of the nuclear fuel cycle cost [8]. For this reason,

after identifying the various time series analysis models that can rationally forecast the uranium price for each year in the future with very high uncertainty, this paper presents the most suitable model. First, an escalation rate model and the theoretical concept of the statistical model, which are being used in the existing engineering cost estimation method, were examined.

2.1. Consumer price escalation rate model: Uranium price forecasting model that factors in the consumer price escalation rate

In the case of the nuclear fuel cycle cost calculation field, which has used a dynamic model until now, the uranium price for a certain standard year was set as shown in Eq. (1) [9], and only the consumer price escalation rate was factored into this value to forecast the future uranium price. These data are used as the input data for the nuclear fuel cycle cost calculation. Because this research paper considers only the consumer price escalation rate, the model was called the "escalation rate model." When the standard year's uranium price is calculated according to the uranium price of the previous year using the consumer price escalation rate model, the uranium price increases in a linear manner [10]. When the uranium price for a year is calculated according to the standard year's uranium price, the uranium price increases as time moves forward. Accordingly, because the uranium price that is forecast with the consumer price escalation rate model continues to increase, a disadvantage is that a significant difference from the actual future uranium price may result. However, the escalation rate model is often used today because of its advantage that the rough future uranium price can be estimated promptly [11].

$$UP_t = UP_b(1 + e)^{(t-b)} \quad (1)$$

where UP_t = uranium price at year t , UP_b = uranium price at base year, e = escalation rate, and b = base year.

2.2. Time-series analysis model

The ARIMA model is one of the time-series analysis models; it is used as a statistical forecasting method, and is also referred to as the Box-Jenkins model [12–15]. By performing model identification, discerned model parameter estimation, and testing statistical

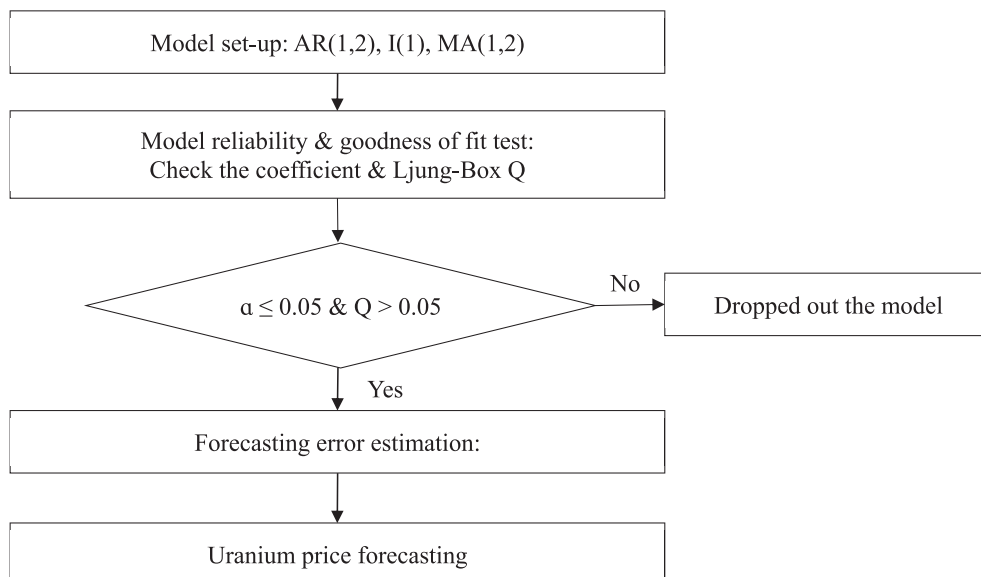


Fig. 1. The procedure of forecasting uranium price using the autoregressive integrated moving average (ARIMA) model.

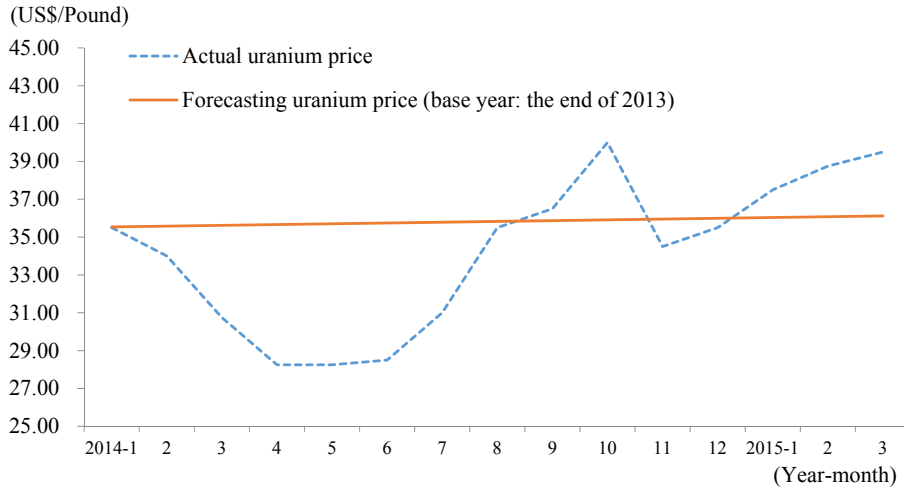


Fig. 2. The comparison between the actual uranium price and the forecasting uranium price with escalation rate method.

significance, this model can forecast the future uranium price [16]. When the time-series data are stationary, the Box-Jenkins model can be classified into the categories of autoregressive model, moving average model, or autoregressive moving average (ARMA) model, as follows.

2.2.1. Autoregressive model

An autoregressive model is a statistical model in which the current values are affected by values such as Year t-1 and Year t-2 of the past. This appears as in Eq. (2) [13–15].

$$Y_t = \mu + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \dots + \alpha_p Y_{t-p} + \varepsilon_t \quad (2)$$

where μ = y-intercept, α = coefficient, Y_{t-1} = random variable at time t-1, and ε_t = error at time t.

Accordingly, the pth-order autoregressive model is marked as AR (p). In other words, it is marked as AR (1) and expressed as shown in Eq. (3) when the value of the previous period exerts an important effect on the current value [13–15,17].

$$\text{AR}(1): Y_t = \mu + \alpha_1 Y_{t-1} + \varepsilon_t, \varepsilon_t \sim N(0, \sigma^2) \quad (3)$$

where N = normal distribution and σ = deviation.

2.2.2. Moving average model

Time-series data are affected by the continuous error term, and can be shown through Eq. (4) [13–15,18]:

$$Y_t = \mu - \beta_1 \varepsilon_{t-1} - \dots - \beta_q \varepsilon_{t-q} + \varepsilon_t \quad (4)$$

where β = coefficient.

Thus, the qth-order moving average model is denoted as MA (q). Accordingly, the moving average model that includes only the error term of (t-1), which is the term defined in the previous paragraph, is as shown in Eq. (5).

$$\text{MA}(1): Y_t = \mu - \beta_1 \varepsilon_{t-1} + \varepsilon_t \quad (5)$$

2.2.3. ARMA model

This is the model in which AR and MA are mixed together, and is the model that is affected by all the past values and past margins of the error values. This is as shown in Eq. (6) [13–15]:

$$Y_t = \mu - \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \dots + \alpha_p Y_{t-p} + \varepsilon_t - \beta_1 \varepsilon_{t-1} - \dots - \beta_q \varepsilon_{t-q} \quad (6)$$

Thus, Eq. (5) is described as ARMA (p, q) and AR (1, 1) which is shown in Eq. (7). AR (1) can be expressed as AR (1, 0).

$$Y_t = \mu + \alpha_1 Y_{t-1} + \varepsilon_t - \beta_1 \varepsilon_{t-1} \quad (7)$$

2.2.4. ARIMA model

When time-series data are nonstationary, the ARIMA model turns into a stationary time-series one through the method of difference; this enables the administering of a statistical analysis. When different time-series are shown as ΔZ_t , as shown in Eq. (8), the ARIMA model can be expressed as Eq. (9) [13–15,19,20]:

$$\Delta Z_t = Z_t - Z_{t-1} \quad (8)$$

$$\Delta^d Z_t = \left(\mu + \alpha_1 \Delta^d Z_{t-1} + \alpha_2 \Delta^d Z_{t-2} + \dots + \alpha_p \Delta^d Z_{t-p} \right) + \varepsilon_t - \beta_1 \varepsilon_{t-1} - \dots - \beta_q \varepsilon_{t-q} \quad (9)$$

where Δ^d = a difference operator and Z_t = the random variable z at time t.

Accordingly, in the case of ARIMA (p, d, q), p signifies the order of the AR, d signifies the order of the difference, and q signifies the order of the MA.

3. Time-series analysis model verification

3.1. Data conformity

To forecast future uranium prices, it is first and foremost necessary to verify the conformity of the time-series analysis model. In other words, it is necessary to calculate the autocorrelation coefficient, the significance of the alpha coefficient value, and the model's conformity level [13–15]. The autocorrelation coefficient of the time-series data for the uranium price data was analyzed. The partial autocorrelation function significantly affects the value prior to Stage 1, as shown in Fig. 3. Accordingly, uranium price fluctuation was analyzed with the time-series data that are most affected by the value prior to Stage 1.

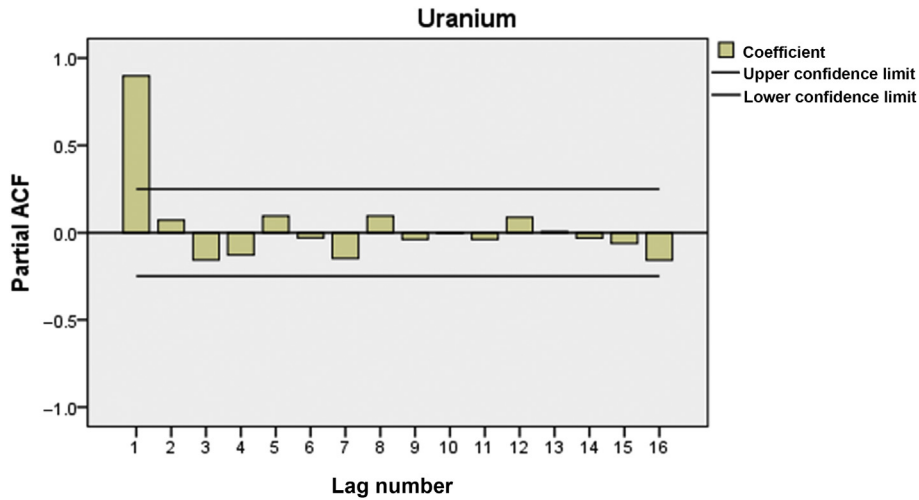


Fig. 3. Partial autocorrelation function. ACF, autocorrelation function.

Fig. 4 shows the uranium price time-series data in graph form. Abnormal time-series patterns are manifested before and after 2007. Thus, the data were converted into normal time-series data, as shown in Fig. 5, by determining the difference. In other words, this study determined the difference to convert the uranium price data that manifested abnormal time-series form into data with a normal time-series form, and used the data as input data for the statistical model.

3.2. Uranium price forecasting margin of error for the time-series analysis model

When the time-series analysis models' uranium forecasting price and the actual price are compared, it is possible to determine which model forecasts the future uranium price more accurately. Table 1 shows the results of forecasting the 2015 uranium price by entering the uranium price information from 2000 to 2014 in the case of the drawn out time-series analysis model.

This paper used each drawn-out model to identify the uranium price forecasting accuracy for the case of the time-series analysis

model, and defined the differences between the forecasted uranium price and the actual price. This was then calculated as shown in Eq. (10) [21].

$$FE_t = \frac{(FP_t - OP_t)}{OP_t} \times 100 \tag{10}$$

where FE_t = the forecasting margin of error of the uranium price at year t , FP_t = the forecasting price at year t , and OP_t = the actual price at year t .

Table 2 suggests the forecasting margin of error for each time-series analysis model's uranium price when using Eq. (1). For example, when the forecasting price for the fourth quarter of 2015 is compared with the actual price, the model with the best forecasting ability was Model Number 5, followed by Model Number 1; the third best was Model Number 7, and the fourth was Model Number 10. Up until Model Number 3, which has the fifth best forecasting ability, the margin of error between the predicted price and the actual price showed the models' good forecasting ability, which was within a 10% margin of error. In the case of

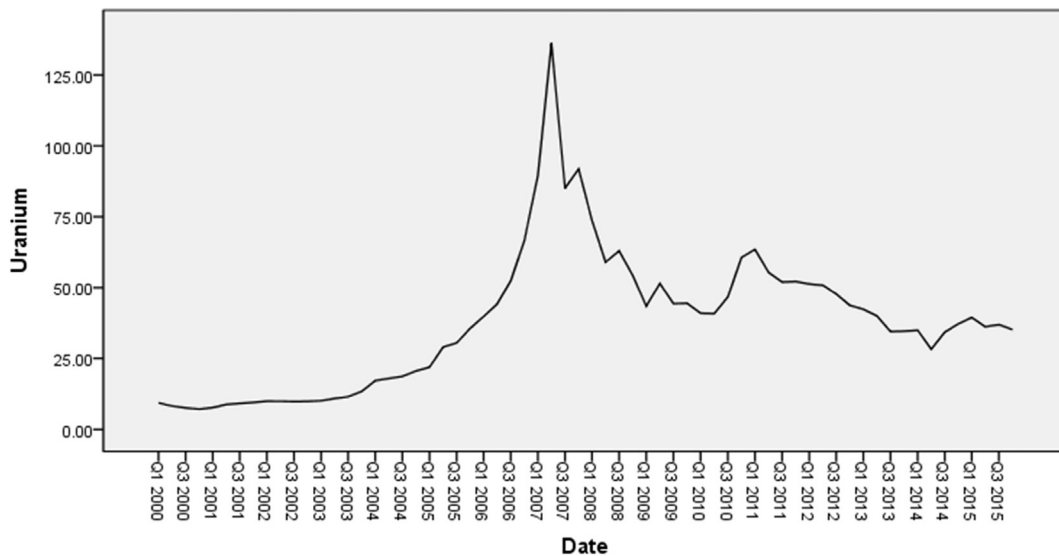


Fig. 4. The uranium price (unit: US\$/pound).

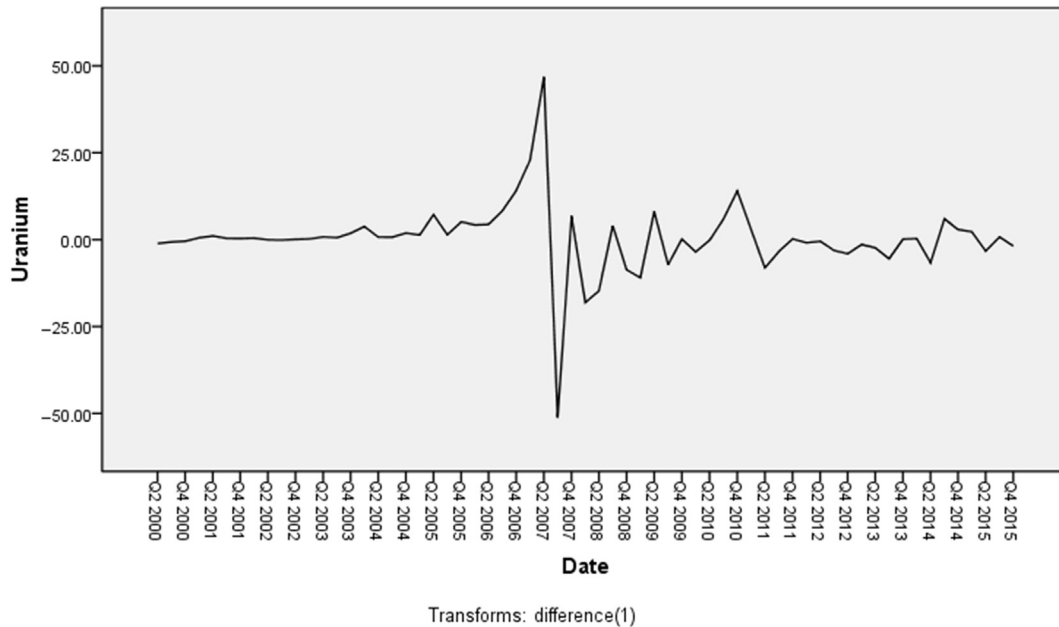


Fig. 5. The uranium price after difference.

Table 1

The forecasting results of uranium prices in 2015 (unit: US\$/pound).

	Actual price	Forecasted price				
		Model 1 (1,0,0)	Model 2 (1,1,0)	Model 3 (0,0,1)	Model 4 (0,1,1)	Model 5 (1,0,1)
2015 1Q	39.41	36.89	37.28	36.32	37.30	36.63
2015 2Q	36.14	36.65	37.80	37.69	37.76	36.41
2015 3Q	36.90	36.43	38.26	37.69	38.23	36.20
2015 4Q	35.10	36.24	38.74	37.69	38.70	36.01
	Actual price	Forecasted price				
		Model 6 (1,1,1)	Model 7 (1,1,1)	Model 8 (2,1,1)	Model 9 (2,1,2)	Model 10 (2,1,2)
2015 1Q	39.41	37.53	37.01	37.82	37.55	37.07
2015 2Q	36.14	38.04	37.06	38.65	39.85	38.92
2015 3Q	36.90	38.50	37.04	39.17	39.02	37.57
2015 4Q	35.10	38.98	37.05	39.7	39.20	37.26

Model Number 5, with the best forecasting ability, the margin of error was not statistically significant. Model Number 1 was not a perfect ARIMA model, and Model Number 7 was also not statistically significant. Model Number 10, however, was statistically significant, in addition to manifesting a good forecasting capability, and was manifested as a perfect ARIMA model. Accordingly, Model Number 10 was analyzed and found to be the most rational

model in terms of uranium price forecasting accuracy level and model conformity level. However, the developed ARIMA model cannot forecast price fluctuations that take place owing to unforeseeable incidents such as those that took place in Fukushima, Japan, as shown in Fig. 6. In other words, it is limited in the sense that it cannot factor in external variables that may occur in the future.

Table 2

The forecasting's margin of error for uranium prices with each time series model (unit: US\$/pound, %).

	Actual price	The margin of error (%)				
		Model 1 (1,0,0)	Model 2 (1,1,0)	Model 3 (0,0,1)	Model 4 (0,1,1)	Model 5 (1,0,1)
2015 1Q	39.41	6.39	-5.40	-7.84	-5.35	-7.05
2015 2Q	36.14	-1.41	4.59	4.29	4.48	0.75
2015 3Q	36.90	1.27	3.69	2.14	3.60	-1.90
2015 4Q	35.10	-3.25	10.37	7.38	10.26	2.59
	Actual price	The margin of error (%)				
		Model 6 (1,1,1)	Model 7 (1,1,1)	Model 8 (2,1,1)	Model 9 (2,1,2)	Model 10 (2,1,2)
2015 1Q	39.41	-4.77	-6.09	-4.03	-4.72	-5.94
2015 2Q	36.14	5.26	2.55	6.95	10.27	7.69
2015 3Q	36.90	4.34	0.38	6.15	5.75	1.82
2015 4Q	35.10	11.05	5.56	13.11	11.68	6.15

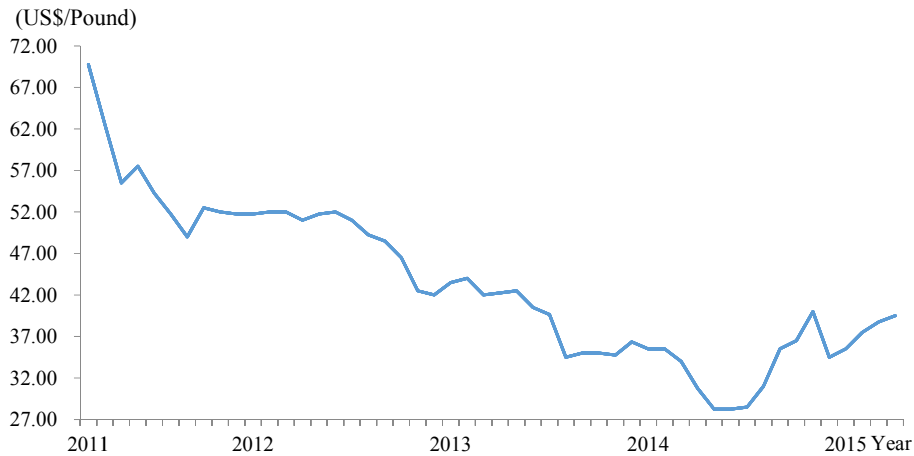


Fig. 6. The uranium price trend after Fukushima accident (March 11, 2011).

3.3. Model conformity

This research paper used 10 models to forecast the future uranium price and verified the models' conformity levels. Moreover, the model was drawn out by utilizing all possible combinations of AR (1, 2), I (1), and MA (1, 2), and the uranium price forecasting value was analyzed afterwards. Table 3 shows the descriptive statistics quantities of the 10 statistical time-series analysis models. For each model to have reliability, not only must the t-value significance be 0.05 or less, but the significance of the value of Ljung-Box Q, which signifies the model's conformity level, should be larger than 0.05. Although Model Number 1 satisfied all conditions, that model is the AR (1) model, which is presumed to lack a

forecasting capability because it is a simple model. Model Number 3 satisfies the significance of the coefficient, but the Ljung-Box Q value is lower than 0.05. Moreover, Model Number 7 excludes the constant term that is not significant in Model Number 6. Model Number 10 excludes the constant term of Model Number, which is not significant. When each model's significance value is examined, only two models, Model Number 10 and Model Number 1, were found to satisfy the model conformity. In other words, the significance level of all coefficients of Model Number 10 and Model Number 1 is lower than 0.05, whereas the Ljung-Box Q values are greater than 0.05. Accordingly, Model Number 10 was proven to be the best in terms of this model conformity level. Thus, all models excluding Model Number 10 and Model Number 1 were rejected as

Table 3
Statistics of the derived 10 time series models.

Model type		Model parameters			Ljung-Box Q			Goodness of fit
Model	Type	Coefficients		t-value (Sig.)	Statistics	DF	Sig.	
1	ARIMA (1,0,0)	Constant	34.325	2.876 (0.006)	8.333	17	0.959	Accepted
		AR Lag 1	0.903	17.614 (0.000)				
2	ARIMA (1,1,0)	Constant	0.416	0.350 (0.728)	10.258	17	0.892	Rejected
		AR Lag 1	-0.137	-1.083 (0.283)				
3	ARIMA (0,0,1)	Constant	37.618	10.491 (0.000)	119.973	17	0.000	Rejected
		MA Lag 1	-0.070	-7.574 (0.000)				
4	ARIMA (0,1,1)	Constant	0.416	0.344 (0.732)	10.317	17	0.890	Rejected
		MA Lag 1	0.109	0.859 (0.394)				
5	ARIMA (1,0,1)	Constant	33.862	2.675 (0.010)	7.982	16	0.949	Rejected
		AR Lag 1	0.916	17.383 (0.000)				
6	ARIMA (1,1,1)	Constant	0.416	0.340 (0.735)	10.174	16	0.857	Rejected
		AR Lag 1	-0.394	-0.525 (0.602)				
7	ARIMA (1,1,1)	MA Lag 1	-0.252	-0.319 (0.751)	10.165	16	0.858	Rejected
		AR Lag 1	-0.397	-0.527 (0.600)				
8	ARIMA (2,1,1)	MA Lag 1	-0.256	-0.323 (0.748)	9.677	15	0.840	Rejected
		Constant	0.406	0.294 (0.770)				
9	ARIMA (2,1,2)	AR Lag 1	0.023	0.021 (0.983)	6.141	14	0.963	Rejected
		AR Lag 2	0.134	0.732 (0.467)				
10	ARIMA (2,1,2)	MA Lag 1	0.147	0.133 (0.895)	6.126	14	0.963	Accepted
		Constant	0.428	0.330 (0.743)				
		AR Lag 1	-0.766	-3.027 (0.004)				
		AR Lag 2	-0.735	-3.341 (0.001)				
		MA Lag 1	-0.626	-2.749 (0.008)				
		MA Lag 2	-0.801	-4.374 (0.000)				
		AR Lag 1	-0.764	-3.040 (0.004)				
		AR Lag 2	-0.735	-3.358 (0.001)				
		MA Lag 1	-0.624	-2.768 (0.008)				
		MA Lag 2	-0.802	-4.412 (0.000)				

ARIMA, autoregressive integrated moving average; DF, degree of freedom; Sig., significance probability.

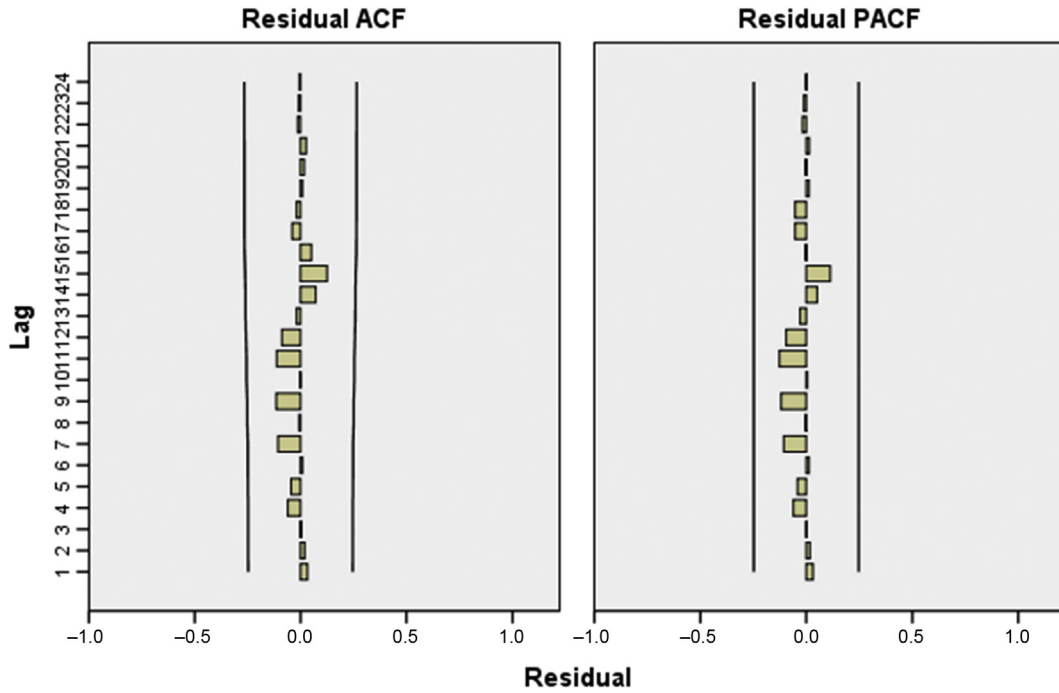


Fig. 7. Residual autocorrelation function (ACF) and residual partial ACF (PACF) in Model 10.

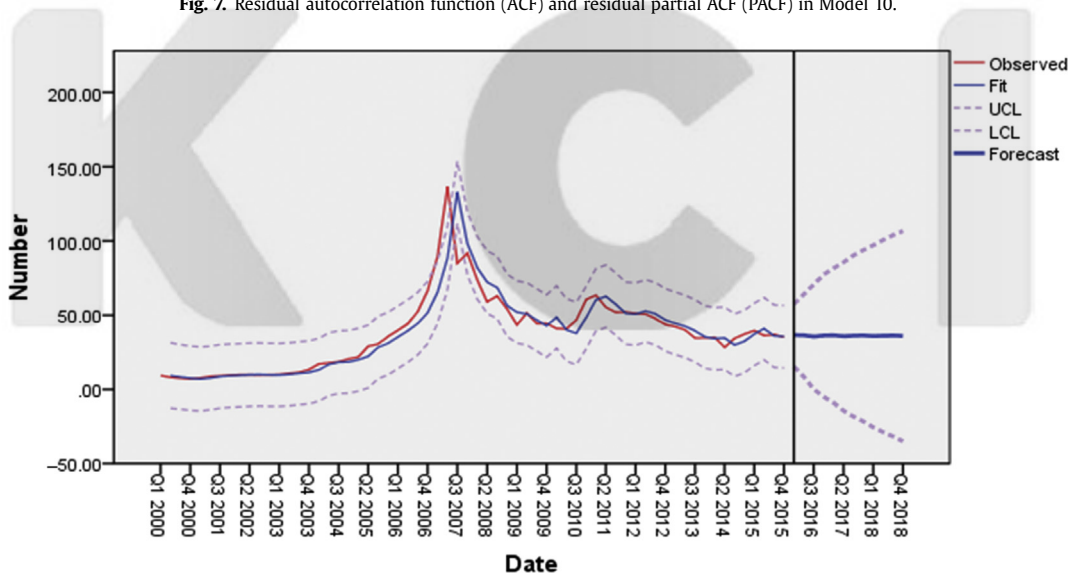


Fig. 8. The forecasting result of uranium price with Model 10 (unit: US\$/pound) - autoregressive integrated moving average (ARIMA) (2,1,2) until 2018. LCL, lower confidence limit; UCL, upper confidence limit.

unfit from a statistical reliability perspective.

The residual was additionally verified to check whether the time-series data of Model Number 10 are statically suitable. Fig. 7 shows the autocorrelation for the residual of Model Number 10 and the partial autocorrelation value. Residual autocorrelation function and partial autocorrelation function are stationary within a confidence interval of 95%.

3.4. Forecasting uranium price results

This study used SPSS version 18.0 software (IBM Corporation, Armonk, New York, USA) to perform the time-series analysis. Ten models were drawn out by combining the p, d, and q values based on the data on the past uranium price, and a statistical model was made for forecasting the future uranium price. However, when the

Table 4

The forecasting uranium price with model 1 and model 10 (unit: US\$/pound).

Time	Model 1 (1,0,0)	Model 10 (2,1,2)
2016 1Q	35.02	36.45
2016 2Q	34.96	36.37
2016 3Q	34.90	35.44
2016 4Q	34.84	36.21
2017 1Q	34.79	36.31
2017 2Q	34.74	35.67
2017 3Q	34.70	36.09
2017 4Q	34.67	36.24
2018 1Q	34.63	35.81
2018 2Q	34.60	36.03
2018 3Q	34.58	36.17
2018 4Q	34.55	35.91

model's conformity level was calculated by assuming a confidence interval of 95% for each model, models excluding Model Number 1 and Model Number 10 were rejected. Fig. 8 shows graphs of the uranium forecasting price trend of Model Number 10. Moreover, Table 4 shows the results of forecasting the uranium price from 2016 to 2018 obtained by entering the price information from 2000 to 2015.

4. Conclusion

ARIMA Model Number 10 was used to forecast future uranium prices, and showed a forecasting margin of error of approximately 5.4% compared to the uranium's actual price in 2015. Accordingly, it was proven that the value of the future uranium price estimated using the ARIMA model, which is a statistical method, is closer to the actual price than is any value obtained by forecasting of the uranium price merely by factoring in the consumer price escalation rate.

When the ARIMA model was used to forecast the uranium price, it was proven that the uranium price forecast is statistically reliable with a confidence interval of 95%. However, because the ARIMA model's uranium forecasting value relies completely on past uranium price data, this model is limited in the sense that it cannot factor in the effect of external variables that may come into play in the future. Despite this limitation, however, the future uranium price forecasted by the ARIMA model comes closer to the actual uranium price than does the value obtained using the escalation rate model, which merely factors in the consumer price escalation rate. Thus, this model is likely to contribute significantly to a reduction of uncertainty regarding nuclear fuel cycle costs.

Conflicts of interest

The authors declare no conflicts of interest.

Acknowledgments

This work was supported financially by the Ministry of Science, ICT and Future Planning under the Nuclear R & D Project, and the authors express their sincere gratitude for the support for this important work.

References

- [1] Organization for Economic Cooperation and Development/Nuclear Energy Agency (OECD/NEA), *The Economics of the Back-end of the Nuclear Fuel Cycle*, OECD/NEA, Paris, France, 2013.
- [2] B.K. Sovacool, Cornucopia or curse? Reviewing the costs and benefits of shale gas hydraulic fracturing (fracking), *Renew. Sust. Energ. Rev.* 37 (2014) 249–264.
- [3] R. Middleton, H. Viswanathan, R. Currier, R. Gupta, CO₂ as a fracturing fluid: potential for commercial-scale shale gas production and CO₂ sequestration, *Energy Procedia* 63 (2014) 7780–7784.
- [4] L. Xia, D. Luo, J. Yuan, Exploring the future of shale gas in China from an economic perspective based on pilot areas in the Sichuan basin—A scenario analysis, *J. Nat. Gas. Sci. Eng.* 22 (2015) 670–678.
- [5] S. Kim, W. Ko, S. Bang, Analysis of unit process cost for an engineering-scale pyroprocess facility using a process costing method in Korea, *Energies* 8 (2015) 8775–8797.
- [6] MIT, *The Future of the Nuclear Fuel Cycle*, Massachusetts Institute of Technology, Cambridge (MA), 2011.
- [7] S.K. Kim, W.I. Ko, Y.H. Lee, Development and validation of a nuclear fuel cycle analysis tool: a future code, *Nucl. Eng. Technol.* 45 (2013) 665–674.
- [8] D.E. Shropshire, K.A. Williams, W.B. Boore, J.D. Smith, B.W. Dixon, M. Duznik-Gougar, R.D. Adams, D. Gombert, *Advanced Fuel Cycle Cost Basis*, Idaho National Laboratory (INL), Idaho Falls (ID), 2007.
- [9] J.D. Park, *Fundamental Cost Management Accounting*, Hyungseul Press, Daegu, 2005.
- [10] S.J. Kang, *The Theory of Cost Estimation*, Dunam Press, Seoul, 2010.
- [11] H.G. Shin, *Intermediate Accounting*, Tamjin Press, Seoul, 2005.
- [12] G. Box, G. Jenkins, *Time Series Analysis: Forecasting and Control*, Holden Day, San Francisco (CA), 1970.
- [13] D.B. Jeong, *Demand Forecasting of Time Series I*, Hannarae Publishing, Seoul, 2009.
- [14] H.J. No, *Well-defined Time Series Analysis Utilizing SPSS/Excel*, YSWPUB, Paju, 2010.
- [15] W.H. Greene, *Econometric Analysis*, Pearson Education, (NJ), 2003.
- [16] F.S. Lasheras, F.J. de Cos Juez, A.S. Sánchez, A. Krzemień, P.R. Fernández, Forecasting the COMEX copper spot price by means of neural networks and ARIMA models, *Resour. Policy* 45 (2015) 37–43.
- [17] P. Ramos, N. Santos, R. Rebelo, Performance of state space and ARIMA models for consumer retail sales forecasting, *Robot. Comput.-Integr. Manuf.* 34 (2015) 151–163.
- [18] K. Taneja, S. Ahmad, K. Ahmad, S.D. Attri, Time series analysis of aerosol optical depth over New Delhi using Box–Jenkins ARIMA modeling approach, *Atmos. Pollut. Res.* 7 (2016) 1–12.
- [19] C. Yuan, S. Liu, Z. Fang, Comparison of China's primary energy consumption forecasting by using ARIMA (the autoregressive integrated moving average) model and GM (1, 1) model, *Energy* 100 (2016) 384–390.
- [20] K. Kandananond, Forecasting electricity demand in Thailand with an artificial neural network approach, *Energies* 4 (2011) 1246–1257.
- [21] J.A. Scott, *Skills & Knowledge of Cost Engineering- Appendix E3*, AACE International Press, Morgantown (WV), 2004.