Research and development of forecasting models for the activities of oil industry entities

Bilimzhanuly Maksat*

Satbayev University, Kazakhstan

**Corresponding author's e-mail: maksatbilimzhanuly@gmail.com*

Abstract

The thesis of the article is devoted to an urgent problem: the development of scientifically based modeling methods in the planning and forecasting of oil and gas production and sales. As you know, in the global market from the successful and efficient sale of oil and gas generally determines the level of economic development of the country that produces and produces this strategic raw material. In this regard, modeling the process of planning and forecasting oil and gas production allows economists at the design stage to determine the best ways to maintain the stability of their implementation at favorable price offers. In this case, of course, from perfection the applied methodology and modeling methods depends on the quality of planning and forecasting. In the thesis of the article, we present the results of a study to further improve the use of one of the most promising econometric methods for modeling the planning and forecasting processes for the production and sale of oil on the sales market, taking into account the peculiarities of the oil industry in Kazakhstan.

Keywords: econometric methods, planning and forecasting oil production.

1 Introduction

The Republic of Kazakhstan is one of the countries with large strategic hydrocarbon reserves and has an impact on the formation of the global energy market. The main national priority that determines the nature of the foreign policy of the leading countries of the world is the reliable provision of energy resources.

In recent years, under the influence of various objective factors, the raw material orientation of the economy of Kazakhstan has been formed, the raw material potential is represented by a variety of fuel and energy resources, among which oil and gas are in the first place.

The oil and gas industry of Kazakhstan, as the basis for the country's industrial development, provides the country with a stable and stable development for a long time, large foreign exchange earnings, and forms the main export block of the economy.

Comparing the statistics of the Agency of the Republic of Kazakhstan for the period from 2002 to 2006, Kazakhstan's crude oil production with world production and with the total production of the CIS countries, presented in Figure I, we can conclude that there is a growth trend in production [1].

According to the Statistics Agency of the Republic of Kazakhstan, in the total industrial production in the republic, crude oil production is more than 16% and 4% falls on the production of oil distillation products [1]. The dynamics of oil production in Kazakhstan is shown in Figure II. In 1998, 25 enterprises engaged in oil production in the Republic of Kazakhstan, the average annual capacity of which in 1997 amounted to more than 30 million tons, but they produced 23 million tons in 1997 when they loaded capacities into three quarters, which amounted to 0.7% of its global production [1].

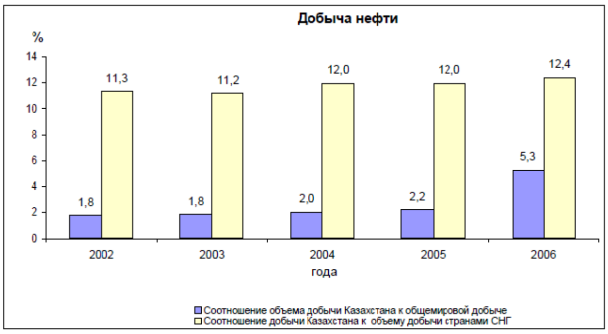

Figure 1 Comparison of crude oil production in Kazakhstan and countries CIS and world production, in % [1]

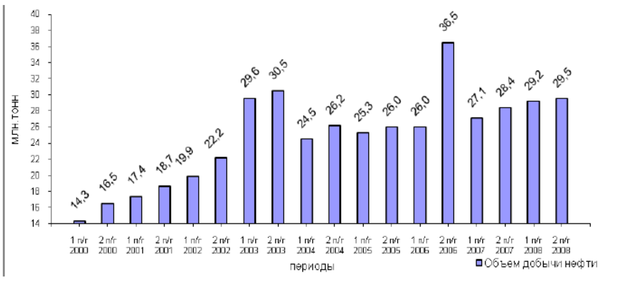

Figure 2 Dynamics of crude oil production in the Republic of Kazakhstan [1]

The procedure which evolves a hypothesis about future events is called Forecasting, and there are a wide variety of forecasting models that predict future events, also they are used in many fields, such as Economics and Science, consequently, the mentioned models are crucial tools in making decisions [2]. An idea of the consequences of an action is provided by ideal forecasts. In addition to this, it serves as a metric for assessing the ability to impact on future events [3].

The task of forecasting and modeling was usually performed either by evolving a model or by implementing methods developed for estimating time series [5]. Various models were applied to forecast data for certain periods [6].

Accurate estimates are required to judge a forecast. The precision of a forecast needs to be analyzed in terms of how the model processes new or raw data that were not previously used to determine the quality of the model [7].

The best indicator for evaluating the model is determined by eliminating the fitting errors associated with classical data prediction. Indistinguishable related predictive downturns suggest inadequate models. Therefore, a good forecasting model should lead to the least number of fitting errors with maximum accuracy.

Econometric methods can improve decision-making opportunities in the face of uncertainty and changes in the levels of factors that have a different impact on the process of economic activity of the oil and gas industry. However, the effective use of these methods for assessing the system of relationships and developing predictive predictions and econometric hypotheses based on it depends on knowledge of the essence of the method. The relationship between performance indicators and various factors of economic activity is caused by the interconnected influence of some phenomena on others. In the study of these relationships, it is necessary to take into account the fact that each individual phenomenon can change under the influence of other phenomena. Therefore, the main methods for assessing relationships and dependencies are regression and correlation analysis and statistical equations of dependencies. But even among these methods, it is necessary to choose a method that most adequately reflects the economic process.

There are two types of time series forecasting models: one-dimensional and multidimensional. Univariate forecasting involves the use of historical data to predict the value of a continuous variable that serves as a response or output variable [8]. Since it provides a quantitative statistical assessment, one-dimensional analysis requires a separate analysis of the results for each corresponding variable in this data set [10]. By Herrera, A.M. and Pesavento, E. (2009) in a one-dimensional analysis, possible relationships between independent variables are not considered [11].

According to Abdel-Aal, R.E. (2008), a one-dimensional time series can give a more accurate forecast than a multidimensional model. By [12], there are the following prediction models such as **Exponential Smoothing (ES), Holt-Winters (HW), and Autoregressive Moving Average (ARIMA)** that use one-dimensional time series.

2 Overview

This thesis of the article focuses on the main decision-making tools, namely time-series-based models. According to [9] an analysis of the accuracy of the **ES** *(modification of the least-squares method)*, **HW**, and **ARIMA** approaches in predicting crude oil prices has been provided and discussed the importance of error conditions in these forecasting models and the significance of achieving minimum errors.

Exponential smoothing (ES) *model (modification of the least squares method)* allows for obtaining an economic model for the economic time series that characterizes not the average level of the process, but the trend that has developed at the time of the last observations. The essence of the method is that the time series is smoothed out using a weighted moving average, in which the weights obey the exponential law. The **ES** framework for time series φ_t is provided by the following formula:

$$\overline{\varphi_t} = \alpha_1 \varphi_t + (1-\alpha_1)\overline{\varphi_{t-1}}\,, \qquad 0 < \alpha < 1 \; and \; t > 0 \; [9].$$

For ES, the *h*-step-ahead forecast equation for time series φ_t is as follows: $\hat{\varphi}_{t+h} = \overline{\varphi}_t$, $h = 1, 2, 3, \cdots, \overline{\varphi}_t$ this formula is the forecast based on period *t*. Also, α_1 is the smoothing parameter [9].

The Holt-Winters (HW) model is a crucial by its own kind. The HW model can be served as an extension of the ES framework. However, it uses a different set of parameters, as opposed to those used in elementary time series, to smooth the slope of values. HW-based forecasting can be performed using three smoothing elements. The HW model is applied to data characterized by seasonality and trend. The **HW** model is given as follows:

$$\overline{\varphi}_t = \alpha_1 \frac{\varphi_t}{S_{t-\delta}} + (1-\alpha_1)(\overline{\varphi}_{t-1} + \beta_{t-1}),\; 0 < \alpha_1 < 1,$$

$$\beta_t = \alpha_2(\overline{\varphi}_t - \overline{\varphi}_{t-1}) + (1-\alpha_2)\beta_{t-1},\; 0 < \alpha_2 < 1,$$

$$S_t = \alpha_3 \frac{\varphi_t}{\overline{\varphi}_t} + (1-\alpha_3)S_{t-\delta},\; 0 < \alpha_3 < 1 . \; [9]$$

In the **HW** model, an h-step-ahead forecast of time series φ_t is prohibited as follows:

$$\hat{\varphi}_{t+h} = (\overline{\varphi}_t + h\beta_t)S_{t+h-\delta}\,, \; [9]$$

where $\overline{\varphi}_t$ is the smoothed value for period *t*, α_1 is the smoothing parameter, φ_t is the actual value at period *t*, $\overline{\varphi}_{t-1}$ - is the average experience of the series of smoothed values in period $t-1$ β_t and β_{t-1} are the trend estimates, α_2 is the smoothing parameter for the trend estimate, S_t is the seasonality estimate, α_3 is the smoothing parameter for the seasonality estimate, h is the number of periods in the forecast lead period and σ is the number of periods in the seasonal cycle [9].

A series transformation such as identification, approximation, diagnosis, and prediction to a state of stationary covariance leads to ***The ARIMA*** model. The function representing **the ARIMA** model is denoted by **ARIMA (p, d, q),** which leads to a stationary function **ARMA (p, q)** upon differentiation with respect to time t. The origin of the **ARMA** model is ***the autoregressive AR*** model of order **p**; **MA**, ***the moving average framework*** of order **q**; and the expressions for **MA (1), AR (2) and ARMA (3)** are as follows [9]:

$$\hat{\varphi}_t = \theta_1\varphi_{t-1} + \theta_2\varphi_{t-2} + \cdots + \theta_p\varphi_{t-p} + \varepsilon_t = \sum_{i=1}^{p}\theta_i\varphi_{t-i} + \varepsilon_t\,, \quad (1)$$

$$\hat{\varphi}_t = \phi_1\varepsilon_{t-1} + \phi_2\varepsilon_{t-2} + \cdots + \phi_q\varepsilon_{t-q} = \sum_{i=1}^{q}\phi_i\varepsilon_{t-i}\,, \quad (2)$$

$$\hat{\varphi}_t = \sum_{i=1}^{p}\theta_i\varphi_{t-i} + \varepsilon_t + \sum_{i=1}^{q}\phi_i\varepsilon_{t-i}\,, \quad (3)$$

where θ_t is the autoregression parameter at time ***t***, ε_t is the error term at time ***t***, and φ_t is the moving-average parameter at time ***t*** [9].

3 Decision

The **ES, HW** and **ARIMA** models have been implemented in

MATLAB. MATLAB has built-in functions that allow us to definee parameters of the mentioned models randomly. The results of the simulation that were obtained by using the **ES**, **HW** and **ARIMA** methods are shown in Figures 1-3. The forecast trends and the real data have been shown with the confidence interval of 95%. The six different metrics are used to identify an accuracy of the mentioned 3 prediction models [9].

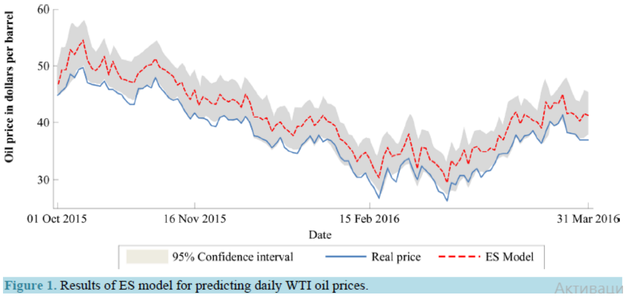

Figure 1 Results of ES model for predicting oil prices

Table 1 Model-accuracy metrics

Table 1. Model-accuracy metrics.

Criteria	Formula	Criteria	Formula
MSE	$\frac{1}{n}\sum_{i=1}^{n}\varepsilon_i^2$	RMSE	$\sqrt{MSE}$
MAE	$\frac{1}{n}\sum_{i=1}^{n}\lvert\varepsilon_i\rvert$	MAPE	$\frac{1}{n}\sum_{i=1}^{n}\left(\left\lvert\frac{\varepsilon_i}{x_i}\right\rvert\right)\times 100$
U₁	$\frac{RMSE}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}+\sqrt{\frac{1}{T}\sum_{i=1}^{n}\hat{x}_i^2}}$	U₂	$\frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n-1}\left(\frac{\hat{x}_{i+1}-x_{i+1}}{x_i}\right)^2}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n-1}\left(\frac{x_{i+1}-x_i}{x_i}\right)^2}}$

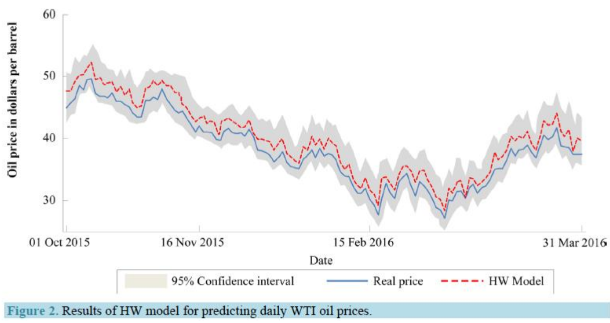

Figure 2 Results of HW model for predicting oil prices

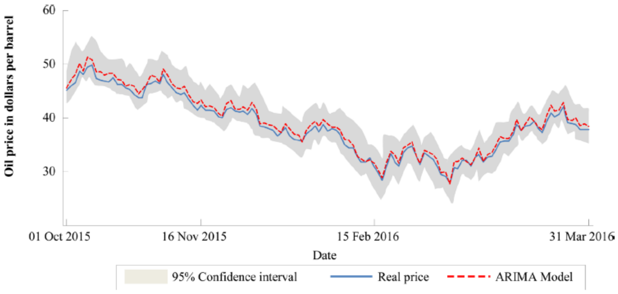

Figure 3 Results of ARIMA model for predicting oil prices

4 Conclusion

In order to make tactical and strategic decisions for the effective management of the oil and gas sector of the economy, it is necessary to choose statistical and econometric methods that contribute to modeling the forecast of key economic indicators and provide a reliable estimate of future indicators. To predict the volumes of crude oil production, it is better to use *the moving average method (MA)* or **ARIMA** because their average values of standard errors are the smallest, according to the autocorrelation coefficients of the levels of the series of volumes of crude oil production, one can judge the increasing linear trend of future periods. Using correlation regression analysis identified factors affecting export volumes and income from the sale of crude oil.

Time series analyses for oil prices data has been used in the given thesis of the article as well as the patterns of statistical predictors were prohibited above. Three types of univariate time-series models were investigated: **ES, HW** and **ARIMA**. The qualities of the given **ES, HW** and **ARIMA** forecasts by comparing the results of the given models with actual data have been determined. The more accurate forecasts have been obtained by the **ARIMA** (2, 1, 2) model than those of the **ES** and **HW** models. The six model-accuracy metrics have been used to quantify the qualities of the forecasts. As a result, the **ARIMA** (2, 1, 2) is the best of the three methods. Predicting future events based on an appropriate time-series model will help all professionals related to the oil industry make decisions and develop more suitable strategic plans.

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