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Multimodel forecasting of non-renewable resources production

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ABSTRACT

The article addresses the complexities of modelling and forecasting of non-renewable resources production (oil, gas, coal, etc.), by means of combining five production trend models with “custom” asymmetry, as well as with six models of fluctuation components: harmonic, independent from the trend; harmonic, proportional to the trend; simultaneous presence of the first and second models of fluctuation components; harmonic with “weighted amplitude”; “frequency-weighted” harmonics.

The purpose of this research is to increase the production forecasting accuracy, by considering the fluctuation components models and by monitoring the models' evolution and fluctuation.

The offered methods provide a production forecasting accuracy increase for oil in the U.S. - by 3.2%, for coal in Germany - by 5%, and gas in the Volgograd region (Russia) - by 25%.

1. Introduction

Curve-fitting models are used to predict the volume of resources extraction, but this forecast also can be useful for assessing the price levels [1] or predicting the value of import/export operations [2]. However, at all levels of aggregation, it is possible to use the bell-shaped trend models of production $T(t)$: Hubbert [3], Gauss [4], Cauchy [5], model of lognormal distribution [6], Skew-normal production-profile model (SNPP) [7] (also known as Weng model [8]). The production trend models, with the exception of the SNPP and model of lognormal distribution, are symmetric in relation to t_0 - the abscissa corresponding to a trend maximum $T_{\max}$. Along with many other researchers, Brandt has shown that the production recession stage is often longer than the production growth stage, and asymmetric models of life cycle production curves are more applicable for the most of them [9].

In these cases, the best results of modelling and forecasting are seen with the models which are more precisely adjusted to the various asymmetries of production trends. At the same time it's necessary to consider not only the known replacement of the constant parameter value in the trend models of Verhulst cumulative logistic function [9] but also search for a complex of other logistic functions: Richards function, classical function with the left asymmetry of Gompertz, the offered Ramsey functions with the left (other) asymmetries and Gompertz function with fixed right asymmetry [10].

With the goal of tuning the asymmetry of production models, the article offers the fluctuation component which is frequently encountered in the practice of production. The widely known occurrence of fluctuations of a production trajectory by Gauss and Hubbert multimodel curves is presented in Ref. [11]. Usage of a multi-cycle Hubbert approach to different levels of data aggregation on an example of oil production in Peru is represented in Ref. [12]. The model from secondary and tertiary polynomials for fluctuation component trajectory is specified in Ref. [13]. The piecewise approach for production curves successfully helps to take into account the asymmetry of the production curve [14]. In some cases, the piecewise set models are applied for a trend of hydrocarbon extraction [9]. A detailed review of oil supply modelling techniques [15] included Hubbert, Gauss, exponential and other trend models. In this review, Brandt evaluated useful of curve-

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fitting models and showed that the greatest promise for future developments in oil production modelling lies in simulation models that combine both physical and economic aspects of oil production. A review of gas production curve-fitting models was presented in Ref. [16]. An example of the Hubbert-type curve-fitting models used for coal production is shown in Ref. [17]. Curve-fitting models can be used to describe both annual and cumulative production [18].

The previous research did not investigate the use of piecewise fluctuation components to describe the resources extraction. Furthermore, previous research proposing the piecewise production models such as [19] did not include a quantitative criterion for determining the time at which model functions change. The novelty of this article lays in the use of several piecewise harmonics fluctuation components with different types of interaction describing a trend and forecasting the non-renewable resources production. Presenting a new approach to the issue of changing the trend models and fluctuation components at various stages of the production life cycle is seen as the main goal of the article. It will help to expand the choices of various production management strategies for modelling in specific segments, countries and groups of countries.

2. Models used

Let's consider the trend models, expressed in the normalized form [10]:

Hubbert

$$T(t) = \frac{T_{\max} \cdot 2}{1 + \cosh\left(\sqrt{2}\,(t - t_0) \cdot \sigma^{-1}\right)},$$

Cauchy

$$T(t) = \frac{T_{\max} \cdot 2\sigma^2}{(t - t_0)^2 + 2\sigma^2},$$

Gauss

$$T(t) = T_{\max} e^{-\ (t-t_0)^2/2\sigma^2},$$

Lognormal

$$T(t) = T_{\max} \frac{t_0}{t} e^{-\ \frac{1}{2} \frac{\ln\frac{t}{t_0} \cdot \left(t_0^2 \cdot \ln\frac{t}{t_0} - 2\sigma^2\right)}{\sigma^2}},$$

SNPP

$$T(t) = T_{\max} \left(e \cdot t_0^{-1}\right)^{t_0^2 \sigma^{-2}} \cdot t^{t_0^2 \sigma^{-2}} e^{-t_0 \sigma^{-2} \cdot t},$$

where σ - parameter defining the slope of the production curve.

To adjust for asymmetry of trend models, we use the following functions:

Verhulst:

$$\sigma = \sigma_1 + (\sigma_2 - \sigma_1) \cdot \left[1 + e^{-\ \frac{t - t_0}{\sigma_T}}\right]^{-1},$$

where σ is given by σ_1 during the growth period and by σ_2 during the production decline period, and the parameter σ_T defines the duration of transition from σ_1 to σ_2 (thus, change of σ parameter);

Richards [20]:

$$\sigma = \sigma_1 + (\sigma_2 - \sigma_1) \cdot \left[1 + e^{-\ \frac{t - t_0}{\sigma_T}}\right]^{-1/\sigma_{T1}};$$

Ramsey [21]:

$$\sigma = \sigma_1 + (\sigma_2 - \sigma_1)\left(1 + \left[1 + \frac{t - t_0}{\sigma_T}\right] e^{-\ \frac{t - t_0}{\sigma_T}}\right);$$

Gompertz [22]:

$$\sigma = \sigma_1 + (\sigma_2 - \sigma_1) e^{-\ 0.7 e^{-\ \frac{t - t_0}{\sigma_T}}}$$

and Gompertz with the right asymmetry [23]:

$$\sigma = \sigma_2 + (\sigma_1 - \sigma_2) e^{-\ 0.7 e^{\frac{t - t_0}{\sigma_T}}}.$$

The Verhulst, Ramsey and Gompertz models use the four parameters - σ_1, σ_2, σ_T and t_0, and the Richards model is supplemented by the additional parameter σ_{T1}, which adjusts the level of the logistic curve asymmetry. By applying these asymmetry functions to the production models and then evaluating the new model accuracies, we should be able to recommend the best patterns for accuracy.

The simplest model of the fluctuation component is the additive structure of the dynamic series, independent from the trend [24]:

$$Y_k = T_k + S_k^A, \tag{1}$$

where Y_k - levels of deterministic component of the time series corresponding to k - th observation (year), T_k - trend levels, S_k^A - levels of fluctuation components, set by the harmonics $S_k^A = \sum_{i=1}^{M} A_i \sin(\omega_i t_k + \varphi_i)$, M − number of harmonics, A_i - amplitude of i -th harmonic, ω_i - frequency of i - th harmonic, φ_i - initial phase of i - th harmonic.

Examples of using the additive fluctuation component for describing the oil and gas production are shown in Fig. 1. Naturally, the observed data Y_k^{data} in (1)–(6) also contain a stochastic component ε_k, which cannot be predicted by the model of components.

The possible proportional multiplicative combination of the fluctuation component with the trend level [25]:

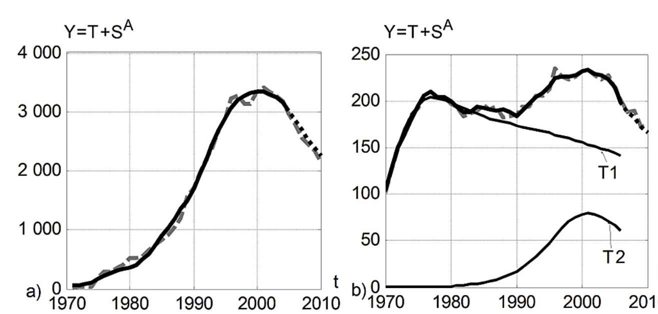

Fig. 1. a) Norway oil production (thous. barrels/day), Hubbert model with Ramsey asymmetry, supplemented by an fluctuation model with two harmonics, b) EU gas production (billion cubic metres per year), Hubbert model with Ramsey asymmetry, supplemented by fluctuation model (1) with three harmonics.