Energy 116 (2016) 746–760

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Mass and energy-capital conservation equations to forecast the oil price evolution with accumulation or depletion of the resources

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ARTICLE INFO

Article history:
Received 15 October 2015
Received in revised form
25 July 2016
Accepted 6 October 2016
Available online 14 October 2016

Keywords:
Oil price forecast
Accumulation or depletion of the oil resources
Mass and energy-capital conservation equations
Consumption rate
Interest rate of non-extracted oil
Interest rate of extracted oil

ABSTRACT

The present work extends the approach of using the mass and energy-capital conservation equations to forecast the price evolution of oil when accumulation or depletion is present. The price evolution is then dependent on the consumption rate of the oil, besides the ratio of mass extraction to mass consumption rates, and the usual economic parameters, e.g. the interest rates of non-extracted and extracted resources. The main conclusions are that a ratio of mass extraction to consumption rates different from unity, i.e. when accumulation or depletion of the oil is present, can modify the approach of the oil price forecast without accumulation or depletion of the resources.

1. Introduction

The price of a non-renewable energy resource as oil is an important variable in the global economy of nowadays. The economics of exhaustible resources was investigated by Hotelling [1], and reviewed by Dasgupta and Heal [2], with the conclusion that its price increases exponentially with the product of time and interest rate of capital.

After the oil crisis of 1973, i.e. during the middle of the 1970's, the problem of oil became a very important issue and several energy models and forecasts were developed and employed. Adelman [3] forecasted a decade of rising oil prices for the US, while DuMoulin and Newland [4] came to the conclusion that a rapid take-off in demand was likely to be followed by a rapid increase of the oil price.

During the 1980's, Pearce [5] presented an overall look at the world energy demand with the conclusion that the judgement, rather than explicit modeling, is used to suggest a world crude oil scenario in which oil prices would rise at 10% per year. Roberts [6] concluded his analysis that through the mid-1980's real crude prices should be flat to down, and thereafter increase at a rate equal to or less than inflation. Curlee [7] concluded that overall assessment of forecasts and recent oil market trends suggested that prices could remain constant in real terms for the remainder of the 1980's, to increase by 2–3% during the 1990's and beyond.

During the 1990's, Angelier [8] concluded his analytical framework with the forecast that in the year 2000 oil prices could not be significantly different from those of 1990's. Abramson and Finizza [9] developed a system that forecasts crude oil prices via Monte Carlo analyses of the network. Fesharaki [10] believed that for the following three to five years oil prices remained at lower levels than generally predicted, because price increases, even when they occur, would not be sustainable for very long. Huntington [11] reviewed forecasts of oil prices over the 1980's identifying the sources of errors due to such factors as exogenous GNP assumptions, resource supply conditions outside the cartel, and demand adjustments to price changes. Santini [12] investigated the statistical model of oil prices examining issues and trends related to both U.S. and world oil supply. Williams [13] examined historical trends and presented the new idea that there is an inverse relationship between crude oil prices volatility and the strength of the relationship between the owners of crude oil (host governments) and the oil companies that develop, refine, market and sell the products.

During the 2000's, Alba and Bourdaire [14] considered the

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http://dx.doi.org/10.1016/j.energy.2016.10.018

actual situation as a 'cohabitation' between oil and other energies, with the oil price extremely volatile, reflecting the trial and error adjustment of the market share left to the other energies. According to the US Energy Information [15] global crude oil prices in 2000 would rise to 24 $/bbl, up by 2 $/bbl from its earlier estimate, while spot prices for West Texas Intermediate crude oil would average more than 22 $/bbl through 2001. Yang [16] reviewed and analyzed the trend of world crude oil price and the prospects on world crude oil price in 2000 predicted. Alvarez-Ramirez et al. [17] studied daily records of international crude oil prices using multifractal analysis methods, where rescaled range Hurst analysis provides evidence that the crude oil market is a persistent process with long-run memory effects, demonstrating that the crude oil market is consistent with the random-walk assumption, only at time scales of the order of days to weeks. Burg et al. [18] developed an econometric modeling of the world oil market, suggesting that world oil prices are likely to fall in the latter part of 2004, and in 2005, as global demand pressures ease. Burg et al. [19] made a market forecast for various energy sources, including oil, gas, and coal, with the conclusion that prices are forecast to decline in 2005 to average 38 $/bbl WTI. Gori and Takanen [20] forecasted the energy demand in a specific country, Italy, where the analysis of the electricity demand was focused, for the first time, on the energy consumption and the possible substitution among the different energy resources, by using a modified form of the econometric model EDM (Energy Demand Model). Moshiri and Foroutan [21] modelled and forecasted daily crude oil futures prices from 1983 to 2003, listed in NYMEX, applying ARIMA and GARCH models, tested for chaos using embedding dimension, BDS(L), Lyapunov exponent, and neural networks tests, and set up a nonlinear and flexible ANN model to forecast the series. The United States Energy Information Administration (EIA) [22] expected worldwide oil demand to increase from 80 million bbl/day in 2003 to 98 million bbl/day in 2015 and to 118 million bbl/day in 2030. The latest forecast's reference case calls for crude oil prices to climb from 31 $/bbl in 2003 to 57 $/bbl in 2030. The present author proposed the approach of using mass and energy-capital conservation equations to investigate the price evolution with time, throughout the use of economic parameters, generalizing the Hotelling rule [23]. The conclusion was that the price of the extracted resources increases exponentially with the product of the time and the difference between the inflation and the extraction rates of the resources, called “Price Increase Factor of Extracted resources”, PIFE. A further generalization was done in Ref. [24] with the introduction of the price of the selling resources, which depends on PIFE and the new parameter, “Price Increase Factor of Sold resources”, PIFS, i.e. the difference between the prime interest rate and the extraction rate of the resources. The political events and many complicated factors, happened in the previous decades, have made oil prices highly nonlinear and even chaotic, with irregularities, random oscillations and linked to the day-to-day events, giving reliability to forecast oil price and consumption in short terms only, by using Adaptive Neural Fuzzy Inference Systems (ANFIS), [25]. Deutsche Bank [26] reported that light, sweet crude oil prices will average 80 $/bbl on the New York Mercantile Exchange in 2008, and that crude oil, in this decade, is likely to average nearly 55 $/bbl. MacAskie and Jablonowski [27] developed a decision-analytic model to value commodity price forecasts in presence of futures markets, and applied the method to a data set on crude oil prices. Hamilton [28] examined the factors responsible for changes in crude oil prices, reviewing their statistical behavior prices, in relation to the predictions of theory, and looking in detail at key features of petroleum demand and supply, discussing the role of commodity speculation, OPEC, and resource depletion. Ghaffari and Zare [29] developed a method, based on soft computing approach, to predict the daily variation of the crude oil price of the West Texas Intermediate. The energy supply curve, i.e. price versus consumption, of non-renewable energy resources was constructed in Ref. [30], where new parameters were introduced to forecast the price evolution of non-renewable resources. This theory has been reviewed and applied to the period from 1966 until 2006 in Ref. [31].

During the 2010's, Gallo et al. [32] have used unit root tests with two endogeneous breaks to analyze the characteristics of oil price, production, and consumption for several countries, and, by taking into account structural breaks, found that in many countries the oil consumption and prices are stationary, while in other countries they are not. A neural network has been introduced to forecast the price of any commercial oil, among seven different crude oils from the Persian Gulf region [33]. Liu [34] made an attempt to characterize and predict petroleum futures prices, using ideas gained from nonlinear dynamical theory. The R/S analysis, the power spectrum and the largest Lyapunov exponent are in close agreement with each other, providing convincing evidence regarding the presence of chaotic behavior in the daily petroleum futures prices series. Nonlinear forecast modeling, based on phase space reconstruction, is applied to petroleum futures prices series. The results indicate the appropriateness of the nonlinear dynamical approach for characterizing and predicting the dynamics of petroleum futures prices. Yaziz et al. [35] obtained the daily West Texas Intermediate (WTI) crude oil prices data, from 2nd January 1986 to 30th September 2009, by using the Box-Jenkins methodology, and the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) approach, which is able to capture the volatility by the non-constant conditional variance. Sughanti and Samuel [36] reviewed several new techniques for energy demand management to accurately predict future energy needs. Traditional methods such as time series, regression, econometric, ARIMA, as well as soft computing techniques, as fuzzy logic, genetic algorithm, and neural networks are being extensively used for demand side management. Support vector regression, colony and particle swarm optimization are new techniques being adopted for energy demand forecasting. Bottom up models, such as MARKAL and LEAP, are also being used at the national and regional levels for energy demand management. Azadeh [37] presented a flexible algorithm, based on artificial neural network (ANN) and fuzzy regression (FR), to cope with optimum long-term oil price forecasting in noisy, uncertain, and complex environments, incorporating the oil supply, crude oil distillation capacity, oil consumption of non-OECD, USA refinery capacity, and surplus capacity as economic indicators. Mingming and Jinliang [38] constructed a multiple wavelet recurrent neural network simulation model, where trend and random components of crude oil and gold prices are considered. Rabbani et al. [39] proposed a new bi-objective fuzzy linear regression model, to fill the gap, in the field of forecasting by using possibilistic programming to be compared with three promising fuzzy linear regression models from literature, in order to forecast the energy consumption in USA, Japan, Canada and Australia, during 2010–2015. Hu et al. [40] attempted to accurately forecast prices of crude oil futures, by adopting three popular neural networks methods, including the multilayer perceptron, the Elman recurrent neural network (ERNN), and the recurrent fuzzy neural network (RFNN), with the conclusion that learning performance can be improved by increasing the training time, and that the RFNN has the best predictive power, and the MLP has the worst one, among the three underlying neural networks. The accuracy of forecasting the price of crude oil can be increased, with a deeper understanding of the market microstructure, by the introduction of a wavelet decomposed ensemble model [41]. A new category of cases, i.e. those with negative inflation rate, has been introduced, within the present theory, in Ref. [42], where some preliminary results have been