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Modeling and forecasting United States oil production along with the social cost of carbon: conventional and unconventional oil

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Abstract

Purpose – The USA is one of the largest oil producers in the world. For this purpose, the authors model and predict the US conventional and unconventional oil production during the period 2000–2030.

Design/methodology/approach – In this research, the system dynamics (SD) model has been used. In this model, economic, technical, geopolitical, learning-by-doing and environmental (social costs of carbon) issues are considered.

Findings – The results of the simulation, after successfully passing the validation test, show that the US unconventional oil production rate under the optimistic scenario (high oil prices) in 2030 is about 12.62 million barrels/day (mb/day), under the medium oil price scenario is about 11.4 mb/day and under the pessimistic scenario (low oil price) is about 10.18 mb/day. The results of US conventional oil production forecasting under these three scenarios (high, medium and low oil prices) show oil production of 4.62, 4.26 and 3.91 mb/day, respectively.

Originality/value – The contribution of this study is important in several respects: First, by modeling SD that technical, economic, proven reserves and technology factors are considered, this paper models US conventional and unconventional oil production separately. In this modeling, nonlinear relationships and feedback loops are presented to better understand the relationships between variables. Second, given the importance of environmental issues, the modeling of social costs of CO_2 emissions per barrel of oil is also presented and considered as a part of oil production costs. Third, conventional and unconventional US oil production by 2030 is forecast separately, the results of this study could help policymakers to develop unconventional oil and plan for energy self-sufficiency.

Keywords Unconventional Oil, United States, CO_2 Emission, Learning by doing, System dynamics, Simulation

Paper type Research paper

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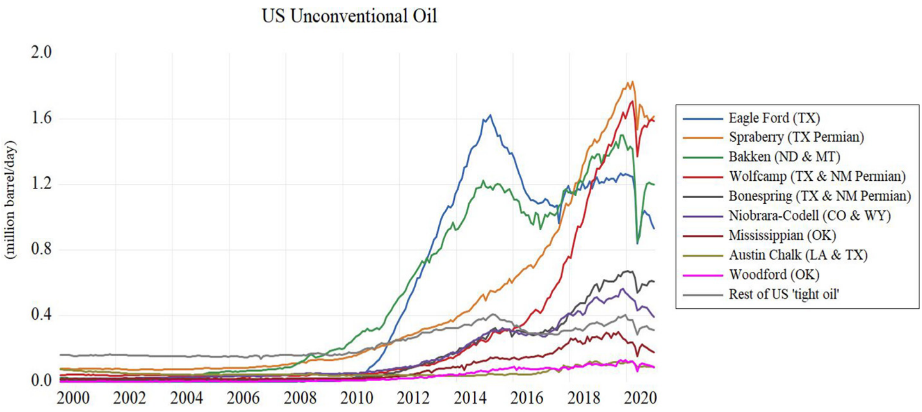
1. Introduction

Oil as the main source of energy in the world accounts for about 0.33% of primary energy consumption (BP, 2020; EIA, 2020). Therefore, any instability and reduction in oil production rates will affect the global economy. For this reason, forecasting oil production in the world is of great importance. From the beginning of the 21st century, unconventional oil production has received special attention, especially in the USA. One of the reasons for the dramatic increase in unconventional oil production in the USA was the rise in oil prices from 2003 to 2013, which led to cost-effective shale oil production. On the other hand, technological advances in horizontal drilling and hydraulic failure reduced production costs (Caporin *et al.*, 2019; Monge *et al.*, 2017). Technology advances in horizontal drilling and hydraulic failure have made large amounts of shale oil previously uneconomical, cost-effective. The Energy Information Administration (EIA) estimates that shale oil resources recoverable in 46 countries are approximately 419 billion barrels (EIA, 2016). The USA owns more than 90% of the world's shale oil production in 2016. Current production in the USA relies heavily on horizontal drilling and hydraulic failure in many wells (Hao *et al.*, 2016). This energy source provides the USA with economic development, self-sufficiency, greater international competitiveness and reduces Organization of the Petroleum Exporting Countries' (OPEC) power. (Smith and Lee, 2017; Solarin *et al.*, 2020). In addition to higher oil prices, other factors such as shale gas history, legal incentives for landowners and advanced oil production infrastructure led to the US shale oil revolution. The USA also has legal and institutional characteristics that make the economic environment attractive to unconventional oil production. Moreover, it has infrastructure that includes numerous advanced drilling rigs, an extensive pipeline network and related refineries (Alquist and Guénette, 2014; Monge *et al.*, 2017).

In 2005, the USA was the world's third-largest producer with 5.8 million barrels of oil per day (mb/day). But now, it is the world's largest oil producer in 2019, with more than 12.2 mb/day (BP, 2020). Oil production in the USA includes both conventional and nonconventional oil production. In 2000, US unconventional oil production at 400,000 barrels per day accounted for 6.9% of total crude oil production, while in 2019, it was 7.75 mb/d, which is more than 63% of its oil production. unconventional oil has boosted US oil production. The shale oil revolution has brought about structural shifts in crude oil production in the USA and global energy security (EIA, 2020; BP, 2020; Temkeng and Fofack, 2021). Although oil demand and prices declined in 2007–2008 due to the recession, this had little effect on the increasing trend of unconventional oil production in the long run due to technological advances in horizontal drilling and hydraulic failure (Wachtmeister and Höök, 2020). Figure 1 shows the amount of conventional and unconventional US oil production.

As can be seen in Figure 1, US unconventional oil production is reported monthly from 2000 to 2020. Eagle Ford (TX) and Bakken (ND and MT) in mid-2015, by about producing 1.6 mb/day and more than 1.2 mb/day are the biggest oil producer in that years. Other regions increase their unconventional oil production with delays. Spraberry (TX Permian) and Wolfcamp (TX&NM) by producing about 1.8 and 1.7 mb/day have higher oil production than other regions by early 2020, respectively. Woodford (OK) and Austin Chalk (LA and TX) have the lowest oil production. Generally, the trend in unconventional oil production has gradually increased since 2008. This trend resulted in a significant increase in subsequent years, as technology evolved and production costs decreased.

Oil production costs have fallen as a result of technological advancements; but the cost of depleted oil increase due to over-extraction. In addition, one of the most important issues for sustainable development of countries is to pay attention to environmental issues and climate change. Given that CO_2 emissions account for about 70% of greenhouse gas emissions, it is



Source: (EIA, 2021)

Figure 1.
US unconventional oil production

important to adopt policies and consider emission costs (Lin and Xu, 2018). Conventional and unconventional oil production is associated with CO_2 emissions. Most previous studies have not considered the CO_2 emission costs from oil production. In this study, the social cost of CO_2 along with other oil production costs is considered. The social cost of CO_2 represents the economic damage caused by the emission of one ton of CO_2 (tCO_2) (Ricke *et al.*, 2018; Van den Bergh and Botzen, 2015). The contribution of this study is important in several respects: First, by modeling system dynamics (SD) that technical, economic, proven reserves and technology factors are considered, we model US conventional and unconventional oil production separately. In this modeling, nonlinear relationships and feedback loops are presented to better understand the relationships between variables. Second, given the importance of environmental issues, the modeling of social costs of CO_2 emissions per barrel of oil is also presented and considered as a part of oil production costs. Third, conventional and unconventional US oil production by 2030 is forecast separately, the results of this study could help policymakers to develop unconventional oil and plan for energy self-sufficiency.

The following of this research is: Section 2 includes the literature review, Section 3 presents the methodology, Section 4 shows SD oil production, Section 5 indicates empirical results and discussion, and finally, Section 6 considers conclusions.

2. Literature review

In this section, we review previous studies in the field of modeling and forecasting oil production. Hubbert (1956) forecasted oil production for 48 US states. Then several studies (Saraiva *et al.*, 2014; Szklo *et al.*, 2007; Nashawi *et al.*, 2010; Ebrahimi and Ghasabani, 2015; J. Wang *et al.*, 2011; Chavez-Rodriguez *et al.*, 2015; Maggio and Cacciola, 2009; Tao and Li, 2007) use Hubbert's theory to predict oil production, whereas some researchers used other models to predict oil production.

Saraiva *et al.* (2014) in a study that predict the oil production of Brazil using the multi-Hubbert model stated that regardless of discoveries depending on the URR scenarios, the oil peak should be between 2.37 mb/day in 2015, 3.33 mb/day in 2022 and 6.59 mb/day in 2035. Szklo *et al.* (2007) in another research for Brazil using the Hubbert model showed that Brazilian oil production curves imply the peak production with more than 15 years lag. Reserves with

75% confidence are 3.27 mb/day in 2020, while reserves with 50% confidence are 3.28 mb/day in 2028, and with 30% confidence are 3.88 mb/day in 2036. Maggio and Cacciola (2009) predicted global oil production using the Hubbert theory. The results express that assuming approximately 2,250–3,000 billion barrels of conventional oil can be finally recovered, it was predicted that oil production between 2009 and 2021 would be 29.3–32.1 billion barrels per year. In another study to predict world oil production using the Hubert multiring model, Nashawi *et al.* (2010) stated that the analysis of 47 major-producing countries estimated the final world's ultimate crude oil reserve at 2,140 billion stock-tank barrels (BSTB) and the remaining recoverable oil at 1,161 BSTB. The results revealed that global production peaked in 2014 at 79 mb/day. OPEC reserves remain 909 BSTB, which is about 78% of global reserves. OPEC production is projected to peak in 2026 at 53 mb/day.

Wang *et al.* (2011) also predicted the world's conventional oil production with two typical multicycle models (Hubbert model and Wong generalized model). The results of both stated that world conventional oil production peaked at 30 billion barrels in 2011. Ebrahimi and Ghasabani (2015) predicted OPEC oil production using a variant multicyclic Hubbert model. The results of the analysis for the 12 major oil-producing countries showed that OPEC's ultimate recoverable resource is up to 1,271 billion barrels. It also reveals that OPEC crude production peaked in 2028 at a production rate of 18.85 billion barrels per year. Chavez-Rodriguez *et al.* (2015) investigated the past and future of oil production in Peru using the Hubbert hypothesis. The findings showed that oil production in Peru has not followed the single-Hubbert pattern, except in an area with more drilling activity.

Some researchers have applied other methods to predict oil production. Tao and Li (2007) simulated the Hubert Peak of Chinese oil production using a SD model. Three scenarios have been used to estimate the peak of China's oil: In Scenario 1, Hubbert peak appears to produce 199.5 million tons of crude oil in 2019, which is about 1.1 times that of 2005. Over the next 20 years, China's crude oil demand is likely to increase by 2%–3% per year, and the gap between domestic supply and aggregate demand may be more than half of that. Hosseini and Shakouri (2016) used the SD method to predict the conventional and unconventional oil production of the world. They indicated that conventional oil production by 2025 is about 80–87 mb/day, while the rate of unconventional oil production is 19.6–28.58 mb/day. Ma and Liu (2018) in a study predicted China and India oil production applying a new multivariate nonlinear model based on ARPs reduction model and Kernel method. They stated that ARPs decline model is qualified to describe the nonlinear relationship of factors affecting oil production and is used to accurately predict oil production in real cases. Aydin (2015) in a survey using linear and nonlinear regression models to predict global oil production pointed out the proposed models can be applied effectively to predict global oil production. The compared results showed that the inverse regression model offers the best prediction performance. Global oil production in 2020 is projected at 4,593 million tons per year, which is 8.84% higher than in 2014.

Aizenberg *et al.* (2016) also predicted oil production using multilayer neural network with multivalued neurons. Hakim Elahi (2019) projected oil production using ensemble-based decline curve analysis. Al-Sagheer and Kotb (2019) envisaged oil production based on deep LSTM recurrent networks. Experimental results show that the proposed DLSTM model performs better than other standard approaches. Al-Shabandar *et al.* (2021) use a deep gated recurrent neural network to predict petroleum production. Experimental results showed that the proposed model works better than the existing approaches. Alipour *et al.* (2017) in a study using the fuzzy cognitive map approach examined the oil production routes of Iran in the post-sanctions period. The performed simulations showed that under all three scenarios, oil production increases. Yang *et al.* (2015) modeled oil production using symbolic regression. The results indicated that world oil production will reach its peak in 2021, and the decline rate after the peak is about half of peak, and a 4% decline from the peak takes nearly 12 years.

Other studies have predicted unconventional oil production. Zhan *et al.* (2019) predicted unconventional resources using machine learning for more than 300 wells. They showed that the average difference between predicted and actual cumulative production in the first 2 years is less than 0.2% with a variance of less than 5%. Mohr and Evans (2010) forecast long-term unconventional oil production under three scenario. The results revealed that unconventional oil was between 49 and 88 barrels per day between 2076 and 2086, before declining. The optimistic scenario of total oil production is expected to peak by 2050. Umekwe and Baek (2017) indicated that oil prices have an asymmetric effect on shale production in the short run, for example, US shale production is more responsive to rising oil prices than falling prices. However, asymmetric effects are not stable over the long term. In another study to predict US shale oil production using a new combination of nonlinear gray model and linear ARIMA residual correction, Wang *et al.* (2018) stated that this new NMGM-ARIMA method can significantly improve the predictive effectiveness. Suhag *et al.* (2017) in a study to predict shale oil production using experimental methods and artificial neural networks disclosed that the predicted values of the ANN network show less than 10% error in estimation.

Velasco *et al.* (2021) foreseen the US compacted oil production using the moving boundary approach. This approach has been applied to evolve the two regions by gradually reducing the reservoir pressure. For both black oil and volatile oil scenarios, the calculations obtained from this analytical framework can match the reservoir pressure, oil and gas volume, and gas and oil cumulative ratios that are determined using the reservoir simulator. Matsumoto and Voudouris (2015) in a study using the ACEGES model examined the possible impact of unconventional oil on the evolution of oil markets, focusing on the four major oil-producing countries (Iran, Saudi Arabia, Venezuela and Canada). The results implied that oil-rich countries like Saudi Arabia and Iran will have more production by 2050, but countries like Canada and Venezuela with unconventional resources will have more production by 2050–2060. Kiani and Pourfakhraei (2010) modeled oil and gas production and consumption policies in Iran using SD. The results showed that export gas in different scenarios will reach between 500 and 620 million cubic meters per day and export revenue will reach $500bn by 2025. Sani *et al.* (2018) Modeled energy mixing in Indonesia using SD method. This study introduces a new approach to creating a national energy landscape and discusses modeling challenges. The modeling results confirm the historical data trend and show that the model may provide a suitable solution for forecasting.

According to earlier studies, various models have been used to predict oil production. In this study, we examine the effects of oil prices on US conventional and nonconventional oil production using a SD approach. Because the oil market is a complex market that is affected by many variables and also the relationships between variables in some cases are nonlinear and in the form of feedback loops. For this purpose, the SD method is one of the most suitable methods for modeling and forecasting in this market. As can be seen, just in a few studies SD method has been used to predict oil production. Also, to our knowledge, so far no studies have examined conventional and unconventional US oil production using the SD approach. Another innovation of this research is the modeling of technological progress in rigs construction, oil production cost, resource depletion costs, short- and long-term profitability, as well as the social costs of CO_2 emissions from oil production simultaneously in one system. The next part of this research introduces the methodology and the conceptual model of SD.

3. Data and methodology

This section is made up of two subsections: Subsection 3.1 provides database specifications and sources. In Subsection 3.2, the research methodology is presented.

3.1 Data

This study deals with the modeling and forecasting of US conventional and unconventional oil trends during the period 2000–2030. The following are the data sources used in this research: Conventional and unconventional oil production is taken from the U.S. Energy Information Administration (EIA, 2021), proven reserves [British Petroleum (BP) and Statistical Review of World Energy, 2021; USGS[1], 2021], number of oil rigs (https://rigcount.bakerhughes.com/). Also, some of the fixed parameters listed in Table 1 are taken from previous studies.

3.2 Methodology

Most researchers would divide a complex system into smaller components. However, this breakdown often results in inconsistencies in the forecasts because of the lack of consideration of parts of the system. The SD method models the various components of a system together with feedback loops (Ansell and Cayzer, 2018). The SD model is a dynamic simulation method for analyzing complex systems and understanding system changes over time (Liu and Xiao, 2018). This model was first introduced by Forrester (1961). Modeling SD has three main components: feedback loops, variables and equations. In feedback loops, three types of variables are applied: stock, flow and auxiliary variables (Aslani *et al.*, 2014; Tan *et al.*, 2018) . Feedback loops include: reinforcing loops (+) or balancing loops (−). The description of these two loops is as follows:

Parameters	Conventional	Unconventional	Unit	Source
Initial time	2,000	2,000	Year	
Final time	2,030	2,030	Year	
Cumulative oil production	1,19,126	450	(Million barrel)	
Market discount rate	0.1	0.1	No unit	
Finance discount rate	0.1	0.1	No unit	
Initial recovery Factor	0.33	0.27	No unit	
Rig count	177	34	Rig	
Cumulative CO_2 emission	691×10^7	741,871	(tCO_2)	
Learning parameter in construction (L)	0.962	0.9289	No unit	
Oil rig lifetime	20	25	1/year	Hosseini and Shakouri (2016)
Oil rig construction time	3	5	Year	Hosseini and Shakouri (2016)
Learning parameter in CO_2 emission cost (b_{ce})	0.3 uncon	0.21	No unit	Méjean and Hope (2013)
CO_2 costs growth rate (α)	0.02	0.027	No unit	Yohe *et al.* (2007) Hope (2008)
Depletion exponent (γ)	1.41	1.07	No unit	Sauner (2000)
Learning parameter in oil production (β)	0.41	0.359	No unit	Kahouli-Brahmi (2009) Méjean and Hope (2008) Hosseini and Shakouri (2016)
Initial social cost of CO_2	21	25	($/$tCO_2$)	Méjean and Hope (2013)

Table 1. Parameters and initial value

(1) Reinforcing loop (**R**): In this loop, the next cycle continues to move in the same direction (increase or decrease) which causes instability and deviation from the equilibrium point.

(2) Balancing loop (**B**): In this loop, the next cycle changes in the opposite direction of movement and causes the system to stabilize.

In this system, after defining the problem and the limitations of the system boundary, we draw the conceptual loops of the system using casual loop. Then we model the system stock–flow relations and write its mathematical equations. Finally, we use validation tests before performing the simulation (Wen and Bai, 2017). Figure 2 indicates the general framework of SD modeling.

In validation, three tests were applied: unit check, extreme conditions and simulation of historical data. The unit check test is used by the software itself to check the appropriateness of the unit of the variable in the model. In extreme conditions tests, the behavior of the model in the boundary state of some important variables is considered. Finally, the historical data simulation test is used to check the simulation results obtained with real historical data. In this research, the mean absolute error percentage (MAPE) is used to check the error rate of the simulated data. If acceptable results are achieved, the model is prepared to put forward a scenario and predict the future trend (Sterman, 2000):

$$MAPE(\%) = \frac{1}{n}\sum\left|\frac{A_t - F_t}{A_t}\right| * 100 \quad (1)$$

A_t, F_t and n, are the actual data, the calculated values and the number of data, respectively.

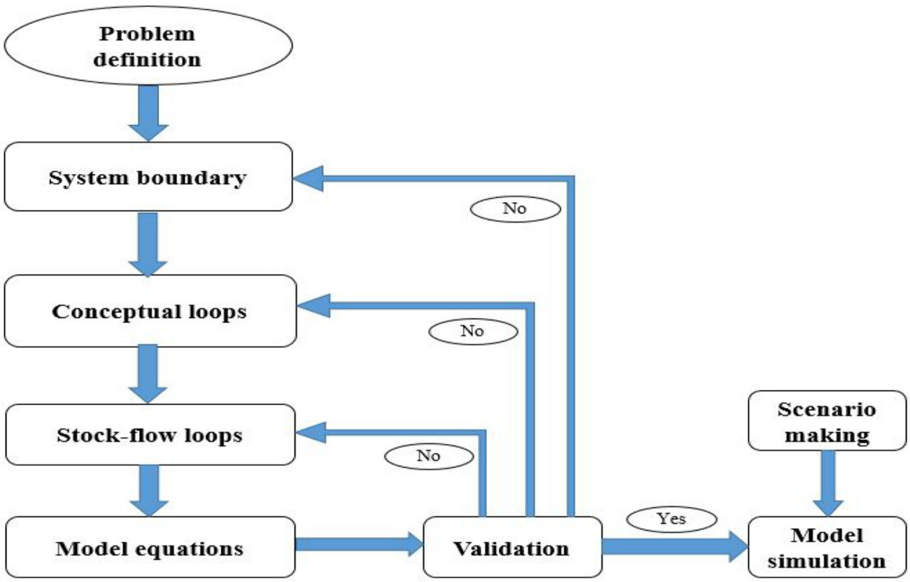


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Figure 2.
System dynamics modeling framework

4. System dynamics of oil production

In this research, many variables have been used that are generally divided into two groups: endogenous or exogenous. The main exogenous variable is oil prices, and endogenous variables include the number of oil rigs, the oil production cost, recovery factor and proven reserves. In this paper, the system boundary comprises the following factors: international oil price, short-term profitability, long-term profitability, the social cost of CO_2 emissions, number of oil rigs, oil production learning coefficient, oil rig construction learning coefficient, proven reserves, recovery factor and several other factors.

4.1 Causal loops and modeling

In this study, the SD method is used for separate modeling of US conventional and unconventional oil. All leading equations and loops are applied separately for conventional and unconventional oil. The SD model is used to examine the impact of different oil price scenarios on US conventional and nonconventional oil production, along with production cost modeling, short-term profitability, long-term profitability, resource reduction rates and social costs of CO_2 emissions from oil production per barrel.

Figure 3 shows the channels affecting oil production rate in the form of feedback loops with respect to the learning effect, short- and long-term profitability and resource constraints.

In the following, the reinforcing (R) and balancing (B) feedback loops related to Figure 3 are given:

$$R(+) : OPR \rightarrow CUMOP \rightarrow OPC \rightarrow STP \rightarrow OPR \tag{1}$$

As shown in loop (1), increasing oil production rate leads to increased cumulative production and, due to learning-by-doing and technology, reduces oil production costs per barrel. Reducing oil production costs, on the one hand, leads to an increase in oil production rate by increasing short-term profitability (reinforcing loop). On the other hand, in the long-term

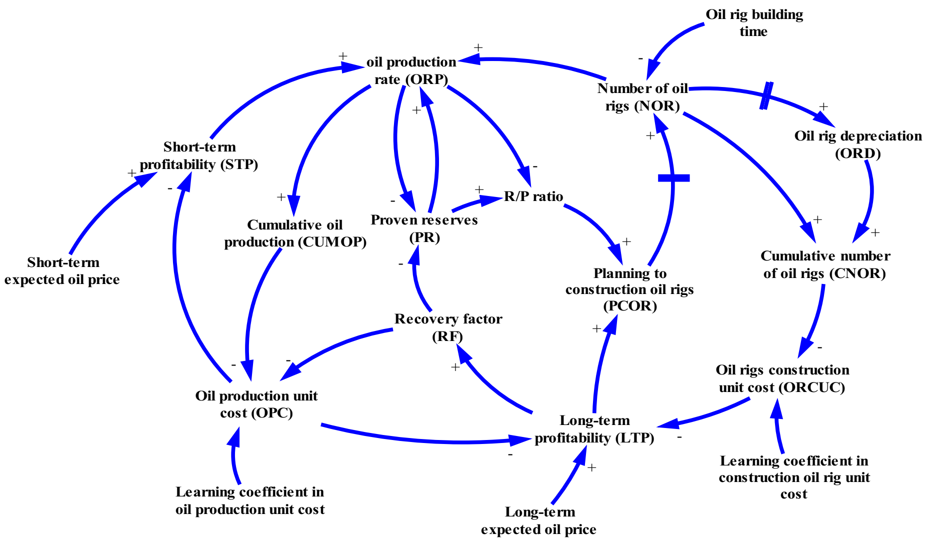

Figure 3.
Short- and long-term profitability and learning coefficient in oil production and oil rig construction

(loop 2), as long-term profitability increases, planning for oil rigs construction increases, which in turn increases the number of oil rigs and consequently oil production rate (reinforcing loop):

$$R(+) : OPR \rightarrow CUMOP \rightarrow OPC \rightarrow LTP \rightarrow PCOR \rightarrow NOR \rightarrow OPR \tag{2}$$

Oil production rate through another channel (loop 3) also affects itself:

$$B(-) : OPR \rightarrow \frac{R}{P} ratio \rightarrow PCOR \rightarrow NOR \rightarrow OPR \tag{3}$$

Thus, increasing the oil production rate reduces the reserves to production ratio, which decreases the planning for the oil rigs construction, and as a result, by reducing the number of oil rigs, oil production also decreases. On the other hand (loop 4) it can be stated that the number of oil rigs through the cumulative oil rigs and learning-by-doing in oil rigs construction, reduces the oil rig construction unit cost, which is effective on long-term profitability. Increasing long-term profitability increases investment in research and development, which in turn increases the recovery factor, and reduces the oil production cost per barrel and this also affects oil production rate through short-term profitability:

$$B(-) : OPR \rightarrow \frac{R}{P} ratio \rightarrow PCOR \rightarrow NOR \rightarrow CNOR \rightarrow ORCUC \rightarrow LTP \rightarrow RF \rightarrow OPC \\ \rightarrow STP \rightarrow OPR \tag{4}$$

After showing the causal loops (see Figure 3), the learning effects on oil production cost and oil rig construction, resource depletion, short- and long-term profitability, their main mathematical equations are given below.

4.2 Oil rig learning curve

The learning effect was first introduced by Wright (1936), this effect states that costs are reduced as experience increases through learning by cumulative production. The learning curve has been widely used in a variety of contexts (Gopal, 2013; Kahouli-Brahmi, 2009; Levy, 1965; Zhou *et al.*, 2019), including the energy sector (Hosseini and Shakouri, 2016; Méjean and Hope, 2008; Méjean and Hope, 2013). As can be seen in Figure 3, one of the variables that affect long-term profitability is the oil rig construction unit cost, which is reduced by the learning effects. This formula is given in equation (1):

$$ORCUC_t = ORCUC_0 * \left(\frac{CNOR_t}{CNOR_0}\right)^{-L} \tag{1}$$

where $ORCUC_t$: oil rig construction unit cost (USD/rigs); $ORCUC_0$: initial oil rig construction unit cost (USD/rigs); $CNOR_t$: cumulative number of oil rigs (rigs); $CNOR_0$: initial cumulative number of oil rigs (rigs); L shows the learning in rig construction or learning coefficient, and this coefficient is positive ($L > 0$) (which here is assumed to be a constant value); and t is time.

4.3 Oil production cost with learning and depletion curve

As mentioned in Section 4.2, by increasing cumulative production through learning, the recovery factor increases and reduces oil production costs. On the other hand, increasing the production rate reduces resources and increases the oil depletion cost (Hosseini and Shakouri, 2016; Méjean and Hope, 2008; Méjean and Hope, 2013). Equation (2) is the oil production cost due to learning and depletion:

$$OPC_{un-con,t} = OPC_{min} + \left(OPC_{un-con,t_0} - OPC_{min}\right)*\left(\frac{CUMOP_{un-con,t}}{CUMOP_{un-con,t_0}}\right)^{-\beta} + OPC_{max}*\left(\frac{CUMOP_{un-con,t}}{URR_{un-con,U}}\right)^{\gamma} \quad (2)$$

where $OPC_{un\text{-}con,t}$ oil production cost per barrel (USD/barrel); OPC_{min} minimum oil production cost per barrel (USD/barrel); OPC_{max} the maximum oil production cost per barrel (USD/barrel); OPC_{un-con,t_0} oil production cost per barrel at time t_0 (USD/barrel); $CUMOP_{un\text{-}con,t}$ cumulative oil production at time t (barrel); $CUMOP_{un-con,t_0}$ cumulative oil production at time t_0 (barrel); $URR_{un\text{-}con,U}$ ultimately recoverable resources as the product of the recovery factor (R) multiplied by the total oil *in situ* (Q) ($URR_{un\text{-}con,U} = Q * R$); β shows the oil production learning coefficient; γ states the depletion rate parameter. In this study, the limitation of the rate of oil production is also taken into account, so that the oil production rate cannot be more than the recovery factor multiplied by proven reserves [equation (3)]:

$$OPR_t \leq PR_t * RF_t \quad (3)$$

where OPR: oil production rate; PR: proven reserve; RF: recovery factor.

4.4 Short- and long-term profitability

As shown in Figure 3, short-term profitability is one of the variables affecting oil production rate. For short-term profitability, we divide the difference between the oil price of the one-year ahead and the current price by the current oil price:

$$STP_t = \left(OP_{t+1} - OP_t\right)/OP_t \quad (4)$$

where STP is short-term profitability, OP_{t+1} indicates oil price one-year ahead; OP_t reveals the current oil price.

Another important factor influencing oil production is long-term profitability (see Figure 3), which is calculated using equation (5) (Park, 2002):

$$LTP_t = \sqrt[m]{\frac{NFV_t}{NPV_t}} - 1 \quad (5)$$

where:

$$NFV_t = LTOP_t \times RF_t \times \sum_{i=0}^{n-1} (1 - DR)^i \times (1 + MDR)^{n-i-1}$$

$$NPV_t = \sum_{i=0}^{p} \frac{ORCUC_t}{k(1+FDR)^i} + OPC_t \times RF_t \times \sum_{i=0}^{m-1} \frac{(1-DR)^i}{(1+FDR)^{p+i}}$$

where the future value of net income (NFV_t) and the present value of net expenses (NPV_t); m: oil rig lifetime; LTP_t: long-term profitability of oil production; $LTOP_t$: long-term oil price; *MDR*: market discount rate; *FDR*: finance discount rate; RF_t: recovery factor; *DR*: decline ratio; *m*: oil rig lifetime; $ORCUC_t$: oil rig construction unit cost; OPC_t: oil production unit cost; *p*: oil rig construction time.

4.5 Social cost of CO_2

In the following, Figure 4 shows the impact of CO_2 social costs with feedback loop.

Oil production is associated with CO_2 emissions, which increase environmental pollution. In this study, the environmental effects of oil production have also been modeled:

$$R(+) : OPR \rightarrow CE \rightarrow CUMCE \rightarrow CER \rightarrow CECP \rightarrow OPC \rightarrow STP \rightarrow OPR \tag{6}$$

As can be seen (Figure 4, Loop 5), increasing oil production rate increases CO_2 emissions. In this section, CO_2 emissions per barrel decrease with learning-by-doing. Reducing CO_2 emissions per barrel reduces the CO_2 emissions cost per barrel, thereby reducing the oil production unit cost. This reduction in the unit cost of oil production increases the profitability and, consequently, the rate of oil production. Equations (7)–(9) relate to the social costs of CO_2.

What most previous studies have overlooked are the environmental threats posed by climate change. Most of these changes are due to CO_2 emissions. The social cost of CO_2 emission is the monetary value of the damage caused by a ton of CO_2 in the atmosphere and is a measure of serious measurement of climate change (Bijgaart, 2016; Tian *et al.*, 2019; Tol, 2019; Tseng and Hung, 2014). To this end, as part of this research, the costs of CO_2 from oil production are considered alongside other oil production costs (Hosseini and Shakouri, 2016; Méjean and Hope, 2013):

$$SCE_{CO_2,t} = SCE_{CO_2,t_0} * e^{\propto(t-t_0)} \tag{7}$$

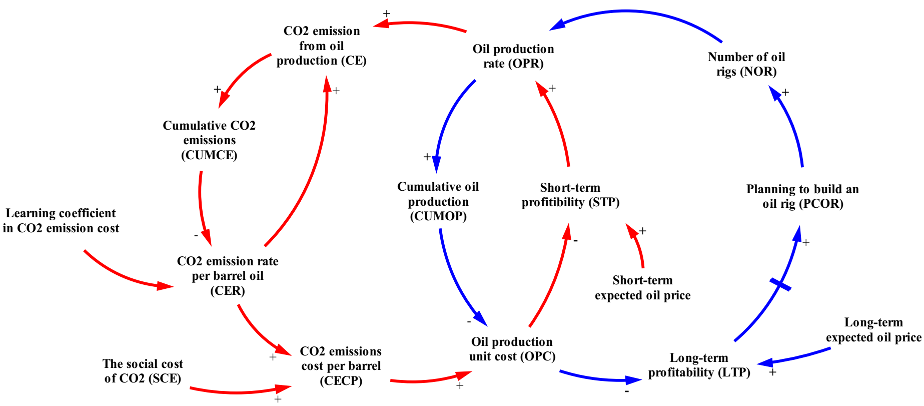

Figure 4. Effect of CO_2 emissions social costs

where $SCE_{CO_2,t}$ is the social cost of CO_2 emissions at time t (USD/tCO_2); SCE_{CO_2,t_0} is the social cost of CO_2 emissions at time t_0 (USD/tCO_2); $\propto$ is the increasing rate in the social cost of CO_2 emissions over time.

4.6 CO_2 emission cost per barrel

Equation (8) calculates the CO_2 emissions cost per barrel of oil produced:

$$CECP_{un-con,t} = SCE_{CO_2,t} * CER_{un-con,t} \tag{8}$$

where $CECP_{un\text{-}con,t}$ CO_2 emissions cost per barrel oil (US\$/barrel); $SCE_{CO_2,t}$ social cost of CO_2 emissions from oil production at time t (USD/tCO_2); $CER_{un\text{-}con,t}$ CO_2 emissions rate per barrel oil (tCO_2/barrel).

Equation (9) shows the amount of CO_2 emissions rate per barrel oil with respect to the learning-by-doing:

$$CER_{un-con,t} = CER_{min} + \left(CER_{un-con,t_0} - CER_{min}\right) * \left(\frac{CUMCE_{un-con,t}}{CUMCE_{un-con,0}}\right)^{-b_{ce}} \tag{9}$$

where $CER_{un\text{-}con,t}$ CO_2 emissions rate per barrel oil at time t (tCO_2/barrel); CER_{un-con,t_0} CO_2 emissions rate per barrel oil at time t_0 (tCO_2/barrel); $CUMCE_{un\text{-}con,t}$ cumulative CO_2 emissions from oil production at time t (tCO_2); $CUMCE_{un\text{-}con,0}$ cumulative CO_2 emissions from oil production at time t_0 (tCO_2); CER_{min} the minimum of CO_2 emissions rate per barrel oil; and b_{ce} expresses the learning parameter in CO_2 emission cost.

4.7 Oil production cost with learning, depletion and CO_2 emission

Figure 5 depicts an overall view of US unconventional (conventional) oil production feedback loops considering the learning effect on oil production, the learning effects of oil rig construction and CO_2 social costs.

Equation (10) is the main formula for calculating the oil production cost per barrel along with learning progress, depletion rate and social cost of CO_2 emission:

$$OPC_{un-con,t} = OPC_{min} + \underbrace{\left(OPC_{un-con,t_0} - OPC_{min}\right) * \left(\frac{CUMOP_{un-con,t}}{CUMOP_{un-con,t_0}}\right)^{-b}}_{learning} \\ + \underbrace{OPC_{max} * \left(\frac{CUMOP_{un-con,t}}{URR_{un-con,U}}\right)^{\gamma}}_{depletion} + \underbrace{CER_{un-con,t} * SCE_{CO_2,t_0} * e^{\propto(t-t_0)}}_{CO_2\ \ emission} \tag{10}$$

This equation consists of three parts: learning affect, resource depletion and CO_2 emission cost. Each component of this equation has described earlier.

5. Result and discussion

In this section, we will experimentally model conventional and unconventional US oil production during the period 2000–2030. This modeling predicts oil production from 2020 to 2030. Model validation must be performed before simulation and scenario making. In this

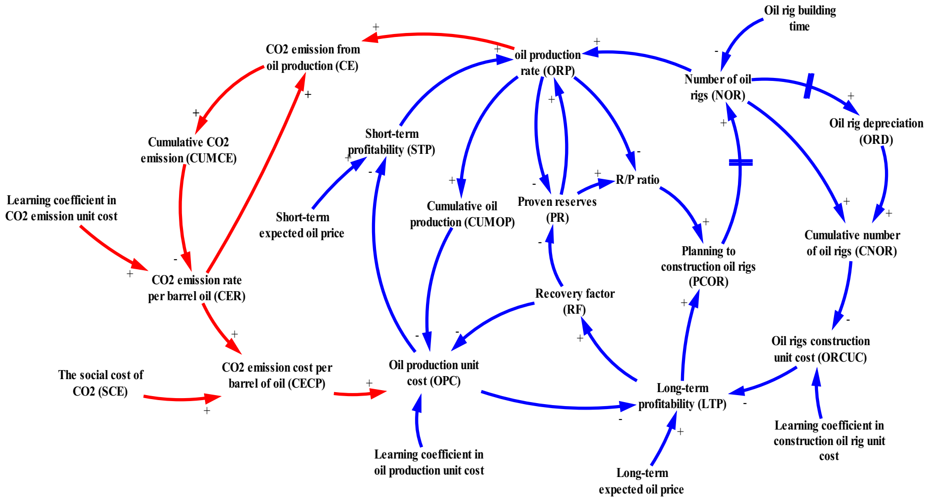

Figure 5.
Oil production model with CO_2 social cost

research, four validation methods have been adopted. First, the unit check test is performed using the software; second, the model behavior is examined in extreme conditions, if the valid model does not show abnormal behavior in the extreme conditions. then boundary adequacy test: this test examines whether the main and influential variables are considered endogenous. And is the desired time period appropriate? The answer is that all the important variables such as proven reserves, number of oil rigs, profitability and recovery factor in the model are considered endogenous. And the time period used in the model is quite appropriate, because the start US unconventonal oil production has been beginning since the 2000, and we considered this period in this study as well. Finally, the most important validation method reproduces the historical data trends. In this survey, unit check and extreme condition testing were performed and verified by the software. The results of the validation test based on historical data are given in Figures 6 and 7.

The average absolute error rate (MAPE) is 6.7% for the unconventional oil production rate and 3.3% for the conventional oil production rate. The higher percentage of errors in unconventional oil production can be attributed to the US government's support and tax defaults on the industry. The SD model is not used for "point" prediction, but the purpose of this system is to depict the actual trend of the system over time (Ziemele *et al.*, 2016). As can be seen from the MAPE results, the reproduced historical data test for both conventional and nonconventional oil production rates have passed the model validation. After confirming the validity of the model, we examine the forecast of conventional and unconventional US oil production under different scenarios (low oil price, medium oil price, high oil price) (Figure 8).

As shown in Figure 8, there are three scenarios (high, medium and low) for oil prices during the period 2020–2030. Then, we will forecast unconventional and conventional US oil production under these scenarios. Figure 9 shows the results of US unconventional oil production forecasts in three scenarios.

As can be seen (Figure 9), the simulation results under the optimistic scenario (high oil prices) show that unconventional oil production in 2030 will reach 4,606.011 (mb/year). In the medium oil price scenario, the oil production rate will reach 4,166.081 (mb/year) in 2030. The US unconventional oil production at a low price scenario indicates that the rate of oil production in

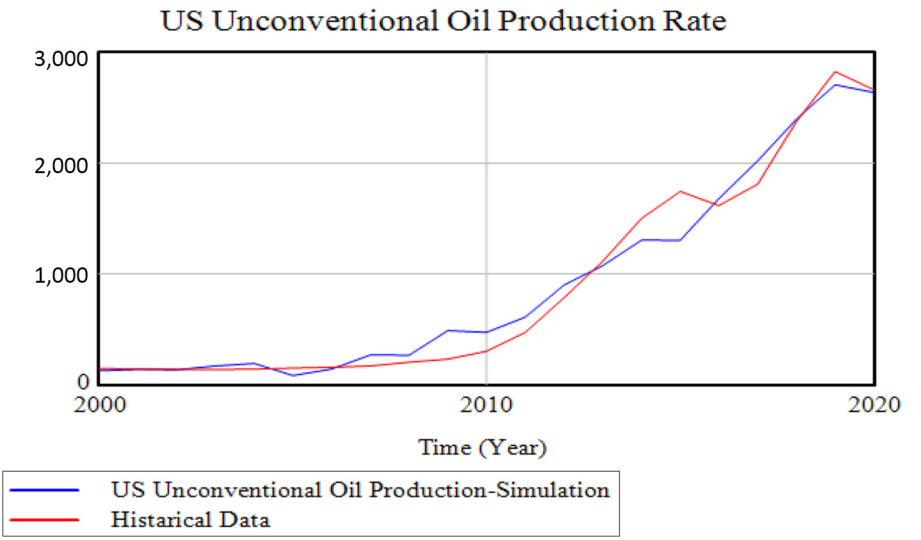

Figure 6.
Historical data and simulations of unconventional US oil production rate (Million barrel/year)

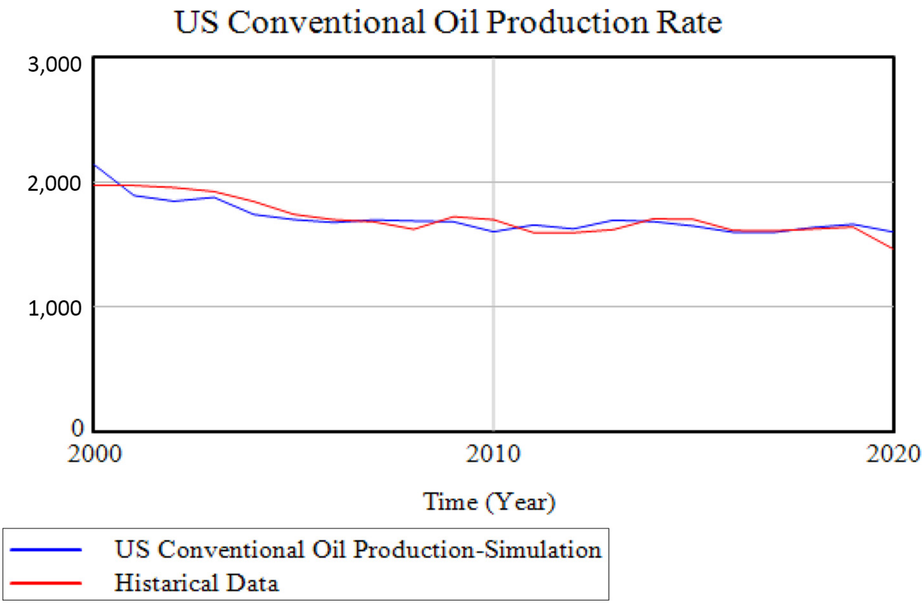

Figure 7.
Historical data and simulations of conventional US oil production rate (Million barrel/year)

2030 will reach 3,715.861 (mb/year). To better understand the forecasting results and validation of this model, we will compare the results of this study with the EIA, International Energy Agency (IEA), OPEC and Rystad Energy. The results of this comparison are shown in Figure 10. Given that the results of the forecasts are based on millions of barrels per day, for this purpose, we change the results obtained in this study from million barrels per year to million barrels per day to be comparable with other forecasts.

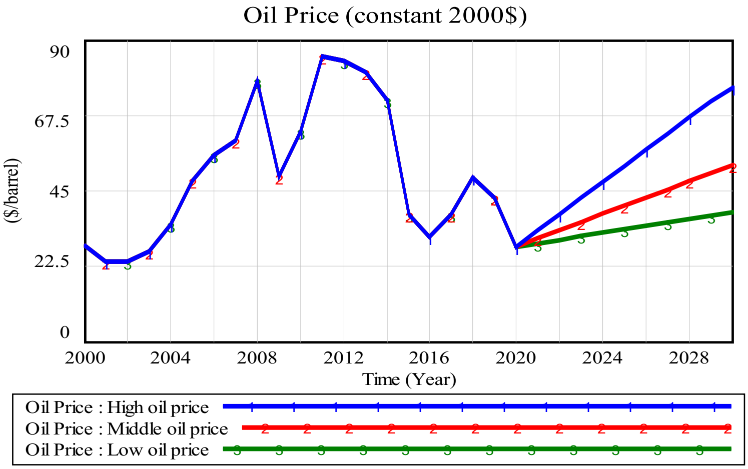

Figure 8.
Oil price (constant $2,000) in a different scenario

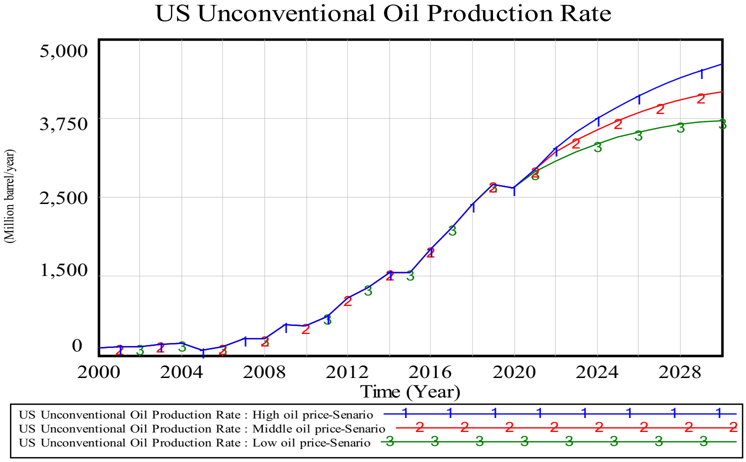

Figure 9.
Forecasting the US unconventional oil production rate under different scenarios

Table 2 shows the forecast results of this study and other forecasts (**Rysted energy**, **EIA**, **IEA** and **OPEC**) based on million barrels per day as shown in Figure 10.

As can be seen (Figure 10, Table 2), the results of various US unconventional oil production forecasts indicate an uptrend. The results of this study under different oil price scenarios (optimistic, middle and pessimistic scenarios) in 2030 are 12.6, 11.4 and mb/day, respectively. The results of **Rystad Energy-Base case**, **EIA-Base case**, **EIA-High oil price**, **IEA** and **OPEC** in 2030 are 14.85, 10.22, 13.33, 8.9 and 8.99 mb/day, respectively. By comparing the results obtained in this study with other predictions, it can be stated that these results are sufficiently valid.

After forecasting unconventional oil production, we now turn to the results of conventional oil forecasting in the USA. The simulation results for the period 2020–2030 are shown in Figure 11.

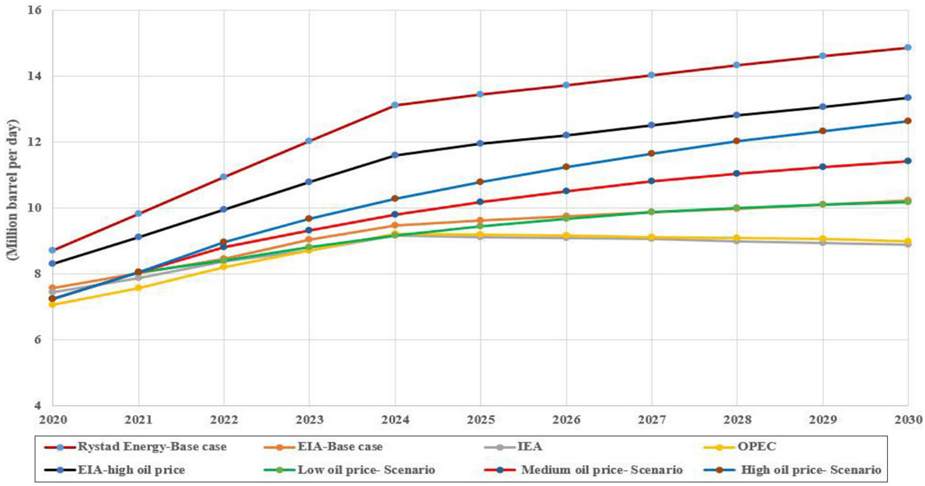

Figure 10.
Comparison of the US unconventional oil production forecasts results in this study with the results of EIA, IEA, OPEC and Rystad Energy [2]

Table 2.
US unconventional oil production forecast (million barrel per day)

	System dynamics forecasting			Other forecasts				
Year	Low oil price	Middle oil price	High oil price	Rystad Energy-Base case	EIA-Base case	EIA-High oil price	IEA	OPEC
2020	7.235225	7.235225	7.235225	8.697803	7.564939	8.291747	7.438686	7.053103
2021	8.05045	8.05045	8.05045	9.810194	8.018767	9.120921	7.868629	7.554702
2022	8.398931	8.795583	8.96876	10.92258	8.462359	9.950096	8.380465	8.203028
2023	8.800582	9.320732	9.676533	12.03156	9.032203	10.77927	8.704628	8.690979
2024	9.157107	9.780087	10.2847	13.11666	9.462145	11.57774	9.161868	9.216464
2025	9.43843	10.1646	10.78023	13.42717	9.60546	11.94626	9.120921	9.175517
2026	9.667232	10.49697	11.22714	13.72062	9.738537	12.19052	9.090211	9.148219
2027	9.86568	10.80022	11.64895	14.01749	9.86479	12.49904	9.052676	9.117509
2028	10.00617	11.04253	12.0098	14.31435	9.963745	12.80756	8.994668	9.076562
2029	10.10734	11.24321	12.32928	14.60781	10.10365	13.05182	8.943485	9.056089
2030	10.18044	11.41392	12.61921	14.85349	10.22308	13.32821	8.871828	8.991256

As shown in Figure 11, the forecast results of conventional oil production under different scenarios (optimistic, moderate and pessimistic) at 2030 are 1,687.31, 1,557.39 and 1,427.47 mb/year, respectively. In this section, to compare the validation of the model forecast results, we compare these results with the EIA forecast. For this comparison, we convert the results obtained from this model from million barrels per year to million barrels per day. Figure 12 shows the results of these predictions.

For a better understanding of the prediction results in Figure 12, these results are also given in Table 3.

As can be seen (Figure 12, Table 3), the results of the conventional oil production simulation under the optimistic scenario (high oil prices) show that oil production will reach to 4.62 mb/day, in 2030. while the EIA forecast implies that oil production will be higher, and it is estimated around 5.1 mb/day. The simulation results of the model under the medium oil price scenario show the conventional oil production rate around 4.26 mb/day, and finally, the model simulation results under the pessimistic scenario (low oil prices) estimate that it will

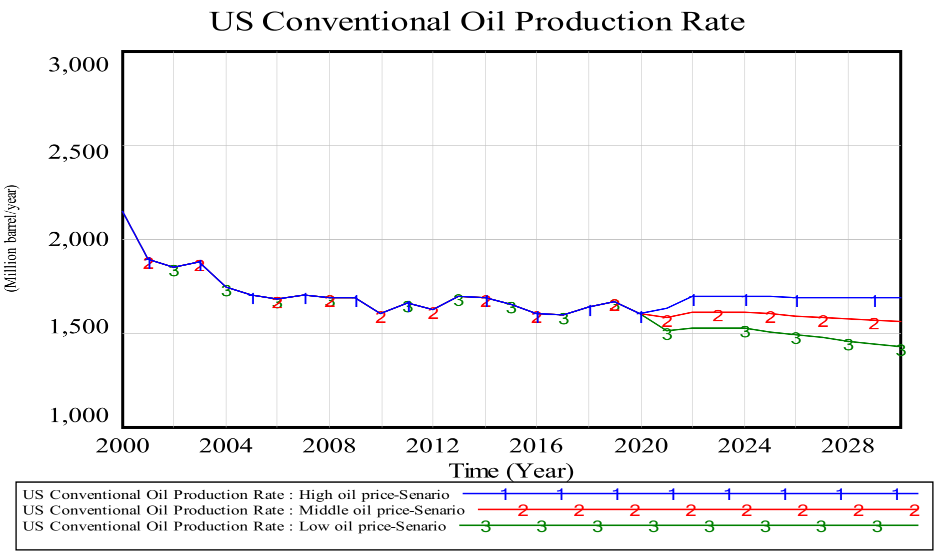

Figure 11.
Forecasting the US conventional oil production rate under different scenarios

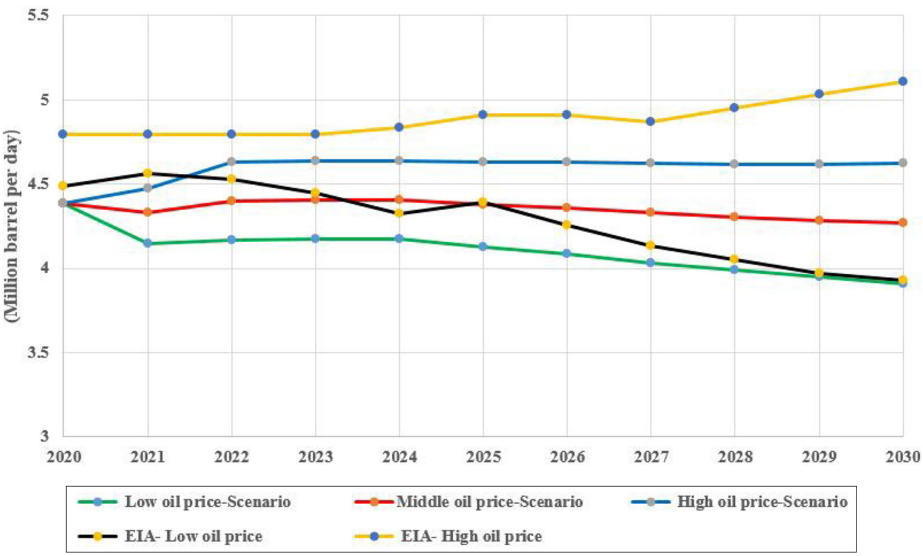

Figure 12.
Comparison of the US conventional oil production forecasts results in this study with the results of EIA

be around 3.91 mb/day, in 2030. The EIA forecast under the low oil price scenario in the final years are consistent with the model simulation. In general, it can be said that although this research examines the amount of US conventional and unconventional oil production under different oil price scenarios, but it can be said that other factors such as increasing unconventional oil reserves, advances in technology and new technologies in oil extraction, which reduces the cost of production, as well as tax incentive policies in local governments, can contribute to the US unconventional oil production process (Wang *et al.*, 2018).

6. Conclusion

In this paper, the SD method is used to model US conventional and unconventional oil production under different oil price scenarios (high, medium, and low) over the period 2000–3030. In this modeling, the effect of training on conventional and unconventional oil production costs through learning-by-doing in oil production, learning-by-doing in oil rig construction, and learning-by-doing in reducing CO_2 emission costs is considered. The study also modeled short- and long-term profitability, recovery factor and social cost of CO_2. Then, after validating the model, the US conventional and unconventional oil production trend during the period 2020–2030 has been predicted.

The results of the US unconventional oil production forecast during the period 2020–2030 show an upward trend. In general, this increase could be due to technological advances in extraction and reduction of production costs. In the meantime, the increase in oil prices, as seen in Figure 9, also plays a key role. The results of this forecast under an optimistic scenario (high price) in 2030 indicate the 12.62 mb/day of unconventional oil production in this country. The results of the medium oil price scenario predict unconventional oil production in 2030 as 11.4 mb/day. Finally, the results of the pessimistic (low oil price) scenario indicate that unconventional oil production in 2030 will be around 10.2 mb/day. As shown in Figure 9, the results of comparing unconventional oil production under different scenarios with the forecasts (**Rysted energy**, **EIA**, **IEA** and **OPEC**) indicate that these forecasts are close to each other, especially with the EIA forecast.

Also, the results of US conventional oil production in different price scenarios (high, medium and low) in 2030 are 4.62, 4.26 and 3.91 mb/day, respectively. The result of simulation is also close to the EIA forecast. In 2020, US unconventional and conventional oil production is around 65% and 35%, respectively, while under the optimistic scenario (high oil prices) in 2030, US total oil production will be around 17.24 mb/day. Of this amount, 73% is due to unconventional oil production and 27% from conventional oil. New government policies on shale oil and gas in the USA will have a sustainable effect on their production. Therefore, the USA must invest in new technologies with higher extraction rates and lower production costs to increase unconventional oil production. By reducing the cost of producing unconventional oil, its competitiveness with conventional oil increases. Also, negative shocks, especially natural disasters such as hurricanes and diseases such as COVID-19, also have negative effects on the unconventional energy sources production. Therefore, the government must intervene in the market, because without government

Table 3. US conventional oil production under this three scenario and EIA forecast

	US conventional oil production (million barrels per day)			EIA forecast	
Year	Low	Medium	High	Low	High
2020	4.386959	4.386959	4.386959	4.485671	4.793507
2021	4.145644	4.328274	4.471644	4.565068	4.793507
2022	4.168411	4.4	4.631589	4.52537	4.793507
2023	4.173534	4.405397	4.63726	4.445973	4.793507
2024	4.17389	4.405781	4.637671	4.326877	4.832822
2025	4.127589	4.380055	4.632548	4.394932	4.911397
2026	4.082027	4.355096	4.628164	4.253178	4.911397
2027	4.034055	4.327479	4.620904	4.131644	4.87211
2028	3.99189	4.306055	4.620247	4.05063	4.950685
2029	3.948521	4.283342	4.618137	3.969616	5.02926
2030	3.910877	4.266822	4.622767	3.929123	5.107836

support, the reduction of unconventional energy production as a result of these disasters will probably be long term. For future research, researchers can model the relationship between shale gas production and energy security in the USA using a dynamic system.

Notes

1. www.usgs.gov/centers/cersc/science/united-states-assessments-undiscovered-oil-and-gas-resources
2. The results of the EIA, IEA, OPEC and Rystad Energy forecasts are presented here. (Source: https://www.rystadenergy.com/newsevents/news/press-releases/us-shale-to-grow-to-14.5-million-bpd-by-2030/).

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