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AN EMPIRICAL STUDY OF INTEGRATED GM (1,1) AND DEA TO PREDICT AND EVALUATE THE BUSINESS PERFORMANCE: A CASE STUDY IN OIL AND GAS INDUSTRY

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AUTHORS' CONTRIBUTIONS

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ABSTRACT

The oil and gas industry is one of the core sectors of the national economy, playing a fundamental role in ensuring energy security. The Covid-19 situation, which has driven companies to innovate, may serve as a catalyst for rethinking the size and role of functional teams, field workers, and management processes required to run an efficient oil and gas company. The slump in global oil consumption due to the pandemic has caused a shock to the Russian economy. To gain comprehensive insights on the performance of the oil and gas industry in Russia, this study aims to develop an integrated methodology that combines the Grey prediction method, a so-called GM (1,1) and Data Envelopment Analysis (DEA) Malmquist model for the prediction and evaluation of the top 10 potential companies in Russia. Grey theory is adopted to predict the companies' data during 2020–2023, and the Malmquist method is used to evaluate their performance over the whole period of 2016–2023, based on three input factors (total assets, total liabilities, cost of revenue), and two output factors (total revenue and net income). During the research period, "Russneft" was found to have performed the most efficiently while "Slavneft" held the least-effective company, despite its efforts to achieve progressive technological changes. Overall, all companies have achieved excellent technological efficiency. Thus, the average total factor productivity indexes of all companies mainly rely on their technical performance. This study assists policymakers and decision-makers in expediting their recovery plans for further sustainable development in the oil and gas industry.

Keywords: Oil and gas industry; grey prediction; data envelopment analysis; frontier; efficiency; decision-making.

1. INTRODUCTION

The oil and gas industry is one of the strongest sectors of the world economy and changes in standard oil prices have a major impact on most manufacturing and consumer sectors [1]. In 2020, the oil world has seen many shocks over the years, as markets, companies, and entire economies reeled from the effects of the global crisis caused by the coronavirus (Covid-19) pandemic, oil prices have decreased [2],

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which dealt a strong blow to the oil and gas market, causing oil prices to plunge and slide to the lowest level in 18 years [3]. Pressure is coming from all sides: global oil demand plummeted as the pandemic has cut fuel consumption, especially in the transportation sector, due to 3 billion people around the world are suffering some form of lockdown because of Covid-19 [2]. By 2020, global oil demand is expected to decline for the first time since the global recession of 2009. However, the situation remains complicated, making it particularly difficult to assess the effects of the virus [4]. Global finance and commodity markets have been disrupted by the spread of Covid-19, as well as the oil and gas industry of the United States. Domestic gasoline demand decreased by 45%, equivalent to nearly 5 million barrels per day [5], the largest crude oil producer in North Dakota, USA, Whiting Oil Corporation (Whiting) with revenue of more than 2 billion USD per year had to file for bankruptcy on April 1st, Total SE-one of France's leading oil and gas companies has reduced investments by more than USD 3 billion and will cut investments below USD 15 billion this year [3].

Russia is the third-largest oil producer in the world, accounting for more than 12 percent of global crude production. The country's economy is heavily dependent on energy exports. Russia was the second-largest oil-exporting region worldwide in 2019 [6]. Oil production was decreased by 8.6% in 2020 and gas output was decreased by 6.2%. This is the first year since 2008, Russia witnessed a decline in petroleum production [7]. In tonnes, oil and gas condensate production dropped to 512.68 million by 2020 from a post-Soviet record high of 560.2 million, or 11.25 million barrels per day, in 2019 [8].

Therefore, the Russian oil and gas industries are currently facing some serious challenges. Of which, Russia faces the challenge of cutting oil production while survival industry Russia's oil producers are confronting the biggest challenge in decades as they try to counter the historic price slump without everlastingly damaging their fields [9].

In the face of that situation, the Russian government offered a policy, a strategy, and an approach to support the country's oil and gas industry. President Vladimir Putin ordered ministers to set a "special rate" at which the pipeline operator Transneft PJSC and the Russian Railway JSC Corporation would charge for the shipping of crude oil and petroleum products, while the OPEC agreement is in potency. Rosneft PJSC is Russia's largest oil producer and has called for an adjustment of transportation prices to match market rates [10]. Also, the development of the gas industry in the year 2020 has been associated with the start of construction and designing of the Power of Siberia 2 gas pipeline which aimed to ensure that Russian will supply gas to China. For this purpose, Gazprom company signed a contract for the regional gas supply and gasification program until the year 2026, which will be beneficial for the gas industry development in the Far East [9,11]. However, Russia is one of the dominant suppliers of energy sources in the world, Russia occupies a confident position in the international energy market. BP analysts predict that within the next 20 years. Russia will continue to be one of the largest energy exporters in the world, meeting more than 5% of the primary energy sources for global demand by 2040 [11].

As a result, in order to enhance competition in the world market, increase oil prices, and limit factors that prevent the development of the oil and gas industry, managers need to continuously measure the performance of the business in order to achieve sustainable performance. Furthermore, the oil and gas market is always changing like nowadays, measuring and evaluating the performance of oil and gas enterprises are necessary. Hence, the Data Envelopment Analysis (DEA), i.e., the Malmquist model is used to calculate the technical efficiency, technological efficiency, total factor productivity efficiency of the top 10 oil and gas companies in Russia, from 2016–2023. Grey theory, GM (1,1), is also used to forecast the future data of DMUs over the 2020–2023 period, also will be applied as the input to the Malmquist model to evaluate the performance of these businesses in the future, using the original data from 2016 to 2019. To our knowledge, there are no previous studies using the combined approach of grey (1,1) and DEA models to evaluate the performance of the oil and gas industry in Russia. The authors expect that the study results will reflect an overview of the oil and gas industry, as a valuable reference for the research of the oil and gas industry not only in Russia but also in any other relevant industry in the world.

The rest part of this paper proceeds as follows. In Section 2, we present the related literature on methodologies approaches, and research gaps. Section 3 contains the theoretical background of the proposed methodology including grey prediction and data envelopment analysis. The case study of the oil and gas industry in Russia with the implementation of the proposed methods and result analysis are presented in Section 4 to exhibit the real-life applicability. In Sections 5 and 6, implications and managerial insights are discussed, while concluding remarks and future research directions are also well-depicted.

2. LITERATURE REVIEW

2.1 Data Envelopment Analysis

Data Envelopment Analysis (DEA) method is used to evaluate the organization of entities (e.g., programs, organizations), which are reliable for using resources to receive outputs of concern. It is a programming model that can include multiple outputs and inputs without requiring clear regulation of functional correlations between inputs and outputs (as in the regression method) [12]. This method has been successfully applied to assess the performance in many fields such as air transport, energy, environment. For instance, Khare et al. [13] applied the DEA model to evaluate the coordinated relationships (CR) between Bus Rapid Transit System (BRTS) and land use of 16 transit-oriented development areas in Bhopal city, India. This paper adopted a quantitative method to provide insight for urban policymaking on station plans. Wang et al. [14] proposed the application of the Malmquist productivity index (MPI) model to analyze the operational efficiency of the top 20 automakers in the world from 2015 to 2018, based on technical change index, technological progress index, and productivity change index of car manufacturers. This study has helped researchers get an overview of the industry. Bang [15] applied the DEA-super efficiency (DEA-SE) to measure efficiency performance for 293 energy research projects, which is used both the weighting method and the SE method; their results indicate that the DEA-SE method can minimize weight problems and provide ranking information on research results that the existing DEA method cannot achieve. Hermoso-Orzáez et al. [16] used DEA to estimate the efficiency of the environment for the 28 member countries of the European Union (EU) from 2005 to 2012. This approach has helped to measure the relative environmental performance (ecological efficiency) and is a very reliable method for measuring the environmental performance of policies in a particular geographic area. Song et al. [17] proposed a three-stage DEA analysis to appreciate the performance of 30 provincial air transport sectors in China. Therefore, the environmental factors in different regions and statistical noise were considered, to evaluate the operating performance of regional ATS. The results revealed that the environmental factors, such as the region's GDP, openness, technical factors, technology development, and consumption level have different effects on ATS's performance.

2.2 Grey Theory

The Grey theory was introduced in 1982 by Deng [18]. Over the past few decades, the Grey theory has been successfully completed in predicting and helping in the decision-making process in many files. For instance, Qian and Wang [19] proposed the Grey model GM (1,1) and the Hodrick-Prescott filter to accurately predict wind power generation in China from 2013 to 2019. The authors not only applied GM (1,1) but also compared it with three existing approaches. The results show that the model generally outperforms existing methods. Hu [20] used the Grey-Markov models based on the GM (1,1) to forecast foreign tourists. This research combined soft computing techniques to propose a novel Grey model. The results show that the GM (1,1) better than other Grey-Markov models considered. Wang et al. [21] have applied a combined approach between Grey theory and DEA to predict and evaluate the performance of e-commerce companies. This paper has provided decision-makers with a clearer overview of the e-commerce industry in the US market. Dai et al. [22] has based on population to accurately forecast CO_2 emissions using Grey model and Least Squares Support Vector Machine (LSSVM) optimized by the Modified Shuffled Frog Leaping Algorithm (MSFLA) (MSFLA-LSSVM) which is also adopted in this paper to predict the CO_2 emissions in China during 2018–2025. The results showed that China's CO_2 emissions will tend to slow down in the next few years. By actively encouraging the application of government policies to reduce emissions, CO_2 emissions will be effectively controlled in the future, and the greenhouse effect will be significantly reduced.

2.3 Motivation of the Research

Over the last few decades, there have been prominent methods for assessing the performance of the global oil and gas industries, which are summarized in Table 1. In terms of methodologies. Some DEA models have been used for evaluating the performance of the oil and gas industry. To measure the efficiency score of DMU, Charnes-Cooper-Rhodes proposed the input-oriented envelopment form of the CCR model [23-29], Banker-Charnes-Cooper (BCC) was applied to identify the score of technical efficiency [27,30,31], while Slack-Based Measure (SBM) model not only evaluates the inefficiency from both an input and output perspective but also determines the slack in efficiency raking [29,32]. Besides, the Malmquist index is used to measure the total factor productivity, including technical change efficiency and technological efficiency, as applied in [31,33,34]. A dynamic DEA model was proposed to calculate the efficiency of periods based on frontiers of all other periods, as can be seen [28,35]. Also, the Common Set of Weights (CSW) DEA models were proposed to overcome problems of assessment using standard DEA models, as proposed in [36]. Bootstrap is a

Table 1. A summary list of methodologies approaches in related studies

Authors	Year	DEA Models	(Fuzzy) MCDM	Other
Hawdon [37]	2003	Bootstrap		
Kashani [33]	2005	Malmquist		SFA
Hanrui and Xun [23]	2011	CCR, Bootstrap		
Eller et al. [47]	2011			SFA, Tobit regression
Al-Najjar and Al-Jaybajy [24]	2012	CCR		
Huang and Sun [38]	2013		Fuzzy logic	
Rabbani et al. [45]	2014		Fuzzy ANP	BSC, COPRAS
Rahdari [41]	2016		Fuzzy AHP, TOPSIS	
Sun et al. [46]	2017			SFA, TFE
Elhuni and Ahmad [43]	2017		Fuzzy AHP	KPIs
Akbaş and Bilgen [40]	2017		Fuzzy QFD, ANP, AHP, TOPSIS	
Tang et al. [39]	2018		Fuzzy logic	
Hosseini and Stefaniec [32]	2019	SBM		
Daryanto and Wibisono [25]	2019	CCR		
Vikas and Bansal [30]	2019	BCC		
Wang et al. [31]	2019	BCC, Malmquist		
Khojastehmehr et al. [42]	2019		Fuzzy AHP, TOPSIS	
Ghazi and Lotfi [36]	2019	CSW		
Tavana et al. [26]	2019	CCR, FDM		
Dalei and Joshi [27]	2020	CCR, BCC		Tobit regression
Nedaei et al. [28]	2020	CCR, Dynamic		
Lu et al. [34]	2020	Malmquist		SVR
Al-Marri et al. [44]	2020		Fuzzy AHP	
Xia et al. [35]	2020	Dynamic		
Sun and Huang [29]	2021	CCR, SBM		

statistical technique based on sampling with repetition on experimental data and relativity estimation tools that improves the accuracy of critical values and confidence intervals, and overcome inherent dependence of the DEA result, as proposed in [23,37]. Fuzzy Dynamic Multi-objective DEA (FDM-DEA) is also used in [26]. Some other methods are widely used to access the performance of the oil and gas sector, including the fuzzy logic [38,39], the framework of Fuzzy Quality Function Deployment (FQFD), the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) was proposed [40-42], Fuzzy Analytic Hierarchy Process (FAHP) [40-44], Fuzzy Analytical Network Process (FANP) [40,45], Support Vector Regression (SVR) [34], The True Fixed Effect (TFF) model [46], The Balanced Scorecard (BSC) method [45], The Complex Proportional Assessment (COPRAS) method [45], Key Performance Indicators (KPIs) [43], Tobit regression [27,47]. From our literature reviews, the authors would like to expand the scope of the methodology by proposing a new approach, a hybrid Grey prediction, GM (1,1) and DEA-based Malmquist productivity are combined to predict and evaluate the performance of oil and gas companies in Russia, helping them to promptly come up with appropriate strategies towards sustainable development.

3. MATERIALS AND METHODOLOGIES

3.1 Research Process

In this paper, a hybrid approach combining the Grey prediction method and the DEA Malmquist model is proposed for the prediction and evaluation of the top 10 oil and gas companies in Russia. In the first step, the Grey model is adopted to predict the companies' data during 2020–2023. In the second step, the Malmquist method is used to evaluate their performance over the whole period of 2016–2023. Based on the importance of financial indicators, this paper considers three input factors including total assets, total liabilities, cost of revenue, and two output factors such as total revenue and net income.

3.2 Grey Prediction Model

This paper used Grey prediction, GM (1,1) model, to predict the companies' data during 2020–2023 based

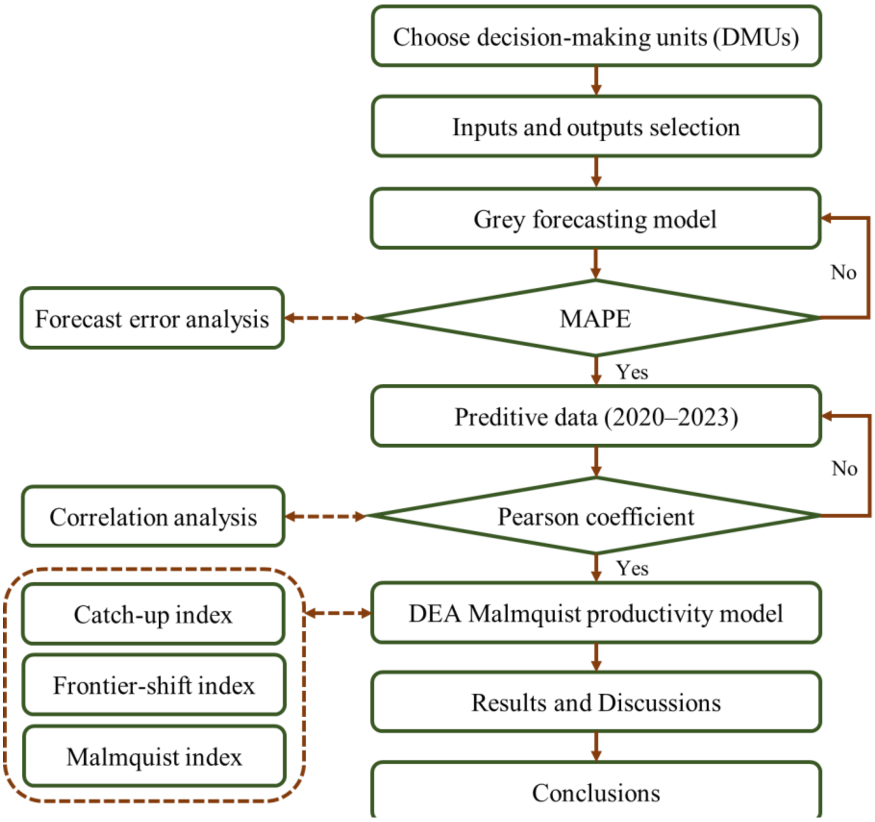

Fig. 1. The overall process of the research

on the historical data from 2016–2019. GM (1,1) model is useful while the historical data is fewer periods (i.e., at least four periods). The calculation of the model of GM (1,1) is presented below [48].

$x^{(0)}(k)$ is a set of data string and n is the total number of data, as Eq. (1).

$$x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)) \tag{1}$$

The one-time Accumulating Generation Operator (1-AGO) of the original string is specified in Eq. (2).

$$x^{(1)} = (x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(n)) \tag{2}$$

where $\begin{cases} x^{(1)}(1) = x^{(0)}(1) \\ x^{(1)}(k) = \sum_{j=1}^{k} x^{(0)}(j) \end{cases}, k = 2, 3, \dots, n.$

$z^{(1)}$ is defined in Eq. (3).

$$z^{(1)} = (z^{(1)}(1), z^{(1)}(2), \dots, z^{(1)}(n)) \tag{3}$$

where $z^{(1)}(k)$ is calculated in Eq. (4).

$$Z^{(1)}(k) = \frac{1}{2}\left(x^{(1)}(k) + x^{(1)}(\mathrm{k}-1)\right), k = 2, 3, \dots, n \tag{4}$$

To construct GM (1,1) model, Eq. (5) and (6) are applied.

$$\frac{dx^{(1)}(k)}{dk} + ax^{1}(k) = b \tag{5}$$

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-ak} + \frac{b}{a} \tag{6}$$

To define the coefficient $[a, b]^T$. The Ordinary Least Squares method (OLS) is used, Eq. (7), (8), and (9).

$$[a, b]^T = (A^T A)^{-1} A^T Y \tag{7}$$

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \dots\dots\dots \\ \dots\dots\dots \\ x^{(0)}(n) \end{bmatrix} \tag{8}$$

$$A = \begin{bmatrix} -\frac{u^{(1)}(2)}{2} & 1 \\ -\frac{u^{(1)}(3)}{2} & 1 \\ \dots\dots\dots & \dots \\ \dots\dots\dots & \dots \\ -\frac{u^{(1)}(n)}{2} & 1 \end{bmatrix} \tag{9}$$

Based on the values of $\hat{x}^{(1)}(k+1)$ in Eq. (6), set $\hat{x}^{(0)}$ become the predicted series in Eq (10).

$$\hat{x}^{(0)} = (\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \ldots, \hat{x}^{(0)}(n)) \tag{10}$$

where $\hat{x}^{(0)}(1) = x^{(0)}(1)$.

Applying the inverse accumulated generation operation. Eq. (11) is achieved.

$$x^{(0)}(k+1) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-ak}(1-e^{a}) \tag{11}$$

The mean absolute percentage error (MAPE) denoted ε, is a measurement related to the predicted error, as in Eq. (12).

$$\varepsilon = \frac{1}{n}\sum\left(\frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)}\right) \times 100\% \tag{12}$$

The value of MAPE < 10% which mean the results of the model is qualified [48].

3.3 DEA Malmquist Model

Pearson coefficients must be checked before applying DEA model. It satisfies the isotonicity and homogeneity conditions. The Pearson correlation of two factors (c) and (d) is calculated, as Eq. (13) [49].

$$r_{cd} = \frac{\sum_{i=1}^{n}(c_i - \overline{c})(d_i - \overline{d})}{\sqrt{\sum_{i=1}^{n}(c_i - \overline{c})^2 \sum_{i=1}^{n}(d_i - \overline{d})^2}} \tag{13}$$

The DEA Malmquist model is applied to assess the productivity change, its decomposition into technical efficiency (catch-up index) and technological effect (frontier-shift index) under multiple inputs and outputs, and multiple periods. The Malmquist index is computed as the combination of technical efficiency and technological effect, i.e., Malmquist index = (Catch-up index) x (Frontier-shift index), using the two time periods symbolized by *t* and *t+1*. The efficiency score of DMUs, $(c_0, d_0)^{k_1}$ is defined based on the frontier technology k_2. It is presented as follows: $D^{k_1}((c_0, d_0)^{k_1})$, ($k_1 = 1, 2$ and $k_2 = 1, 2$) [50].

The catch-up index (C) is defined as Eq. (14).

$$C = \frac{D^2((c_0, d_0)^2)}{D^1((c_0, d_0)^1)} \tag{14}$$

The frontier-shift index (F) is defined as Eq. (15).

$$F = \left[\frac{D^1((c_0, d_0)^1)}{D^2((c_0, d_0)^1)} \times \frac{D^1((c_0, d_0)^2)}{D^2((c_0, d_0)^2}\right]^{\frac{1}{2}} \tag{15}$$

After calculating the catch-up index (C) and the frontier-shift index (F), the Malmquist index (MI) is calculated, as can be seen in Eq. (16).

$$MI = \left[\frac{D^1((c_0, d_0)^2)}{D^1((c_0, d_0)^1)} \times \frac{D^2((c_0, d_0)^2)}{D^2((c_0, d_0)^1)}\right]^{\frac{1}{2}} \tag{16}$$

The results of the Malmquist index are presented as follows, (1) $MI > 1$ denotes increasing in productivity. (2) If $MI = 1$, denotes equally productivity. (3) If $MI < 1$, denotes a decrease in productivity [50].

Technical efficiency is an aspect of the manufacturing process. Hence, technical efficiency assessment in the oil and gas industry is essential to help businesses increase their competitiveness through structural changes, factory operations, and production capacity. The catch-up index (C) is used to assess changes in the technical field of oil and gas companies in Russia in the period from 2016 to 2019 and the forecast period from 2020 to 2023.

The frontier-shift index (F) is used for assessing the technological efficiency of 10 DMUs in the considered periods. Investing in technology in production will improve labor productivity and directly enhance the competitiveness of companies. Therefore, in Russia, lots of oil and gas companies made high-quality products that rely on new research and technology. By contrast, several companies still have very low performance in technological applications. Hence, these companies need to pay attention to its technological aspect to enhance their competitiveness in the market.

The Malmquist index (MI) represents the productivity change which is a combination of the catch-up and frontier-shift indexes. Therefore, in order to develop and dominate not only the domestic but also the overseas market, these companies need to invest heavily in technical and technological innovation which is a prerequisite for oil and gas companies in Russia.

4. RESULT ANALYSIS

4.1 Data Collection

The selection of inputs and outputs will directly affect the accuracy of the results given by the DEA Malmquist model. Based on the importance of the financial indexes in the oil and gas industry from the relevant previous studies (Table 2), this paper considered three input factors including total assets, total liabilities, cost of revenue, and output factors which are total revenue and net income. These indexes are used to evaluate and predict the performance of oil and gas in Russia are described as follows.

4.1.1 Input factors

- Total assets represent the total assets owned by oil and gas companies.
- Total liabilities represent the aggregate debt and financial obligations owned by oil and gas companies.

Table 2. The list of input and output factors used in relevant studies

Authors	Year	Inputs	Outputs	Scope
Song and Zhang [51]	2009	Manpower cost Operation cost	Return on capital employed Operation cost added value Manpower cost added value Total assets added value	12 Chinese fuel type oil refining enterprises
Eller et al. [47]	2011	Number of employees Oil reserves Natural gas reserves	Revenue	78 firms worldwide
lke and Lee [52]	2014	Oil reserves Gas reserves Employees	Oil and gas production Revenue	50 global oil and gas companies
Sun et al. [46]	2017	Number of employees Total assets	Operating income	10 oil companies in China
Vikas and Bansal, [40]	2019	Materials Employee Capital investment	Operating revenues Profit after tax	22 Indian oil and gas companies
Wang et al. [31]	2019	Innovative stuff Innovative expenditure Non-technical innovative	Innovative product patent rate Innovative product sales rate Innovative products share	10 Chinese petroleum plans
Dalei and Joshi [27]	2020	Energy consumed Fuel consumption and loss Total crude processed	Distillate production	12 Indian oil refineries
Atris [53]	2020	Number of employees Total assets Total cash investments	Total revenue Net income Total enterprise value	4 global regions
Lu et al. [34]	2020	Total assets Number of employees Total operating costs	Total operating income Net profit	50 Chinese petroleum companies

- Cost of revenue represents the total costs of producing and distributing products and services of oil and gas companies.

4.1.2 Output factors

- Total revenue represents the total amount of money that will be earned by the sale of goods and services.
- Net income represents the remaining amount of revenue after deducting all taxes and fees.

Table 3 shows the list of the top 10 oil and gas companies in Russia and their profit in 2019, including Gazprom, Lukoil, Rosneft, Bashneft, Tatneft, Transneft, Russneft, Slavneft, E&P Russie, Exxon Neftegas. The authors collected the original data of input and output factors during the period 2016–2019 from the annual financial statements of oil and gas companies, which are published on the official website [54]. A summary of statistical data of the inputs and outputs for 10 oil and gas companies during 2016–2019 is shown in Table A1 (Appendix A).

Table 3. The list of 10 oil and gas companies in Russia and their profit in 2019

No.	DMUs	Companies	Profit (Million USD)
1	OGR-01	Gazprom	1,202.89
2	OGR-02	Lukoil	640.18
3	OGR-03	Rosneft	708.00
4	OGR-04	Bashneft	76.60
5	OGR-05	Tatneft	177.97
6	OGR-06	Transneft	179.39
7	OGR-07	Russneft	24.36
8	OGR-08	Slavneft	7.21
9	OGR-09	E&P Russie	11.27
10	OGR-10	Exxon Neftegas	14.34

4.2 Result of Grey Prediction Model

In this paper, the Grey theory, GM (1,1), is used to predict the future value of DMUs (2020–2023) based on historical data (2016–2019). In this part, the following procedures present the example of the calculation of OGR-10 (Exxon Neftegas), i.e., total assets, other factors are calculated as the same procedures. Table 4 shows the input and output factors data for the years 2016–2019 of OGR-10 (Exxon Neftegas).

Step 1: Original data series $x^{(0)}$, as Eq. (1).

$$x^{(0)} = (x^{(0)}(1) + x^{(0)}(2) + x^{(0)}(3) + x^{(0)}(4)) = (330.31, 348.69, 346.20, 362.60)$$

Step 2: Calculate data $x^{(1)}$ from $x^{(0)}$, as Eq. (2).

$$x^{(1)} = (x^{(1)}(1) + x^{(1)}(2) + x^{(1)}(3) + x^{(1)}(4) = (330.31, 679.00, 1025.20, 1387.80)$$

Each of the above data is calculated as follows.

$$x^{(1)}(1) = x^{(0)}(1) = 330.31$$
$$x^{(1)}(2) = x^{(0)}(1) + x^{(0)}(2) = 679.00$$
$$x^{(1)}(3) = x^{(0)}(1) + x^{(0)}(2) + x^{(0)}(3) = 1025.20$$
$$x^{(1)}(4) = x^{(0)}(1) + x^{(0)}(2) + x^{(0)}(3) + x^{(0)}(4) = 1387.80$$

Step 3: Calculate data $z^{(1)}$from $x^{(1)}$, Eq (3) and (4).

$$z^{(1)}(2) = \frac{1}{2}(330.31 + 679.00) = 504.66$$
$$z^{(1)}(3) = \frac{1}{2}(679.00 + 1025.20) = 852.10$$
$$z^{(1)}(4) = \frac{1}{2}(1025.20 + 1387.80) = 1206.50$$

Step 4: Calculate the values for the coefficients *a* and *b*, Eq. (5)–(9).

$$A = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ -z^{(1)}(4) & 1 \end{bmatrix} = \begin{bmatrix} -504.66 & 1 \\ -852.10 & 1 \\ -1206.50 & 1 \end{bmatrix}$$
$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ x^{(0)}(4) \end{bmatrix} = \begin{bmatrix} 348.69 \\ 346.20 \\ 362.60 \end{bmatrix}$$
$$\begin{bmatrix} a \\ b \end{bmatrix} = (A^T A)^{-1} A^T Y = \begin{bmatrix} -0.02 \\ 335.49 \end{bmatrix}$$

Step 5: Construct GM (1,1) model, Eq. (10) and (11). The predicted data of OGR-10 (Exxon Neftegas), i.e., total assets are shown in Table 5.

Table 4. Historical data collection of input and output factors for ORG-10

ORG-10	Total assets	Total liabilities	Cost of revenue	Total revenue	Net income
2016	330.31	156.48	179.50	218.61	7.84
2017	348.69	154.19	182.24	237.16	19.71
2018	346.20	147.67	211.60	279.33	20.84
2019	362.60	163.66	199.63	255.58	14.34

Table 5. Value of the predicted data of OGR-10 (Exxon Neftegas) total assets

***k* (year)**	$\hat{x}^{(1)}(k)$	**Value**	$\hat{x}^{(0)}(k)$	**Value**
k = 0, (2016)	$\hat{x}^{(1)}(0)$	330.31	$\hat{x}^{(0)}(0)$	330.31
k = 1, (2017)	$\hat{x}^{(1)}(1)$	674.74	$\hat{x}^{(0)}(1)$	345.50
k = 2, (2018)	$\hat{x}^{(1)}(2)$	1026.07	$\hat{x}^{(0)}(2)$	352.44
k = 3, (2019)	$\hat{x}^{(1)}(3)$	1384.44	$\hat{x}^{(0)}(3)$	359.52
k = 4, (2020)	$\hat{x}^{(1)}(4)$	1749.99	$\hat{x}^{(0)}(4)$	366.75
k = 5, (2021)	$\hat{x}^{(1)}(5)$	2122.88	$\hat{x}^{(0)}(5)$	374.13
k = 6, (2022)	$\hat{x}^{(1)}(6)$	2503.24	$\hat{x}^{(0)}(6)$	381.65
k = 7, (2023)	$\hat{x}^{(1)}(7)$	2891.22	$\hat{x}^{(0)}(7)$	389.32

Following that, other factors are calculated as the same procedures. All predicted value is shown in Table A2–A5 (Appendix A).

Step 6: Check the accuracy of the results. The average MAPE of each DMU is shown in Table 6. The average MAPE of all DMUs is 3,74%, which is less than 10%, which means that the GM (1,1) model can provide accurately predicted future data.

Table 6. The average MAPE of DMUs in the forecast model

DMUs	Symbol	Average
OGR-01	Gazprom	5.50%
OGR-02	Lukoil	4.06%
OGR-03	Rosneft	7.30%
OGR-04	Bashneft	2.55%
OGR-05	Tatneft	4.50%
OGR-06	Transneft	2.21%
OGR-07	Russneft	2.80%
OGR-08	Slavneft	2.07%
OGR-09	E&P Russie	2.81%
OGR-10	Exxon Neftegas	3.66%
Average		3.74%

4.3 Result of DEA Malmquist Model

4.3.1 Pearson correlation

Tables A6 and A7 (Appendix A) indicate the Pearson correlation coefficients between the input and output factors for both the historical data set (2016–2018) and the predicted data set (2020–2023). The results show that all Pearson values are from 0.4967 to 1 and 0.43052 to 1 for the historical and predicted data, respectively, which shows a positive linear relationship, and the dataset can be used for the DEA Malmquist model in the next step.

4.3.2 Technical efficiency change

Table 7 illustrates the technical efficiency change of the 10 DMUs from 2016–2023. It clearly shows that the catch-up score of every DMU changed the technical efficiency. Overall, the average catch-up score of all DMUs fluctuated remarkably from 2016 to 2019, then it saw stable growth in the forecast period 2020–2023. With the average score of 0.95225 in 2016–2017, 0.92734 in 2017–2018, and 1.02795 in 2018–2019, it can be implied that most DMUs had ineffective technical changes in the 2016–2018 period. Meanwhile, the catch-up score started to reduce slightly in 2019–2020 with a regressive score of 0.96064. From 2020 to 2023, the technical efficiency change of oil and gas companies of Russia is predicted to be greater than 1 with scores of 1.10500, 1.02610, 1.04117 in 2020–2021, 2021–2022, and 2022–2023, respectively. It can be suggested that most DMUs will achieve high technical efficiency changes in the future. Over the whole period, the average of all DMUs is 1.00578, the maximum average score is 1.26347 (OGR07-Russneft), while the minimum of all average scores is 0.79505 (OGR08-Slavneft). It proved that although there are only four out of 10 DMUs achieved the average score which was greater than 1 (OGR03-Rosneft, OGR04-Bashneft, OGR05-Tatneft, OGR07-Russneft), the average score of these four companies had a huge effect on all 10 companies studied, which is highly related to the emphasis on technical upgrading and new technical applications. Therefore, while the 10 companies emphasize the improvement of comprehensive technical efficiency, they must also pay attention to the improvement of technical progress and maintain a more sustained and stable development of various companies.

Specifically, in the period 2016–2017, there were four of the 10 DMUs achieved technical efficiency (average C > 1), which were OGR02-Lukoil, OGR3-Rosneft, OGR04-Bashneft, OGR05-Tatneft. In which, OGR04-Bashneft achieved the highest efficiency with C = 1.24080. By contrast, OGR08-Slavneft had the lowest technical efficiency with C = 0.63450. For average, compared to the period 2016–2017, there was a modest decrease in technical efficiency, having an average score of 0.92734 during the years 2017–2018. Moreover, in this period, there was only OGR05-Tatneft achieving technical efficiency with C = 1.69270. From the 2018–2019 period, the DMUs began to increase slightly their technical performance with an average score of 1.02795. Especially, for OGR03-Rosneft, OGR04-Bashneft, OGR05-Tatneft, OGR06-Transneft, OGR08-Slavneft, OGR10- Exxon Neftegas, which saw its catch-up score significant increase compared to the previous period, 2017–2018. In the next period, 2019–2020, the average catch-up score of all companies marginally declined to 0.96064, OGR03-Rosneft, OGR04-Bashneft remained efficiency performance of C = 1.03411, 1.06550, respectively. In addition, OGR02-Lukoil achieved the technical efficiency of C = 1.01602, having a slight increase compared to the 2018–2019 period.

In the future period, all DMUs are estimated to change technical efficiency more stable than in the past, as the average indexes are greater than 1 in over the entire projection period with 1.10500 in 2010–2021, 1.02610 in 2021–2022, 1.04117 in 2022–2023. It is projected that four DMUs out of the 10 DMUs will achieve high technical efficiency, which are OGR03-Rosneft, OGR04-Bashneft, OGR05-Tatneft, OGR07-Russneft. Starting with 2020–2021, the average catch-up score of OGR07-Russneft is projected to be the highest at 2.24513, then it will decrease sharply to 1.32663 in 2021–2022 before slightly increasing to 1.35444 in 2022–2023. Meanwhile, OGR03-Rosneft is projected to have the lowest index of 1.09768 in 2020–2021, then gradually rise to a peak of 1.37040 in 2022–2023. Likewise, OGR04-Bashneft and OGR05-Tatneft are projected to only increase and decline modestly over the period of four years, 2020–2023.

Fig. 2 illustrates the line graph view of DMUs and the catch-up efficiency in the whole period, 2016–2023. It is the most outstanding view in the chart of OGR07-Russneft. Overall, most DMUs fluctuated catch-up indexes over the entire period researched. In which, Tatneft obtained the peak of 1.69270 in the 2017–2018 period, followed by a remarkable decrease in the next periods, while OGR07-Russneft is projected to be the sharp increase to a peak of 2.24513 in 2020–2021 before decreasing gradually to 1.35444 at the end of the period, making it become the highest average index of all DMUs.

4.3.3 Technological efficiency change

Table 8 reveals technological efficiency changes of the 10 DMUs from 2016–2023. Overall, the average frontier-shift indexes of all DMUs fluctuated remarkably in 2016–2019, but then it witnessed relatively stable growth in the forecast period 2020–2023. Starting with 2016–2017, the average score of all DMUs was 1.17714, this figure rose marginally to 1.23249 in 2017–2018, then decreased quickly to 0.92478 in 2018–2019, it can be suggested that most DMUs had poor technological efficiency in the 2018–2019 period, hence, these oil and gas companies of Russia must make efforts to further improve the technical efficiency to achieve the desired performance. Conversely, the average catch-up index began to increase slightly in 2019–2020 with a score of 1.10510. From 2020 to 2023, the average frontier-shift index of all DMUs is predicted to be more than 1 with scores of 1.06492 in 2020–2021, 1.11257 in 2021–2022, 1.11078 in 2022–2023. It can be suggested that most DMUs will achieve high technological efficiency change in the future period. In addition, OGR07-Russneft is expected to have the highest technological performance with an average

Table 7. Catch-up index (2016–2023)

Catch-up	2016–2017	2017–2018	2018–2019	2019–2020	2020–2021	2021–2022	2022–2023	Average
Gazprom	0.84399	0.89571	0.92117	0.92443	0.96046	1.03852	0.99482	0.93987
Lukoil	1.11163	0.98829	0.91913	1.01602	1.01253	1.00798	0.92443	0.99715
Rosneft	1.04962	0.88026	1.27425	1.03411	1.09768	1.12914	1.37040	1.11935
Bashneft	1.24080	0.66820	1.04255	1.06550	1.04763	1.05249	1.04535	1.02322
Tatneft	1.05182	1.69270	1.03718	0.97638	1.03137	1.03872	1.04248	1.12438
Transneft	0.68022	0.66759	1.05203	0.91172	0.94608	0.95092	0.95542	0.88057
Russneft	0.99487	0.98546	0.96034	0.97740	2.24513	1.32663	1.35444	1.26347
Slavneft	0.63450	0.57563	1.08798	0.76492	0.82825	0.83396	0.84012	0.79505
E&P Russie	0.94643	0.96371	0.97459	0.94431	0.93653	0.93711	0.93765	0.94862
Exxon Neftegas	0.96866	0.95582	1.01026	0.99157	0.94436	0.94549	0.94658	0.96611
Average	0.95225	0.92734	1.02795	0.96064	1.10500	1.02610	1.04117	1.00578
Max	1.24080	1.69270	1.27425	1.06550	2.24513	1.32663	1.37040	1.26347
Min	0.63450	0.57563	0.91913	0.76492	0.82825	0.83396	0.84012	0.79505
SD	0.18764	0.30850	0.10334	0.08381	0.40745	0.13302	0.17943	0.13458

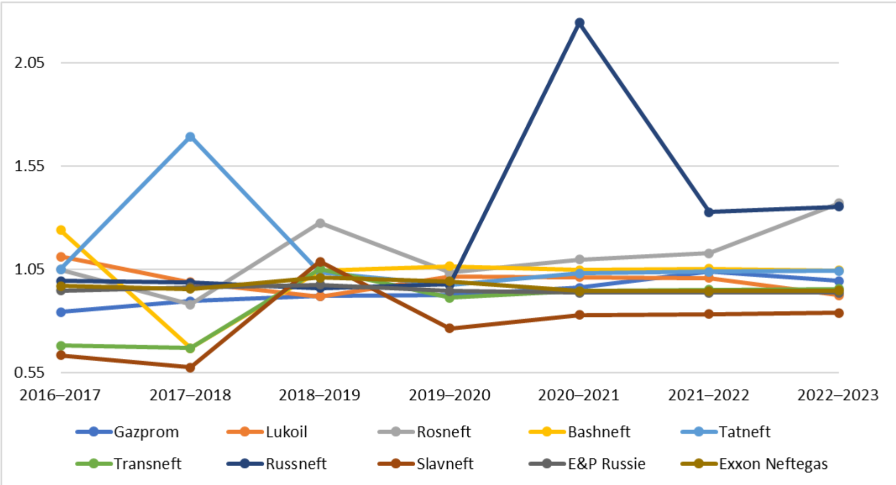

Fig. 2. Technical efficiency change (2016–2023)

frontier-shift of 1.16568 over the entire period. Especially, all DMUs have an average frontier-shift index greater than 1. This proves that all these oil and gas companies of Russia have technological progression in the whole period.

In the period 2016–2017, the frontier-shift index of OGR08-Slavneft was the highest at 1.53576, then it declined remarkably to 1.36943 before dropping sharply to 0.80184 which was the lowest efficiency of the whole period. Meanwhile, OLR06-Transneft had the third-highest technological progression in 2016–2017 with a score of 1.15872, then it increased steeply to a peak of 1.50602 in the 2017–2018 period, followed by dropping of 0.90318 in the 2018–2019 period. Likewise, except for OGR05-Tatneft, other DMUs also increased in the 2017–2018 period before decreasing significantly in the period 2018–2019. Nevertheless, all DMUs went up modestly in the 2019–2020 period, suggesting that these oil and gas companies underwent a marked improvement compared to the 2018–2019 period.

The average frontier-shift index of all DMUs is predicted to sustain high technological efficiency over the 2020–2023 period, with expected frontier-shift indexes greater than 1. In which, the most prominent is OGR07-Russneft, starting in 2020–2021 period is the lowest index in the future period of 1.05605, then it will increase dramatically to 1.35082 before reaching a peak of 1.3573 at the end of the period, whilst other companies will just increase or decline slightly with expected frontier-shift indexes higher than 1.

Fig. 2 reveals the frontier-shift efficiency over the entire period, 2016–2023. Starting with the 2016–2017 period, the technological performance of OGR08-Slavneft is anticipated to be the best efficiency but then falling remarkably in the 2017–2018 period before continuing to drop sharply in the next period, 2017–2018. From the next period, 2018–2019 to the end of the research period, this company made a significant effort to improve the technological efficiency to reach the fourth position among all the studied companies. In addition, OGR06-Russneft is also expected to rise to the top of frontier-shift indexes at the end of the period, leading to improvements in technological efficiency.

4.3.4 Total productivity change

Table 9 shows the results of the Malmquist index (MI) in the period of 2016–2023. Overall, most DMUs declined in the 2018–2019 period, which is predicted to increase gradually in the next periods with all efficiency indexes greater than 1. It means that all companies are expected to continue maintaining the stability of productivity in the future period. However, it is worth noting that with the average score of all DMUs at 0.95000 in 2018–2019, it suggests that in this period, all DMUs achieved poor productivity performance, hence, these companies need to try harder in the next periods. In addition, the productivity factor is affected by the technological factor, because according to Table 8 (technological efficiency change), all DMUs had poor technological efficiency so it is followed by ineffective productivity in the same period. For over the entire period, the average index of all DMUs is 1.10365, whilst the highest index of all average indexes is 1.47288 (OGR07-Russneft), the lowest index is 0.89439 (OGR08-Slavneft), it demonstrated that the importance of the progressive factors of productivity among the DMUs is relatively remarkable.

Table 8. Frontier-shift index (2016–2023)

Frontier	2016–2017	2017–2018	2018–2019	2019–2020	2020–2021	2021–2022	2022–2023	Average
Gazprom	1.18317	1.22151	0.98970	1.10665	1.07857	1.07596	1.11408	1.10995
Lukoil	1.11747	1.21412	0.93208	1.07008	1.03114	1.03812	1.07984	1.06898
Rosneft	1.17771	1.22482	0.98063	1.10663	1.07464	1.25653	1.14746	1.13835
Bashneft	1.07264	1.24741	0.90490	1.05024	1.03152	1.03178	1.03790	1.05377
Tatneft	1.14672	1.06323	0.91729	1.16479	1.07815	1.07433	1.07239	1.07384
Transneft	1.15872	1.50602	0.90318	1.10574	1.07578	1.07229	1.06905	1.12726
Russneft	1.12113	1.19070	0.97680	1.10693	1.05605	1.35082	1.35734	1.16568
Slavneft	1.53576	1.36943	0.80184	1.17885	1.08378	1.08786	1.09393	1.16449
E&P Russie	1.11886	1.12923	0.94316	1.10401	1.07291	1.07198	1.07108	1.07303
Exxon Neftegas	1.13921	1.15839	0.89819	1.05711	1.06668	1.06603	1.06477	1.06434
Average	1.17714	1.23249	0.92478	1.10510	1.06492	1.11257	1.11078	1.10397
Max	1.53576	1.50602	0.98970	1.17885	1.08378	1.35082	1.35734	1.16568
Min	1.07264	1.06323	0.80184	1.05024	1.03114	1.03178	1.03790	1.05377
SD	0.13011	0.12510	0.05495	0.04157	0.01924	0.10457	0.09166	0.04270

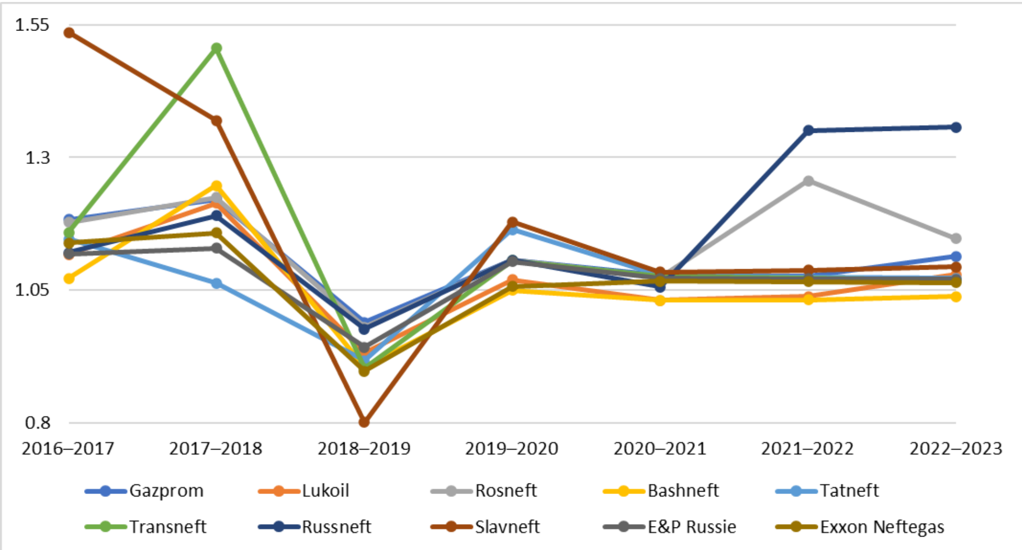

Fig. 3. Technological efficiency change (2016–2023)

In the period 2016–2017, except for OGR01-Gazprom, OGR6-Transneft, OGR08-Slavneft, all other companies attained high total factor productivity. OGR04-Bashneft had an outstanding index of 1.33094, while OGR06-Transneft had an MI of just 0.78819, making it to become the worst-performing company among the companies studied. Despite this, the average of all DMUs is still 1.10544 in this period.

From 2017 to 2018. OGR05-Tatneft had an excellent increase in total factor productivity (MI = 1.79973), this proves that this company has been very active in keeping up with the development trend of the oil and gas market in Russia in this period with MI = 1.20615, from 2016 to 2017. Likewise, OGR01-Gazprom, OGR06-Transneft, OGR07-Russneft, ORG09-E&P Russie, ORG10-Exxon Neftegas also tended to increase the productivity performance. In contrast, the remaining companies showed opposite trends afterward, the worst productivity was OGR4-Bashneft, ORG8-Slavneft which had an MI < 1 with 0.83352, 0.78829, respectively. However, the average MI index of all DMUs was 1.11680.

During 2018–2019, all DMUs showed ineffective productivity with MI < 1, the average MI index was 0.95000. It proves that the technological improvement process had greatly affected productivity efficiency with average frontier-shift indexes of 0.92478 in the same period. But then, all DMUs had a remarkable increase in the next period, 2019–2020 with an average MI index of 1.05934. There was only OGR08-Slavneft which had inefficient productivity with an MI index of 0.90172.

From 2020–2023, all DMUs are expected to be more stable than in the past periods, the average total factor productivity indexes are more than 1 in over the whole projection periods with 1.17507 in 2010–2021, 1.15159 in 2021–2022, 1.16730 in 2022–2023. Especially, the productivity efficiency of OGR07-Russneft is predicted to reach the highest production efficiency of all studied DMUs with an average MI = 1.47288, starting with 2020–2021, the maximum MI index is 2.37096, then dropping sharply to 1.79203 in 2021–2022 before increasing modestly to 1.83844 at the end of the period. Meanwhile, OGR03-Rosneft, OGR05-Tatneft, OGR08-Slavneft are expected to increase continuously in the next periods, however, OGR08-Slavneft is predicted to be ineffective productivity over the whole period, making it become the worst-performing company of all DMUs. By contrast, OGR09-E&P Russie is predicted to decline slightly in productivity performance in the next periods. On the other hand, the remaining companies will increase slightly in 2021–2022, but then fall marginally in the 2022–2023 period. Over the entire research period from 2016 to 2023, lots of DMUs (OGR01- Gazprom, OGR02-Lukoil, OGR03-Rosneft, OGR04-Bashneft, OGR05-Tatneft, OGR07-Russneft, OGR09-E&P Russie, OGR10-Exxon Neftegas will have obtained good total factor productivity with average MI indexes greater than 1.

Fig. 4 gives a line graph view of DMUs' productivity changes from 2016 to 2023. During 2016–2017, the MI index of OGR04-Bashneft is the highest MI index of all DMUs, then OGR05-Tatneft surpassed OGR04-Bashneft in 2016–2017 period to reach a peak of productivity efficiency in the next period before falling rapidly the productivity index in 2018–2019. However, after continuous efforts to improve productivity, the OGR07-Russneft is expected to rise to the highest MI index position in the 2020–2021 period, then decrease significantly at the end of the period but it remains at the forefront of the entire research process.

4.3.5 Effects of technical and technological on productivity change

Fig. 5 is used to clearly explain the effects of the technical and technological changes on the productivity change of ten oil and gas of Russian companies. In addition, it also illustrates the ranking changes among the catch-up index, frontier-shift index, and Malmquist index. Fig. 5 also highlights a DMU (OGR07-Russneft), which has the farthest catch-up index and technological index with a catch-up index greater than 1.2 and frontier-shift index greater than 1.1, and both of those indexes also hit the top of all studied DMUs. That proves that the highest productivity change (MI index) of this DMU is decided by both the technical change and technological change. On the other hand, the technical efficiency change, and technological efficiency change of OGR03-Rosneft ranked only at the third position of all studied DMUs, but the productivity growth index still reached the second position. It can be implied that two indexes of the technical change and technological change of this DMU have an interdependent relationship, making it increase the productivity efficiency change index. Moreover, OGR04-Bashneft has a technical change index which only ranked the fourth position, while the

Table 9. Malmquist index (2016–2023)

Malmquist	2016–2017	2017–2018	2018–2019	2019–2020	2020–2021	2021–2022	2022–2023	Average
Gazprom	0.99858	1.09412	0.91168	1.02302	1.03592	1.11741	1.10831	1.04129
Lukoil	1.24221	1.19991	0.85671	1.08722	1.04406	1.04641	0.99824	1.06782
Rosneft	1.23614	1.07816	1.24957	1.14438	1.17961	1.41879	1.57248	1.26845
Bashneft	1.33094	0.83352	0.94340	1.11904	1.08065	1.08594	1.08497	1.06835
Tatneft	1.20615	1.79973	0.95139	1.13728	1.11197	1.11593	1.11794	1.20577
Transneft	0.78819	1.00541	0.95018	1.00812	1.01777	1.01966	1.02139	0.97296
Russneft	1.11539	1.17339	0.93806	1.08191	2.37096	1.79203	1.83844	1.47288
Slavneft	0.97444	0.78829	0.87238	0.90172	0.89764	0.90723	0.91903	0.89439
E&P Russie	1.05892	1.08825	0.91919	1.04253	1.00482	1.00456	1.00430	1.01751
Exxon Neftegas	1.10350	1.10721	0.90740	1.04820	1.00733	1.00793	1.00789	1.02707
Average	1.10544	1.11680	0.95000	1.05934	1.17507	1.15159	1.16730	1.10365
Max	1.33094	1.79973	1.24957	1.14438	2.37096	1.79203	1.83844	1.47288
Min	0.78819	0.78829	0.85671	0.90172	0.89764	0.90723	0.91903	0.89439
SD	0.15926	0.27487	0.11000	0.07253	0.42667	0.26220	0.29642	0.16816

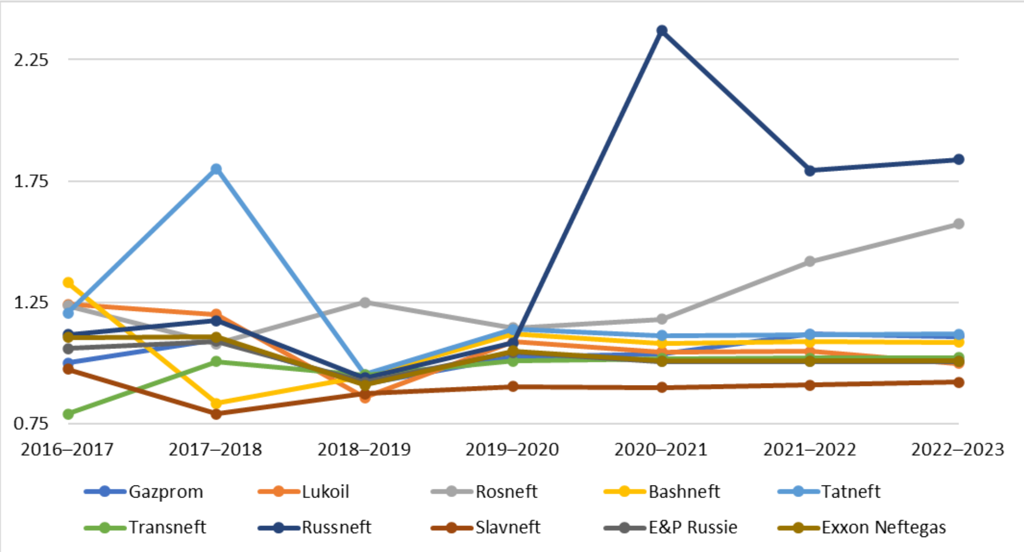

Fig. 4. Malmquist productivity change (2016–2023)

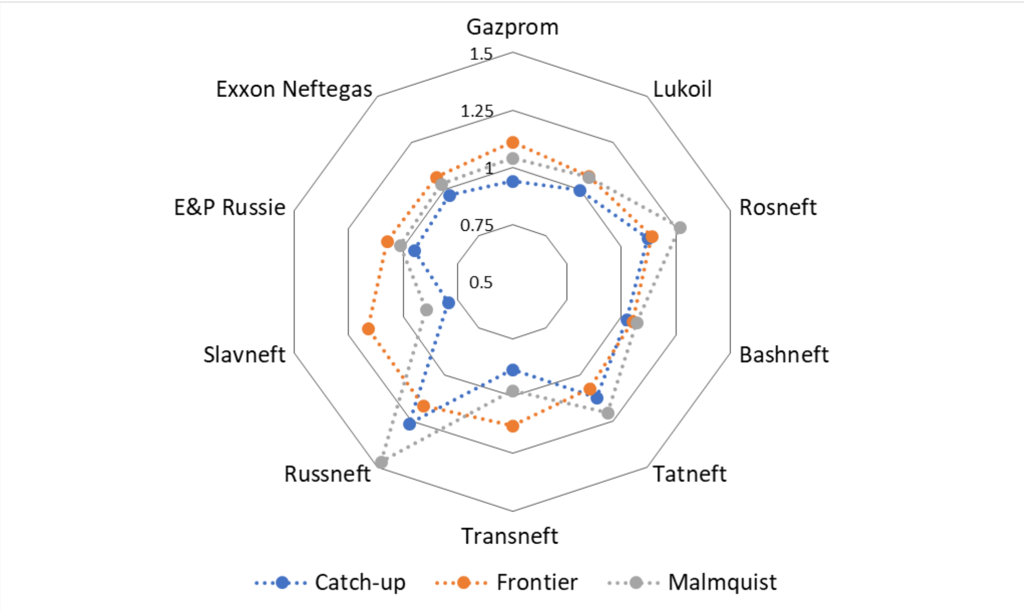

Fig. 5. Effects of technical and technological on productivity change

technological change index was the worst of all with its index only overcoming line level 1 a bit which is the same all DMUs as shown in Fig. 5 but it still holds the fourth position of all DMUs, it proves that ranking of the productivity change index of this company is determined mainly due to the adequate technical progress. The lowest productivity change index is OGR08-Slavneft, this is because the technical change efficiency index is only close to the line level of 0.75, even though its technological change index achieves the second position, but its index is only near the line level of 1. It proves that if this company wants to increase the productivity change index, OGR08-Slavneft's decision-makers need to make efforts to increase the technical efficiency such as the application of scientific knowledge to bring practical value such as designing of operating machines, manufacturing processes, and systems in the most efficient and economical way, otherwise it must increase technology efficiency even more.

5. RESULT DISCUSSIONS

Performance evaluation and prediction methods can assist decision-makers of companies in allocating and managing resources to maintain sustainable development. Hence, Grey prediction theory, GM (1,1), is applied to predict the accuracy of the data in the future period. This is proven by many previous studies of the Grey theory [19-21,48]. On the other hand, the DEA Malmquist model is also approached to provide an insight into the performance operation of the top 10 oil and gas companies of Russia, which are Gazprom, Lukoil, Rosneft, Bashneft, Tatneft, Transneft, Russneft, Slavneft, E&P Russie, Exxon Neftegas for both the past period of 2016–2019 and the future period, 2020–2023. In order to evaluate efficiency, three input factors are total assets, total liabilities, cost of revenue, and for output factors, two outputs are total revenue, net income has been considered for this study. The results show that except for the period 2018–2019, in other periods, all companies achieved high technological progress. Especially, the average frontier-shift indexes of all DMUs are also greater than 1, ranging from 1.05377 to 1.16568, indicating that the average total factor productivity indexes of all DMUs change largely and depend on the technical change indexes.

In the aspect of technical change efficiency, Rosneft, Bashneft, Tatneft, Russneft are only four companies that have high technical efficiency with average technical change indexes greater than 1, of which, Russneft is the best technical performance company, while it had inefficiency technical change in the 2016–2020 period with all indexes less than 1, but suddenly it is projected to be a peak the performance in the 2020–2021 period before decreasing significantly in the periods. By contrast, Transneft is the worst-performing of all companies, but it makes a huge effort to become the second-largest company in terms of technology with average technological change indexes that are only behind Russneft's position. In particular, all the remaining oil and gas companies have high technology efficiency since all average frontier-shift indexes are also higher than 1. This proves that all companies have caught up with the technology progress very timely in the era of industrialization and modernization nowadays. As the production change index is a combination of both technical efficiency change and technological efficiency change. Based on research results, Russneft continues to maintain its leading position in increasing productivity efficiency, it is still expected to be the most outstanding index in the period 2020–2021. Moreover, despite being affected by the current Covid-19 pandemic, RussNeft has a management team with high standards and experience in corporate governance, hence, it has the advantage to continue trying to keep high positions among oil and gas companies in Russia. RussNeft plans to increase oil production to 6.5 million tons by 2021, which is predicted to increase by 2% compared to 2020. According to operation data in the current year, the production will be 6.38 million tons which are observed with the terms of the Organization of Petroleum Exporting Countries and Agreement [55]. Conversely, Slavneft company, despite its efforts to achieve high progress in technological change, is still the worst-performing company in productivity change. This means that Slavneft company needs to come up with the right strategy to improve technical efficiency, helping it increase productivity.

6. CONCLUSIONS AND FUTURE STUDIES

Based on analysis of the grey model and Malmquist index model, this paper has used historical data of the top ten oil and gas companies in Russia for the period 2016–2019 as the subject sample for forecast data in the future, 2020–2023 period, and the Malmquist method is used to evaluate the performance of over the whole period of 2016–2023. The research gap of this paper is as follows:

- This is the first study to provide a case study of assessing the performance in Russia's oil and gas business using the proposed techniques (i.e., Grey and Malmquist).
- The paper proposes an evaluation approach of the oil and gas industry that combines the Grey prediction model GM (1,1) and the Malmquist model, based on Malmquist indexes (MI), with MI < 1, leaders should proactively observe, improve technical progress, or enhance technological innovation to improve productivity in the future. Using Grey theory helps to accurately predict data in the future period, the average MAPE of all DMUs is less than 10%, which is considered a reliable prediction in this paper. Besides, these model's results can assist policymakers and decision-makers in identifying a company's weaknesses or strengths in order to make a timely strategic adjustment, hence, it helps leaders reduce the burden of how to improve efficiency, enhance competitiveness that is placed on the shoulders of business managers.
- The empirical results of this paper provide comprehensive and practical insights into the top 10 Russian oil and gas companies' performance in recent years. The authors expect that the findings will reflect the current situation of Russia’s oil and gas sector, particularly in terms of technical and technological progress, as evidenced by the performance of a few successful oil and gas companies. The study's conclusions have significant implications for policymakers and company executives. Hence, managers,

policymakers, and investors, not just in Russia but in any firm around the world, can regard this paper as a guideline for sustainable development and successful investment decisions in the oil and gas industry.

However, this paper still has some potential limitations. Firstly, there are only 10 companies covered in this paper due to the lack of available datasets. More companies should be included to provide a more overview of the industry. Secondly, due to the current global volatility caused by the Covid-19 pandemic, the source of oil and gas consumption in Russia is also heavily affected by travel restrictions [56,57], but this paper has not detailed the impact of supply and demand problems on production. Finally, this paper only covers three input factors and two output factors in financial factors, inputs directly related to oil and gas activities companies such as wells and emissions have not been considered. Future studies may consider focusing on these issues to expand more research results.

DISCLAIMER

The products used for this research are commonly and predominantly use products in our area of research and country. There is absolutely no conflict of interest between the authors and producers of the products because we do not intend to use these products as an avenue for any litigation but for the advancement of knowledge. Also, the research was not funded by the producing company rather it was funded by personal efforts of the authors.

CONSENT

It is not applicable.

ETHICAL APPROVAL

It is not applicable.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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APPENDIX A

Table A1. Statistical data of the inputs and outputs during 2016-2019 (unit: million USD)

Year	Statistics	Total assets	Total liabilities	Cost of revenue	Total revenue	Net income
2016	Max	16,918.94	7,304.00	3,622.97	6,111.05	951.64
	Min	74.54	22.28	16.76	26.65	6.20
	Average	3,825.94	1,678.47	1,021.51	1,789.14	176.62
	SD	5,441.40	2,445.14	1,372.74	2,257.31	271.67
2017	Max	18,238.77	8,044.00	3,727.71	6,546.14	714.30
	Min	54.64	17.17	18.84	27.48	5.46
	Average	4,128.85	1,823.61	974.24	2,050.12	185.29
	SD	5,910.37	2,731.42	1,293.75	2,565.79	215.54
2018	Max	20,810.44	8,486.00	5,272.00	8,224.18	1,456.27
	Min	73.81	29.68	18.24	28.80	6.72
	Average	4,577.86	1,952.07	1,449.70	2,636.22	321.02
	SD	6,648.83	2,962.24	2,024.19	3,332.48	433.66
2019	Max	21,882.35	7,798.00	5,528.06	7,841.25	1,202.89
	Min	90.22	38.88	19.47	30.79	7.21
	Average	4,716.52	1,955.54	1,323.60	2,672.24	304.22
	SD	6,877.66	2,846.75	1,841.22	3,347.88	387.72

Table A2. Predicted data of GM (1,1) model in 2020 (unit: million USD)

DMUs	Companies	Total assets	Total liabilities	Cost of revenue	Total revenue	Net income
OGR-01	Gazprom	24,166.16	7,932.43	2,845.54	8,598.00	1,619.91
OGR-02	Lukoil	6,386.16	2,049.43	6,797.19	9,265.51	802.33
OGR-03	Rosneft	13,508.16	7,871.79	4,863.93	9,443.96	1,144.33
OGR-04	Bashneft	849.61	281.47	474.19	916.70	53.44
OGR-05	Tatneft	1,318.34	540.98	96.12	1,110.90	225.84
OGR-06	Transneft	3,598.18	1,235.55	515.86	1,168.32	187.05
OGR-07	Russneft	312.81	229.69	161.86	228.18	43.21
OGR-08	Slavneft	115.17	56.41	19.50	32.50	8.36
OGR-09	E&P Russie	289.73	167.82	145.65	197.49	13.22
OGR-10	Exxon Neftegas	366.75	165.11	215.20	275.51	13.82

Table A3. Predicted data of GM (1,1) model in 2021 (unit: million USD)

DMUs	Companies	Total assets	Total liabilities	Cost of revenue	Total revenue	Net income
OGR-01	Gazprom	26,403.53	8,551.56	3,022.98	9,229.23	1,954.55
OGR-02	Lukoil	6,804.07	2,195.63	8,140.96	10,490.50	967.43
OGR-03	Rosneft	13,889.87	7,755.98	5,465.79	11,366.31	1,807.82
OGR-04	Bashneft	896.19	264.22	565.42	1,032.50	38.71
OGR-05	Tatneft	1,392.91	606.22	94.92	1,281.74	260.43
OGR-06	Transneft	3,858.38	1,305.85	588.50	1,280.52	181.57
OGR-07	Russneft	348.86	261.12	190.59	270.11	85.03
OGR-08	Slavneft	146.60	81.52	19.83	34.41	9.55
OGR-09	E&P Russie	307.52	183.80	154.83	213.22	14.91
OGR-10	Exxon Neftegas	374.13	170.36	224.53	285.12	12.06

Table A4. Predicted data of GM (1,1) model in 2022 (unit: million USD)

DMUs	Companies	Total assets	Total liabilities	Cost of revenue	Total revenue	Net income
OGR-01	Gazprom	28,848.05	9,219.01	3,211.49	9,906.79	2,358.31
OGR-02	Lukoil	7,249.33	2,352.25	9,750.39	11,877.45	1,166.51
OGR-03	Rosneft	14,282.36	7,641.88	6,142.13	13,679.95	2,856.00
OGR-04	Bashneft	945.33	248.03	674.19	1,162.92	28.05
OGR-05	Tatneft	1,471.69	679.34	93.73	1,478.84	300.32
OGR-06	Transneft	4,137.38	1,380.15	671.36	1,403.50	176.26
OGR-07	Russneft	389.07	296.85	224.41	319.74	167.33
OGR-08	Slavneft	186.62	117.82	20.17	36.44	10.90
OGR-09	E&P Russie	326.40	201.30	164.58	230.21	16.81
OGR-10	Exxon Neftegas	381.65	175.77	234.27	295.07	10.51

Table A5. Predicted data of GM (1,1) model in 2023 (unit: million USD)

DMUs	Companies	Total assets	Total liabilities	Cost of revenue	Total revenue	Net income
OGR-01	Gazprom	31,518.88	9,938.56	3,411.75	10,634.10	2,845.48
OGR-02	Lukoil	7,723.74	2,520.05	11,678.00	13,447.76	1,406.55
OGR-03	Rosneft	14,685.94	7,529.45	6,902.15	16,464.55	4,511.92
OGR-04	Bashneft	997.16	232.84	803.89	1,309.82	20.32
OGR-05	Tatneft	1,554.94	761.27	92.55	1,706.26	346.32
OGR-06	Transneft	4,436.57	1,458.67	765.89	1,538.28	171.10
OGR-07	Russneft	433.91	337.47	264.24	378.49	329.29
OGR-08	Slavneft	237.55	170.28	20.52	38.58	12.45
OGR-09	E&P Russie	346.44	220.47	174.95	248.54	18.96
OGR-10	Exxon Neftegas	389.32	181.35	244.43	305.37	9.17

Table A6. Pearson correlation coefficients (2016-2019)

Factors	Total assets	Total liabilities	Cost of revenue	Total revenue	Net income
2016					
Total assets	1.00000	0.91398	0.74338	0.89463	0.89136
Total liabilities	0.91398	1.00000	0.78241	0.79973	0.63924
Cost of revenue	0.74338	0.78241	1.00000	0.92789	0.49675
Total revenue	0.89463	0.79973	0.92789	1.00000	0.77820
Net income	0.89136	0.63924	0.49675	0.77820	1.00000
2017					
Total assets	1.00000	0.92567	0.71005	0.88649	0.87026
Total liabilities	0.92567	1.00000	0.69445	0.82376	0.65922
Cost of revenue	0.71005	0.69445	1.00000	0.95119	0.74798
Total revenue	0.88649	0.82376	0.95119	1.00000	0.88377
Net income	0.87026	0.65922	0.74798	0.88377	1.00000
2018					
Total assets	1.00000	0.92759	0.67362	0.86027	0.95180
Total liabilities	0.92759	1.00000	0.74527	0.80002	0.78174
Cost of revenue	0.67362	0.74527	1.00000	0.91835	0.62918
Total revenue	0.86027	0.80002	0.91835	1.00000	0.87909
Net income	0.95180	0.78174	0.62918	0.87909	1.00000
2019					
Total assets	1.00000	0.94172	0.60963	0.84485	0.96921
Total liabilities	0.94172	1.00000	0.63914	0.85632	0.89733
Cost of revenue	0.60963	0.63914	1.00000	0.93476	0.75461
Total revenue	0.84485	0.85632	0.93476	1.00000	0.92774
Net income	0.96921	0.89733	0.75461	0.92774	1.00000

Table A7. Pearson correlation coefficients (2020-2023)

Factors	Total assets	Total liabilities	Cost of revenue	Total revenue	Net income
2020					
Total assets	1.00000	0.94749	0.57122	0.81922	0.97219
Total liabilities	0.94749	1.00000	0.62307	0.85028	0.94892
Cost of revenue	0.57122	0.62307	1.00000	0.93380	0.73171
Total revenue	0.81922	0.85028	0.93380	1.00000	0.92443
Net income	0.97219	0.94892	0.73171	0.92443	1.00000
2021					
Total assets	1.00000	0.95521	0.52255	0.78709	0.93908
Total liabilities	0.95521	1.00000	0.57823	0.84481	0.97816
Cost of revenue	0.52255	0.57823	1.00000	0.92238	0.71707
Total revenue	0.78709	0.84481	0.92238	1.00000	0.92901
Net income	0.93908	0.97816	0.71707	0.92901	1.00000
2022					
Total assets	1.00000	0.96248	0.47549	0.75026	0.87161
Total liabilities	0.96248	1.00000	0.53244	0.82888	0.96222
Cost of revenue	0.47549	0.53244	1.00000	0.90647	0.68110
Total revenue	0.75026	0.82888	0.90647	1.00000	0.92460
Net income	0.87161	0.96222	0.68110	0.92460	1.00000
2023					
Total assets	1.00000	0.96912	0.43052	0.70967	0.77771
Total liabilities	0.96912	1.00000	0.48668	0.80326	0.90397
Cost of revenue	0.43052	0.48668	1.00000	0.88625	0.62700
Total revenue	0.70967	0.80326	0.88625	1.00000	0.91177
Net income	0.77771	0.90397	0.62700	0.91177	1.00000