Energy stability and decarbonization in developing countries: Random Forest approach for forecasting of crude oil trade flows and macro indicators

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The paper observes the dependence of the main macroeconomic indicators in developing countries from the change in world prices for crude oil. We analyzed a system of simultaneous equations, which makes it possible to verify some of these hypotheses, and developed the model to forecast the impact of oil prices on budget revenues. The practical significance of this work lies in the structuring of existing knowledge on the impact of oil crisis. The results of this work can be considered confirmation of the hypothesis of the sensitivity of U.S. macroeconomic indicators to the dynamics of oil prices. Outcomes assume stable growth even in the period of shock prices for oil, which is confirmed by the statistics that were used in the model. Deep decarbonization modeling is a trend in industrial facilities that are used by developing countries. The major challenge is the issue of availability that is applicable to the countries that want to utilize this facility in their communities. Industrial modeling toward decarbonization is now a developing mechanism to curb the growing issue of atmospheric pollution. This paper proves the relevance of promoting deep decarbonization applied by the developing countries.

KEYWORDS

investment export, gross national product, normality of distribution, oil price forecasting, budget revenues, oil and gas impact

Introduction

The aim of the paper is real-time macroeconomic monitoring and forecasting of crude oil trade flows in exporting countries based on the structure of the economy and raw material export potential. The falling prices for crude oil, as history shows, almost inevitably lead to a drop in real GDP growth, investment, and exports.

The higher net household income due to lower oil prices led to an increase in consumer spending of 0.61%, while a decrease in drilling volumes reduced the inflow of investments by 0.62%, negating almost all the advantages of the low oil price period. Shale oil production is still crucial for the United States economy. This again underscores the important role that the oil industry plays in the United States economy and what benefits the country has received from the slate revolution (Zhai et al., 2017; Xu et al., 2019; Zhang M. et al., 2020a; Zhang Q. et al., 2020b; Wang et al., 2020; Wang and June 2020; Wang et al., 2021).

It is obvious that without the slate revolution, the United States economy's reaction to the recent decline in oil prices would have been different, had it not been for the low level of oil and gas production for GDP. A question that is of real interest to the authorities is will the growth of investments in the oil sector help offset the negative impact on private consumption in the future recovery of real oil prices.

Deep decarbonization modeling is an initiative to limit carbon emissions into the atmosphere. The drive is under the initiative of a variety of inter-governmental agencies to improve the world's climate and atmosphere. Since the world's environment is slowly threatened by pollution from industrial facilities, the condition of the atmosphere starts to deteriorate. The main reason behind this is the increasing number of carbon molecules that are now suspended in the atmosphere, which makes the quality of the air poor. With the advent of technology, there are new facilities that are developed to improve the quality of air in the world's atmosphere to prevent negative or harmful consequences. Deep decarbonization is regarded as one of the most promising solutions to prevent the growing harmful effects of air pollution.

Developing countries are some of the most affected areas due to the increasing concentration of carbon in their own atmospheres. These are the countries that are still under the process of rebuilding their economic, political, and infrastructure developments to stabilize trade, peace, and governance. Government units are busy concentrating on rebuilding their infrastructure developments, which prompts several public officials to neglect environmental awareness and preservation. The growing negative environmental effects of ecological neglect and preservation are now prompting several government institutions to establish a new plan to preserve the environment. Deep decarbonization modeling is one solution to challenge the growing industrial wastes that are slowly degrading the condition of the atmosphere.

Literature review

The paper fills the gap in the dependence of the main macroeconomic indicators in developing countries from the change in world prices for crude oil.

Oil consumption in other countries is growing, but not as fast as previously thought. In developing countries, primarily China, there is an increase in the efficiency of oil. The sensitivity of macroeconomic indicators to changes in world oil prices attracted the attention of scientists.

Researchers proposed an interesting model for analyzing structural changes in an open economy, oriented on the export of raw materials; some aspects of this model were applied in this work (Romero-Ávila, 2008; Spellman, 2013; Thorbjörnsson et al., 2015; Tsagkanos and Siriopoulos, 2015; Vad Mathiesen, 2015; Schmidt et al., 2019; Tsagkanos et al., 2022).

The path beyond deep decarbonization can drastically improve environmental conditions. This is mainly due to the installation of environmental rehabilitation projects to improve the quality of air in the atmosphere. Developing countries are seriously considering developing and implementing deep decarbonization modeling procedures. Over the years, environmental challenges have caused concern in the affected developing countries. Government officials realize that there was a significant period of neglect due to the overconcentration of political stabilization. Government officials are now creating new laws that enable the society to improve the conditions of their environment. The improvement of deep decarbonization is a promising plan to reduce carbon emissions in the environment. After developed countries successfully initiated a campaign to promote deep decarbonization modeling applications, developing countries are also following a similar action plan. The main purpose is to increase the number of participants to decrease the number of carbon concentrations that are currently suspended in the atmosphere. Developing countries already have funds and environmental departments to ensure that they can start balancing the present condition of their environment (Armaroli and Balzani, 2016; Bataille et al., 2016; Fanchi, J. and Fanchi, C., 2016; Babonneau et al., 2018; Venturini et al., 2018).

The improvement of the deep decarbonization modeling capacity for developing and developed countries has one major goal. This is to improve the climate conditions that can benefit current and future generations. These nations aim to save the environment by starting to act early on managing carbon emissions through the application of the deep decarbonization process (Li R. et al., 2021a; Li X. et al., 2022; Plakandaras and Ji, 2022).

Developed and developing nations are allocating a significant amount of budget to ensure that they can successfully invest to build more facilities across areas affected by environmental risks and hazards across the society (Wang et al., 2019; Li T. et al., 2021b; Li et al., 2022a).

Politicians always presume that this new, promising program is yet to prove its worth to the public by slowly convincing other countries to approve facilities to patronize these alternative energy resources. The only challenge is the pricing structure of the decarbonizing process. Since only a few countries are using this procedure, it is certain that constructing a decarbonization plant is very expensive (Lohrmann and Luukka, 2018; Naeem et al., 2021).

The relationship between deep decarbonization and sustainable energy is that developing countries may apply this model due to the potential beneficial impact for the next couple of decades. Due to the use of fuel, developing countries will urge petroleum companies to start converting fuel to other sources of energy-generating facilities. These are the use of smart growth of alternative energy sources, energy-efficient industries, biomass fuels, and electricity decarbonization, power-to-gas, fuel switching, and remaining emissions.

In the future, these alternative energy-generating industries will soon dominate the entire community (Neaime et al., 2018; Ozili, 2018; Noori et al., 2020; Oxford Economics, 2022).

Research innovation points are that the challenge of changing the traditional energy source to alternative renewable energy is the sustainability the world is looking for. One major issue is the uncertainty of companies and government institutions to conduct experimentation first before approving a new actual power plant to generate a new energy source (Neaime, 2015; Narayanamoorthy et al., 2019).

However, the total predictability of returns and the predictive power of changes in oil prices varied significantly between markets (Wang and Zhang, 2021; Li et al., 2022b; Li et al., 2022c). However, the total predictability of budget returns and the predictive power of changes in oil and gas revenues varied significantly between different countries (Phoumin and Kimura, 2014; Parker and Liddle, 2017; Ozimek, 2020; Parker and Bhatti, 2020; Pham et al., 2020).

Methodology

The main idea of random forests is the separation of solutions into branches. Random forest is time-consuming, but the accuracy is better than that of other machine learning algorithms. The number of trees can affect the performance and increase the efficiency of the random forest algorithm, increasing the propensity to retrain random forest. Random forest retraining can be eliminated by changing the number of trees. Fine-tuning gives optimally selected parameters (hyperparameters). In addition to the number of trees in the random forest model, the number of features that the random forest tree will use for its branches is important. Therefore, random forest is ideal for modeling with real-time macroeconomic data and forecasting crude oil trade flows. The data have a long time series (more than 20 years) and are uploaded to the database (Mikhaylov, 2022).

The main method is the random forest model with real-time macroeconomic data and forecasting of crude oil trade flows. The random forest tree formula is as follows:

$$N = \{(x_1, y_1), (x_2, y_2), (x_n, y_n)\}. \tag{1}$$

It combines the data flows into the random forest K.

$$K = \{k_1(x), k_2(x), k_j(x)\}, \tag{2}$$

where j is the number in the universe of trees.

The utility is calculated using the following formula:

$$U = \{d_{i1}, d_{i2}, d_{im}\}, \tag{3}$$

where m is the number in the universe of variables.

$$K_j(x) = k(x/d_i). \tag{4}$$

The regression split criterion is the mean squared error (MSE).

$$MSE = \frac{\sum_{t=1}^{n}(g_t - f_t)^2}{n}, \tag{5}$$

where g_t is the actual meaning, f_t is the forecasted meaning, and n is the number of meanings.

The next step is transformation in accordance with

$$F' = \sum_{i=1}^{B} Fi(x). \tag{6}$$

The root mean squared error (RMSE) is calculated as follows:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(g_t - f_t)^2}{n}}, \tag{7}$$

where gt is the actual meaning, ft is the forecasted meaning, and n is the number of meanings.

The mean absolute error (MAE) measures the difference between variables as follows:

$$MAE = \frac{\sum_{t=1}^{n}|g_t - f_t|}{n}. \tag{8}$$

The mean absolute percentage error (MAPE) is the same instrument.
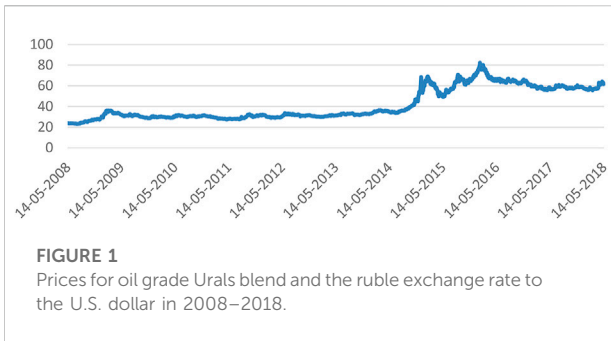
$$MAPE = \left[\frac{1}{n}\sum \frac{|g_t - f_t|}{g_t}\right] * 100. \tag{9}$$

The importance calculation is expressed as follows:

$$Fi_i = \frac{\sum_i^j Ni_j}{\sum_k Ni_k}, \tag{10}$$

where Fi_i is the impact of feature I, Ni_j is the impact of node j, and Ni_k is the impact of all nodes k.

The next step is normalization, which is expressed as follows:

FIGURE 1
Prices for oil grade Urals blend and the ruble exchange rate to the U.S. dollar in 2008–2018.

$$\text{norm Fi}_i = \frac{Fi_i}{\sum_j Fi_j}. \tag{11}$$

The final step is as follows:

$$\text{TFi}_i = \frac{\sum_j normFi_{ij}}{T}, \tag{12}$$

where TFi_i is the impact of feature I from all the trees and T is the quantity of trees.

We investigated the effect of oil prices in oil-exporting countries (the United States and Russia) and found that positive shocks in oil prices negatively affect macroeconomic indicators. After random forest modeling, the system of econometric equations is deployed, which consists of Eqs 13–15. The regression model is presented in a log-linear form.

$$GDP = C_1 + C_2 \ln(consu_t) + C_3 \ln(inv_t) + C_4 \ln(\exp_t), \tag{13}$$

$$\begin{aligned} INV &= C_5 + C_6 \ln(inv_{t-1}) \\ &\quad + C_7 \ln(oil_t) + C_8 \ln(gdp_t - gdp_{-1}), \end{aligned} \tag{14}$$

$$\begin{aligned} Exp &= C_9 + C_{10} \ln(oil_{t-1}) + C_{11} \ln(consu_t) \\ &\quad + C_{12} \ln(inv_t - inv_{t-1}), \end{aligned} \tag{15}$$

where *GDP* is the gross domestic product in real terms, *INV* is the investment in real terms, *C* is the constant, *consu* is the consumption in real terms, EXP is the export in real terms, *oil* is the price of crude oil, and *t* is the index of the year.

Eq. 15 specifies the value of real GDP, the size of which, in the author's opinion, consists of three basic pillars: domestic consumption, export value, and investment. As the main factors of formation of the volume of exports, the level of oil prices and the exchange rate of the ruble against the U.S. dollar are considered (assuming that the weakening of the ruble stimulates exports).

In order to take into account the seasonality of export deliveries, quarterly dummy variables are introduced in Eq. 16.

$$\sum(S_n {}^* T_n) = \sum \left[\frac{M_n + 2}{3}\right], \tag{16}$$

where *M* is the coefficient of change of the export duty on oil products.

This paper used a qualitative research design throughout its discussion to support the empirical analysis of real-time macroeconomic monitoring and forecasting of crude oil trade flows in developing countries.

Results

Based on the results of the verification of significance, we can say with confidence that the real values of the significance level of the consumption factor and investment are less than 0.05. This means that we cannot discard these factors in the equation under consideration.

The impact of these factors on GDP is significant. The coefficients under the factors are positive, that is, the relationship of indicators is direct. At the same time, the factor of domestic consumption is of overwhelming importance (Table 1).

Figure 1 shows that the ruble export price of Urals oil even increased compared to 2014, that is, the ruble tax base for income should not suffer much as a result of such sharp changes in asset prices.

Based on the results of the verification of significance, we can say with confidence that the real significance level of the significance of all factors is less than 0.05. This means that we cannot discard any of the factors in the equation under consideration. Also, the impact of these factors on investment is significant. The coefficients under the factors are positive, that is, the relationship of indicators is direct. We draw attention to the fact that the price of oil has a direct impact on investment, which confirms our hypothesis. In particular, when the price of crude oil is increased by 1%, the investment will increase by 5.2% (Figure 2,3).

The obtained results confirm the hypotheses put forward on the dependence of the export level on the oil price level. On the example of the consumption function, we check the consistency of the conclusions we have drawn, for which we will check the quality of the model. We analyzed the function for normality in the EViews package and conducted the Jarque–Bera test. Based on the results, the distribution of model errors is really slightly different from normal. We tested for heteroscedasticity and plotted the calculated, actual, and residual values (Figure 3). Having made a visual analysis of the graph of the residues, we concluded heteroscedasticity because there are groups of observations with a small dispersion of values and with a large spread. Therefore, the probability of heteroscedasticity is quite large, which confirms our previous conclusions. Having carried out these tests, we can confidently state the sufficient accuracy of the model (Table 2).

To use the previously mentioned model, we will use data from the economic development ministry forecast for 2015. In accordance with the main directions of the budget policy of the Russian Ministry of Finance, the budget for 2015 includes the

TABLE 1 Impact of factors on GDP.

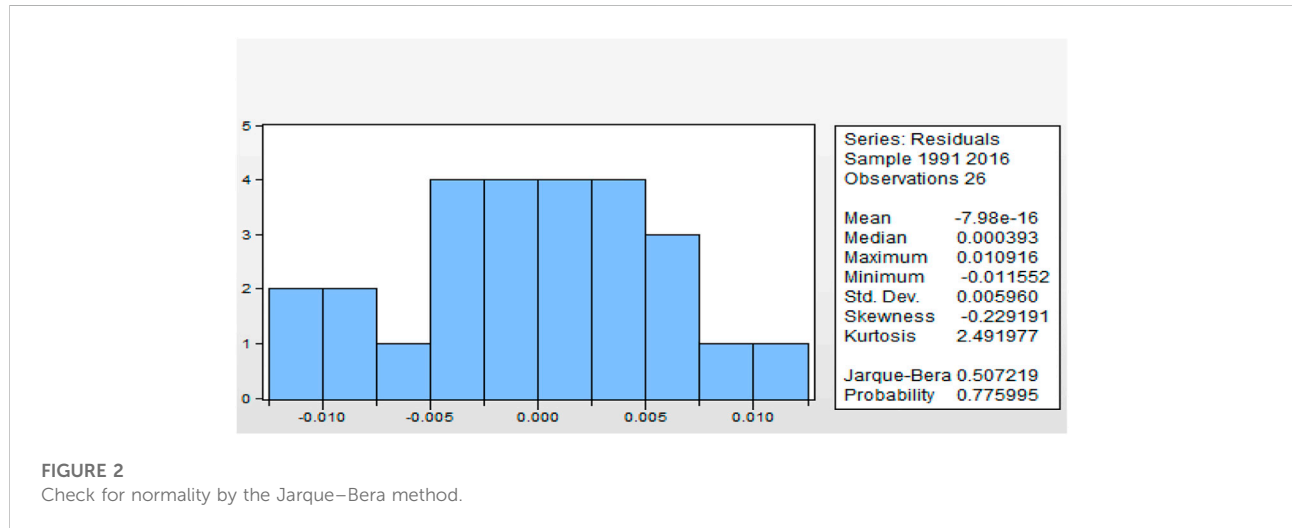| Parameter	Consumption	Investment in real terms	Export in real terms	Price of crude oil
Significance	0.02	0.03	0.06	0.07

FIGURE 2
Check for normality by the Jarque−Bera method.

following forecast values: 1) the average annual price for Urals oil is 96 dollars per barrel. 2) The average rate of the dollar is 37 rubles to U.S. dollar. 3) Oil and gas revenues at the level of 6818 bln. Russian rubles. Taking into account the preservation of structural proportions, revenues from the production and export of petroleum products were projected at 5,420 bln. Russian rubles and revenues from gas production and export at 1,398 bln Russian rubles (Figure 4).

Figure 5 indicates the forecast for deep decarbonization modeling in developing countries for the next 30 years until 2050.

The result of paper also proves that the use of fuel has been responsible for converting it into gaseous substances in order to generate energy that is applicable for the developing countries in the next couple of decades. Fuel is the most dominant source of energy generation, allowing countries with the largest petroleum reserves to profit from the worldwide demand. The problem with fuel is that it produces a significant amount of energy that is responsible for saturating the atmosphere with a high amount of carbon emissions. The changes may take place after a couple of decades and after a series of approvals and disapprovals. This is brought about by the gradual changes with the supply of energy and the presence of renewable energy facilities that are installed by government institutions.

Figure 6 presents the top six carbon-emitting countries and regions, including the EU (European Union), as of 2014. China ranks first as the country with the largest carbon emissions than any other country around the world with over 10 million tons of carbon dioxide emissions. The United States ranks second with at least five million tons of carbon dioxide. The EU nations account for at least three million tons of carbon dioxide particles. The Russian Federation ranks fourth, while Japan ranks fifth with one million tons of carbon dioxide each. India is the rising star in this position with at least two million tons of carbon dioxide emissions as of 2014. Both India and China are expected to increase their carbon emissions due to the growing manufacturing and other industrial developments across their nations.

It is obvious that even though China is considered one of the richest countries in the world in terms of nominal gross domestic product, the whole economic situation of the country is still under a developing status. This is similar to India's economic situation, wherein it is still tagged as a developing nation. There are still numerous areas across these two nations that have a significant number of people living below the poverty line. The increasing number of carbon emissions each year indicates China and India's developing status. This means that the government in these two nations has yet to create a concrete solution to control the country's growing concern over carbon emissions.

As a strategy, one important aspect is the identification of the countries responsible for causing a concern in terms of increasing carbon emissions. Countries with the largest area, population, and industrial capacity to produce numerous commodities have one of the highest carbon emission rates. Identifying the factors responsible for causing several environmental hazards through
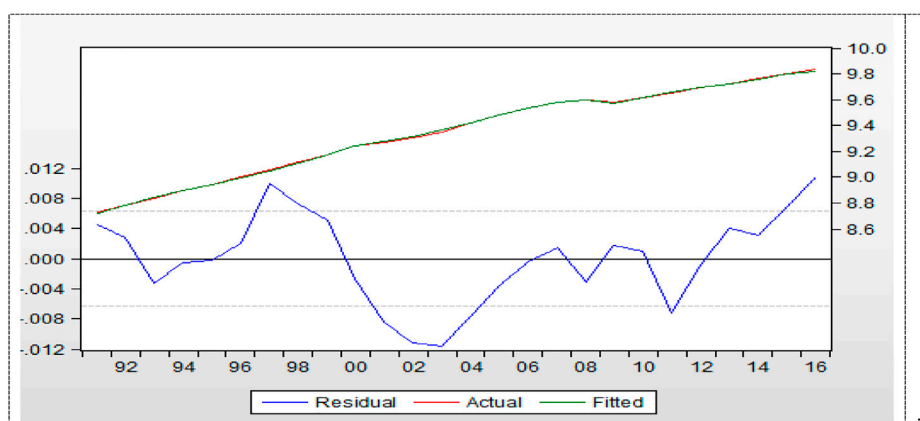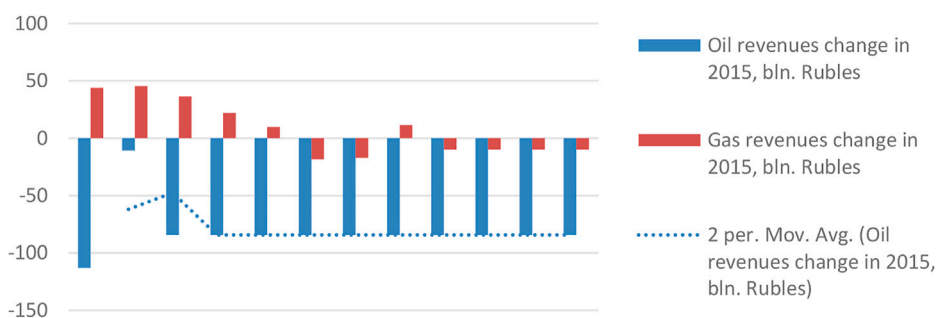
FIGURE 3
Check for heteroscedasticity.

FIGURE 4
Revenue change in 2015, bln Russian rubles.

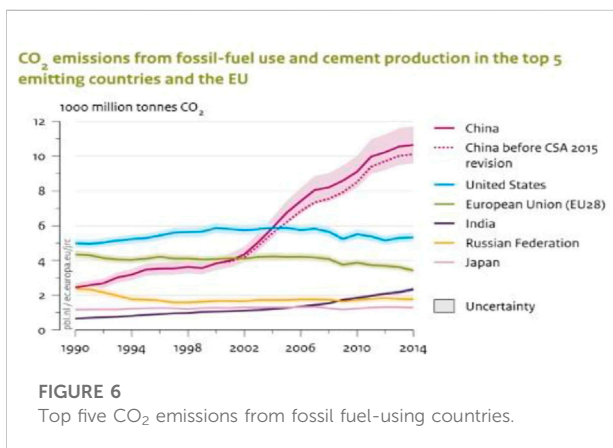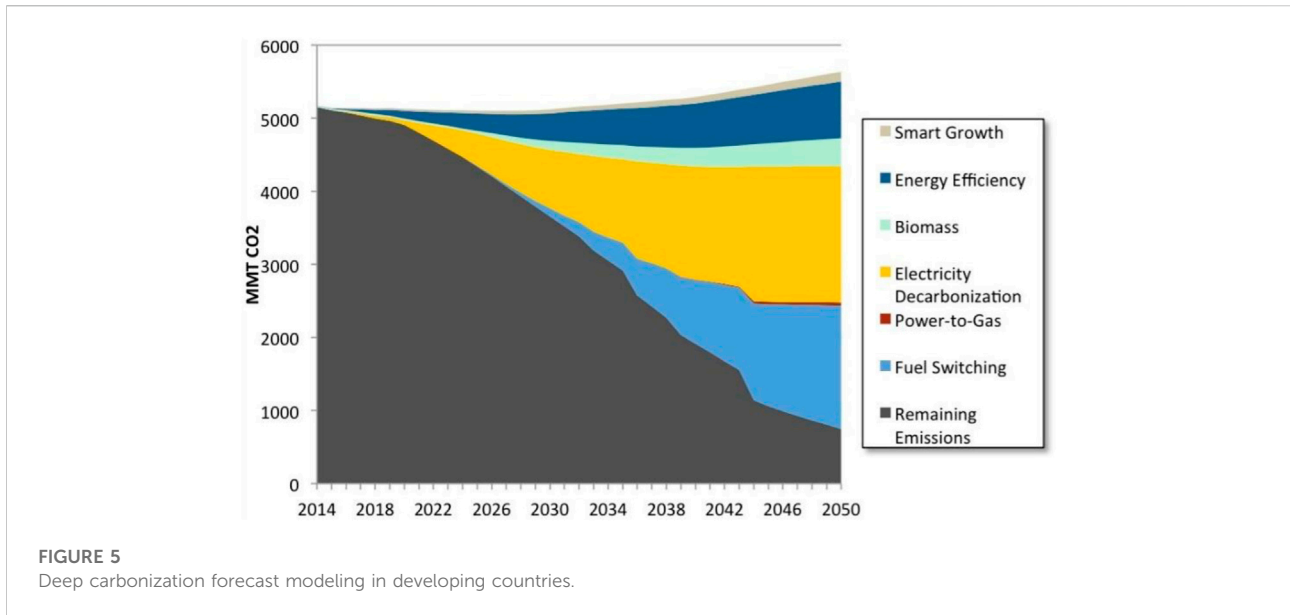**TABLE 2 Model efficiency summary.**

MAPE	MAE	RMSE
0.0072	0.0662	0.0764

the emission of carbon particles enables the development of an efficient and accurate deep carbonization modeling. Identifying the main product of concern responsible for emitting high amounts of hazardous carbons in the atmosphere will be applied. Technological developers may soon convert it into a decarbonized compound.

Figure 7 illustrates five considerable questions to determine an effective deep carbonization modeling procedure. The first is the electricity mix that mixes renewables, nuclear, and fossil fuels with CCS (carbon capture and storage). The alternative use of biomass supply is a promising decarbonizing solution to replace

diesel resources that produce high amounts of carbon. This is similar to the balancing of fuel or the application of fuel switching. Petroleum products are now under the process of being converted into a safer emission of other gas components other than carbon.

The most interesting fact about deep carbonization modeling is the application of CCS, which is essential for improving the carbon density of the atmosphere. The carbon capture and coal consumption may result in penalties with the energy sector of communities. The use of CCS is one of the most efficient alternative solutions to ensure that there will be less carbon released into the atmosphere once new emissions are released by factories. Developing countries are conscious of the pricing of CCS due to their limitation of carbon sources responsible for improving the environment. This is because some highly developed countries are also having similar problems with regard to the increasing carbon emissions brought about by fuel sources.

FIGURE 5
Deep carbonization forecast modeling in developing countries.

FIGURE 6
Top five CO_2 emissions from fossil fuel-using countries.

Discussion

Deficits in technical capacity

There are significant deficits in technical capacity as related to the measurement of carbon emissions brought about by fuel and electric resources. In developing countries, it has been revealed that most industries heavily use fossil fuels and petroleum deposits. These are the raw materials responsible for producing large amounts of carbon in the atmosphere. At first, developing countries are benefiting the resourceful impacts of fossil fuels that provide energy resources to their industries. The only problem is the increasing carbon particles that are now disposed into the atmosphere. For as long as there will be new industries that are fully developed, this will be the time that developing countries will attempt to diversify their existing

energy resources to alternative products. The deficits in this observation from the presentation of graphs are the lack of alternative renewable resources.

Developing countries are heavily relying on traditional energy-producing products that are potentially hazardous to their environment. Fossil fuels are relatively cheaper than generating alternative renewable resources. Government officials of developing countries perceive alternative energy fuels that are not a practical solution to decrease carbon emissions. The main reason is due to the cost of each raw material, construction, and the maintenance of each facility. Most developing countries still prefer the cheapest form of energy resource to power and produce energy supply and concentrate on more serious political and economic issues (Pye and Bataille, 2016; Robalino-López et al., 2016; Rodríguez and Pena-Boquete, 2017; Raza et al., 2019; Rana et al., 2020).

Changes in the economic structure

Developing countries that already industrialized most of their neighborhoods and communities are now starting to consider the deep decarbonization process (Van Mathiesen, 2015). As some of the countries are already industrialized enough that they are now capable of developing a long-term solution to save the environment, there are numerous companies that are now willing to participate in decarbonizing the atmosphere using alternative energy sources. As there are more companies that are willing to participate in the introduction of new decarbonization facilities, it signifies that there is a promising change in the economic structure of a
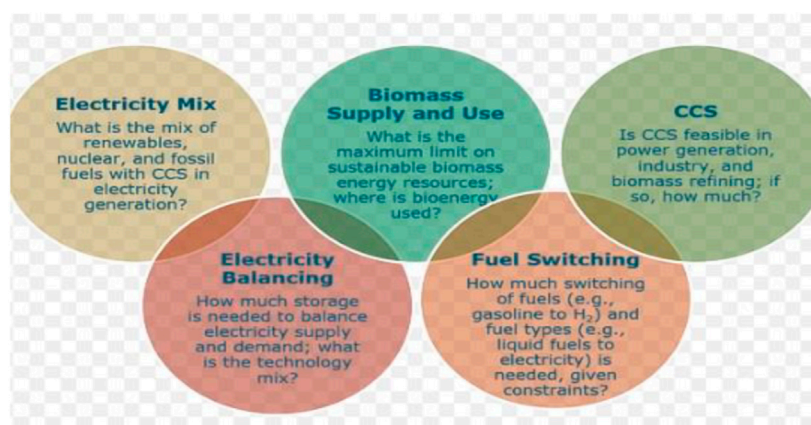
FIGURE 7
Decarbonizing solution applied for developing countries.

country (Gura et al., 2020; Moiseev et al., 2020; Varyash et al., 2020; Baboshkin et al., 2022).

Developing countries are now trying to conduct a feasibility study on several areas that have the potential to facilitate alternative energy resources. These are renewable energy sources that are capable of harnessing energy from different sources. Companies and local government units start to assess the terrain, environmental conditions, and population involved before installing new structures. The need to identify the most utilized energy-generating industries that can be replaced will be included with the assessment. These are traditional and cheap sources such as fossil fuels that can change the atmospheric condition of the community once it starts to install new facilities for development.

De facto sub-optimal energy supply

The introduction of CCS is essential for the community to start decreasing its carbon emissions. Developing countries that are now slowly becoming highly industrialized countries are starting to adapt this mechanism in order to save their environment and protect existing ecosystems. Using renewable resources is now resourcing to jobs that harness renewable energy, which allows more human resources to produce healthier energy. Increasing manpower resources prompts the production of new technological facilities to ensure that the environment will no longer suffer from the negative consequences of producing harmful carbon into the atmosphere.

Using a variety of alternative renewable energy resources is one of the best solutions to promote decarbonization in developing countries. Amaroli and Balzani (2016) mentioned that solar electricity provides a decarbonizing solution to improve energy-generating facilities to prevent environmental damages. Other decarbonizing solutions are installing hydropower plants, wind farm installations, tidal energy plants, and geothermal power plants, which are essential to stimulate alternative energy power. Developing countries are rich in natural resources, which are essential to produce energy rather than rely on fossil fuels that produce harmful chemicals that can potentially destroy the environment and natural habitats.

The results identify the factors responsible for causing several environmental hazards through the emission of carbon particles, enabling the development: high oil prices can stimulate investment and, consequently, job creation, which in general contributes to GDP growth.

Conclusion and recommendation

The result of this work can be considered a confirmation of the hypothesis of the sensitivity of macroeconomic indicators on the dynamics of oil prices. The world economy is currently diversified, so we can assume stable growth even in the period of shock prices for oil, which is confirmed by the statistics that were used in the model. By the way, the key question is whether the growth of investments in the oil industry will help cope with the negative consequences for the economy of higher oil prices. Under current conditions, higher, ever-predicted oil prices are not required for investment in shale oil production, given the speed with which shale can react to price changes compared to conventional oil production. High oil prices can stimulate investment and, consequently, job creation, which in general contributes to GDP growth.

The results of this work can be used by governments and private investors in the oil projects. This study helps decide the main real-world problem (climate change). The beneficiaries of this study are all population of the world.

It has been concluded that deep carbonization modeling in developing countries is not that prevalent due to their preference for using cheaper resources. Most developing countries are now

opting to utilize natural resources in order to produce alternative energy resources. Countries that have significantly large and vast potential resources have the ability to generate an alternative energy resource to keep up with the growing demand of the general population. The only problem with developing countries is the practicality of energy-generating resources. Public officials still prefer cheaper resources that generate energy from their lands. Developing countries are always relying on fossil fuels as a form of an important source of energy in order to generate a power source to their facilities. However, officials and operators are not aware of the degenerative effects that it can apply to the environment.

The recommendation on deep decarbonization modeling in developing countries is to increase awareness regarding the byproducts of fossil fuels and renewable energy resources. It is obvious that some developing countries are still recovering from a recent conflict that heavily impacted their political legitimacy and economic degeneration. As a result, companies are helping affected countries to improve their socio-economic regeneration in order to create a sustainable livelihood to improve the lifestyle and livelihood before starting to concentrate on rebuilding decarbonization. If a certain community has already built a sustainable infrastructure, this is the time to plan for an alternative resource production to sustain its environmental preservation. Briefings involved stakeholders regarding the integration of deep decarbonization, which eliminated doubts and personal uncertainties and prevented the formation of a negative impression toward the use of renewable energy resources.

The limitation of the study is concentrated on the deep decarbonization modeling in developing countries. This is at the level of utilizing deep decarbonization, which seeks to improve the environmental condition of the affected nations. The factors indicated for improving atmospheric and environmental issues can significantly predict the readiness of developing countries to improve the air quality of their community and society as a whole. With the application of decarbonization modeling in developing countries, the need to establish a new set of facilities is an important manifestation to ensure that there are new procedures that can improve the quality and structure of removing carbon from our environment.

Developing countries are still yet to concentrate on preserving the environment due to the imbalances that are confronted by its political and economic development. As a result, the country needs to stimulate further economic sustainability while public officials start concentrating on building new laws on environmental awareness. One example is to associate developing countries with the preservation of the environment and ecology through the application of climate change.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

Conceptualization, AN; writing—original draft preparation, AM; writing—review and editing, SMM, VY, ABM, IPP, SB, NF, GR, and KS.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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