Dynamic Efficiency Model on Oil and Gas Production in Ghana

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Contents

1 Overview and Motivation

Welcome to my Shiny app, the "Dynamic Efficiency Model on Oil and Gas Production in Ghana." This app leverages a multitude of data science techniques, including machine learning, sentiment analysis, natural language processing, and web scraping, to provide a real-time, comprehensive analysis of Ghana's oil and gas sector. The goal is to enhance information efficiency, market efficiency, and resource management efficiency, making it a valuable tool for practitioners, academics, and policymakers alike.

2 Dashboard Tab

The Dashboard tab serves as the summary of the most critical visualizations from all the other tabs. It's designed to give a quick overview, helping you grasp the essential insights without delving into each tab individually. Whether you're a policymaker, industry practitioner, or academic, the Dashboard ensures you have the most relevant data at your fingertips.

3 Sentiment Analysis Tab

3.1 Description

The Sentiment Analysis tool is one of my favorite features. It allows users to search any topic and find a sentiment summary. This tool is pivotal in creating a real-time geopolitical risk metric. By analyzing sentiments from news sources worldwide, we gauge the political stability of key oil-producing countries, which in turn influences global oil prices.

3.2 Significance

In energy economics, understanding sentiment is vital because political stability directly impacts oil supply and prices. Positive sentiments around Saudi Arabia's political situation, for instance, could indicate lower risk and stable oil prices, whereas negative sentiments could signify potential disruptions and price volatility.

3.3 Methodologies

To perform sentiment analysis, I used the syuzhet library for sentiment scoring and the httr and jsonlite libraries to fetch news data via API. The API key is used to access the NewsAPI, and the sentiment of news articles is analyzed to provide an overall score. Here's the formula used for sentiment analysis:

$$\text{Sentiment Score} = \sum(\text{positive} - \text{negative})$$

4 Machine Learning Oil Exploration – Beta Tab

4.1 Description

This ambitious tool applies machine learning to geospatial data to predict the probability of finding oil worldwide. Although it's still in beta due to geospatial data constraints, the potential is immense.

4.2 Significance

By training machine learning models on existing geological and geophysical data, we can enhance oil exploration efficiency and reduce costs, exemplifying the application of technology in improving resource management efficiency—a core concept in energy economics.

4.3 Methodologies

The model intended to utilize ML algorithms. The data frame includes features such as latitude, longitude, depth, temperature, pressure, salinity, and sediment type. The probability of oil discovery is color-coded and visualized using the leaflet library. The probability formula used is:

$$P(\text{oil discovery}) = \frac{\sum(\text{relevant instances})}{\sum(\text{all instances})}$$

5 Production and Reserves Estimates Tab

5.1 Description

This tab provides reserve audit data and average production data for oil and gas in Ghana and globally. It also includes estimates of oil field sizes, coordinates, and production data, visualizing key players, oil fields, and market shares.

5.2 Significance

Understanding production and reserves is fundamental in energy economics. It helps in calculating the remaining life of reserves and planning future exploration activities. The visualizations in this tab make it easier to comprehend Ghana's position in the global oil market.

5.3 Methodologies

I utilized data from sources like EIA Worldometer and OEC, visualized using the ggplot2 and plotly libraries for interactive graphs, and the leaflet library for mapping oil fields.

6 Supply Tab

6.1 Description

This tab features a basic supply model tool, with results indicating the elasticity of supply for Ghana's oil production. The champion model, Random Forest, revealed a price elasticity of supply at 1.01.

6.2 Significance

In energy economics, the elasticity of supply measures how responsive the quantity supplied is to a change in price. An elasticity greater than 1 indicates high responsiveness, which is crucial for understanding market dynamics and planning production strategies.

6.3 Methodologies

The supply model was built using reactive programming with the shiny library, applying the Random Forest algorithm from the randomForest library. The supply data is visualized using ggplot2. The formula for price elasticity of supply is:

$$\text{Price Elasticity of Supply} = \frac{\%\Delta\text{Quantity Supplied}}{\%\Delta\text{Price}}$$

7 Demand Tab

7.1 Description

Similarly, the Demand tab showcases a basic demand model tool, illustrating elasticity of demand based on global consumption data from the US federal report (-0.10).

7.2 Significance

Understanding demand elasticity is equally important in energy economics as it helps in predicting how changes in price influence consumption patterns.

7.3 Methodologies

The demand model is reactive, utilizing the shiny library and ggplot2 for visualizations. The model calculates projected demand based on GDP growth, population growth, and efficiency improvements. The formula for price elasticity of demand is:

$$\text{Price Elasticity of Demand} = \frac{\%\Delta\text{Quantity Demanded}}{\%\Delta\text{Price}}$$

8 Market Price Tab

8.1 Description

This tab integrates real-time data from Yahoo Finance to plot price summaries of oil and gas. It also scrapes implied volatility data from CME via barchart.com and computes historical volatilities in real-time.

8.2 Significance

Volatility indicates the degree of variation in trading prices over time. High volatility suggests significant price fluctuations, impacting investment and production decisions.

8.3 Methodologies

Data retrieval is done using the quantmod library. Historical volatility calculations and real-time data visualization are implemented with ggplot2 and plotly. The formula for historical volatility is:

$$\sigma = \frac{1}{N-1}\sum_{i=1}^{N}(r_i - \bar{r})^2$$

where r_i is the return at time i and $\bar{r}$ is the average return.

9 Risk Tab

9.1 Description

Here, I present a unique geopolitical risk framework developed using sentiment analysis. By analyzing sentiments around the political situations of major oil-exporting countries, we assess the risk of volatile global oil prices. This tab also evaluates the economic conditions of Ghana's main export destinations to gauge the impact on Ghana's oil demand.

9.2 Significance

Geopolitical stability directly affects supply security and price stability. This framework provides a real-time, data-driven approach to evaluating geopolitical risks.

9.3 Methodologies

Sentiment analysis uses the syuzhet library, while data visualization is achieved through leaflet for interactive maps. The risk assessment integrates real-time sentiment scores to compute risk levels. The risk score formula is:

$$\text{Risk Score} = \frac{\text{Negative Sentiment}}{\text{Positive Sentiment} + \text{Negative Sentiment}}$$

10 Derivatives Tab

10.1 Description

This tab offers tools for pricing oil and gas derivatives using Monte Carlo simulations, binomial models, and Black-Scholes formulas. It provides real-time implied volatility and commodity prices.

10.2 Significance

Derivatives are financial instruments whose value depends on the underlying asset—in this case, oil and gas. By enabling dynamic pricing, this tool enhances market efficiency, allowing for better risk management and investment strategies.

10.3 Methodologies

Monte Carlo simulations and binomial models are implemented using R's statistical functions, while Black-Scholes pricing is calculated using specific financial formulas. Visualizations are created with ggplot2. The Black-Scholes formula for call and put options are:

$$C = S_0 N(d_1) - K e^{-rT} N(d_2)$$

$$P = K e^{-rT} N(-d_2) - S_0 N(-d_1)$$

where

$$d_1 = \frac{\ln(S_0/K) + (r + \sigma^2/2)T}{\sigma\sqrt{T}}$$

$$d_2 = d_1 - \sigma\sqrt{T}$$

11 Carbon Pricing Tab

11.1 Description

Designed for producers, investors, and policymakers, this tool estimates potential carbon costs. By inputting various parameters, users can project carbon costs, facilitating carbon abatement strategies.

11.2 Significance

Carbon pricing assigns a cost to carbon emissions, promoting reduced greenhouse gas emissions. This tool aids in planning effective carbon reduction measures.

11.3 Methodologies

The model calculates carbon costs using user inputs for price, emissions, growth rate, and policy duration. Data is visualized using ggplot2. The formula for calculating carbon costs is:

$$\text{Carbon Cost} = \text{Annual Emissions} \times \text{Carbon Price}$$

12 Sustainability Tab

12.1 Description

The Sustainability tab is dedicated to presenting a comprehensive Environmental, Social, and Governance (ESG) overview of the oil and gas industry in Ghana. This includes real-time carbon dioxide (CO2) emission estimates based on oil and gas production, market concentration metrics of foreign firms, and highlighting the local content and financial sustainability for Ghanaians.

12.2 Significance

Sustainability in energy economics is critical as it ensures that the extraction and use of resources do not compromise the environment, social equity, or economic viability for future generations. This tab helps in understanding the carbon footprint and sustainability practices within the industry, promoting transparency and encouraging better practices among producers.

12.3 Methodologies

CO2 emissions are calculated using data on oil and gas production. The formula used to estimate CO2 emissions is:

$$\text{CO2 Emissions} = \text{Production} \times \text{Emission Factor}$$

where the emission factor varies for oil and gas. The app uses emission factors specific to oil and gas:

- For oil: 405 kg CO2 per barrel of oil equivalent (boe)
- For gas: 600 kg CO2 per million cubic feet (mcf)

Data visualization is implemented using plotly and ggplot2. For example, the calculation of total annual CO2 emissions from oil production is:

$$\text{Total Annual CO2 Emissions} = \text{Daily Production} \times 365 \times 405$$

ESG scores are represented using value boxes, while CO2 emissions from oil fields and producers are tabulated for clarity. The market concentration metrics are visualized using pie charts to depict the distribution between local and foreign entities. The Herfindahl-Hirschman Index (HHI) is calculated to assess market concentration:

$$HHI = \sum_{i=1}^{N} s_i^2$$

where s_i is the market share of firm i.

13 Static Efficiency Model Tab

13.1 Description

The Static Efficiency Model tab offers a detailed view of how market structures impact production, pricing, and social welfare over time under static conditions. It incorporates parameters such as initial reserves, demand intercept, demand slope, interest rate, and marginal cost to calculate these economic indicators.

13.2 Significance

Static efficiency is fundamental in understanding how resources can be allocated optimally to maximize welfare without considering future time periods. This model helps in assessing the immediate impacts of different market structures (e.g., perfect competition vs. monopoly) on production efficiency, consumer surplus, producer surplus, and overall social welfare.

13.3 Methodologies

The model uses fundamental economic concepts and formulas to calculate various outputs:

1. Quantity and Price Calculation:
   - For competition: $Q = \frac{(P-MC)}{|\text{demand\_slope}|}$
   - For monopoly: $Q = \frac{(P-MC)}{|\text{demand\_slope}|} \times 0.75$
2. Consumer Surplus (CS): $CS = \frac{P \times Q}{2}$
3. Producer Surplus (PS): $PS = (P - MC) \times Q$
4. Social Welfare (SW): $SW = CS + PS$

The data is visualized using plotly to show the trends over the selected number of years.

14 Dynamic Efficiency Model Tab

14.1 Description

The Dynamic Efficiency Model tab extends the analysis from the static efficiency model by incorporating time, allowing us to observe how resource extraction, pricing, and economic indicators evolve over multiple years. This model takes into account future growth rates, backstop prices, and the depletion of reserves to provide a more holistic view of the resource's lifecycle.

14.2 Significance

Dynamic efficiency is crucial for long-term resource management and policy-making in the energy sector. It considers how decisions made today impact future availability and economic outcomes, promoting sustainability and optimal resource use over time. By accounting for the depletion of resources and changes in demand over time, this model helps in formulating strategies that ensure the efficient use of resources while maximizing economic welfare.

14.3 Methodologies

The dynamic model calculates various economic indicators over multiple years, considering growth rates and depletion of resources:

1. Quantity and Price Calculation:
   - For competition: $Q_t = \frac{(P_t - MC)}{2 \times |\text{demand\_slope}|}$
   - For monopoly: $Q_t = \frac{(P_t - MC)}{2 \times |\text{demand\_slope}|} \times 0.75$
2. Consumer Surplus (CS): $CS_t = \frac{P_t \times Q_t}{2}$
3. Producer Surplus (PS): $PS_t = (P_t - MC) \times Q_t$
4. Social Welfare (SW): $SW_t = CS_t + PS_t$
5. Depletion and Growth:
   - Future quantity and price adjustments are made considering growth rates and depletion: $Q_{t+1} = Q_t \times (1 + \text{growth\_rate})^t$
   - $P_{t+1} = \text{demand\_intercept} + \text{demand\_slope} \times Q_{t+1}$
   - Backstop technology price: $P_{t+1} = \min(P_{t+1}, \text{backstop\_price})$

The results are plotted using plotly to visualize how these economic indicators evolve over time under different market structures and conditions.

15 Chatbot Tab

15.1 Description

The Chatbot tab integrates a conversational AI feature within the app, allowing users to interact with the application through natural language queries. This feature uses a chatbot to provide insights, answer questions about the data, and help users navigate the various functionalities of the app.

15.2 Significance

The integration of a chatbot enhances user experience by making the app more interactive and accessible. Users can ask questions in plain language and receive immediate responses, which can be particularly useful for those who may not be familiar with navigating complex data visualizations or technical terminologies.

15.3 Methodologies

The chatbot functionality is implemented using natural language processing (NLP) techniques. Key components include:

1. User Input Handling:
   - Captures user queries and processes them to understand the intent.
2. NLP Processing:
   - Utilizes libraries such as syuzhet for sentiment analysis and other NLP techniques to interpret user queries.
3. Response Generation:
   - Generates appropriate responses based on the interpreted intent, querying the underlying data and models as needed.
4. Interactive Features:
   - The chatbot can guide users to specific tabs, explain data visualizations, and provide real-time updates on economic indicators.

For instance, if a user asks about the current CO2 emissions, the chatbot processes this request and retrieves the latest CO2 emissions data from the Sustainability tab. It then constructs a response that provides the user with the requested information in a clear and concise manner.

16 Conclusion

Integrating these functionalities into the app ensures that it not only provides a comprehensive analysis of the oil and gas industry in Ghana but also makes this analysis accessible and user-friendly. By leveraging advanced data visualization techniques, economic modeling, and conversational AI, the app serves as a powerful tool for policymakers, industry stakeholders, and the general public to understand and engage with the energy sector's economic dynamics.

Through the use of well-established economic formulas and concepts, such as consumer surplus, producer surplus, and social welfare, the app provides a robust framework for evaluating the efficiency and sustainability of resource extraction and usage. Additionally, the incorporation of dynamic efficiency modeling underscores the importance of considering long-term impacts and resource depletion in decision-making processes.

Overall, this app represents a significant step forward in harnessing the power of data science and economic theory to promote better resource management and sustainability practices in the energy sector.