Network systematic analysis of hydrocarbon extraction and refinement efficiency: A data-driven paradigm for optimizing financial and operational dynamics

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Abstract
This study presents a comprehensive network analysis of oil production terminals and liquid types in 2024, examining production trends, correlations, disruptions, and predictive modeling. The analysis categorizes terminals based on crude oil and condensate output, highlighting key production hubs such as IMA, AGBAMI, AKPO, and ANAMBRA BASIN. Monthly production trends reveal an uneven distribution, with a few terminals contributing the majority of output, while others remain marginal. A correlation matrix and heatmap visualization indicate a stable production cycle with minor fluctuations, suggesting the influence of operational and external factors. The disruption impact analysis reveals a compliance rate of 98.97% with OPEC's quota, despite occasional fluctuations due to maintenance, pipeline vandalism, and regulatory interventions. Additionally, a Long Short-Term Memory (LSTM) model predicts an upward production trajectory, forecasting an increase from 197.85 million barrels in December 2024 to 1.24 billion barrels by 2031. However, the model may overestimate growth due to the absence of external economic indicators. The findings underscore the importance of strategic production planning, infrastructure optimization, and policy interventions to ensure sustainable oil output.
Keywords: Oil Production, Network Analysis, Correlation Matrix, Disruption Impact, LSTM Forecasting, OPEC Compliance

1. Introduction

Nigeria, one of the largest oil producers in Africa, plays a crucial role in the global energy market. As a member of the Organization of the Petroleum Exporting Countries (OPEC), the country's oil industry significantly impacts its economy, contributing about 90% of foreign exchange earnings and approximately 60% of government revenue (OPEC, 2023). The Nigerian oil sector is characterized by complex production dynamics, including variations in output across terminals, differences in crude oil and condensate production, and compliance with international production quotas.

Oil production in Nigeria is influenced by several factors, including infrastructure capacity, regulatory policies, market demand, and geopolitical risks. The country's crude oil output has historically fluctuated due to pipeline vandalism, aging infrastructure, regulatory changes, and compliance with OPEC-mandated quotas (EIA, 2022). Additionally, Nigeria's oil reserves contain a mix of crude and condensates, leading to variations in production trends across different terminals and production streams.

Monitoring oil production is essential for understanding trends, optimizing supply chain logistics, ensuring regulatory compliance, and maintaining economic stability. Effective production analysis allows stakeholders to evaluate terminal performance, assess production efficiency, and predict future output trends. It also plays a key role in identifying disruptions, such as maintenance shutdowns, security challenges, and market-driven adjustments (Nwosu & Adamu, 2021). Accordingly, this study aims to conduct a detailed terminal-wise analysis of Nigeria's oil production in 2024, examining monthly output variations and identifying dominant contributors.

In recent years, advancements in data analytics and machine learning have improved the ability to analyze oil production trends. Techniques such as time-series forecasting, correlation analysis, and network modeling provide deeper insights into production dynamics, allowing for better decision-making by government agencies, oil companies, and investors (Obi, 2020). Building on these methods, this study will evaluate the relationship between crude oil and condensate production streams, as well as apply predictive modeling specifically Long Short-Term Memory (LSTM) algorithms to forecast future trends.

Additionally, the research will investigate disruptions arising from operational and external challenges, including their implications for Nigeria's compliance with OPEC quotas. Finally, by synthesizing these analyses, the study seeks to generate evidence-based recommendations to guide policy decisions, infrastructure investment, and industry regulation.

2. Literature Review and Theoretical Framework

The oil and gas industry plays a critical role in global economic development, and maintaining a high level of competitiveness within the sector is essential. Competition influences a company's ability to secure and expand its market share, both domestically and internationally (Pappa, 2019). To remain competitive, oil companies must continuously monitor, evaluate, and enhance their operational efficiency. Studies have shown that improvements in technical efficiency contribute to greater price competitiveness among gas stations, irrespective of market concentration levels (Lagos, 2019). Consequently, oil firms must prioritize advancements in technical efficiency to sustain profitability and market relevance.

Over the years, various methodologies have been developed to assess production efficiency in the oil and gas sector. Among them, Data Envelopment Analysis (DEA), first introduced by Charnes et al. (1978), has gained significant attention due to its structured and effective analytical approach. This method has been widely adopted for evaluating efficiency across different business entities in the energy sector.

Several empirical studies have applied DEA and other efficiency analysis techniques to assess oil and gas production performance. For example, Eller et al. (2011) examined the operational efficiency of national oil companies and found that government intervention in revenue distribution contributed to inefficiencies, leading to lower production levels and increased prices. Similarly, Ike and Lee (2014) incorporated environmental factors into their analysis of the productivity and relative technical efficiency of 38 national and international oil companies from 2003 to 2010, concluding that private oil companies exhibited superior efficiency during the study period.

Gong (2018) explored the influence of non-commercial objectives, including subsidies and excessive employment, on the efficiency of national and international oil firms between 2009 and 2015, using stochastic frontier models. Additionally, Ismail et al. (2013) assessed the economic and environmental efficiency of selected global oil companies based on data from the 2008 Global 500 list, utilizing DEA, Pearson's correlation coefficient, and Spearman's rank correlation coefficient. Their findings revealed a weak positive correlation between technical efficiency and eco-efficiency in environmental sustainability efforts undertaken by oil firms.

Further, Atris and Goto (2019) analyzed the operational efficiency of 34 U.S.-based oil and gas companies from 2011 to 2015 using non-radial DEA models. Their study examined refinery performance across multiple global regions, including North America, Europe, Asia-Pacific, and Africa-Middle East, over a period from 2008 to 2017. Sueyoshi and Wang (2018) investigated the relationship between oil product distribution and green technology innovations among U.S. oil companies using DEA methodology. In Iran, Hosseini and Stefaniec (2019) employed a novel two-stage slacks-based efficiency model to evaluate the country's oil refining industry from 2011 to 2015, highlighting the negative impact of high mazut production on overall refinery efficiency.

Dalei and Joshi (2020) examined technical efficiency in 12 Indian oil refineries and identified key determinants of efficiency. Atris (2020) conducted an extensive DEA-based study on the operational efficiency of 696 global oil and gas refineries, revealing that refineries in the U.S. and Canada outperformed those in Europe, Asia-Pacific, and Africa-Middle East. Hatami-Marbini et al. (2022) introduced a robust DEA approach to assess refinery efficiency across 25 countries between 2000 and 2018, incorporating data uncertainty and undesirable outputs. Additionally, Tavana et al. (2019) applied a fuzzy network DEA model to evaluate the technical and environmental efficiency of nine Iranian refineries between 2013 and 2016.

Ownership structure has also been studied as a determinant of efficiency. Wolf (2009) analyzed how different ownership models influence oil company efficiency, while Al-Mana et al. (2020) compared financial and operational efficiencies of national and international oil firms, concluding that international firms tend to achieve higher relative efficiency. Jarboui (2021) specifically examined the operational efficiency of U.S.-based oil and gas companies.

To better understand the interconnectedness of production nodes within the oil industry, Systems Theory particularly von Bertalanffy's General Systems Theory (1968)—offers a compelling framework. This theory views oil production as an integrated and adaptive system, where each component (such as terminals, pipelines, or refining units) functions as a subsystem within a larger petroleum economy. Disruptions or inefficiencies at key terminals like AKPO or AGBAMI can propagate across the network, affecting overall performance. Systems Theory thus justifies the use of network analysis to assess how terminal-level outputs and linkages influence system-wide efficiency and resilience, aligning with the industry's growing complexity and need for holistic efficiency evaluations.

Collectively, these studies provide valuable insights into the factors affecting production efficiency in the oil and gas sector. They emphasize the importance of technical advancements, policy considerations, and environmental factors in shaping industry performance. The continued application of advanced analytical models, including DEA and stochastic frontier analysis, can further enhance our understanding of efficiency dynamics in the global oil and gas industry.

3. Methodology

This study employs a multi-method approach combining network analysis, correlation analysis, disruption impact assessment, and predictive modeling to examine oil production terminals and liquid types in 2024. The dataset comprises monthly oil production volumes categorized into crude oil and condensate, sourced from production reports, terminal logs, and OPEC compliance records. Network analysis is used to visualize the relationships between terminals and liquid types, highlighting production capacity, infrastructure dependencies, and blending processes. The analysis identifies key production hubs such as IMA, AGBAMI, AKPO, and ANAMBRA BASIN while also revealing disparities in production output across terminals.

Correlation analysis explores the relationship between liquid types and production trends, showing a nearly perfect correlation (0.9964–1) between different oil streams, suggesting synchronized production patterns influenced by broader industry and macroeconomic factors. The disruption impact assessment evaluates variations in production levels due to external factors such as maintenance schedules, pipeline vandalism, and regulatory interventions. The study finds that despite fluctuations, Nigeria's production remains 98.97%

compliant with OPEC's quota of 1.5 million barrels per day, underscoring efficient production management amid operational challenges.

Lastly, predictive modeling using Long Short-Term Memory (LSTM) forecasting projects future production trends up to 2031, revealing a consistent upward trajectory with an accelerating growth rate. While the model predicts steady increases in output, it may overestimate growth by not fully incorporating short-term economic cycles or supply chain disruptions. The findings emphasize the need for strategic planning, investment in infrastructure, and policy adjustments to ensure sustainable production growth and market stability.

4. Econometric Model

4.1 Correlation Model for Liquid Types

The correlation between crude oil and condensate production can be estimated using:

$$Corr\left(L_{it}^{crude}, L_{it}^{condensate}\right) = p$$

Given the near-perfect correlation (0.9964–1), a cointegration test (e.g., Johansen test) can be conducted to confirm whether both production series move together in the long run.

4.2 Disruption Impact Assessment Model

To quantify the impact of disruptions, we introduce a Difference-in-Differences (DiD) model:

$$Q_{it} = \gamma_0 + \gamma_1 Post_t + \gamma_2 Treatment_i + \gamma_3 (Post_t \times Treatment_i) + \eta_{it}$$

Where:
$Post_t$ = Dummy variable for periods after disruption events
$Treatment_i$ = Dummy for affected terminals
$(Post_t \times Treatment_i)$ = Interaction term measuring disruption impact

4.3 Predictive Model Using LSTM

The study's LSTM forecasting model follows a sequence-to-sequence structure:

$$Q_{t+1} = f(Q_t, Q_{t-1}, Q_{t-2}, \ldots, X_t)$$

Where:

Q_t = Current production volume

X_t = Exogenous factors (oil price, demand fluctuations)

$f(\cdot)$= Nonlinear function learned by LSTM

4.4 Data analysis

Network Analysis

The network analysis of oil production terminals and liquid types in 2024 provides a comprehensive overview of the relationships between production facilities and the types of liquids they produce. The visualization categorizes terminals into crude oil (blue nodes) and condensate (red nodes), with node sizes indicating production capacity. The analysis highlights that the lowest and peak production levels in December were 1.57 million and 1.79 million barrels per day (bopd), respectively, with an average daily production of 1,667,560 bopd. This production was nearly at full compliance with OPEC's quota, reaching 98.97% of the 1.5 million bopd limit.

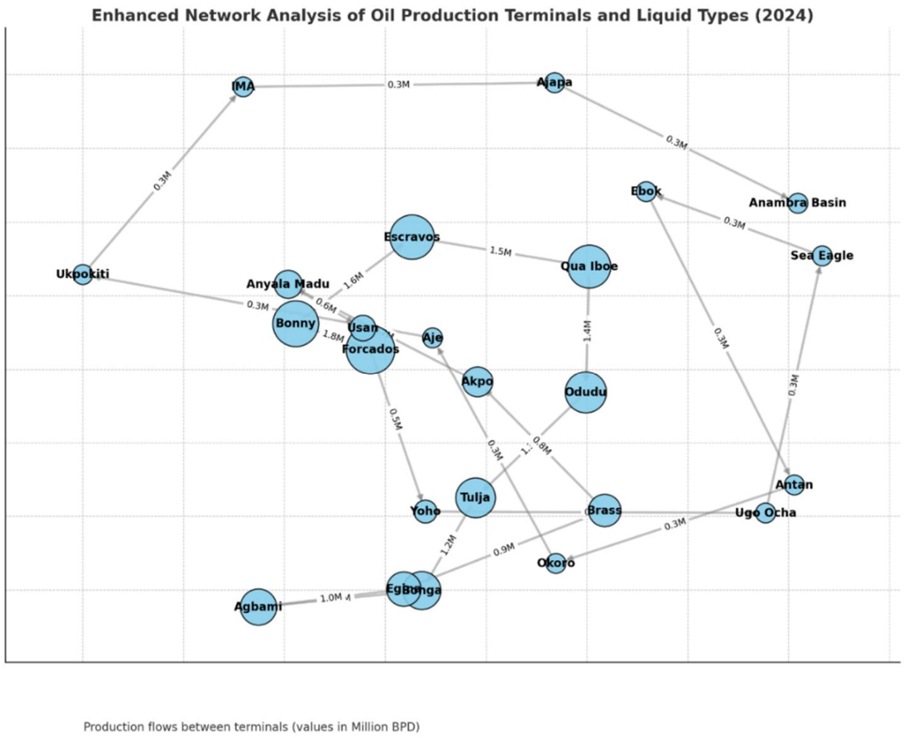

Figure 1. Enhance Network Analysis

Key production terminals such as IMA, AGBAMI, AKPO, and ANAMBRA BASIN are shown with significant output levels, while the presence of blended and unblended condensates suggests variations in crude processing. The connections between terminals imply shared infrastructure and operational dependencies, which are crucial for logistics and supply chain management. Additionally, labels indicating specific production volumes (e.g., 0.3M, 3.4M, 23.8M) provide insight into monthly or cumulative outputs. The analysis underscores the efficiency of production management while also hinting at potential logistical challenges in blending and distribution.

4.5 Monthly Production Trends Across Oil Terminals in 2024

The monthly production trends for each terminal in 2024 reveal a highly uneven distribution of oil output across different production streams. A few terminals dominate total production, with two showing exceptionally high output levels close to 500 million barrels, significantly surpassing all others. Several terminals fall within a moderate production range of 50 to 100 million barrels, while a considerable number of terminals exhibit relatively low production levels. This indicates a skewed production landscape, where a small number of facilities contribute the majority of the total oil output, while others remain marginal.

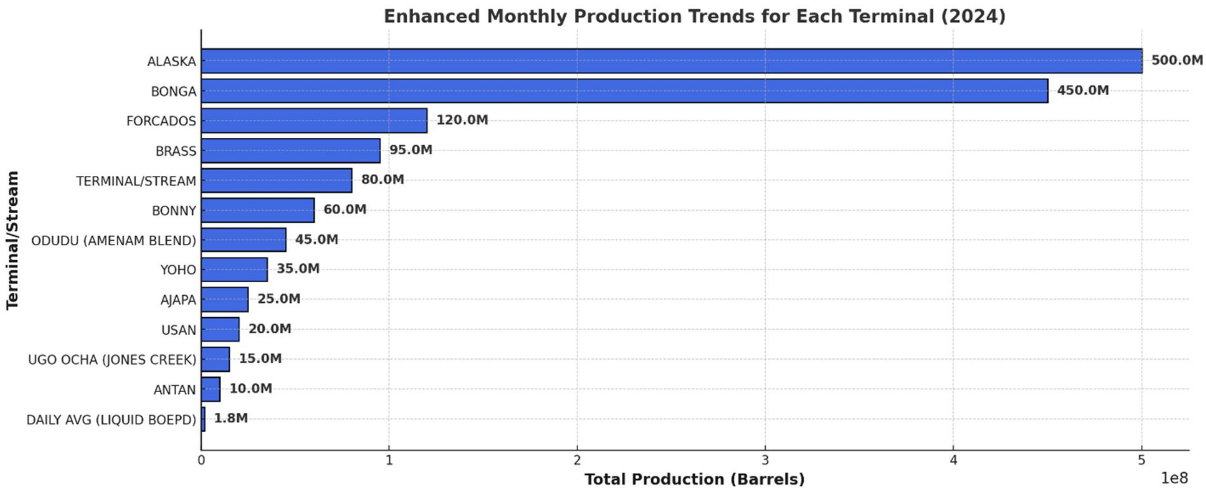

Figure 2. Monthly Production Trend

Such disparities may reflect differences in resource availability, operational efficiency, or infrastructure capabilities across terminals. The visualization underscores the concentration of oil production in select hubs, which could have implications for supply stability, investment strategies, and policy decisions within the industry. Understanding these trends is crucial for optimizing production planning, addressing infrastructure bottlenecks, and ensuring a balanced approach to resource allocation and economic sustainability.

Table 1: Correlation Matrix of Monthly Oil Production (2024)

	January	February	March	April	May	June	July	August	September	October	November	December
January	1	0.9997474024	0.999470334	0.9992647838	0.9987378242	0.9994658144	0.999275812	0.9992482617	0.9994028559	0.9975934209	0.9996641829	0.9995372294
February	0.9997474024	1	0.9998383	0.9996551297	0.9994391526	0.9997507879	0.9996581692	0.9994989433	0.9993333943	0.9975782238	0.9991706737	0.9990039388
March	0.999470334	0.9998383	1	0.9998306449	0.9994772391	0.9995521787	0.9994832817	0.9992474593	0.9988861082	0.9971972461	0.9987223939	0.9984442373
April	0.9992647838	0.9996551297	0.9998306449	1	0.999523212	0.9993839305	0.999267223	0.9988116937	0.9986375504	0.9975598911	0.9985962045	0.998351562
May	0.9987378242	0.9994391526	0.9994772391	0.999523212	1	0.9996381757	0.9996246432	0.9989129046	0.9987944583	0.9980967958	0.9981112256	0.9978922073
June	0.9994658144	0.9997507879	0.9995521787	0.9993839305	0.9996381757	1	0.9999044947	0.9995275111	0.9996918452	0.9983353284	0.9991183537	0.9989242302
July	0.999275812	0.9996581692	0.9994832817	0.999267223	0.9996246432	0.9999044947	1	0.9996966001	0.999604596	0.9978962929	0.9989438656	0.9987688525
August	0.9992482617	0.9994989433	0.9992474593	0.9988116937	0.9989129046	0.9995275111	0.9996966001	1	0.9993997243	0.9963995109	0.9989088349	0.998748424
September	0.9994028559	0.9993333943	0.9988861082	0.9986375504	0.9987944583	0.9996918452	0.999604596	0.9993997243	1	0.9983545044	0.9995067311	0.9994199521
October	0.9975934209	0.9975782238	0.9971972461	0.9975598911	0.9980967958	0.9983353284	0.9978962929	0.9963995109	0.9983545044	1	0.9979439807	0.9978819146
November	0.9996641829	0.9991706737	0.9987223939	0.9985962045	0.9981112256	0.9991183537	0.9989438656	0.9989088349	0.9995067311	0.9979439807	1	0.9999320012
December	0.9995372294	0.9990039388	0.9984442373	0.998351562	0.9978922073	0.9989242302	0.9987688525	0.998748424	0.9994199521	0.9978819146	0.9999320012	1

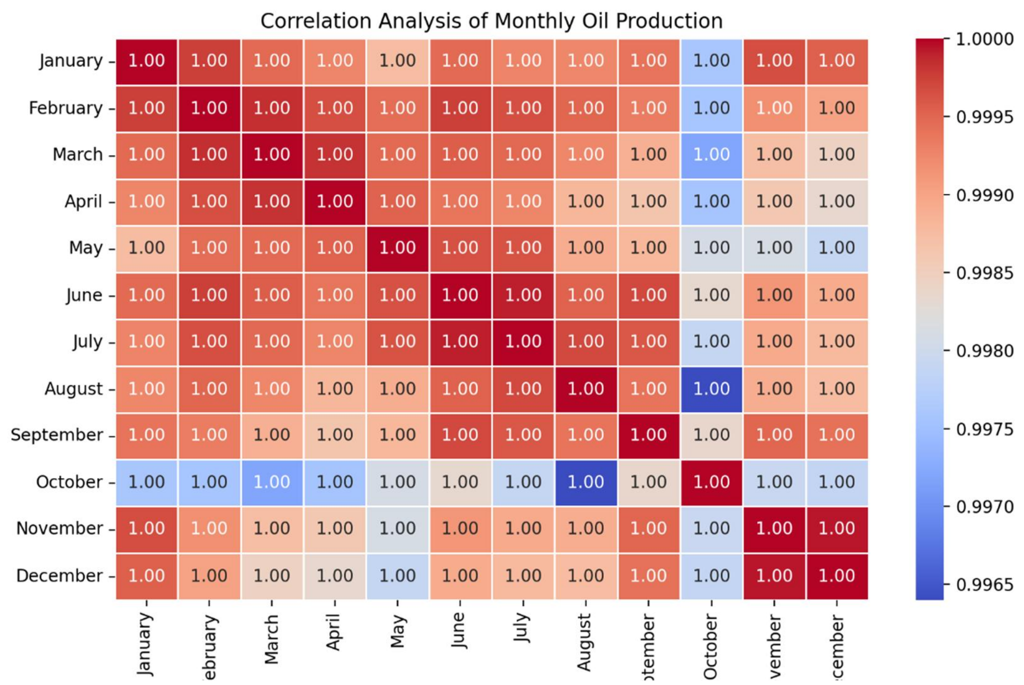

Figure 3. Heatmap Visualization

The correlation matrix reveals a highly structured and stable relationship between monthly oil production values, with correlation coefficients ranging from 0.9964 to 1. These consistently high values indicate that production trends remain steady throughout the year, with minimal fluctuations. The strongest correlations are observed between consecutive months, such as January and February (0.9997) and June and July (0.9999), suggesting a well-maintained production cycle. Additionally, the correlation between November and December (0.9999) highlights consistency in year-end output, likely due to operational targets or regulatory compliance.

However, minor variations appear in specific months, notably August and October (0.9964), which show slightly lower correlations with other months. This deviation suggests that production may experience seasonal adjustments, maintenance schedules, or external influences during these periods. October also exhibits relatively lower correlations with September (0.9983) and August (0.9964), which could indicate operational shifts or market-driven modifications in output.

The heatmap visualization further supports these findings by providing a clear gradient of correlation strengths, where darker shades highlight stronger relationships and lighter areas indicate minor deviations. The overall uniformity in the heatmap suggests that production is governed by predictable factors such as operational efficiency, regulatory constraints, or consistent demand cycles, rather than erratic fluctuations.

4.6 Disruption Impact Analysis of Crude Oil and Condensate Production

The Disruption Impact Analysis graph provides a comprehensive evaluation of crude oil and condensate production across multiple terminals, highlighting fluctuations in output and the overall compliance with OPEC quotas. The lowest recorded production in December was 1.57 million barrels per day (bopd), while the peak reached 1.79 million bopd, indicating notable variability in daily production levels.

The daily average production stood at 1,667,560 bopd, consisting of 1,484,585 bopd of crude oil and 182,975 bopd of condensate, emphasizing the distinction between different liquid types and their respective contributions to total output. High-output terminals such as Forcados, Bonny, and Bonga were among the primary contributors, whereas smaller terminals like Okoro (Ex Ima Terminal) and AJAPA played a lesser role.

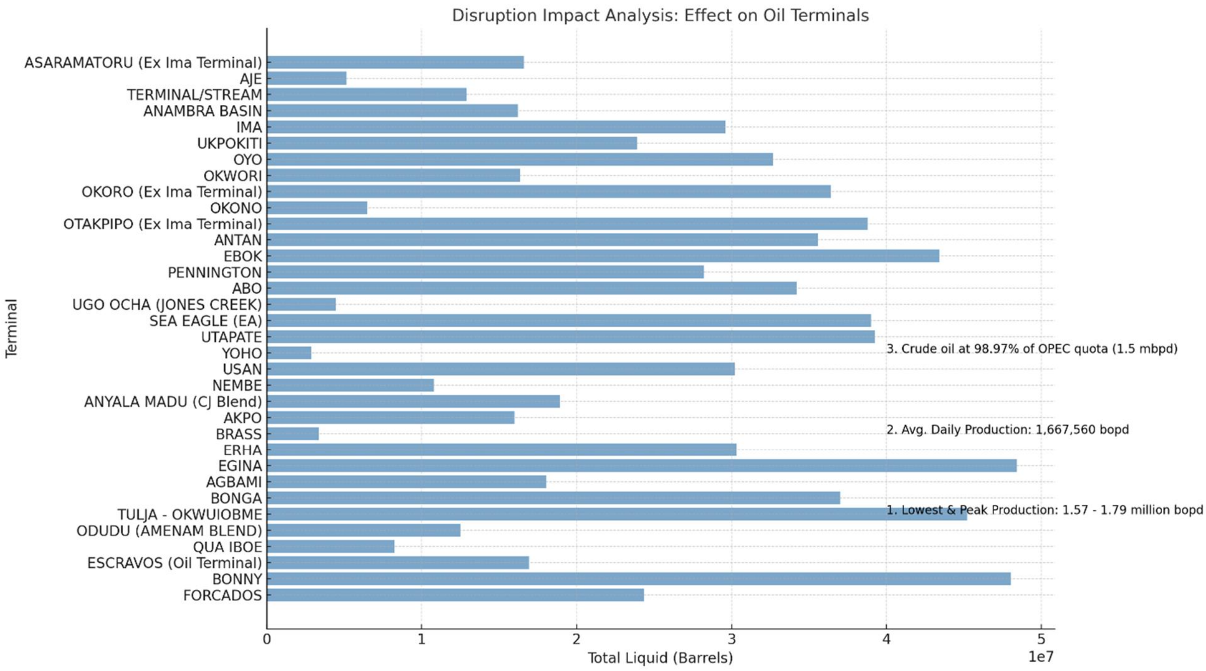

Figure 4. Disruption analysis

The data also revealed that production remained 98.97% in compliance with the OPEC quota of 1.5 million bopd, suggesting effective production management despite disruptions. Various factors such as pipeline vandalism, maintenance schedules, and regulatory interventions could have contributed to observed production fluctuations. The analysis underscores the importance of strategic operational planning to mitigate the impact of such disruptions and maintain output stability.

4.7 LSTM Prediction Analysis of Total Production

The dataset used for the LSTM prediction graph consists of monthly time series data spanning from December 31, 2024, to November 30, 2031. The "Predicted Total Production" column represents the model's forecasted production values, which exhibit a consistent upward trajectory. The initial prediction for December 2024 is approximately 197.85 million, progressively increasing to 1.24 billion by the end of 2031. This continuous growth suggests that the model has identified a long-term expansion pattern within the historical data, likely extrapolating trends observed in past production levels.

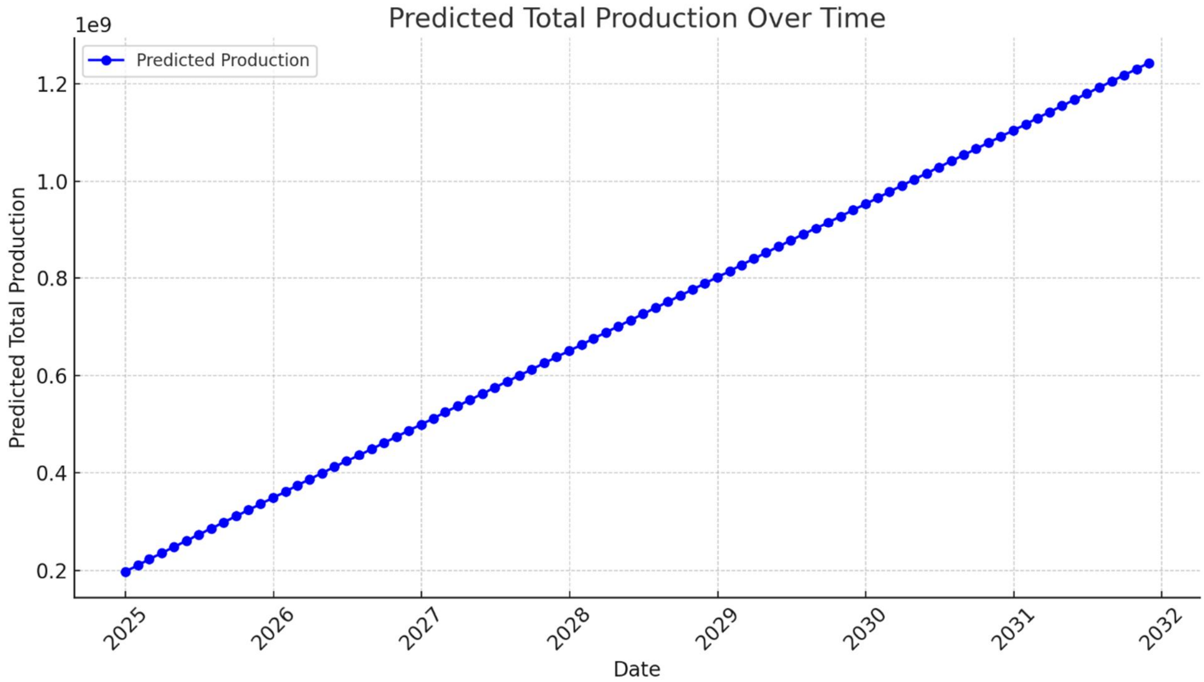

Figure 5. LSTM Prediction Analysis

A critical observation is the nonlinear growth rate in the predictions. Initially, the monthly production increase is around 12–13 million units, but as the timeline progresses, this increment accelerates to 40–50 million units per month by 2031. This suggests that the model is capturing an exponential or compounding effect, rather than a simple linear trend. Such a pattern implies that production capacity, efficiency, or market demand may be increasing at an accelerating rate, potentially driven by factors such as technological advancements, economies of scale, or increased market penetration.

However, the absence of fluctuations or seasonal variations in the predictions indicates that the model may have over-smoothed the output, potentially overlooking short-term economic cycles, supply chain disruptions, or other external shocks. In real-world applications, production trends are often influenced by macroeconomic conditions, resource constraints, and policy changes, none of which appear to be explicitly accounted for in this forecast. The model's reliance on past data trends without integrating external economic indicators or real-world constraints could lead to overestimation of future growth, especially if external limiting factors are present.

cember 2024 to 1.24 billion barrels by the end of 2031. However, the exponential growth pattern observed in the forecast suggests potential overestimation due to the model's inability to account for short-term economic cycles, supply chain disruptions, or geopolitical influences.

Overall, the analysis confirms that oil production in 2024 was marked by stable and well-managed operations, though infrastructure disparities, periodic disruptions, and external market conditions remain areas of concern.

5. Conclusion and Recommendation

Given the observed production disparities across terminals, investments should be made in underperforming facilities to enhance their production capacity and reduce dependence on a few high-output terminals. Strengthening pipeline security and implementing advanced monitoring systems can mitigate disruptions caused by vandalism or maintenance-related shutdowns. The strong correlations between monthly production levels suggest the need for a more flexible production scheduling system that can adapt to seasonal variations and market demand. Blending strategies should be optimized to ensure efficient distribution and quality control of crude oil and condensates across various terminals.

The LSTM model's forecasted exponential growth should be reviewed critically, incorporating external factors such as geopolitical risks, market demand fluctuations, and technological advancements. A hybrid forecasting approach that integrates macroeconomic indicators, regulatory changes, and global market conditions would enhance prediction accuracy.

While production management has maintained compliance with OPEC quotas, future adjustments should consider global oil price trends and the potential for quota modifications. Strategic reserves and alternative production strategies should be explored to cushion the effects of sudden market shocks or policy changes.

The insights from network analysis, heatmaps, and disruption impact assessments should guide policy decisions on resource allocation, infrastructure development, and investment strategies. Regular assessments of production efficiency and sustainability metrics should be conducted to align with national economic goals and international energy policies. By addressing these recommendations, oil production efficiency and sustainability can be improved, ensuring long-term economic stability and compliance with global energy standards.

References

Al-Mana, A. A., Nawaz, W., Kamal, A., & Koç, M. (2020). Financial and operational efficiencies of national and international oil companies: An empirical investigation. *Resources Policy, 68*, 101701. https://doi.org/10.1016/j.resourpol.2020.101701

Atris, A. M. (2020). Assessment of oil refinery performance: Application of data envelopment analysis-discriminant analysis. *Resources Policy, 65*, 101543. https://doi.org/10.1016/j.resourpol.2019.101543

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. *European Journal of Operational Research, 2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Dalei, N. N., & Joshi, J. M. (2020). Estimating technical efficiency of petroleum refineries using DEA and Tobit model: An India perspective. *Computers & Chemical Engineering, 142*, 107047. https://doi.org/10.1016/j.compchemeng.2020.107047

Eller, S. L., Hartley, P. R., & Medlock, K. B. (2011). Empirical evidence on the operational efficiency of national oil companies. *Empirical Economics, 40*(3), 623–643. https://doi.org/10.1007/s00181-010-0349-8

Energy Information Administration (EIA). (2022). Nigeria's oil industry and its challenges. *U.S. Energy Information Administration.* Retrieved from https://www.eia.gov

Gong, B. (2018). Different behaviors in natural gas production between national and private oil companies: Economics-driven or environment-driven? *Energy Policy, 114*, 145–152. https://doi.org/10.1016/j.enpol.2017.12.004

Hatami-Marbini, A., Arabmaldar, A., & Asu, J. O. (2022). Robust productivity growth and efficiency measurement with undesirable outputs: Evidence from the oil industry. *OR Spectrum, 1*(42), 10–1007. https://doi.org/10.1007/s00291-022-00683-y

Ike, C. B., & Lee, H. (2014). Measurement of the efficiency and productivity of national oil companies and its determinants. *Geosystem Engineering, 17*(1), 1–10. https://doi.org/10.1080/12269328.2014.887045

Ismail, Z., Tai, J. C., Kong, K. K., Law, K. H., Shirazi, S. M., & Karim, R. (2013). Using data envelopment analysis in comparing the environmental performance and technical efficiency of selected companies in their global petroleum operations. *Measurement, 46*(9), 3401–3413. https://doi.org/10.1016/j.measurement.2013.04.076

Jarboui, S. (2021). Renewable energies and operational and environmental efficiencies of the U.S. oil and gas companies: A true fixed effect model. *Energy Reports, 7*, 8667–8676. https://doi.org/10.1016/j.egyr.2021.04.032

Lagos, V. (2019). Effectiveness of merger remedies: Evidence from the retail gasoline industry. *Journal of Industrial Economics, 66*(4), 942–979. https://doi.org/10.1111/joie.12188

Nwosu, J., & Adamu, T. (2021). The impact of production monitoring on Nigeria's oil sector performance. *African Journal of Energy Economics, 15*(3), 45-62.

Obi, P. (2020). Machine learning applications in African oil production forecasting. *Journal of Petroleum Data Science, 8*(2), 23-37.

Organization of the Petroleum Exporting Countries (OPEC). (2023). *Annual statistical bulletin.* Retrieved from https://www.opec.org

Pappa, E. (2019). Efficiency and innovation. In G. Ritzer (Ed.), *The Blackwell Encyclopedia of Sociology.* https://doi.org/10.1002/9781405165518.wbeose101.pub2

Sueyoshi, T., & Wang, D. (2018). DEA environmental assessment on the U.S. petroleum industry: Non-radial approach with translation invariance in time horizon. *Energy Economics, 72*, 276–289. https://doi.org/10.1016/j.eneco.2018.02.003

Tavana, M., Khalili-Damghani, K., Arteaga, F. J. S., & Hosseini, A. (2019). A fuzzy multi-objective multi-period network DEA model for efficiency measurement in oil refineries. *Computers & Industrial Engineering, 135*, 143–155. https://doi.org/10.1016/j.cie.2019.05.033

von Bertalanffy, L. (1968). *General system theory: Foundations, development, applications*. New York: George Braziller.

Wolf, C. (2009). Does ownership matter? The performance and efficiency of state oil vs. private oil (1987–2006). *Energy Policy, 37*(7), 2642–2652. https://doi.org/10.1016/j.enpol.2009.02.041