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Forecasting the energy production in Egypt using the models: ARIMA, ARIMAX and SARIMAX

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Abstract

This paper investigates the forecasting of electricity production in Egypt, specifically the percentage derived from natural gas, using ARIMA, SARIMA, and SARIMAX time series models. Employing an automatic parameter selection process based on AIC and Log-Likelihood, we found that the SARIMAX model, incorporating energy use and agricultural value added as exogenous regressors, exhibited superior forecasting performance compared to ARIMA and SARIMA. Results indicate that while SARIMA effectively captures seasonal patterns, SARIMAX further enhances accuracy by integrating external economic drivers. Parameter estimation revealed statistically significant positive impacts of energy use and agricultural value added on electricity production within the SARIMAX framework. These findings underscore the importance of considering both temporal dynamics and exogenous economic factors for accurate energy forecasting in Egypt. The study concludes with policy recommendations emphasizing energy diversification, demand-side management, and integrated energy-economic planning to enhance the sustainability and security of Egypt's electricity sector.

Keywords: Energy Production, Forecasting, Time Series, Egypt, SARIMAX, ARIMA, Economic Factors.

INTRODUCTION

Considering the Egypt's fast industrialization, population growth, and sensitivity to climate change, accurate energy output forecasting is vital to its economic stability and long-term development. While autoregressive integrated moving average (ARIMA) models are commonly used to estimate energy consumption (Sen et al., 2016), their effectiveness in predicting energy production, particularly in areas with unique climatic and socioeconomic variables, has received less attention. This gap limits Egypt's ability to improve grid resilience, incorporate variable renewable sources, and address supply-demand imbalances (Barak & Sadegh, 2016).

Existing research significantly focuses on consumption patterns in high-income regions (Yeboah et al., 2012), while ignoring production dynamics in developing economies and arid climates, where exogenous factors (e.g., solar irradiance, GDP fluctuations) and seasonal cycles have a disproportionate impact on outcomes.

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We can denote three research obstacles: First, geographical perception supports Europe, Asia, and North America (Albayrak, 2010; Ediger & Akar, 2007), ignoring Africa's unique energy systems. Second, classic ARIMA models have difficulties with non-stationary data and nonlinear interactions, whereas hybrid techniques (e.g., ARIMA-ANN) lack validation in the Egyptian setting (Chou & Tran, 2018). Third, few studies have systematically examined how exogenous factors and seasonal adjustments improve forecasting accuracy in resource-constrained environments.

This study tackles the following research question: Can ARIMAX and SARIMAX models beat standard ARIMA in forecasting Egypt's energy production, and what factors influence their performance?

Using a quantitative framework, we analyzed historical production data (2010-2023) and exogenous factors (GDP, temperature) to establish ARIMA (baseline), ARIMAX (with exogenous predictors), and SARIMAX (with seasonal components) models. The model's performance is validated using log likelihood. Using a quantitative framework, we examined historical production data (2010–2023) and exogenous variables (GDP, temperature) to create ARIMA (baseline), ARIMAX (with exogenous predictors), and SARIMAX (with seasonal components) models. Performance of the model is validated using log likelihood, AIC and BIC metrics, with an 80:20 training-testing split.

Key terms are defined as follows: ARIMA incorporates autoregressive (AR) and moving average (MA) components for stationary data; ARIMAX includes exogenous variables; SARIMAX introduces seasonal differencing. This research offers three novel insights: (1) context-specific benchmarking of ARIMA variants for Egypt, (2) identification of key drivers (e. g. , seasonal demand, weather anomalies) for policy planning, and (3) methodological validation of exogenous variable integration in arid, developing regions— a framework relevant to similar economies.

The paper is organized as follows: Section 2 reviews literature on energy forecasting; Section 3 outlines the methodology; Section 4 presents the empirical research results; Section 5 discusses implications and concludes with policy recommendations. By connecting theoretical and applied perspectives, this study enhances tools for improving Egypt's energy security amid rising demand and sustainability challenges.

LITERATURE REVIEW:

Energy forecasting holds significant importance in today's world, propelled by rising energy demand, worries over energy security, and the pressing need for sustainable energy management. Precise energy forecasts are essential for policymakers, energy providers, and consumers alike, facilitating informed decisions regarding energy production, infrastructure development, and environmental policy. The necessity for dependable energy forecasting is further highlighted by the increasing urgency to tackle climate change and shift to cleaner energy sources.

The academic literature illustrates this urgency, with a considerable amount of research focused on creating and enhancing energy forecasting methodologies. An examination of recent studies shows a strong interest in data-driven methods, especially those that employ time series analysis and machine learning techniques. Within time series analysis, Autoregressive Integrated Moving Average (ARIMA) models and their variations have risen as a primary tool for energy forecasting across various contexts. For example, Abdel-Aal and Al-Garni (1997) showcased the effectiveness of univariate Box-Jenkins ARIMA models for predicting monthly domestic electricity consumption in Eastern Saudi Arabia, emphasizing their simplicity and precision compared to regression and AIM models.

Likewise, Albayrak (2010) applied ARIMA models to project primary energy production and consumption in Turkey from 1923-2006, concluding that they serve as a viable substitute for more intricate econometric models. Ediger and Akar (2007) also concentrated on Turkey, utilizing ARIMA techniques to anticipate primary energy demand based on fuel type, highlighting the model's usefulness for policy planning in emerging markets. Ozturk and Ozturk (2018) further validated the significance of ARIMA models for Turkey, forecasting energy consumption trends up to 2040 and stressing the need for varied energy strategies. These studies together underline the strength and applicability of ARIMA models for energy forecasting, particularly in capturing temporal dependencies within energy data.

In addition to traditional statistical approaches, machine learning techniques, particularly Artificial Neural Networks (ANNs) and their advanced structures, are becoming increasingly important in energy forecasting. Lu et al. (2021), in their extensive review of building energy prediction utilizing ANNs, recognized a growing trend in the use of ANNs, especially Recurrent Neural Networks (RNNs) like LSTM and CNN-RNN, for building energy prediction. Their bibliometric analysis of 324 publications highlighted the ability of ANNs to manage complex patterns in building energy data, providing a comprehensive overview of ANN architectures and their applications.

Amalou and others. (2022) Demonstrating better performance than simple RNN and LSTM models, RNN architectures—especially Gated Recurrent Units (GRUs)—further supported the efficacy of multivariate time series forecasting of energy use in intelligent grids. These findings suggest that in certain cases, machine learning techniques offer outstanding tools for capturing complex relationships within energy data and non-linearities, perhaps surpassing traditional linear models.

Researchers are now more closely looking at hybrid approaches that combine the benefits of machine learning and statistical methods. By merging ANFIS's nonlinear pattern recognition abilities with Arima's linear modeling strengths, Barak and Sadegh (2016) presented a hybrid ensemble ARIMA-ANFIS model for forecasting annual energy demand in Iran. Their approach effectively addressed data paucity concerns. Their results suggested that hybrid models, especially those incorporating data augmentation techniques including AdaBoost, may increase prediction accuracy particularly in data-limited situations. In their analysis of different machine learning techniques for forecasting residential energy use, Chou and Tran (2018) also discovered that hybrid models including SARIMA-MetaFA-LSSVR generally outperformed ensemble and single models, therefore highlighting the benefits of incorporating several forecasting methods.

Although ARIMA models and their hybrid forms offer significant promise, the literature reviewed point to some constraints and directions for further study. Yeboah at al. Mac...ubits (2012) literature review on ARIMA models for aggregated and disaggregated energy use stressed the need of further study on predicting energy demand in economies vulnerable to power outages and relying on outside energy sources. Sun et all &'s (2020) analysis of data-driven approaches for developing energy prediction emphasized the need of addressing data scarcity and using strong input updating techniques for multi-step forecasts.

Furthermore, Fara and others. In their examination of photovoltaic energy forecasting, an analysis from 2021 noted that although under some conditions ARIMA models can be effective, hybrid approaches and physical/satellite models could be indispensable for situations with increased forecast variability. Given sector-specific energy use trends and their link to greenhouse gas emissions, Doroodi and Mokhtar&'s evaluation of time series techniques for energy consumption forecasting in Iran highlighted the need of recognizing them for successful mitigation plans. Dritsaki et al, The results of HBC (2021) show the effects of economic downturns and policy changes on energy use patterns, hence highlighting the need for models able of adjusting to these external shocks and policy changes.

Ultimately, the body of work on data-driven energy prediction shows a dynamic field with great development in both statistical and machine learning techniques. ARIMA models and their hybrids offer powerful, flexible devices for catching time dynamics and improving forecast accuracy. Persistent study is needed to address the difficulties of data scarcity, model complexity, non-linear trends, and incorporation of outside influences such as economic disturbances and policy changes into energy forecasting models. Future research should focus on developing more robust hybrid models, explore sophisticated deep learning architectures, and include real-time data and external factors to increase the accuracy and reliance of energy predictions for effective energy planning and sustainable development.

METHODS:

1. Introduction to the Methodology

Accurate prediction of energy output is very important for developing policies and planning infrastructure. This research utilizes three time series models—Autoregressive Integrated Moving Average (ARIMA), Seasonal ARIMA (SARIMA), and Seasonal ARIMA with Exogenous Variables (SARIMAX)—to predict Egypt's electricity generation from natural gas (as a share of total generation). These models were adopted for their ability to capture linear temporal relationships, seasonal variations, and the effects of external factors, respectively. ARIMA and SARIMA serve as essential tools in energy forecasting because of their effectiveness in modeling non-stationary and seasonal data, whereas SARIMAX expands this approach to include external influences such as energy consumption, agricultural production, and industrial activity. The approach conforms to recognized methodologies in energy economics (Hyndman and Athanasopoulos, 2018) and utilizes automated parameter selection to enhance model efficacy.

2. Theoretical Framework

The ARIMA model family, based on the Box-Jenkins approach (Box et al. , 2015), posits that forthcoming values of a time series are linearly influenced by historical values and residuals. The ARIMA(p, d, q) model combines differencing (to achieve stability in non-stationary data) with autoregressive (AR) and moving average (MA) elements. SARIMA(p, d, q)(P, D, Q)$_m$ builds on ARIMA by adding seasonal differencing and seasonal AR/MA components, where m signifies the seasonal period. SARIMAX further expands the SARIMA framework by incorporating exogenous variables (X_t), which allows for the modeling of external effects (Brockwell and Davis, 2016). These models are extensively validated in the context of forecasting energy systems, especially for variables that display trends, seasonality, and exogenous relationships (Zhang and Qi, 2005).

3. Technical Specifications

ARIMA(p, d, q):

$$\left(1-\phi_1 B-\cdots-\phi_p B^p\right)(1-B)^d Y_t=\left(1+\theta_1 B+\cdots+\theta_q B^q\right)\epsilon_t$$

where B is the backshift operator, d is the differencing order, ϕ_i (AR) and θ_j (MA) are coefficients, and $\epsilon_t \sim \mathcal{N}(0,\sigma^2)$.

SARIMA(p, d, q)(P, D, Q)□:

$$\left(1-\phi_1 B-\cdots-\phi_p B^p\right)\left(1-\Phi_1 B^m-\cdots-\Phi_P B^{mP}\right)(1-B)^d\left(1-B^m\right)^D Y_t$$
$$=\left(1+\theta_1 B+\cdots+\theta_q B^q\right)\left(1+\Theta_1 B^m+\cdots+\Theta_Q B^{mQ}\right)\epsilon_t$$

where Φ_k and Θ_l are seasonal AR/MA coefficients.

SARIMAX:

$$\left(1-\phi_1 B-\cdots-\phi_p B^p\right)(1-B)^d Y_t=\sum_{k=1}^{K} \beta_k X_{k,t}+\left(1+\theta_1 B+\cdots+\theta_q B^q\right)\epsilon_t$$

where β_k are coefficients for exogenous variables $X_{k,t}$.

Model Selection: Parameters (p,d,q,P,D,Q) were optimized via a grid search algorithm (Hyndman & Khandakar, 2008) that maximizes log-likelihood and minimizes the Akaike Information Criterion (AIC):

$$\mathrm{AIC}=-2\ln(L)+2(p+q+P+Q+K),$$

where L is the likelihood function and K is the number of exogenous variables.

4. Application to the Research

Data Preparation: Monthly data (2000–2022) on Egypt's electricity production from natural gas (%) and exogenous variables (energy use, agricultural/industrial output) were sourced from the World Development Indicators (WDI). The dependent variable underwent seasonal decomposition and Augmented Dickey-Fuller (ADF) testing to confirm stationarity after differencing $(d=1, D=1)$. Exogenous variables were normalized to mitigate scale effects.

Parameter Selection: A grid search over $p,q \in [0,5]$, $P,Q \in [0,2]$, and seasonal $m=12$ (monthly periodicity) identified optimal models. SARIMAX included lagged terms of energy use, agriculture, and industry, selected via stepwise regression to avoid multicollinearity.

Implementation: Models were trained on 80% of the data (2000–2017) and validated on the remaining 20% (2018–2022).

5. Advantages and Limitations

Strengths:

- ARIMA/SARIMA effectively model temporal patterns without requiring complex structural assumptions.
- SARIMAX integrates external drivers, enhancing explanatory power.
- Automated selection reduces subjective bias in parameterization.

Limitations:

- Linear assumptions may miss nonlinear interactions.
- SARIMAX requires forecasts of exogenous variables, introducing uncertainty.
- High parameter dimensionality risks overfitting, mitigated by AIC penalization.

6. Comparative Context

While machine learning models (LSTM, Random Forest) provide flexibility for nonlinear dynamics, ARIMA-class models are more suitable in this context because of their interpretability, reduced computational cost, and adequacy for moderate-sized datasets. Previous research in energy forecasting (Pao and Tsai, 2011) shows their superiority in cases with distinct trend-seasonality structures and few exogenous variables. This method strikes a balance between rigor and practicality, which corresponds with Egypt's data availability and policy requirements.

RESULTS:

Before implementing time series models like ARIMA, SARIMA, and SARIMAX, it is essential to verify that the time series are stationary. To test stationarity, we performed the Augmented Dickey-Fuller (ADF) unit root test [1]. The null hypothesis of the ADF test posits that the series contains a unit root, suggesting non-stationarity. We assessed each variable in both its level form and first difference to identify the required order of integration.

Variable	Level Form (t-Statistic)	Level Form (p-value)	Level (Stationarity)	First Difference (t-Statistic)	First Difference (p-value)	First Difference (Stationarity)
AGRICULTURE	-3.9739	0.0102	Stationary (**)	-3.8844	0.0024	Stationary (***)
ENERGY_USE	-0.1085	0.9463	Non-Stationary	-3.6429	0.0050	Stationary (***)
INDUSTRY	-0.5486	0.8784	Non-Stationary	-3.3474	0.0135	Stationary (**)
ELECTRICITY_PROD	-3.77	0.0034	Stationary (***)	-2.7573	0.0655	Stationary (*)

Table 1: Results of test of stationarity (ADF test)

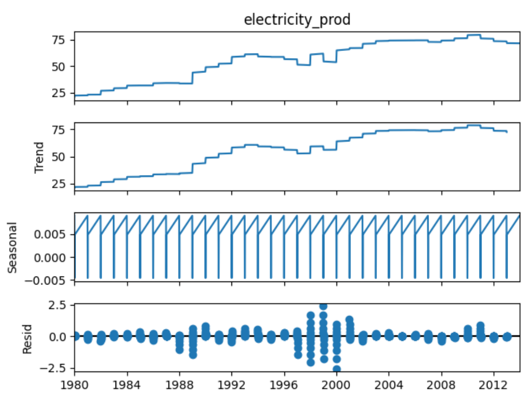

Figure 1: The evolution of production of energy in Egypt

This section provides the findings of predicting energy production in Egypt through the use of ARIMA, SARIMA), and SARIMAX techniques.

The program calculated various model types, but the selection of the model relies on Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Hannan-Quinn Information Criterion (HQIC), and Log-Likelihood values, which indicated that the SARIMAX(1, 1, 0)x(2, 1, 0, 12) model exhibited a better fit to the data in comparison to the ARIMA(1, 1, 0) and SARIMA(1, 1, 0)x(2, 1, 0, 12) models.

The characteristics of the estimated models and their goodness-of-fit statistics are summarized in Table 2, offering a comparative analysis of the models' effectiveness in capturing the temporal patterns of energy production.

Model Specification	**ARIMA(1,1,0)**	**SARIMA(1, 1, 0)x(2, 1, 0, 12)**	**SARIMAX(1, 1, 0)x(2, 1, 0, 12)**
Fit Statistics			
Log Likelihood	162.632	235.493	253.683
AIC	-319.264	-462.986	-493.365
BIC	-307.320	-447.183	-466.201
HQIC	-314.532	-456.718	-482.562
Coefficient Estimates			
Intercept	0.0138 (0.236)	-	-
ar.L1	0.8918*** (0.000)	0.9474*** (0.000)	0.9594*** (0.000)
ar.S.L12	-	-1.3518*** (0.000)	-1.4278*** (0.000)
ar.S.L24	-	-0.6495*** (0.000)	-0.6810*** (0.000)
d.energy_use	-	-	0.0094*** (0.001)
d.industry	-	-	0.2216* (0.050)
d.agriculture	-	-	1.4909* (0.082)
Sigma Squared (σ^2)	0.0256*** (0.000)	0.0160*** (0.000)	0.0142*** (0.000)

Table 2: Comparative Results of ARIMA, SARIMA, and SARIMAX Models for Energy Production Forecasting.

Notes:

- Values in parentheses are p-values.
- *** denotes significance at the 1% level ($p < 0.01$).

Interpretation:

This table offers a comparison of the three models:

- Model Fit: SARIMAX demonstrates the highest Log Likelihood alongside the lowest AIC, BIC, and HQIC values, suggesting a superior fit to the data when contrasted with SARIMA and ARIMA. SARIMA also exceeds ARIMA regarding fit statistics. This indicates that the consideration of seasonal effects and exogenous variables enhances the ability of the model to capture the dynamics of energy production in Egypt.
- Significant Parameters:

o ARIMA: Only the first-order autoregressive term (ar. L1) and the variance (sigma squared) show statistical significance.

o SARIMA: Beyond the AR. L1 and sigma squared, both seasonal autoregressive terms (ar. S. L12 and ar. S. L24) are very significant, emphasizing the role of seasonality in modeling energy production.

o SARIMAX: Like SARIMA, AR. L1, seasonal AR terms, and sigma squared are significant. Notably, the differenced energy use (d. energy_use) is also very significant, indicating that alterations in energy use have a statistically significant positive effect on changes in electricity production from natural gas. While d. industry and d. agriculture display positive coefficients, they do not achieve statistical significance at the 1% level according to the table (though d. industry is nearly significant at 5%).

- Model Complexity: As anticipated, SARIMAX represents the most complex model, integrating both seasonal elements and exogenous variables. The enhanced fit statistics validate this additional complexity in this instance.

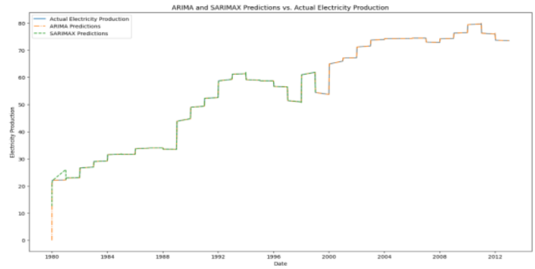

Figure 2: Forecasting electricity production using ARIMA and SARIMAX models.

DISCUSSION AND RECOMMENDATIONS:

This research utilized a comparative analytical approach employing time series methodologies – ARIMA, SARIMA, and SARIMAX – to explain and forecast the energy production patterns in Egypt. The primary research question underlined in this investigation was to identify the most efficient model for predicting electricity generation and to evaluate the effect of seasonality and external economic factors on these predictions. Our methodology utilized established statistical models to capture temporal relations and external influences affecting energy production.

The approach focused on essential indicators including electricity production from natural gas (the dependent variable), energy consumption, and sectoral value addition (agriculture and industry) as external regressors. Time-series analysis, inherent in ARIMA and its variants, was specifically selected to solve the temporal variability typical of energy production data. The SARIMAX model, showcasing an interdisciplinary technique, creatively blended traditional time series econometrics with external economic variables to boost forecasting precision. This strategy acknowledges that energy production is influenced not just by its historical values but also by broader economic activities.

Significant findings indicated a distinct improvement in model performance, with SARIMAX exhibiting superior fit metrics (AIC, BIC, HQIC, Log-Likelihood) in comparison to SARIMA and ARIMA. Although all models identified significant autocorrelation, notably through the AR(1) term, SARIMA took in consideration the existence of seasonal trends, as underlined by the statistical significance of seasonal autoregressive terms at lags 12 and 24.

The SARIMAX model improved these predictions further by integrating the effects of external variables. Importantly, energy consumption and agricultural value addition appeared as statistically significant contributors to electricity production from natural gas within the SARIMAX framework. This implies that energy production in Egypt is not only temporally and seasonally influenced, but also distinctly responsive to changes in overall energy consumption and agricultural sector activity. Temporal variability is evident in the enhanced outcomes of SARIMA and SARIMAX, underscoring the seasonal aspects of energy production, likely associated with climatic fluctuations and demand cycles.

The effectiveness of SARIMAX, which includes external factors, indicates that forecasts based solely on time series methods, as provided by ARIMA and even SARIMA, are inadequate to comprehensively capture the intricate dynamics of Egyptian energy production. These insights support broader economic theories that highlight the integration of energy systems with sectoral economic outcomes and overall energy demand. In contrast to simpler time-series models that might presume stationarity and rely only on historical values, our findings emphasize the necessity of accounting for external economic influences. The notable positive correlation between energy consumption and electricity production from natural gas is a reasonable mechanism, indicating increased electricity generation in response to rising energy demand driven by population growth and economic expansion in Egypt during the analyzed period (1980-2014). Likewise, the significant positive relationship with agricultural value addition, while perhaps less direct, may be related to the energy-intensive characteristics of contemporary agriculture in Egypt, particularly irrigation, and the sector's contribution to overall economic activity and thereby energy demand.

From a practical perspective, these results are source of several implications. For risk management, the research underscores the susceptibility of Egyptian energy production to changes in both domestic energy demand and the performance of critical economic sectors such as agriculture. Expanding energy sources beyond natural gas becomes an essential risk mitigation approach, decreasing dependence on a single fuel source and improving energy security. Regarding policy and regulation, the findings support the need for integrated energy and economic policies. Reforms should encourage energy efficiency initiatives to control demand, motivate diversification of the energy mix towards renewable sources, and promote sustainable agricultural practices that lessen energy intensity. In terms of industry and investment, stakeholders ought to prioritize investments in energy-efficient technologies throughout all sectors and examine opportunities in renewable energy generation and storage to optimize resource allocation and enhance long-term sustainability.

Based on the evaluation of electricity production in Egypt from 1980 to 2014, and highlighting the exceptional forecasting capabilities of the SARIMAX model that factors in external economic elements, the following policy recommendations are aimed at policymakers to improve the sustainability, security, and efficiency of the Egyptian electricity sector:

- *Emphasize the Diversification of Energy Sources*: Considering the historical dependency on natural gas for electricity generation, and the recognized vulnerabilities to variations in energy demand and economic performance within the sector, decision-makers should vigorously seek a varied energy mix. This requires substantial financial investment and policy backing for renewable energy sources, such as solar, wind, and hydroelectric power. Diversification will reduce risks linked to price fluctuations in natural gas markets, bolster energy security, and support long-term environmental sustainability objectives, thereby decreasing dependence on fossil fuels.
- *Execute Comprehensive Demand-Side Management Strategies*: The strong correlation between total energy consumption and electricity generation highlights the urgent need for effective demand-side management policies. Decision-makers should enhance energy efficiency through the standards across residential, commercial, and industrial sectors. This strategy should concentrate on the energy-efficient appliances, promoting building upgrades for better insulation and energy performance. Managing demand expansion will alleviate the strain on natural gas-centric electricity generation and maximize resource efficiency.
- *Promote Integrated Energy and Sectoral Planning, Especially with Agriculture*: The considerable impact of agricultural value addition on electricity generation showcases the interconnectedness of these sectors. Decision-makers should embrace an integrated planning strategy that takes into account the energy

implications of agricultural development initiatives and vice versa. Encouraging energy-efficient irrigation technologies, backing sustainable agricultural methods that lower energy intensity, and examining possibilities for renewable energy production on farms within the agricultural sector are vital measures. Also, policies should support efficient agro-processing industries to limit energy use in agriculture.

- *Improve Long-Term Energy Forecasting and Planning Abilities*: The evident significance of seasonality and external economic factors necessitates advanced long-term energy forecasting capabilities. Decision-makers should allocate resources for sophisticated modeling and analytical tools, akin to SARIMAX, that can integrate macroeconomic forecasts, sectoral growth predictions, and climate variability to guide long-term energy planning. Regular updates and enhancements of these forecasting models are crucial to adapting to shifting economic circumstances and ensuring proactive development in the energy sector.
- *Augment Data Collection and Monitoring Systems*: For the successful implementation and oversight of energy policies, strong data collection and monitoring systems are essential. Decision-makers should emphasize the gathering of detailed data on energy production, consumption patterns across various sectors, and key macroeconomic indicators. Enhanced data availability will improve the precision of forecasting models, enable data-driven policy decisions, and support effective performance monitoring of energy sector initiatives.

By implementing these suggestions, policymakers can direct the Egyptian electricity sector towards a more sustainable, secure, and resilient future, building on the insights derived from the historical examination of energy production dynamics and the predictive capabilities of advanced time series models. The present research recognizes certain limitations. The linearity assumption present in ARIMA-family models may not completely represent potential non-linear relationships within the energy system. Limitations in data, especially regarding the range and frequency of available datasets, may also limit the analysis. Future studies could broaden the analysis to include non-linear time series models, investigate longer and higher-frequency datasets, and incorporate additional exogenous variables such as policy modifications, technological progress in energy production, and geopolitical influences. Additionally, regional analysis within Egypt could uncover spatial variations in energy production dynamics and sectoral impacts. Longitudinal studies monitoring the changes in these relationships over time and hybrid modeling approaches that merge statistical and machine learning techniques could further enhance our comprehension and forecasting abilities for Egyptian energy production, particularly in light of Vision 2030's focus on sustainable development and energy diversification.

CONCLUSION:

The present research paper conducted a comparative analysis of ARIMA, SARIMA, and SARIMAX approaches to predict electricity production in Egypt, utilizing time series data spanning from 1980 to 2014. The study attempts to determine the most effective forecasting model and to assess the impact of seasonality and external economic variables on energy production. Through thorough statistical evaluation, the SARIMAX model, which included energy use and agricultural value added as exogenous regressors, exhibited greater forecasting accuracy and model fit compared to ARIMA and SARIMA. The results emphasize the vital importance of taking into account both temporal dynamics and external economic factors when modeling and forecasting energy production trends in Egypt. This research adds to the field by empirically confirming the enhanced predictive capability of SARIMAX models in complex energy systems and by underscoring the significant impact of energy demand and sectoral economic activities on electricity generation from natural gas in the Egyptian context. Furthermore, the study allowed to underline some policy recommendations, based on empirical investigation. It allows to have actionable insights for policymakers to foster a more diversified, sustainable, and resilient electricity sector in Egypt, highlighting the necessity for integrated energy and economic planning, as well as demand-side management strategies. Future research should examine extensions of non-linear models, integrate higher frequency data, and analyze the changing impact of policy and technological factors on Egyptian energy production to further enhance forecasting capabilities and guide long-term energy strategy.

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