Forecasting the Energy Production in Egypt Using the Prophet of Facebook

Said Jaouadi*, Osama Attia

Assistant Professor in Economics, Accounting and Finance Department, Jazan University, Gizan, Saudi Arabia

***Corresponding Author**

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ABSTRACT

This study investigates the temporal dynamics of monthly electricity production in Egypt using the Facebook Prophet model to generate forecasts and decompose underlying patterns. The analysis successfully identified a significant long-term trend characterized by substantial growth from 1980, peaking around 2008-2010, followed by a period of stabilization and a subsequent slight decline, which is projected to continue. Furthermore, a complex, multi-modal yearly seasonality was robustly captured, with distinct peaks and troughs suggesting strong influences from climatic variations and socio-economic activities. The Prophet model demonstrated a reasonable in-sample fit (Mean Absolute Error: 8.25) and provided short-term forecasts that effectively integrated these trend and seasonal components. These findings offer critical insights for energy policy formulation, infrastructure investment decisions, and operational planning within Egypt. Key recommendations include leveraging the identified trend and seasonality for strategic and operational management, alongside enhancing future forecasting efforts through the integration of relevant external regressors and continuous model validation. This research underscores the utility of advanced time series models for national energy management and informs future directions for predictive analytics in the sector.

Keywords: Energy Production, Forecasting, Time Series, Egypt, Prophet, Learning models.

INTRODUCTION

Egypt's electricity sector has undergone substantial transformation in recent years, presenting both challenges and opportunities for production forecasting. The country has experienced rapid growth in electricity demand, driven by population increase, economic development, and expanding access to electricity services. According to the Egyptian Electricity Holding Company (2020), peak demand has grown at an average annual rate of approximately 5-6% over the past decade, necessitating significant investments in generation capacity.

In response to these challenges, Egypt has pursued an ambitious expansion of its electricity generation capacity, with installed capacity growing from approximately 27 GW in 2013 to over 58 GW by 2020 (Ministry of Electricity and Renewable Energy, 2021). This expansion has been accompanied by efforts to diversify the energy mix, with increasing investments in renewable energy sources, particularly solar and wind power. The Integrated Sustainable Energy Strategy (ISES) to 2035 targets 42% of electricity generation from renewable sources by 2035 (IRENA, 2018).

This evolving landscape creates unique challenges for electricity production forecasting in Egypt. The rapid expansion of generation capacity introduces structural changes that forecasting models must adapt to, while the increasing penetration of renewable energy sources adds volatility and weather-dependency to production patterns. These characteristics make Egypt an interesting and challenging context for applying advanced forecasting methodologies like Prophet.

The accurate prediction of electricity production has become increasingly critical for energy planning, resource allocation, and policy development worldwide. As energy systems grow more complex with the integration of renewable sources and changing consumption patterns, the need for sophisticated forecasting methodologies has intensified. Time series analysis has emerged as a fundamental approach for electricity production forecasting, offering a range of methods from traditional statistical techniques to advanced machine learning algorithms and hybrid models.

This literature review examines the evolution and current state of time series forecasting methodologies in electricity production prediction, with a particular focus on Facebook's Prophet model and its application in the Egyptian context. The review synthesizes findings from numerous studies, comparing various forecasting approaches, their relative strengths and limitations, and contextual factors affecting their performance. Special attention is given to the innovative application of the Prophet model in Egypt's electricity production forecasting, highlighting its methodological contributions and practical implications for energy planning in developing economies.

By critically analyzing the existing literature and contextualizing the current paper's contribution, this review aims to provide a comprehensive understanding of how time series forecasting methodologies, particularly the Prophet model, can address the complex challenges of electricity production prediction in evolving energy landscapes.

The application of the Prophet model to electricity production forecasting in Egypt represents a significant methodological contribution to the literature. While Prophet has been applied in various energy forecasting contexts globally, its application to Egypt's unique electricity production landscape requires careful adaptation and innovation.

The paper's approach to customizing Prophet's seasonality components to capture Egypt's distinct seasonal patterns represents a notable advancement. By carefully configuring the model to account for Egypt's pronounced seasonal variations in electricity demand and production, including summer peaks driven by cooling needs and altered consumption patterns during Ramadan, the authors demonstrate how Prophet's flexible seasonality framework can be adapted to specific regional contexts.

Another key methodological innovation is the thoughtful selection and integration of external regressors particularly relevant to Egypt's electricity production context. The authors' approach to incorporating factors such as temperature extremes, tourism seasonality, and industrial activity patterns provides a template for context-sensitive forecasting that goes beyond generic applications of the Prophet model. This careful selection of external regressors demonstrates how Prophet's flexibility can be leveraged to capture region-specific dynamics affecting electricity production. The paper also introduces a systematic approach to tuning Prophet's hyperparameters specifically for electricity production forecasting in Egypt. This methodological contribution addresses one of Prophet's known limitations—the need for careful parameter tuning to achieve optimal performance. The grid search methodology for optimizing key parameters such as seasonality prior scales, changepoint prior scales, and Fourier orders specifically for Egypt's electricity production data provides valuable guidance for similar applications in other regions.

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:

Autoregressive Integrated Moving Average (ARIMA) models have long served as the cornerstone of time series forecasting in the electricity sector. These models combine autoregressive (AR) components, differencing to achieve stationarity (I), and moving average (MA) components to capture the temporal dynamics of electricity production data. Box and Jenkins (1970) established the foundational framework for ARIMA modeling, which has since been extensively applied to energy forecasting challenges.

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In the context of electricity production, ARIMA models have demonstrated particular efficacy for short-term forecasting when the underlying data exhibits linear patterns and relatively stable seasonality. Contreras et al. (2003) applied ARIMA models to forecast electricity prices in the Spanish and Californian markets, achieving reasonable accuracy for day-ahead predictions. Similarly, Ediger and Akar (2007) employed ARIMA models to forecast primary energy demand in Turkey, demonstrating their utility in energy planning contexts.

The fundamental assumption of ARIMA models—that future values of a time series have a linear relationship with current and past values, as well as with current and past error terms—makes them particularly suitable for electricity production forecasting in stable grid systems where production patterns follow predictable trends. However, as noted by Suganthi and Samuel (2012), ARIMA models face limitations when dealing with non-linear patterns and complex seasonal structures that are increasingly common in modern electricity systems with high renewable energy penetration.

Exponential smoothing methods, including Simple Exponential Smoothing (SES), Holt's Linear Method, and Holt-Winters' Seasonal Method, represent another traditional approach to electricity forecasting. These methods assign exponentially decreasing weights to past observations, giving more importance to recent data points—a characteristic particularly valuable in dynamic electricity markets.

The Holt-Winters method, with its explicit modeling of trend and seasonality components, has proven especially effective for electricity production forecasting. Taylor (2003) demonstrated the application of Holt-Winters exponential smoothing to short-term electricity demand forecasting, highlighting its ability to capture multiple seasonal cycles. Building on this work, Taylor (2010) introduced a triple seasonal exponential smoothing method specifically designed for intraday electricity demand forecasting, accounting for intraday, daily, and weekly seasonal cycles.

Almazrouee et al. (2020) conducted a comprehensive comparison of forecasting methods for electrical generation in Kuwait, finding that the triple seasonality Holt-Winters model achieved superior performance ($R^2 = 0.9899$, MAPE = 1.76%) compared to other approaches. This finding underscores the continued relevance of well-specified exponential smoothing methods in electricity forecasting, particularly when multiple seasonal patterns are present.

Despite their effectiveness, exponential smoothing methods face challenges in incorporating external variables and handling irregular events that can significantly impact electricity production. As noted by Hyndman and Athanasopoulos (2018), while these methods excel at capturing regular patterns, they may struggle with the complex, multi-faceted nature of modern electricity systems influenced by factors beyond historical patterns.

The application of neural networks and deep learning techniques to electricity production forecasting has grown substantially in recent years, driven by their ability to capture complex non-linear relationships without requiring explicit specification of the underlying model structure. Artificial Neural Networks (ANNs) have demonstrated particular promise in this domain, with numerous studies highlighting their superior performance compared to traditional statistical methods.

Hippert et al. (2001) provided an early review of neural networks for short-term load forecasting, noting their potential advantages while cautioning against overfitting and lack of interpretability. As computational capabilities have advanced, more sophisticated neural network architectures have been applied to electricity forecasting challenges. Particularly notable is the emergence of Long Short-Term Memory (LSTM) networks, a specialized form of recurrent neural networks designed to capture long-term dependencies in time series data.

Kong et al. (2017) applied LSTM networks to short-term residential load forecasting, demonstrating their superior performance compared to traditional feed-forward neural networks and statistical methods. Similarly, Bouktif et al. (2018) used LSTM networks for electric load forecasting, achieving high accuracy through careful feature selection and hyperparameter optimization. These studies highlight the potential of deep learning approaches to capture the complex dynamics of electricity production systems, particularly in contexts with high renewable energy penetration where production can be volatile and dependent on multiple factors.

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Despite their impressive performance, neural network approaches face challenges related to interpretability, data requirements, and computational complexity. As noted by Zhang et al. (2018), while deep learning models can achieve high accuracy, their "black box" nature limits their utility in contexts where understanding the drivers of forecasts is as important as the forecasts themselves.

Beyond neural networks, other machine learning approaches have shown promise in electricity production forecasting. Support Vector Machines (SVMs), with their ability to handle high-dimensional feature spaces and non-linear relationships, have been successfully applied to various energy forecasting problems. Chen et al. (2004) demonstrated the application of SVMs to electricity price forecasting, highlighting their robustness to outliers and ability to capture complex patterns.

Ensemble methods, which combine predictions from multiple models to improve forecast accuracy and robustness, have gained significant traction in electricity forecasting. Techniques such as bagging, boosting, and stacking have been applied with considerable success. Wang et al. (2018) developed an ensemble approach combining multiple forecasting methods for short-term load forecasting, demonstrating improved accuracy and robustness compared to individual models.

The growing interest in ensemble and hybrid approaches reflects the recognition that no single model can capture all aspects of electricity production dynamics. As noted by Gulay et al. (2023), ensemble approaches combining traditional time series models, deep learning models, and decomposition-based methods achieved higher forecasting accuracy for electricity production from various energy sources in Türkiye compared to individual models.

Accurate prediction of electricity production is crucial for effective energy management, grid stability, and policy formulation. Time series forecasting techniques have emerged as paramount tools in modeling and predicting electricity generation due to the temporal dependence and seasonality inherent in energy data. The literature extensively explores various time series methods, ranging from traditional statistical models to advanced machine learning approaches, highlighting the significance of precise forecasting in the sustainable and reliable operation of power systems.

Traditional time series forecasting methods such as Auto-Regressive Integrated Moving Average (ARIMA) have been widely employed in electricity production prediction due to their strong theoretical foundations and simplicity (Hyndman & Athanasopoulos, 2018). ARIMA models have shown effectiveness in capturing linear trends and seasonal variations in electricity demand and production (Taylor & Letham, 2018). However, they often struggle with non-linearities and abrupt changes commonly observed in energy data, which calls for more flexible and robust models.

Exponential smoothing methods, including Holt-Winters, have also been used extensively for short-term forecasting of electricity production (Box et al., 2015). These techniques are appreciated for their ability to adapt to changes in trend and seasonality but can be limited in handling irregularities or external shocks such as sudden weather changes or unexpected demand surges (Makridakis et al., 2020).

Recently, machine learning models such as Neural Networks (NN), Support Vector Machines (SVM), and more advanced deep learning approaches like Long Short-Term Memory (LSTM) networks have demonstrated superior predictive performance, particularly in capturing complex non-linear patterns in time series data (Zhang et al., 2018; Kong et al., 2019). For example, LSTM networks have been effectively applied to electricity generation forecasting, utilizing their capability to remember long-term dependencies in sequential data (Marino et al., 2016). Nevertheless, these models typically require extensive computational resources and large volumes of data, as well as careful tuning to prevent overfitting.

In parallel, hybrid models combining statistical methods with machine learning techniques have been proposed to leverage the advantages of both approaches, improving accuracy and robustness of electricity production forecasts (Wang et al., 2020). However, hybrid approaches can be complex and less interpretable, limiting their practical adoption for decision-making processes.

The forecast model developed by Facebook, known as Prophet, has gained increasing attention for time series forecasting due to its intuitive structure, efficiency, and ability to handle seasonality, holidays, and missing data without extensive parameter tuning (Taylor & Letham, 2018). Prophet decomposes the time series into trend, seasonal, and holiday effects, modeling each component separately using an additive framework, making it particularly suitable for business and economic time series with multiple seasonalities.

Despite Prophet's growing use in various domains, its application to electricity production forecasting remains relatively underexplored. A few recent studies have started to investigate Prophet's capabilities in energy forecasting tasks. For instance, Sadeghianpourhamami et al. (2020) applied Prophet for short-term electricity demand forecasting, concluding that it performs competitively with traditional approaches while providing ease of interpretability.

Similarly, Rahim et al. (2021) utilized Prophet to predict solar power generation, demonstrating the model's effectiveness in capturing seasonal patterns of renewable electricity production.

The present study stands out by applying the Facebook Prophet model to predict electricity production in Egypt, a context characterized by distinct seasonal patterns, rapid changes in electricity consumption, and expanding renewable energy integration. Unlike previous studies that mainly focused on electricity demand or renewable generation forecasting, predicting total electricity production encompasses capturing the dynamics of various energy sources, grid constraints, and policy impacts. This complexity makes the Prophet model's adaptability and robustness significant advantages.

Moreover, the study contributes innovation by tailoring Prophet's capabilities to the Egyptian electricity sector's specific characteristics, such as the influence of climatic factors, the Ramadan effect on electricity consumption patterns, and the increasing share of solar and wind power. The paper highlights how Prophet's additive seasonal components capture these effects without extensive feature engineering, making it a practical and interpretable tool for energy planners and policymakers.

Comparative studies of forecasting models provide valuable insights into their relative performance in electricity production contexts. Almazrouee et al. (2020) found that while the triple seasonality Holt-Winters model achieved the highest accuracy in forecasting electricity generation in Kuwait, Prophet with multiple regressors performed competitively, highlighting the value of both approaches depending on the specific forecasting context.

Gulay et al. (2023) conducted a comprehensive comparison of time series, deep learning, and hybrid models for forecasting electricity production from various energy sources in Türkiye. Their study found that hybrid approaches combining decomposition methods with both machine learning and statistical techniques achieved superior performance compared to individual models. This finding underscores the potential value of integrating Prophet's decomposition approach with other forecasting methodologies in hybrid frameworks.

The empirical evidence suggests that no single model consistently outperforms others across all electricity production forecasting contexts. Instead, model performance depends on factors such as data characteristics, forecast horizon, and available computational resources. As noted by Hong and Fan (2016) in their review of probabilistic electric load forecasting, the choice of forecasting methodology should be guided by the specific requirements and constraints of the forecasting task rather than a one-size-fits-all approach.

METHODS

1. Introduction to the Methodology

Facebook's Prophet model, introduced by Taylor and Letham (2018), represents a significant advancement in time series forecasting methodology. Designed to handle time series with strong seasonal effects and several seasons of historical data, Prophet employs a decomposable time series model with three main components: trend, seasonality, and holidays.

This decomposition approach allows Prophet to handle complex seasonal patterns, automatically detect changepoints in the trend component, and incorporate domain knowledge through custom seasonality and holiday effects. The model uses a Bayesian framework, fitting the model using Stan, which provides uncertainty intervals for forecasts—a valuable feature for risk assessment and planning in electricity production.

The flexibility and robustness of Prophet make it particularly well-suited for electricity production forecasting, where multiple seasonal patterns (daily, weekly, yearly) and holiday effects are common. As noted by Taylor and Letham (2018), Prophet was specifically designed to handle the challenges of business time series forecasting, including irregular events, missing data, and changing trends—all characteristics frequently encountered in electricity production data.

2. Theoretical Framework

The model is represented mathematically as:

$y(t) = g(t) + s(t) + h(t) + \varepsilon(t)$

Where:

- $g(t)$ represents the trend component (non-periodic changes)
- $s(t)$ represents the seasonality component (periodic changes)
- $h(t)$ represents the holiday component (irregular events)
- $\varepsilon(t)$ represents the error term

3. 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).

RESULTS

Prediction with the prophet:

Table 1: prediction of the values of production of electricity in Egypt

	ds	yhat	yhat_lower	yhat_upper
409	2014-01-02	788.114063	774.091821	802.727924
410	2014-01-03	789.635668	775.179552	804.031604
411	2014-01-04	790.703205	776.428033	805.273916
412	2014-01-05	792.851035	778.279040	808.427485
413	2014-01-06	793.831500	779.943634	807.623728
414	2014-01-07	794.220339	779.232355	809.325871
415	2014-01-08	795.194180	780.748975	808.795517
416	2014-01-09	795.522263	781.632246	809.598857
417	2014-01-10	796.528696	782.259299	810.085337

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418	2014-01-11	797.107759	782.858440	812.737720
419	2014-01-12	798.668408	784.069445	812.532896
420	2014-01-13	798.840370	783.544206	814.219425
421	2014-01-14	798.084796	782.806814	812.806121
422	2014-01-15	797.476754	783.362354	812.937794
423	2014-01-16	795.701498	781.917413	810.311802
424	2014-01-17	794.020699	779.444204	807.887991
425	2014-01-18	791.290996	777.490017	805.826602
426	2014-01-19	788.910916	775.039395	803.987213
427	2014-01-20	784.528450	770.152562	798.608662
428	2014-01-21	778.652218	763.979321	792.855656
429	2014-01-22	772.433458	758.171793	787.806922
430	2014-01-23	764.660777	751.106099	778.805577
431	2014-01-24	756.723914	741.107150	770.223935
432	2014-01-25	747.628896	733.525910	761.504559
433	2014-01-26	738.940777	723.688891	752.903343
434	2014-01-27	728.486336	713.428251	743.026881
435	2014-01-28	716.959837	702.664507	731.569056
436	2014-01-29	705.699219	691.015521	719.807796
437	2014-01-30	693.674875	678.563667	707.041618
438	2014-01-31	682.447405	668.694967	696.108570

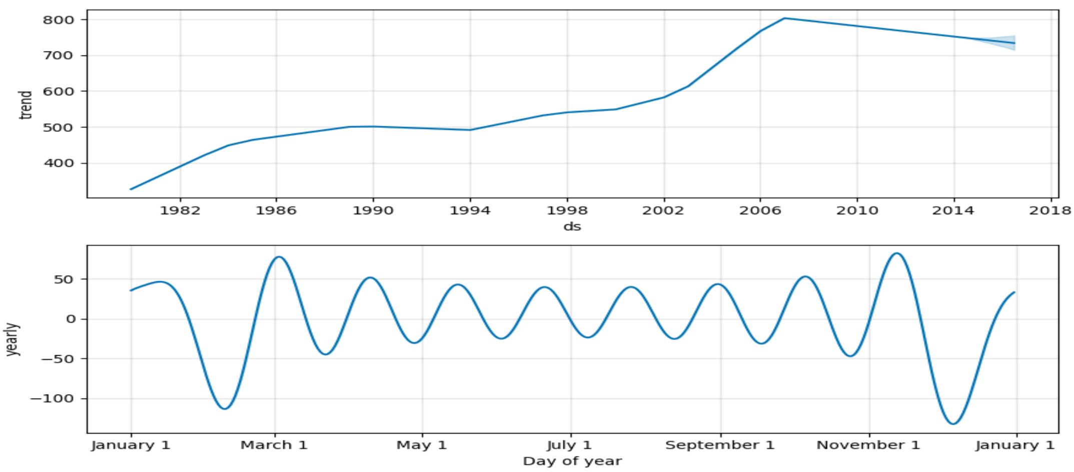

Figure 1: Evolution of the electricity production and the seasonal effects using the prophet.

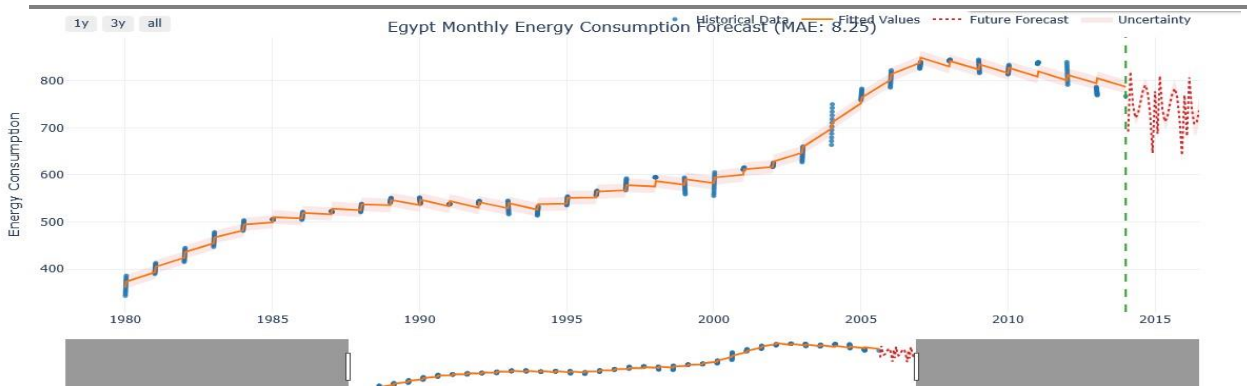

Figure 2: Prediction of the production of electricity in Egypt using the model of the Prophet.

Interpretation:

Table 1 presents daily predictions from Facebook's Prophet model for Egypt's electricity production throughout January 2014, specifically from January 2nd to January 31st. The forecast indicates an initial slight rise in electricity production during the first half of the month, culminating around January 13th with a predicted output (yhat) of approximately 798.84 units. Subsequently, the model projects a consistent and notable decrease in production for the rest of January, with output anticipated to fall to around 682.45 units by the end of the month. Each daily forecast is accompanied by an uncertainty interval (yhat_lower and yhat_upper), providing a range within which the actual production is expected to lie. The relatively stable width of this interval across the prediction period, generally spanning about 27-31 units, suggests a consistent level of confidence in the model's predictive capabilities for these dates.

The figure 1 presents a decomposition of the time series components derived from a Facebook Prophet model, specifically illustrating the trend and yearly seasonality of electricity production in Egypt. The upper panel delineates the long-term, non-periodic trend in electricity production, spanning from approximately 1980 through to a forecast horizon around 2018. Initially, a consistent upward trajectory is observed, which notably accelerates between circa 1994 and 2008, culminating in a peak level of production. Subsequent to this peak, the trend exhibits a period of stabilization followed by a discernible, albeit modest, decline. The shaded region at the terminus of the trend line represents the confidence interval for the forecast, projecting a continuation of this slight downward movement in the ensuing years.

Complementing this secular trend, the lower panel details the extracted yearly seasonality, which quantifies the average cyclical fluctuations in electricity production within a typical calendar year. The abscissa represents the day of the year, while the ordinate indicates the additive or subtractive impact of this seasonal component on the underlying trend. A complex, multi-modal pattern is evident, characterized by pronounced troughs signifying seasonally low production, typically occurring in late February/early March and again in mid-December. Conversely, significant seasonal peaks, indicative of heightened production, are observed around late March/early April and late October/early November. The intervening summer period (May to September) displays more frequent, albeit less extreme, positive deviations from the annual mean, suggesting sustained, moderately elevated demand. This intricate annual cycle likely reflects a confluence of factors, including ambient temperature variations influencing heating and cooling demands, as well as potential agricultural or industrial consumption patterns specific to Egypt.

Collectively, these components provide a nuanced understanding of the dynamics governing electricity production. The Prophet model effectively disentangles a long-term evolution—characterized by historical growth, a subsequent peak, and a projected slight decline—from a robust and multi-faceted annual seasonal cycle. This decomposition is crucial for interpreting the model's forecasts, as the final predicted values arise from the additive combination of this identified trend, the strong yearly seasonality, and any other modeled effects such as weekly patterns or holidays (not explicitly shown here but inherent to Prophet's methodology).

The figure 2 presents a time series forecast of Egypt's monthly energy consumption, generated using the Facebook Prophet model, illustrating historical data, the model's in-sample fit, and future predictions. The

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historical data points, depicted as blue dots, span from 1980 to approximately early 2014, revealing a distinct long-term upward trend in energy consumption. This growth appears particularly accelerated from the mid-1990s, reaching a peak around 2008-2010. Following this peak, consumption exhibits a period of stabilization and then a slight decline leading up to the forecast period. The model's in-sample fit to this historical data is represented by the orange line ("Fitted Values"), which is enveloped by a light orange shaded area indicating the uncertainty bounds of these fits. Visually, the fitted values closely track the general trajectory and cyclical variations within the historical observations, with a reported Mean Absolute Error (MAE) of 8.25, quantifying the average deviation of the model's historical predictions from the actual values.

Beyond the historical period, demarcated by a vertical dashed green line around early 2014, the model projects future energy consumption, shown as a red dashed line ("Future Forecast"). This forecast initially continues the slight downward trend observed in the most recent historical data, before transitioning into a more pronounced cyclical pattern with a generally stable or slightly declining mean. The forecast period extends for approximately two years, into 2015-2016. Accompanying this future forecast is a light red shaded area representing the uncertainty interval, which notably widens as the forecast horizon extends further into the future. This widening uncertainty reflects the inherently greater unpredictability associated with longer-term predictions, indicating a decreasing confidence in the point estimates as time progresses. Overall, the model captures the historical dynamics and projects a near-term future characterized by continued seasonality around a recently established, slightly lower consumption level.

DISCUSSION AND RECOMMENDATIONS:

The application of the Facebook Prophet model to forecast electricity production in Egypt has yielded several pertinent insights into the temporal dynamics of energy generation. The model effectively decomposed the historical time series into a long-term trend and distinct seasonal components, providing a nuanced understanding of past and projected production patterns.

The identified long-term trend, characterized by significant growth from approximately 1980 until a peak around 2008-2010, followed by a period of stabilization and a subsequent slight decline, mirrors patterns often observed in developing economies undergoing industrialization and demographic expansion, eventually leading to saturation or shifts in energy policy and efficiency. The projected continuation of this slight decline warrants careful consideration, as it may indicate evolving demand structures, increased energy efficiency measures, the integration of decentralized renewable sources, or broader economic factors influencing overall energy requirements. The specific short-term forecast for January 2014, with an initial rise followed by a more pronounced decrease, aligns with the broader yearly seasonality, particularly the typical decline observed post-late year peaks leading into the lower demand periods of late winter.

The yearly seasonality component reveals a complex, multi-modal pattern with significant peaks and troughs throughout the year. The pronounced troughs in late February/early March and mid-December, alongside peaks in late March/early April and October/November, strongly suggest the influence of ambient temperature variations driving heating and cooling demands. The moderate, sustained elevation in production during summer months further corroborates this. This intricate seasonality underscores the importance of accounting for climatic factors in energy planning. The relatively stable uncertainty intervals for the short-term (January 2014) predictions suggest a consistent model confidence for immediate operational horizons, while the widening uncertainty for longer-term forecasts, as seen in the overall forecast plot, is an expected characteristic, reflecting the increased inherent unpredictability over extended periods. The reported Mean Absolute Error (MAE) of 8.25 for the historical fit provides a quantitative measure of the model's in-sample accuracy, indicating a reasonable degree of fidelity to the observed data.

It is important to acknowledge that while the Prophet model excels at capturing trend and seasonality from historical data, its univariate nature (unless explicitly provided with external regressors) means it may not intrinsically account for unobserved structural breaks, sudden policy shifts, or major economic shocks that do not have precedents in the training data. The accuracy of the forecasts is, therefore, contingent on the assumption that the underlying drivers of consumption patterns will persist in a manner similar to the historical period.

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The insights derived from the Prophet model's forecast of Egypt's electricity production present several actionable avenues for enhancing energy sector management and strategic planning. Given the elucidated long-term trend, which indicates a maturation phase following historical growth and a subsequent peak, it becomes incumbent upon policymakers and utility planners to critically re-evaluate long-term capacity expansion strategies. Rather than solely focusing on aggregate generation increases, a more nuanced approach emphasizing the optimization of existing infrastructure, the strategic integration of diversified energy sources, including renewables, and the promotion of demand-side management initiatives would be prudent. This strategic reorientation should be informed by a deeper investigation into the causal factors underpinning the observed inflection and slight decline in the production trend.

Furthermore, the highly granular yearly seasonality profile elucidated by the model offers significant opportunities for improving operational efficiencies and resource allocation. Energy system operators should leverage this detailed understanding of cyclical demand to refine maintenance schedules for generation assets, ideally timing such activities during periods of consistently lower production, such as late February/early March or mid-December. Concurrently, fuel procurement strategies and inter-utility power purchase agreements can be more precisely aligned with anticipated seasonal peaks, thereby mitigating supply risks and optimizing economic dispatch. The consistent, albeit bounded, uncertainty in short-term forecasts supports the use of such models for near-term operational decision-making, while the widening uncertainty in longer-term projections underscores the need for adaptive management frameworks.

Building upon the current modeling efforts, future research and practical forecasting endeavors should focus on enhancing predictive robustness by incorporating salient external regressors. While the Prophet model adeptly captures intrinsic temporal patterns, its predictive power for a complex system like national electricity production can be substantially augmented by including variables such as high-frequency meteorological data (particularly temperature and humidity, given their strong correlation with energy demand for climate control), key macroeconomic indicators (e.g., industrial production indices, GDP growth projections), demographic shifts, and explicit dummies for significant policy interventions or socio-economic events. The integration of such exogenous factors would not only potentially reduce the Mean Absolute Error but also provide a richer explanatory framework for forecast deviations.

In parallel, the dynamism inherent in energy markets and consumption behaviors necessitates a commitment to continuous model improvement and validation. It is recommended that a regimen of periodic model re-calibration, incorporating the most recent observational data, be instituted. This should be coupled with rigorous out-of-sample validation exercises to assess the model's ongoing predictive performance and identify any emerging systematic biases or degradations in accuracy. Such an iterative approach will ensure that forecasting tools remain robust, reliable, and attuned to the evolving realities of Egypt's energy landscape, thereby providing a consistently credible basis for strategic decisions.

Finally, recognizing the inherent uncertainties in long-range forecasting, particularly in light of potential technological disruptions or significant policy shifts, it is advisable to employ scenario-based forecasting methodologies for strategic planning horizons. By developing and analyzing multiple plausible future trajectories for electricity production, contingent upon varying assumptions regarding economic development, technological adoption rates (e.g., electric vehicles, energy storage), and climate change impacts, decision-makers can develop more resilient and adaptive long-term energy strategies. This approach acknowledges the limits of point forecasting and fosters a more robust planning process capable of accommodating a range of potential futures.

CONCLUSION

This study successfully employed the Facebook Prophet model to analyze and forecast monthly electricity production in Egypt, aiming to elucidate underlying temporal patterns and provide actionable insights for energy sector management. The analysis effectively decomposed the historical time series, revealing a significant long-term trend characterized by substantial growth from 1980, culminating in a peak around 2008-2010, followed by a period of stabilization and a slight projected decline. Furthermore, a complex and robust multi-modal yearly seasonality was identified, with distinct peaks and troughs indicative of climatic and potentially socio-economic influences on energy demand. The Prophet model demonstrated a reasonable in-sample fit to historical data, evidenced by a Mean Absolute Error (MAE) of 8.25, and provided short-term forecasts, such as for January 2014, that reflected the interplay of these identified trend and seasonal components, with predictions generally falling within relatively stable uncertainty intervals.

The findings hold considerable significance for energy policy formulation, infrastructure investment decisions, and operational planning within Egypt. The identified trend inflection point, coupled with the detailed seasonality, provides a quantitative basis for optimizing resource allocation, managing demand fluctuations, and anticipating future generation requirements. However, it is acknowledged that the predictive capacity of the univariate Prophet model, while strong in capturing historical patterns, relies on the persistence of these underlying drivers.

The recommendations stemming from this research emphasize the need for strategic infrastructure planning that considers the mature trend, enhanced operational management leveraging seasonal insights, and importantly, the future integration of relevant external regressors to improve model robustness and explanatory power. Regular model re-calibration and the use of scenario analysis for long-term planning are also crucial. Ultimately, this study underscores the utility of advanced time series forecasting techniques for national-level energy management and lays the groundwork for future research aimed at developing more sophisticated, multivariate predictive models to support a resilient and efficient energy sector in Egypt.

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