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Assessing the Economic Effects of Energy Access Inequalities between Rural and Urban Areas in Egypt Based on the Random Forest Algorithm

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ABSTRACT

This research aims to determine the impact of energy entry in rural and urban areas on industrial growth in Egypt. The study relied on the Random Forest algorithm as one of the machine learning algorithms to determine this. The research concluded that the RF algorithm is more accurate than the remaining algorithms. The paper found that access to electricity in rural areas has the most significant impact on the growth of the industrial sector in Egypt, increasing by 85%, compared to a 15% increase in access to electricity in urban areas. Additionally, the paper confirmed a positive relationship between the growth of the industrial sector in Egypt and the rate of electricity access in both rural and urban areas. Hence, the paper finds that the electricity access to rural areas supports the Egyptian industrial sector and, consequently, development. This indicates the spread and concentration of small projects in rural areas.

Keywords: Machine Learning Algorithms, Random Forest, Electricity Access in Urban Areas, Electricity Access in Rural Areas, Industrial Value Added

JEL Classifications: Q4, C63, C80, C81, C87

1. INTRODUCTION

Energy access is crucial for fostering economic development, industrial growth, productivity, and societal well-being. Yet significant disparities in energy availability between urban and rural areas lead to economic inequalities, especially in developing countries where infrastructure and resources are distributed unevenly. In Egypt, which is experiencing rapid urbanization and industrial growth, the ongoing gap in electricity access between these regions presents a significant challenge. This inequality affects the quality of life for millions and has broader implications for the country's economic performance. Developing effective policies that encourage inclusive growth and sustainable development requires understanding the economic impacts of disparities in energy access.

Research consistently demonstrates a significant relation between electricity and industrial production. The capacity of a nation to manufacture goods, generate employment, and build wealth is reflected in its industrial output, which serves as a key indicator of economic health when expressed as a percentage of GDP. Nevertheless, there is limited understanding of how unequal energy supply affects industrial output in Egypt, particularly between urban and rural areas. This study aims to fill the gap in understanding the economic consequences of energy inequality by investigating the impact of electricity access on industrial output.

This study uses urban and rural electricity access rates as independent variables reflecting levels of electrification. These variables refer to the reliable electricity available to households and businesses, which is essential for industrial activity and economic productivity. This study aims to assess the economic impact of energy access disparities and determine whether these disparities between rural and urban areas support economic expansion by promoting the secondary sector or have a negative impact on it.

This study employs a machine learning technique renowned for handling complex nonlinear interactions and generating reliable predictions through Random Forest algorithms to enhance analysis. This method is especially valuable for research as it reduces the risk of overfitting, uncovers interactions between predictors, and assesses the importance of variables. The study employs this sophisticated analytical technique to illustrate the differential impact of energy availability on industrial output and GDP growth in urban versus rural settings.

Egypt serves as a typical case for this research due to its status as a middle-income country and the evident disparity between rural and urban areas. The country faces distinct challenges in balancing economic growth with equitable resource distribution. While urban centers, notably Cairo and Alexandria, benefit from comparatively high electricity access, rural areas frequently suffer from power outages and inadequate infrastructure. This division hinders rural industrial development and worsens economic inequalities between regions. Therefore, this study enriches the broader discourse on energy economics and development by focusing on Egypt, providing context-specific insights to inform policy actions.

The anticipated findings of this research are expected to have profound implications for policymakers, development experts, and stakeholders in the energy sector. Research examining the economic effects of differences in energy access can help us assess whether inequality helps or hinders industrialization. A methodological innovation, random forest algorithms (RFAs), demonstrates how machine learning (ML) can improve our understanding of complex socioeconomic phenomena. This study aims to optimize resource allocation and clarify the importance of energy access for the economic growth of the Arab Republic of Egypt.

2. LITERATURE REVIEW

Energy availability is crucial for economic development, and the disparity between rural and urban areas exacerbates socioeconomic problems. The availability and dependability of energy directly impact national growth, household well-being, and industrial productivity. Recent research has focused on assessing policy initiatives, finding sustainable solutions, and comprehending the root causes of poverty and energy inequities to bridge the urban-rural energy gap. These studies examine not only the technical aspects of energy accessibility but also its broader economic and social implications, providing insights into practical strategies for achieving equitable energy distribution.

Alola (2024) examines the factors contributing to the clean energy access divide. Economic growth and literacy inequalities exacerbate energy inequities, whereas innovative approaches help to bridge the urban-rural energy gap. Similarly, Opoku et al. (2024) explore the role of governance in addressing energy inequality, concluding that strong governance enhances the effectiveness of energy policies and reduces environmental damage. El-Aal et al. (2024) approved that clean energy has the most significant influence on global GDP growth compared to non-renewable and nuclear energy.

Zhang et al. (2024) study energy poverty in China, showing that economic growth and foreign investment favor urban areas, while unemployment limits electricity access in rural locations. Ghosn (2025) highlights significant differences in rural and urban development in the Middle East and suggests strategies to achieve inclusive growth. The Middle East and North Africa (MENA) energy poverty nexus is examined by El-Katiri (2014), who complements these viewpoints by presenting it as a domestic distributive problem as opposed to a merely infrastructure one. The analysis identifies the root causes and suggests specific legislative measures to improve fair access to energy in the area.

Improvements to energy policy are crucial for addressing these gaps. According to El Hamidi's (2016) study on the impacts of energy subsidy reforms in Egypt, lower-income households are disproportionately affected by the removal of subsidies. Similarly, Nie et al. (2024) examine the effect of energy price fluctuations on the gap between urban and rural areas, noting that rural households consume more electricity, while metropolitan regions are experiencing faster growth.

Many research studies have examined the relationship between urbanization and energy access. Hua et al. (2022) highlighted regional differences in energy availability by identifying a U-shaped connection between urbanization and variations in electricity usage. Another study on energy efficiency and adequacy in rural and urban settings, conducted by Sun and Tong (2024), found that the energy consumption gap has narrowed considerably. El-Aal et al. (2024) confirmed that Egypt's urbanization does not significantly impact CO_2 emissions, indicating that the industry sector relies on clean energy.

Research has also examined the connection between energy access and economic transformation. Djeunankan et al. (2024) discover that reducing energy poverty is crucial for industrialization in Africa, with human capital and income acting as mediators. Falchetta (2021) advocates for a holistic approach to rural electrification, linking investments in energy access to agricultural profitability.

A key focus area is the advancement of technology in rural electrification. Latimer et al. (2013) explore small-scale, household-decentralized energy solutions, focusing on efficient solar PV, wind, and pico-hydro options. Singh and Balachandra (2019) evaluate the cost-effectiveness of hybrid electrical systems designed for rural regions.

The historical context of rural energy development is crucial. Barnes and Floor (1996) analyze successful programs that enhance energy access and encourage market-oriented strategies. Kaygusuz (2010; 2011) links energy services to poverty alleviation, emphasizing the transformative effects of electrification in developing regions. In a supplementary contribution, Lawrence (2009) examines current perspectives on development and energy and suggests a different paradigm that is focused on sustainability. His paradigm emphasizes the significance of fair and sustainable access outside of the grid and gives priority to long-term energy solutions that are suited to the unique requirements of rural and remote people.

Research by Acheampong et al. (2024) suggests that international remittances have a significant impact on reducing rural energy poverty and help bridge the gap between rural and urban energy access. Neto-Bradley et al. (2021) employ Bayesian multilevel modeling to examine spatial inequality in energy availability across metropolitan India and to assess fuel-use disparities. Kruseman and Vullings (2007) conducted a study targeting conditional income support for rural development in Egypt, emphasizing the socio-economic benefits of agricultural intensification. Stern (1997) discusses the significance of rural electrification for development, highlighting the importance of sustainable biofuels and modern fuel alternatives.

Gyawali et al. (2020) emphasize the role of modern energy access in sustainable rural development, while Djeunankan et al. (2024) investigate the relationship between energy poverty and industrialization in Africa. Additionally, Falchetta (2021) examines the significance of rural electrification investments in fostering agricultural profitability and local income generation.

This study employs random forest algorithms to statistically assess the economic impacts of rural-urban energy disparities in Egypt, despite previous research having extensively explored the causes and consequences of inequities in energy access. Unlike most earlier studies, which focus on qualitative analyses or policy evaluations, this research provides a data-driven analysis that correlates industrial output as a percentage of GDP with electricity access in urban and rural areas. This study aims to deliver more accurate and predictive insights to support sustainable economic planning and enhance policymaking by utilizing machine learning techniques.

3. DATA

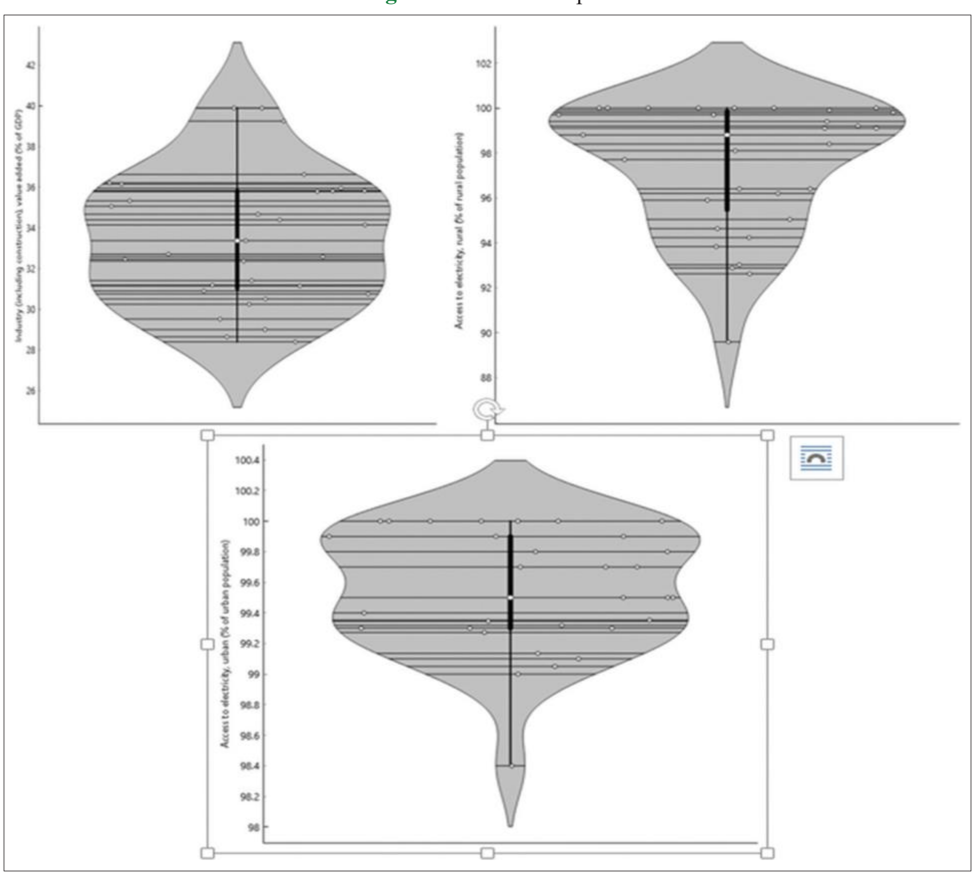
The data used in the analysis were collected from the World Bank dataset. The data covers the period from 1992 to 2022 for industrial value added, Access to electricity, rural population (%), and urban

Table 1: Data statistics and descriptions

Variables	Abbreviation	Source of data	Mean	Mode	Median	Dispersion	Min	Max
Industrial value added	IVA	World bank	33.5	28.4	33.37	0.093	24.8	39.9
Access to electricity in rural areas (% of rural population)	AER	World bank	97.4	100	98.8	0.029	89.6	100
Access to electricity in urban (% of urban population)	AEU	World bank	99.6	100	99.5	0.0038	98.4.	100

Source: Compiled by the author

Figure 1: Data violin plot



Source: Compiled by the author

population (%). Table 1 shows the statistical descriptive data, and the data stability is shown in the violin plot in Figure 1.

The violin plots provide insight into Egypt's industrial sector and the access to energy of rural and urban communities. According to the distribution's central tendency, Egypt's industrial contribution to GDP falls between 30% and 36%.

Based on the plot, 98-100% of Egypt's rural areas have access to power. Although there may be slight variations, Egypt's rural electrification is generally more advanced than that of the other nations in the dataset. However, the extended lower tail suggests that access may occasionally fall below 95%, possibly due to infrastructural issues in isolated locations. With values clustered around 99.5-100%, the plot indicates that nearly all Egyptians residing in cities have access to electricity.

4. RANDOM FOREST ALGORITHM AND RESULTS

In addition to its capacity to handle intricate, non-linear interactions, the RF method was selected due to its superior accuracy, as demonstrated in Table 2. Employing this ensemble learning method, multiple decision trees are constructed, and their expected results are aggregated. The following steps are part of the implementation process (Breiman, 2001).

Table 2: Comparison between RF prediction values and actual values

Year	Industry value added (% of GDP)	RF prediction value
1992	31.41	30.70
1993	31.15	30.60
1994	30.50	30.54
1995	30.25	30.54
1996	29.52	30.35
1997	29.00	29.65
1998	28.65	29.37
1999	28.40	29.37
2000	30.75	31.87
2001	30.90	30.54
2002	32.58	31.84
2003	33.37	34.78
2004	34.67	33.09
2005	34.15	34.93
2006	36.15	35.81
2007	35.07	34.78
2008	36.21	37.52
2009	35.82	35.14
2010	35.78	35.73
2011	35.95	35.73
2012	39.25	38.84
2013	39.89	38.09
2014	39.89	37.52
2015	36.63	36.42
2016	32.46	33.59
2017	34.40	33.59
2018	35.33	33.59
2019	35.83	33.59
2020	32.37	33.59
2021	31.19	33.59
2022	32.71	33.59

Source: Compiled by the author

4.1. Data Splitting

The dataset comprises a training part representing 70% of the data and a testing set containing 30%. The training set is used to build the model, while the testing set is used to evaluate its performance.

4.2. Model Training

The RF. This method builds multiple decision trees by leveraging resampling, randomly selecting a subset of the data, and feature pooling, randomly selecting a set of features. This randomization reduces overfitting and enhances generalization.

4.3. Hyper Parameter Tuning

Key parameters are refined through grid search cross-validation. Adjustments involve the number of trees (n_estimators), the maximum depth of trees (max_depth), and the minimum number of samples needed to split a node (min_samples_split). This process guarantees optimal model performance.

4.4. Prediction

Using the testing data, the trained model forecasts industrial output as a percentage of GDP. The predictions are then compared to actual values to evaluate the model's accuracy. Table 2, and Devrative's Figure 2 show that:

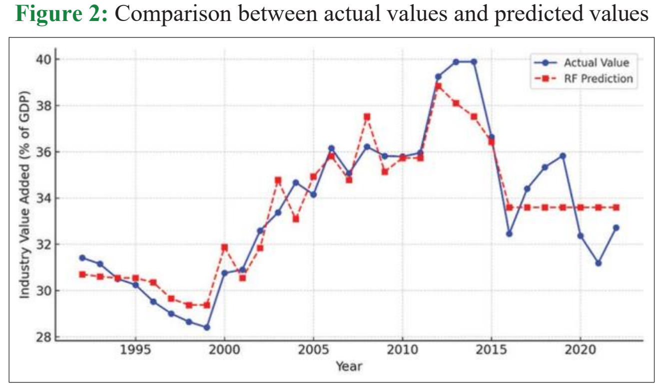
Figure 2 illustrates the performance of the RF algorithm for GDP growth as a function of the independent variable values. We note that the values predicted by Random Forest from 2016 to 2022 are stable, which is due to the stability of the values of the two variables: the rate of electricity access in rural and urban areas.

4.5. Model Evaluation

The following measures are used to evaluate the performance of the random forest regressor.

- Mean squared error (MSE) quantifies the average squared difference between predicted and actual values.
- Mean absolute error (MAE): This metric measures the average absolute difference between predicted and actual values.
- Mean absolute percentage error (MAPE): This metric expresses prediction accuracy as a percentage, calculating the average percentage error by comparing the absolute differences between predicted and actual values to the exact values.
- R-squared (R^2): Represents the proportion of variance in the dependent variable explained by the independent variables.

Figure 2: Comparison between actual values and predicted values



Source: Compiled by the author

Table 3: The ML algorithm's accuracy

Models	MSE	RMSE	MAE	MAPE	R^2
RF	3.89	1.97	1.64	0.048	0.608
GB	4.26	2.06	1.63	0.048	0.57
KNN	4.33	2.08	1.59	0.046	0.56
DT	4.69	2.11	1.55	0.044	0.55
SVM	4.81	2.19	1.85	0.054	0.51

Source: Compiled by the author

Table 4: The RF feature importance score

Variables	Feature score (%)
Access to electricity, urban areas	15
Access to electricity, rural areas	85

Source: Compiled by the author

Table 5: Pearson correlation

Independent variables	Dependent variable	Correlation coefficient
Access to electricity, urban areas	Industry value added (% of GDP)	0.41
Access to electricity, rural areas	Industry value added (% of GDP)	0.67

Source: Compiled by the author

The paper compared five machine learning algorithms to determine the most accurate one, specifically random forest, gradient boosting (GB), k-nearest neighbor (KNN), decision tree (DT), and support vector machine (SVM). Table 2 clearly shows this comparison.

Table 3 shows that the RF algorithm is more accurate than the remaining algorithms, so the paper depends on it for its analysis.

4.6. Feature Importance Analysis

The random forest algorithm provides a feature importance metric, which measures the contribution of each independent variable (urban and rural electricity availability) to the prediction of industrial production. When a variable is removed, the mean drop in accuracy or the mean decrease in impurity (Gini significance) determines feature relevance. This analysis identifies the factors that most significantly impact industrial output; Table 4 clearly illustrates this.

From Table 4, we find that access to electricity in rural areas has the most significant impact on the growth of the industrial sector in Egypt, accounting for 85%, compared to access to electricity in urban areas, which contributes 15%. However, the question arises: Will the relationship between access to electricity in rural areas and the growth of the industrial sector be direct, and thus will its role in rural development be increased or inverse, as determined by Table 5.

From the table, we find a direct relationship between the growth of the industrial sector in Egypt and the rate of electricity access in both rural and urban areas

5. CONCLUSION

This study examined the economic impacts of disparities in energy access between rural and urban areas in Egypt, with a particular focus on the implications for industrial growth. Utilizing the Random Forest (RF) algorithm, a robust machine learning method, the research offered data-driven insights into how access to electricity correlates with industrial value added as a percentage of GDP. The results reveal that rural electricity access has a significant influence on industrial growth, at 85%, while urban access accounts for 15%. However, the relationship between rural electrification and industrial development is positive, as is the case with urban electrification.

These results underscore Egypt's complex dynamics of energy access and industrial development. The inverse relationship in rural areas suggests that increased electrification may divert resources and focus away from urban industrial areas, where industrial activity is concentrated. This phenomenon underscores the difficulties of balancing rural development with the need to sustain urban industrial growth. The findings emphasize that rural electrification is crucial for enhancing the quality of life and reducing inequalities. However, it may not directly lead to development in the industrial sector due to existing industry concentration in urban centers.

In summary, this study contributes to the ongoing debate on energy economics and development by demonstrating the differential impacts of rural and urban electrification on Egypt's industrial growth sector. It also accelerates energy policy that balances encouraging rural development with maintaining high economic growth rates, both in general and in particular, industrial growth rates.

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