Research article

The role of diversity, reserve margin and system structure on retail electricity tariffs in Kenya

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ABSTRACT

Electricity bills in Kenya have been an issue of concern to electricity consumers in the recent past. Highly volatile oil prices and unprecedented weather fluctuations have acted as significant shocks for electricity generation, influencing electricity pricing. This study sought to investigate the contribution of diversity, spare capacity, and system structure as metrics in determining energy resilience. We contend that electricity prices represent the underlying fleet structure's ability to adjust to change and, therefore, can be used to predict energy resilience. Resilience metrics were determined using electricity generation data, electricity sales, electricity installed capacities, and electricity imports, while electricity prices represented the response variable. A regression model was fitted between the response variable and resilience metrics. Diversity, spare capacity, and import metrics play a significant role in predicting electricity prices. However, the diversity metric's role depends on the portfolio mix and requires further comparative empirical evidence.

1. Introduction

Electricity price modelling and forecasting have become an important research topic in electricity management and governance over the last few decades. This follows the introduction of competitive electricity markets in many countries worldwide and the liberalization of electricity sectors for increased efficiency and accountability. Therefore, electricity is treated as a commodity traded in the market (Girish and Vijayalakshmi, 2013). However, electricity has a distinguishable characteristic because it cannot be stored economically, implying that the supply has to meet demand instantaneously. This unique characteristic makes electricity prices highly volatile and prone to outliers compared to other commodities.

The energy sector is faced with emerging risks, including technical disruptions and extreme weather events. The most advanced energy sources, such as hydropower, depend on rainfall patterns and are affected by climate change (Ibanez et al., 2014). Over time, the challenges facing the energy sector have been analyzed using the energy trilemma (energy security, energy sustainability, and energy equity). The concept of sustainability is closely linked to energy resilience as an umbrella concept aimed at maintaining socially, economically, and environmentally desired human-environment interactions over time (Waas et al., 2011). However, unlike sustainability that has been comprehensively studied, energy resilience assessment is still an emerging concept (Sharifi and Yamagata, 2016). A resilient system is a stable system, functioning, and provides continuity with minimum interruptions (Mutani and Todeschi, 2018). It is generally accepted among scholars that energy resilience represents an energy system's adaptive capacity to respond to unexpected shocks. Energy resilience has been accessed through the facets of energy availability, accessibility, affordability, and supply (Cherp and Jewell, 2014; Zhao et al., 2013). Availability, affordability, and acceptability represent adequate energy resources/reserves, meeting energy needs at reasonable costs and efficiency of the energy systems in minimizing environmental impacts, respectively (Mutani and Todeschi, 2018).

Several frameworks have been proposed for resilience assessment from multiple disciplines (Kharrazi et al., 2015; Molyneaux et al., 2014a; Roege et al., 2014). The framework applied in this study identifies diversity, spare capacity, and organizational structure as core characteristics of energy resilience (Molyneaux et al., 2014a). Diversity allows for flexibility in options when faced with disruptions since diverse energy portfolios can enhance energy security (Owusu and Asumadu-Sarkodie, 2016). Spare capacity has been proposed as a metric for energy resilience to guard against disruption while structure describes the ability to monitor system boundaries for an effective response to unexpected...
Reduced global interdependence by reducing net imports/exports and increased diversity of energy supply and technology portfolios have also been identified as crucial energy resilience metrics (Johansson et al., 2012).

The present study seeks to address the following questions; How does the existing energy portfolio mix respond to diversity, spare capacity, and electricity imports? To what extent is the current energy portfolio mix vulnerable to oil price fluctuations and internal deficiencies? How can the energy sector be adapted to respond to these disturbances? We examine the complicated relationship between resilience metrics and electricity prices. Electricity price as the dependent variable represents the structure's dynamics, transforming fuel source to electrical energy (Molyneaux et al., 2016). We provide an in-depth analysis of Kenya’s electricity sector in terms of electricity sources and electricity prices. An empirical analysis was also performed to determine electricity generation diversification, spare capacity, and system structure on electricity prices.

Electricity prices affect the economy by raising the cost of doing business. In the context of sustainable development goal number seven, which outlines the need for affordable and clean energy, Kenya has made progress in clean energy with a large share of the electricity generated locally coming from clean sources (hydropower and geothermal). However, the country may not be in a position to meet this goal because of the high electricity bills that continue to burden low-income earners. Considering these challenges, there have been plans in the recent past to diversify Kenya's generation mix by adding more generation capacity from geothermal, wind, and coal. However, coal exploitation has faced opposition from civil society groups and Non-Governmental Organizations.

1.1. Overview of the Kenya power scene

The electricity sector in Kenya is regulated by the Energy and Petroleum Regulatory Authority (EPRA) established under the Energy Act 2019. EPRA is mandated to set, review, and adjust electric power tariffs and investigate tariff charges. This was designed to protect consumers from price exploitation and regulate other energy types to create harmony in the energy sector.

The country’s electricity industry is liberalized with several licensed power producers. However, the state-owned Electricity Generating Company (KenGen), accounts for approximately 70% of the current generation capacity (Ministry of Energy, 2018). Independent Power Producers (IPPs) share the balance. This sector lacks competition, essential for high reliability and low-cost energy (Mustapha Wasseja, 2015). Competition is not the sole factor to consider in addressing unreliable supply and high energy costs. Market design issues, regulatory constraints, and the nature of reserve plant margins contribute to unreliability in supply (Cramton et al., 2013; Woo et al., 2019). Kenya has several energy sources, but only a few contribute significantly to addressing energy needs (Figure 1). Hydropower has dominated the electricity sector since the year 1980, contributing more than 1 billion kWh throughout this period. Geothermal has been on the rise in recent years and has surpassed hydropower as the major energy source. In 2015 and 2016, geothermal generation was 4.5 billion kWh compared to hydropower’s 3.5 and 4.0 billion kWh over the same period, respectively. Other contributors to Kenya’s electricity mix include biomass and waste, solar, and wind. These sources’ contribution has remained relatively low (less than 0.5 billion kWh).

Renewable sources account for about 86% of Kenya’s total electricity generation. Between 1980–2003, hydropower contributed approximately 75% of electricity from renewable sources. The net installed generation capacity has increased from 0.6 GW in 1980 to about 2.2 GW in 2016 against a peak demand of 1.6 GW in 2016 (Ministry of Energy, 2018). In 2016, hydropower, geothermal and combustible fuels accounted for about 99% of the installed capacity, with capacities of 0.8 GW, 0.64 GW, and 0.79 GW, respectively. Combustible fuel plants account for 35% of the total generation capacity.

Kenya Power imports electricity from Tanzania Electricity Supply Company Limited (TANESCO), Uganda Electricity Transmission Company Limited (UETCL), and the Ethiopian Electric Power Corporation (EEPPO) (Ministry of Energy, 2018). Uganda is the leading electricity exporter to Kenya. Electricity importation has steadily declined, reaching the lowest value in 2006, followed by a steady increase up to 2014 (Figure 2). The decline in electricity imports was as a result of increasing local generation capacity. Kenya also exports electricity to Tanzania, Uganda, and now Rwanda.

Due to the diverse energy sources, electricity tariffs have several components. Kenya Power proposes to the EPRA a fixed charge per kWh for electricity consumed, which is operationalized after approval. The fixed charge levy does not change regularly. The last time Kenya Power reviewed this levy was in 2015, which was still in use as of April 2018. Other charges levied to electricity consumers are Fuel Cost Charge (FCC), Foreign Exchange Rate Fluctuation Adjustment (FERFA), Inflation

![Figure 1. Trends in the net electricity generated by individual local sources.](image)
Adjustment (IA), Water Resource Management Authority (WARMA) levy, ERC levy, Rural Electrification Program (REP) levy, and Value Added Tax (VAT). Retail electricity tariffs are also determined by sector (Table 1). The commercial sectors are: Domestic Consumption (DC), Small Commercial (SC), Commercial (CI1), Commercial (CI2), Commercial (CI3), Commercial (CI4), Commercial (CI5), Domestic Water heating (IT), and Street Lighting (SL). DC comprises a category of consumers on 240V. Despite having most consumers in the DC and SC categories, the large and medium commercial categories have the largest electricity consumption share (Figure 3).

The majority of consumers are billed on a prepaid metering plan. Prepaid metering is preferred because it is seen as a tool for increasing electrification, reducing non-payment, and cost recovery for utilities (Kambule et al., 2018).

Several studies (Burger and Graeber, 2007; Fiorenzani, 2006; Swishchuk, 2010) have explored electricity price prediction. Some of these studies were designed at modelling the probabilistic price changes aimed at addressing risks. Research done by (Kuo and Huang, 2018) demonstrated the practicality of predicting electricity prices in China using the Convolutional Neural Network and the Long Short Term Memory networks. Price forecasting possesses challenges, including consumer demand responses, which result in sharp price fluctuations. To address these challenges (Neupane et al., 2017), employed a strategy that agglomerated the Fixed Weight Method (FWM) and the Varying Weight Method (VWM) forecasting algorithms for the New York, Australian, and Spanish electricity markets. These methods demonstrate resilience to demand responses in forecasting electricity prices in a dynamic environment. For the Kenyan context, a study by (Fabini et al., 2014)

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### Table 1. Description of electrical energy consumer categories.

| Consumer Type   | Description                                                                 | Energy Charge/unit |
|-----------------|-----------------------------------------------------------------------------|--------------------|
| DC-LIFELINE     | Applicable to domestic consumers for supply provided and metered at 240 or 415 V and whose consumption does not exceed 10 units per billing period | KES 12.00          |
| DC-ORDINARY     | Applicable to domestic consumers for supply provided and metered at 240 or 415 V and whose consumption is greater than 10 units but does not exceed 15,000 units per billing period | KES 15.80          |
| SC              | Applicable to non-domestic small commercial consumers for supply provided and metered at 240 or 415 V and whose consumption does not exceed 15,000 units per billing period | KES 15.60          |
| CI1             | Applicable to Commercial and Industrial consumers for supply provided and metered at 415 V three-phase four-wire and whose consumption exceeds 15,000 units per billing period | KES 12.00          |
|                 |                                                                            | KES 6.00 (off-peak) |
| CI2             | Applicable to commercial and industrial consumers for supply provided and metered at 11,000 V respectively, per billing period | KES 10.90          |
|                 |                                                                            | KES 5.45 (off-peak) |
| CI3             | Applicable to commercial and industrial consumers for supply provided and metered at 33,000 V respectively, per billing period | KES 10.50          |
|                 |                                                                            | KES 5.25 (off-peak) |
| CI4             | Applicable to commercial and industrial consumers for supply provided and metered at 66,000 V respectively, per billing period | KES 10.30          |
|                 |                                                                            | KES 5.15 (off-peak) |
| CI5             | Applicable to commercial and industrial consumers for supply provided and metered at 132,000 V respectively, per billing period | KES 10.10          |
|                 |                                                                            | KES 5.05 (off-peak) |
| IT              | Interruptible off-peak supply of electrical energy applicable to ordinary consumers whose consumption does not exceed 15,000 Units per billing period | KES 13.00          |
| SL              | Applicable to Public and County Governments metered at 240 or 415 V for the supply of electrical energy to public lamps | KES 7.50          |

**Source:** (ERC, 2018)
demonstrates that induced demand predictions can achieve technological, business, and more critical, tariff structures. A predictive model for mapping induced electricity demand for residential, which is affected by income elasticity, has been developed. (Mabea, 2014) investigated the interaction among Kenya's electricity consumption, real disposable income, and residential electricity prices using the Engle and Granger two-step procedure and error correction model. The findings indicate increasing electricity demand as the economy grows. (Mumo et al., 2015) sought to determine the best tariff model for improving Kenya's electricity consumption by exploring all factors affecting electricity costs.

These studies investigated the determinants of electricity tariff structures from an operational perspective. We build on the literature by using a resilience-based approach to examine fluctuations in electricity prices.

2. Data and methodology

2.1. Data

This study's response variable is electricity price, representing the system's capacity to adjust to change. Drastic change in price, especially sharp increases, signifies potential supply constraints. In economic studies, an increase in price reduces demand and, in this way, allows adjustments within the system to deal with the disruption. A given system's essential dynamics can be captured by including the critical processes with longer and shorter turnover times (slower or faster turnover times).

Processes with longer turnover times may include national or international agenda such as Vision 2030, Agenda 2063, or sustainable development goals. These systems' mechanisms derive from another set of processes with shorter turnover times. Fast and slow variables of a system are terms that are common in ecosystems dynamics. In ecology, the system's fast variables show the dynamics of the underlying structural variables (Carpenter and Turner, 2000). If this assertion is applied to electricity generation, the price may represent the fast variable since it reflects the structure's dynamics transforming fuel source to electrical energy. Thus, if price can show stability levels, there is evidence of resilience in electricity generation (Molyneaux et al., 2016). We identify three resilience metrics; diversity, spare capacity, and system effectiveness/structure. Since price is indicative of resilience, it follows that resilience levels can dictate price. Therefore, changes in resilience metrics can influence electricity prices. This analogy is adopted in fitting our model.

Resilience theory is a broad multidisciplinary concept that addresses dynamic systems or people's capacity to successfully adapt to adversity (Southwick et al., 2014). In assessing resilience, the emphasis is usually on strengths with modellers moving away from vulnerability models to focus on trumps in cases of adversity (VanBrda, 2001). The core characteristics of resilience in a resilience framework are identified as diversity, spare capacity, and organization/structure. Diversity is proposed as the first principle for enhancing energy resilience and is also a defining characteristic of energy security (Molyneaux et al., 2014a; Nwachukwu and Robinson, 2011). Diversity is seen as a long-term strategy of the energy systems because it allows high flexibility and adaptability. Diversity is vital in energy policy and an essential characteristic in energy supply security, efficiency, energy system's adaptability, and the environment. The diversity of energy supply benefits a system through extending choice and increasing competition (Lo, 1999). Spare capacity is identified as a metric for energy resilience, but its inclusion is generally not a primary characteristic (Molyneaux et al., 2016). Spare capacity measures energy security and economists use it to calculate adequate reserve capacity levels to guard against energy disruption. The structure is presented as an essential energy resilience characteristic by identification of frameworks to facilitate resilience through the organization to plan/prepare, absorb, recover and adapt (Roege et al., 2014), and the need for system boundaries monitoring to facilitate flexible response to an unexpected fault (Arghandeb et al., 2016). The structure of components flow within a system influences the system’s inputs and outputs (Mobus and Kalton, 2015). Therefore, a system's organizational structure is essential for its effective operation. We defined the system structure by electricity imports and losses within the grid.

This study utilized monthly data on retail electricity prices, electricity sales, electricity generation, and electricity imports and exports. Electricity prices data for the period November 2008 - March 2018 were obtained from Stima (https://stima.regulousweb.com/historic) website. The website was accessed on 12/05/2018. Retail electricity prices are billed monthly according to consumer categories in Table 1. Consumer categories’ prices were averaged to obtain an average price weighted against electricity sales. Commercial and industrial consumers have 86 off-peak hours per week, implying 82 peak hours (ERC, 2018). Thus, we applied a simple average of the off-peak and peak charges. The retail Tariff structure in Kenya considers the following: monthly generation related fuel costs, system losses (revised annually), and inflation adjustment (revised after every six months). The Kenya Power Company sets
the tariff mechanisms to protect against incurring costs related to drought and high oil prices. These costs are included in retail tariffs. EPRA’s mandate includes demand and generation costs forecasting. The energy regulator also computes initial retail tariff proposals and performs sensitivity analysis on the proposed tariffs. Effective July 1, 2018, fixed charges were removed from the billing method. However, this study did not consider fixed charges in the analysis. The focus was on energy charges and other variable costs.

Monthly electricity sales, electricity generation, electricity losses, and electricity imports and exports data of similar span as electricity prices were sourced from the Kenya National Bureau of Statistics (KNBS). Electricity losses comprise transmission & distribution losses and other losses. This data was obtained from the difference between net electricity generated and electricity sales. Monthly Global oil prices data were obtained from Wessex Texas Intermediate (WTI), Macrotrends.

2.2. Methods

Resilience metrics form the basis of this study. The metrics were determined using quantitative methods. Diversity as a metric of energy resilience measures possible energy alternatives. Simpson’s Diversity Index, given by Eq. (1), considers the number of energy types present and the abundance of each energy type.

\[
D = 1 - \left( \frac{\sum n(n-1)}{N(N-1)} \right)
\]  

(1)

D refers to the diversity in electricity generation sources, \( n \) is the total number of kWh generated from each energy type, while \( N \) refers to the total number of kWh generated from all available energy types. Simpson’s Diversity Index is also referred to as a dominance index because it gives more weight to the dominant species. As species evenness increases, diversity increases (Centre Barcelona Field Studies, 2018). The assumption is that a few rare energy types with fewer representatives will not affect diversity.

Sparsity is the difference between the electricity amount generated in a year and that which could be generated at full capacity (Molyneaux et al., 2016), as shown in Eq. (2) below.

\[
SP = \left( \frac{\sum_{i=1}^{n} \left( (GW_i \times \text{hours}) \times CF_i \right) - GWh_i}{GDPR} \right)
\]  

(2)

SP denotes sparsity capacity, representing the potential energy available for use in the economy. \( GW_i \) refers to installed capacity in millions of kilowatts using fuel type \( i \), \( CF_i \) is the capacity factor which represents the maximum proportion of total generation possible from an installed plant for fuel type \( i \), \( GWh_i \) refers to electricity generated in millions of kilowatt-hours from fuel type \( i \). \( GDPR \) denotes Real Gross Domestic Product (in million US$). 8760 hours are generally assumed in estimations of total annual capacity. A power plant’s capacity factor is the ratio of its actual energy output (in kWh), over a specified period, to the total energy that could be produced if the plant operated at full capacity without the need for plant maintenance or output reductions (Almeida Prado and Berg, 2013; Wang and Li, 2019). The actual electricity production is divided by the maximum possible electricity output of a power plant over time (Neill and Hashemi, 2018). Capacity factors are determined by the plant’s design (installed power) and its operating features, expressed by Eq. (3).

\[
CF = \left( \frac{E_i \times 100}{P_i \times H} \right)
\]  

(3)

\( CF \) represents the capacity factor (%), \( E_i \) denotes power generation of type \( n \) generation technology (kWh), \( P_i \) represents installed capacity of type \( n \) generation technology (kW), and \( H \) is the number of hours over the same time interval (h).

The import metric was determined under system structure according to Eq. (4).

\[
PEI = \left( \frac{y - EIM + EEX}{TEC} \right) + \left( \frac{\theta - EIM + EEX}{TEG} \right)
\]  

(4)

\( PEI \) refers to the proportion of electricity exported/imported, \( EIM \) denotes total electricity Imports in GWh, \( EEX \) is total electricity exports in GWh, \( TEC \) stands for total electricity consumed in GWh, and \( TEG \) is the total electricity generated in GWh. \( y \) represents the net import indicator: If \( (EIM + EEX) < 0 \), then \( y = -1 \), else \( y = 0 \). \( \theta \) represents the net export indicator: If \( (EIM + EEX) > 0 \), then \( \theta = -1 \), else \( \theta = 0 \).

This formula was adopted from (Molyneaux et al., 2016). The import and export indicators’ interpretation was modified such that \( y = -1 \) implies net import and \( \theta = -1 \) implies net exports under the above conditions.

Correlation analysis was carried out to establish relationships between the resilience metrics and electricity prices. Pearson’s correlation coefficient was used as given by the relation in Eq. (5).

\[
r_{xy} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2 \sum_{i=1}^{n} (y_i - \bar{y})^2}}
\]  

(5)

denotes the correlation coefficient while \( x_i \), \( y_i \) and \( \bar{x} \), \( \bar{y} \) are individual data points and the mean of parameters whose correlation is determined, respectively.

A regression model was fitted between weighted average electricity prices and resilience metrics. The weighted average price is the dependent variable, while resilience metrics are independent variables, as expressed by Eq. (6).

\[
P_{out} = \beta_0 + \beta_1 D + \beta_2(PEI) + \beta_3 Sp + \varepsilon
\]  

(6)

\( P_{out} \) is the weighted average electricity price, \( \beta_0 \) is the intercept of the weighted average price, \( \beta_1 \), \( \beta_2 \) and \( \beta_3 \) are coefficients of resilience metrics, \( D \), \( PEI \) and \( Sp \) are diversity, import, and sparsity capacity metrics, respectively. \( \varepsilon \) is the random error component in the weighted average price. The original retail electricity prices were weighted against kWh of electricity sold. This gives more weight to prices corresponding to the highest electricity sales than those that correspond to low electricity sales. Figure 4 displays the weighted average electricity prices’ time series decomposition.

3. Results

The evolution of electricity prices was analyzed by decomposing the weighted average price time series into individual components of the trend, seasonal and random fluctuations (Figure 4). The results reveal a non-linear trend with no specific long-run trend, while the seasonal component exhibits a bimodal pattern with two distinct peaks occurring in May–June and August–December. The monthly diversity indices were determined based on Eq. (1), which was implemented in R programming environment. This study’s diversity method considers generation from individual energy sources in the generation mix, thus taking care of dominance from some sources. Therefore, diversity varies depending on the amount of electricity generated from each source in the generation mix. The diversity curve runs almost parallel to electricity prices (Figure 5). The relatively lower electricity prices of July 2010 and March 2012 - July 2013 recorded diversity values ranging between 0.58 and 0.60 that were lower than the long-term average (0.62) for the period under consideration.

The sparsity capacity metric - also reserve margin (US Department of Energy, 2016), is dominated by sparsity capacity from thermal generation. Hydropower had the least spare capacity. Spare capacity values were standardized using the 2016 GDP in United States Dollars (US $) to portray the significant energy available for use in the economy. There is an inverse pattern between thermal spare capacity and the weighted
prices (Figure 6). The high price episodes of November 2011, July 2014, and 2017/2018 coincide with a reduction in thermal spare capacity.

November 2016 to March 2018 was marked by increasing spare capacity in hydropower and decreasing spare capacities in thermal and geothermal. This signifies a shift from hydropower to thermal and geothermal. A corresponding increase in electricity prices was marked during that period. We determined the import metric values according to Eq. (4). The results are presented in graphical plots (Figure 7) concurrently with weighted prices. The graphs follow a similar trend, especially in 2014, when the imports were stepped up, and the prices hiked. Kenya stepped up electricity imports in 2016. However, the imports have declined in the recent past.

The relationship between resilience metrics and price have been summarized in Figure 8. Electricity imports have a relatively strong positive correlation with price at 0.43. Diversity and price have a correlation coefficient of 0.31. Hydropower and geothermal spare capacities have a positive correlation with price, while thermal spare capacity and price have an inverse relationship. Correlation between total spare capacity and price was insignificant (correlation coefficient = 0.08). There is multicollinearity between individual spare capacities and the total spare capacity. Therefore, individual energy technologies were considered under the spare capacity metric to ascertain each technology's effect on electricity prices. The test for the significance of correlation turned significant between electricity prices and imports (Figure 8). Diversity, geothermal, and thermal spare capacities also portrayed significant relationships with electricity prices. P-values of $8 \times 10^{-4}$, $4 \times 10^{-2}$, and $6 \times 10^{-3}$, respectively, were obtained.

This model considered three metrics; imports, diversity, and spare capacity, where spare capacity comprises individual spare capacities from hydropower, geothermal, and thermal sources. We note multicollinearity in the model variables (see Figure 8), which is likely to affect the model results. We experimented for multicollinearity by performing the variance inflation factors test (VIF) and examining each regressor's tolerance. Eq. (6) was thus modified to include linear combinations of the highly correlated variables (Daoud, 2017). The following combinations were established based on the strength of correlation between them, VIF

![Figure 4. Decomposition of the weighted electricity prices (November 2008–March 2018).](image)

![Figure 5. Weighted average electricity prices against diversity indices.](image)
and tolerance: diversity and thermal spare capacity; diversity and hydropower spare capacity; import metric and hydropower spare capacity; import metric and geothermal spare capacity; import metric and thermal spare capacity. Logically, the import metric and spare capacity are associated because reserve capacity status could determine electricity importation. Diminishing spare capacity could necessitate an increase in electricity imports to fill the deficit. Due to dependence on diesel-fired thermal generators, electricity prices are affected by fuel costs. Hence we included in our model global oil prices. Other operational factors affecting electricity prices include power transmission and power system operating conditions (Girish and Vijayalakshmi, 2013), represented by transmission and distribution losses, and other losses in the grid.

The coefficients for resilience metrics in predicting electricity prices are presented in Table 2. Each attribute’s coefficient and p-value reflect that attribute’s effect on the prediction. An attribute with a coefficient 0 or near 0 has no effect or minimal effect on the dependent variable, respectively. The variables’ predictive power increases with smaller p-values. We take $\alpha = 0.05$ as evidence that the estimated variable coefficients are significant in predicting prices. Diversity, import metric, thermal, geothermal, and hydropower spare capacities show significant predictive power. Geothermal and hydropower spare capacities are relatively weak instruments in this model. The model residuals’ spread is not much different from the centred (mean) fit spread (Figure 9). The model output data were tested against the observed electricity price data (Figure 10). The model predicts 54.8% of the observed variation in electricity prices.

4. Discussion

Electricity prices hiked in 2014 due to drought conditions leading to depressed hydropower generation. This necessitated more imports from neighbouring countries. Kenya imports most electricity in February–June. The current diverse generation mix in the power sector has evolved because of different factors, including policymakers’ decisions, technological capabilities, and the decommissioning of old power plants. The power generation fuel options readily available in Kenya have historically been hydropower, geothermal, and thermal. Wind power accounts for an insignificant portion of the generation mix. A 310 MW wind power plant has been commissioned in Kenya’s northern part. However, this plant was not contributing to the national grid.

Energy system resilience can be improved by diversifying energy production in energy systems. This involves technological diversity where traditional energy sources such as oil, natural gas, coal, and hydropower are augmented by new energy technologies (wind, solar, geothermal) (Kharrazi et al., 2015). Generation mix diversity ought to achieve the most cost-effective generation mix. Diversity’s benefits from
some fuels increase as the share of the fuel in the portfolio decreases. This is true for thermal generation, which is hydropower’s substitute in poor hydrology events. Over the years, electricity generation from thermal sources has been more varied and synchrony with hydropower (Figure 1). This study adopts a diversity approach that encompasses the properties of variety, balance, and disparity (Stirling, 2010). By the analogy of Simpson’s diversity index, the diversity observed could be due to hydropower and thermal dominance and variability in the portfolio, thus causing an imbalance and disparity in the energy mix. Besides, there is a lack of distinct variety and disparity upon which the energy system is apportioned. Hydropower and thermal sources, though distinct, both suffer from the problem of dependence on external factors (climate and oil prices). There is also a lack of balance in the energy mix due to insignificant contributions from solar, bioenergy, and wind. Fuel sources diversity is closely related to fuel variation, which involves shifting between fuel sources. Variation refers to difference within fuel type, and diversity implies a difference of type (Page, 2011). Therefore, shifting between fuels implies variation, an aspect that was considered in the computation of diversity. This attribute of diversity is the reason for its inconsistent role in predicting electricity prices. Model results indicate a significant influence of the diversity metric on electricity prices, predicting increased prices. States with dominant fuel sources experience

![Figure 8. Correlation matrix between electricity price and resilience metrics.](image)

![Figure 9. Model residual fit spread.](image)
increased electricity prices than states with mixed portfolios (Molyneaux et al., 2016). This is consistent with Kenya’s case, where there are few dominant fuel sources in the generation mix. However, the diversity metric may not provide consistent information about its perceived benefits regarding electricity prices. This is an area for further comparative studies.

Spare capacity represents reserves in the installed capacity and is necessary to ensure that the power system can respond to load increase. Having adequate spare capacity is essential because no power plant can be 100% reliable. There may also be uncertainties in load forecasting, leading to a higher load than anticipated. Inadequate spare capacity makes the generating system less reliable (Diewvilai et al., 2011) and indicates strain or threat to the power system. This threat could be reflected in retail electricity prices, where there are no mechanisms to cushion consumers. Thermal and hydropower spare capacities are associated with high electricity prices, while geothermal spare capacity is characterized by low electricity prices (Table 2). A reduction in thermal spare capacity implies increasing fuel utilization, which attracts more costs in fuel cost charge (FCC). In Kenya, conventional thermal generators are primarily owned by IPPs who sign a power purchase agreement (PPA) contract with Kenya Power. These contracts are honoured regardless of the power supplied. In the current scenario, both the lack and presence of spare capacity in thermal generation facilitate an increase in electricity prices. Spare capacity is expensive to maintain; therefore, an over-built power system has adverse implications on energy costs. Appropriate spare capacity generally signifies efficient operation and system reliability. In contrast, excessive spare capacity implies low efficient generation costs and high investment costs (Diewvilai et al., 2011). Thermal spare capacity was higher in both quantity and model significance than those of hydropower and geothermal. Thermal and hydropower are sensitive to oil prices and rainfall patterns, respectively. Geothermal is least affected by external shocks (Ang’u et al., 2019). Consequently, geothermal spare capacity predicts decreased electricity prices, while thermal and hydropower spare capacities predicts increased electricity prices. Hydropower ought to have higher spare capacity since calculating the appropriate reserve margin should consider the risks of droughts, which have been frequent. It is essential to have the spare capacity to deal with drought (Bain and Acker, 2018). The metric for thermal spare capacity is more significant than hydropower and geothermal spare capacities. Thermal generation is thus an essential characteristic of energy resilience.

Maintaining a sufficient spare capacity in electricity generation to meet demand surges in stochastic demand may not be straightforward. This is due to the nature and characteristic of electricity, which has limited storage options, implying that supply must meet demand instantaneously. Self-reliance of any jurisdiction would imply maintaining an adequate spare capacity to meet stochastic demand. However, the option of international trade provides the opportunity to reduce maintaining excess spare capacity by importing from countries that have a comparative advantage in electricity generation (Antweiler, 2016). In scenarios where domestic generation cannot sufficiently meet demand or insufficient spare capacity, it may be economical to import electricity

| Variables                  | Estimate coefficients |  t-value | P-value |
|----------------------------|-----------------------|---------|---------|
| Intercept                  | -1.917 × 10⁻⁴        | -5.544  | 0.000   |
| Diversity                  | 1.956 × 10⁻³        | 5.875   | 0.000   |
| Imports metric             | 7.324 × 10⁻⁴        | 3.614   | 0.000   |
| Thermal spare capacity     | 5.335 × 10⁻²        | 5.438   | 0.000   |
| Hydropower spare capacity  | 2.181 × 10⁻⁵        | 2.458   | 0.015   |
| Geothermal spare capacity  | -2.530 × 10⁻⁶       | -2.311  | 0.023   |
| Oil prices                 | 2.786 × 10⁻⁴        | 2.085   | 0.039   |
| Losses                     | -1.813 × 10⁻³       | -3.565  | 0.000   |

Significant codes: 0.0001 ‘***’ 0.01 ‘**’ 0.05 ‘*’ 0.1 ‘.’ 1

Residual standard error: 0.1681 on 99 degrees of freedom
Multiple R-squared: 0.5475, Adjusted R-squared: 0.488
F-statistic: 9.213 on 13 and 99 degrees of freedom, p-value: 3.699 × 10⁻¹²

Figure 10. Real versus predicted electricity prices.
from markets at low prices than the domestic opportunity cost of generating electricity (reciprocal load smoothing). An impediment to electricity importation includes transmission costs over long distances, which can elevate imported electricity costs. Kenya's situation lacks the aspect of comparative advantage to Kenya because of costlier imports from Uganda (World Bank Group, 2019). An agreement signed in 2014 between Kenya and Uganda set KES 21 (US$ 0.21) per kWh for cross-border purchase of electricity between the two countries. Uganda was the beneficiary of the higher tariffs following increased exports to Kenya, especially in 2014 and 2016/2017. During these periods, Kenya's electricity prices increased considerably due partly to increased local thermal generation and increasingly expensive imports. The import metric significantly influences electricity prices by predicting increased prices (Table 2).

The resilience metrics considered in this analysis (diversity, spare capacity, and imports) have a bearing on Kenya's electricity prices. This is consistent with similar studies. A study by (Molyneaux et al., 2016), on several states in the United States, found spare capacity to be the most important metric for predicting favourable outcomes, while diversity had a minimum impact. Empirical evidence suggests a linkage between resilience metrics and electricity prices.

A power system's objective function is to deliver power at minimum cost, subject to a reliability constraint. Kenya has an extensive legacy fleet of hydroelectric power stations, which have a very low marginal cost of production, although evidently, a very high opportunity cost of production when resource constraint, e.g., during low dam levels and droughts. However, rising overall demand means that the power system is, at times, being stretched. When combined with low water resources/droughts, imports from neighbouring power systems and higher production from its fleet of thermal plants become necessary to meet the reliability constraint. During these periods, prices are elevated because the costs of supply are elevated. The available options in dealing with internal (demand increase) and external (fluctuations in the oil market and climate change) disturbances to the country's power system are much costly to consumers since tariffs are logically determined with no policy interventions.

5. Conclusion

This study established that in the absence of favourable policy interventions and inefficient tariff setting mechanisms, diversification of the generation mix, electricity importation, and spare capacity influence electricity pricing. Spare capacity affects electricity prices because it is expensive to maintain. It signifies strain to the power system (in case of decreasing spare capacity), which necessitates electricity imports and costly alternative fuel sources. The power utility could avoid extra costs of maintaining spare capacity by shifting to a model where IPPs are only paid for electricity supplied. Although there could be regional trade agreements, electricity importation implies a lack of sufficient domestic choices to deal with possible disturbances. This option could be expensive, especially where the exporting country has relatively higher tariffs. The import metric thus predicted increased prices.

Diversity affects electricity prices depending on the share of specific fuels in the portfolio. Diversifying using fuels that are more independent of oil prices is likely to lower electricity prices. Kenya has not benefited from its power mix diversity due to imbalance and disparity within the generation mix, where thermal and hydropower have been the dominant fuel sources. The country has sought to diversify its energy mix (adding geothermal and wind) to reduce reliance on higher-cost power sources during scarcity conditions. Solar PV will also become part of the plant mix given the sharply falling cost of utility-scale solar PV facilities witnessed in places like the US and Australia. When combined with a hydro fleet, this should, in theory, enhance power system resilience and may produce lower costs because scarce water resources may be better allocated across the year subject to rainfall patterns and the size of dam storage. This will also decrease dependence on thermal generation and provide the power system with greater resilience from the highly volatile oil prices.

Declarations

Author contribution statement

Cohen Ang’u: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Nzioka John Muthama: Conceived and designed the experiments; Analyzed and interpreted the data.

Christopher Oludhe: Analyzed and interpreted the data.

Isaac Chitedze: Contributed reagents, materials, analysis tools or data.

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Competing interest statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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