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PAPER

Energy price modeling in sub-Saharan Africa: an systematic literature review

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Abstract

Researchers have found that despite a wide range of renewable energy sources in sub-Saharan Africa (SSA), renewable energy pricing policies have focused extensively on metered electricity energy, an early source of renewable energy. Supply, access, and regulation of price for metered electricity energy is mostly controlled by the governments across SSA. There is an increasing use of other renewable energy sources including portable electricity, solar power, and wind power. However, in SSA, the pricing for domestic renewable domestic renewable power such as portable electricity, rechargeable cookstoves, and portable solar power sources are left to the market to legislate, with energy prices dependent on forces of demand and supply and seldom on clear scientific models. This commercially focused energy market means businesses operating in the energy industry are more interested in profits and set prices relative to their market perceptions. The main problem with the energy market in SSA is the lack of a participatory approach where customers, businesses, the government, and other stakeholders are involved in the pricing for energy. We further note that lack of a participatory approach in energy pricing is a major challenge in uptake and demand for the domestic renewable energy sources. Through a systematic literature review, including a review of peer-reviewed journals, documents from energy utility companies, and published information on the websites for energy companies, this review analyzes the current application of energy price modeling and hypothesizes that mobile technology and a participatory pricing approach can improve pricing for domestic renewable power. Our initial literature review showed that energy price modeling had received little attention in SSA, especially for domestic renewable power energy sources. This paper, therefore, fills this gap by using a systematic literature review to consolidate knowledge on how energy price modeling has been applied in the SSA context. The systematic literature review results reveal four commonly used models: time series, artificial neural network, hybrid iterative reactive adaptive, and hybrid models. These energy pricing models are mainly applied to metered electricity power, the predominant source of energy in SSA. The literature hypothesizes that applying mobile technology to energy pricing and a participatory approach involving the consumers and energy supply businesses can move SSA closer to transitioning to renewable energy. Although other factors have hindered this transition, a participatory energy pricing approach incorporating relevant pricing models and market information creates potential solutions to these challenges. In the discussion, we hypothesize that a participatory approach to price modeling with the incorporation of mobile technology can be used at the household level to improve energy decision-making. For this to work, energy price modeling for domestic renewable sources should be simplified, user-friendly, and accessible to households. In conclusion, we recommend that SSA governments develop a more holistic view of energy price modeling to better harness the potential for domestic renewable energy sources.

1. Introduction

In a market where private businesses are showing more investment in energy, pricing for domestic renewable power in sub-Saharan Africa (SSA) is often left to the market to decide. Access to renewable energy in Africa is one of the major energy challenges, with other challenges include affordability, regulatory challenges, cartelization, and technology. Across the SSA region, 70% of the population relies on traditional and unsafe energy fuels such as biomass and kerosene, resulting in poor health outcomes [1]. The energy-poverty situation in SSA is a potential hindrance to the targets set forth by SDG 7 that advocates for universal access to clean and affordable energy [2]. Of the renewable energy used across the continent, metered electricity power is the most dominant source of energy [3, 4]. The table in appendix A shows metered electricity power access (geographic connectivity) across different countries in SSA. Despite nearly 51% geographic connectivity to electricity, 70% of the population still uses non-renewable energy [1]. Researchers have indicated that household energy uptake is low due to pricing, access, income, housing types, and a general lack of support from energy stakeholders [5]. This study hypothesizes that a participatory pricing approach that includes incorporating energy price models and technology together to help consumers understand how their energy is priced can solve the pricing problem and move SSA closer to transitioning to renewable energy.

Governments are vital stakeholders in the energy sector in the SSA region with varied roles, including regulation, rural energy development, and energy price setting. However, SSA governments mainly focus on electricity and petroleum. The two are the main sources of energy across the SSA market [6]. However, they are not the widest used energy sources because most SSA populations use biomass fuels for domestic use [6]. When setting the price for electricity and petroleum, governments in SSA engage a range of stakeholders, often experts and utility companies. However, households and small businesses are involved at the public participation stage, a late stage in the energy price setting. Lack of participation from stakeholders has often alienated the consumers and slowed down the pace of energy transitions to renewable energy across SSA.

Evidence from many sub-Saharan African countries shows the government actively involved in setting tariffs and prices for energy through parastatals and other government agencies [3, 7]. Portable energy is also increasingly becoming popular as private businesses leverage government advancement in rural electrification and increased focus on sustainable energy [3, 8]. Private businesses have increased investment in energy in sub-Saharan countries. With the promotion of SDG 7 across Africa, different energy companies focused on different forms of energy like solar energy and portable electric energy have increased their investments across the SSA region. The prospects for better uptake for these energy forms depend on community involvement through participatory approaches that leverage available resources and technologies.

Evidence from Nigeria, Ghana, Ethiopia, Chad, DRC, Mozambique, South Africa, Angola, Tanzania, and Kenya shows governments being responsible for the pricing of metered electricity, petroleum, LPG, and LNG through various parastatals, government departments and agencies, and ministries [9]. The cost of these energy sources for the consumers depends on government-set tariffs, which apply pricing strategies commensurate with the government's objectives regarding the energy sources. Consumers often pay the price set for these energy sources without understanding how they are set. There is no participation, nor is there a platform through which consumers can estimate their own energy prices. Household energy prices are continually perceived to be high despite increased access because there is low demand, insufficient to meet the supply costs at a customer-friendly price. Developing better models to understand the prices and facilitate price comparison through technology can help SSA leverage the continent's renewable energy potential.

Energy commercialization and pricing for domestic electric energy sources is particularly necessary to encourage more investment into renewable energy, increase the involvement of the private sector, and facilitate better energy transitions to renewable energy through a participatory pricing approach. The African continent has the highest potential for generating renewable energy in the world [10]. Estimates show that SSA can produce 350 GW for metered electricity power, 110 GW from wind, 15 GW from geothermal, and 1000 GW from solar [11]. A combination of financial constraints to invest in sustainable energy, lack of the required technology on the continent, lack of political goodwill, and inadequate investment in energy-related research and training have slowed down the exploitation of Africa's energy potential [12]. Progressively, there is positivity towards renewable energy adoption in SSA. Policy frameworks and benchmarking with other countries have intensified. For example, renewable energy forms 90% of the energy mix in Kenya, although 61% of the people still use at least one form of unsustainable energy such as biomass and kerosene [13]. In Sierra Leone, petroleum and biomass are the leading energy sources, making up nearly 96% of the country's energy [14]. Furthermore, 96% of the cooking needs in the country are met through biomass. In Cote D'Ivoire, 60% of the energy needs are met through fossil fuels [15]. This data shows that there is a potential gap for renewable energy in SSA.

By definition, energy price modeling is a section of energy economics that focuses on predicting the forward and spot prices for different forms of energy in each jurisdiction area, like a country or a region [16].

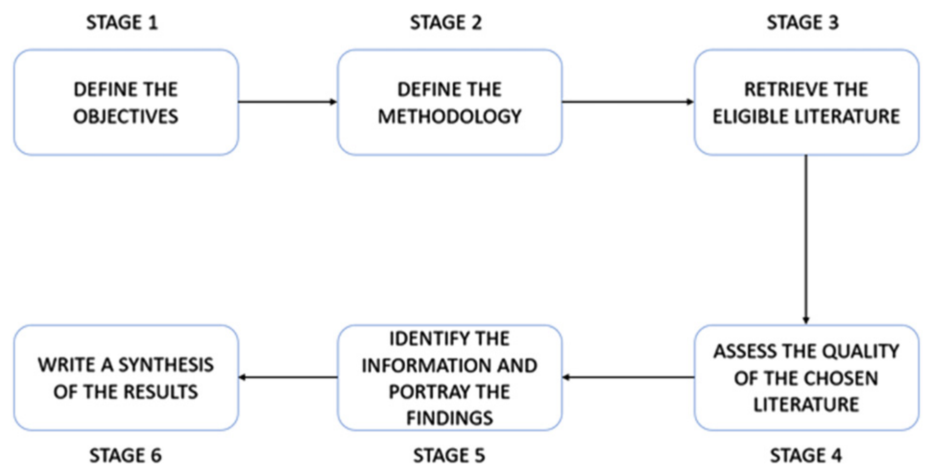

Figure 1. The systematic literature review process adopted in this research [17, 18].

Price modeling in energy is critical in determining profitability and affordability for different forms of energy [16]. Most of the energy price models do not include consumer-side factors and participation. They include scientific determinants of the price and energy-based aspects. As such, many businesses are likely to sell energy without understanding the basis of their pricing. Consumers are also likely to shy away from certain energy sources with little economic or tangible reasons. Such challenges can be bridged through a participatory pricing approach, including incorporating different energy pricing models in technologically accessible platforms that households and businesses can use. This paper explores various energy pricing models used across SSA and their incorporation of price fluctuations to facilitate this. It then hypothesizes how technology can incorporate these models into a customer-centered participatory approach, making them easier to understand, less technical, and useful in a participatory pricing environment.

2. Methods

This paper applies a systematic literature review of the common energy price modeling approaches used in 46 SSA countries. Peer-reviewed journals and organizational websites with critical price modeling information are key information sources for the paper. In total, 29 sources, which provided a range of information on energy price modeling and SSA energy economics, were reviewed.

2.1. The research protocol

We used a specified research protocol that follows the standard systematic literature review framework. The protocol defined stages in our research as outlined in figure 1.

To collect only relevant data, table 1 shows the keywords and strings used. It also shows the number of sources collected from different sources using these keywords (table 1).

2.2. The inclusion criteria

The following criteria were satisfied by all the sources included in the study:

(a) Only sources published from 2011 or later were included because of the need to use recent sources to keep the results of the study current and relevant.
(b) Sources with a clear abstract and methodology were used.
(c) Sources from peer-reviewed journals, especially journals indexed globally, were included.
(d) Sources that contained specific information on energy price models and energy price modeling were included.
(e) Sources from the 46 SSA countries, the SSA region, or addressing energy price modeling in the countries and regions were included.
(f) Data from utility companies and energy pricing parastatals with critical information on how energy is priced in the specific countries was included.

Table 1. Summary of research protocol results.

Keywords	Search strings	Search databases	Number of new sources found	Number of sources included
Sub-Saharan Africa, energy economics, energy pricing energy pricing, model	Energy + {(price Saharan Africa modeling + sub-	• Scopus	• Scopus (311)	29 (appendix B)
	Energy) or price modeling or price model or pricing model	• Google scholar • Google scholar • Google scholar • Google scholar • Ebscohost • Proquest • Parastatals and utility companies • Google scholar (97) • Ebscohost (109) • Proquest (162) • Parastatals and utility companies (7)		

2.3. Research process

Analysis of the energy pricing models applied in SSA started with data collection as outlined above. The initial search produced 679 journal articles. We removed all sources published before 2010 and retained only 112 on the list. The use of more recent information was necessary for two reasons. First, using recent information ensured that the models applied had not become obsolete. Second, it ensured that the research sources were published during or after developing the millennium development goals, which increased Africa's focus on sustainable energy. We read the abstracts of the articles to ensure they had information relevant to the research. The abstracts helped us understand the source's main thematic area and its relevance to the research questions. At this stage, 51 sources passed the inclusion criteria and were moved to the next level of analysis. An in-depth review of the remaining sources excluded 22 sources. Some of the elements we considered at this level of the review process included whether they address the issue of energy price modeling in SSA, whether the methodology for gathering and analyzing the information is clear, and the content discussed. The result of the systematic literature review consisted of 29 sources. The 29 sources were systematically reviewed, as shown in appendix B.

To achieve the results of this study, the sources were used in three major ways. First, their focus on the specific energy pricing models was considered, including the type of energy these models focused on. Some of the sources had technical information on how the models are applied and their potential drawbacks. Second, the web pages and articles, including legal documents that helped to indicate how governments and utility companies use the energy pricing models, were noted for their direction on how the models are applied. Lastly, a critical analysis of the sources, including their weaknesses and potential gaps, helped to understand missing elements in applying the energy pricing models in SSA.

3. Results

3.1. Common energy pricing models in SSA

Across the 46 SSA countries, several models are commonly applied. They include the ARIMA model, the GARCH model, artificial neural networks, hybrid models, and HIRA. The energy pricing models are explained in detail in this section, including their computation, extraction, and variables. This section also explores the application of technology and participatory approaches to energy pricing across SSA.

3.1.1. Time series modeling

Regression and time series have been used in pricing energy in different sectors, including metered electricity power, wind power, and LPG. The nonlinear models provide for conditional volatility in price while keeping the demand relatively stable [19]. The auto-regressive integrated moving average (ARIMA) and the autoregressive conditionally heteroskedastic (GARCH) are common statistical models useful in price prediction and price determination applicable to unstructured markets like those in SSA. The ARIMA model has been used in energy price forecasting by governments in different variations and adjusting variables. In Kenya, for example, the government uses the ARIMA model to forecast the price of electricity [20]. In Kenya, the electricity utility company applies the ARIMA model results to other models, which are then observed for the final price passed on to the consumers. See appendix C for the mathematical derivation and variables in the ARIMA and GARCH models.

Time series price setting is used by various utility companies and organizations across SSA. In Kenya, the Energy and Petroleum Regulatory Authority (EPRA) sets energy prices using various pricing models, including ARIMA and GARCH [21]. Similarly, Uganda sets the prices for metered electricity energy and petroleum using a combination of models, including ARIMA and GARCH [22]. In West Africa, Ghana has modified the ARIMA and GARCH models to apply time series in energy price forecasting and trend prediction [23]. Other countries that use time series for their utility companies include South Africa, Rwanda, Nigeria, Ethiopia, and Mozambique.

The common characteristic between these companies is the government's position in energy pricing, with all the energy regulatory entities in these countries tied to the government as either parastatals or energy utility companies with the government as the majority shareholder. Findings from energy price-setting entities in Kenya, Uganda, Ghana, South Africa, and Zimbabwe do not show any involvement of the consumers in energy pricing [20–23]. Furthermore, as much as web technology is used for all these organizations to give information on energy price adjustments and fluctuations on their websites, the websites do not have any interactive platforms for households, businesses, wholesalers, or any other party other than the entities controlling the sites [20–23]. ARMA formula (before adjustment with the I variable) is given by;

$$Y_t^* = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \theta_1 Y_{t-1} - \theta_2 Y_{t-2} - \cdots - \theta_p Y_{t-p} + \mu_t.$$

$Y^*{}_t$ is the predicted price,
ε_t is the possible error in the formula.
t is time in years.
Y represents a period is the price.

The results reveal several challenges in using time series modeling for energy prices. First, load prediction is a challenge, which makes the expected outputs, error in computation, and price fluctuations hard to predict, thus making predictions for future price challenging [26]. The main challenge with non-participatory pricing strategies is a perception that a predicted price can apply to the whole population. However, consumption, load usage, and other demand-side factors depend on localized usage such as counties or estates [26]. The existing non-participatory models do not have such consideration. Energy consumption variation trends are also hard to predict due to the uneven nature of energy intermittency and challenges in costing such intermittency, which is common across the SSA [25]. With too many externalities, energy prices are vulnerable to wrong prediction or volatility from market forces.

3.1.2. Using the artificial neural network methods

According to ANN, the price of energy is nonlinear. While they can produce relatively accurate price estimates with a high degree of confidence, the nonlinear nature of prices, including unforeseeable increases and drops in prices, presents significant challenges [27]. Neural network-dependent models are common in predicting and setting the electricity price but can be applied to other forms of energy with nonlinear variable prices. The three primary forms of neural networks that have been tested in Spain and Pennsylvania include the feed-forward, cascade-forward, and generalized-regression neural networks [28]. The ANN methods apply sensitivity analysis and statistical modeling to give price estimates based on the nature of the data specific to the form of energy and behavior and sensitivity to programmed features of the market. Such features include demand, taxation, government policies, shortages, and seasonality.

ANN methods in SSA are often used as predictors of energy consumption rather than predictors of price. For example, in South Africa, the country's energy consumption has been researched and predicted, with ANN used as one of the statistical approaches [29, 30]. ANN models, including the MGM and MCEM models, have been used to estimate energy demand in Central African countries [31]. The result has been more efficient demand prediction, although the incorporation of price prediction has often been elusive. Other countries using ANN in consumption prediction include Ghana, Ethiopia, Tanzania, Rwanda, and Angola [30–32]. One of the main challenges of nonlinear energy prediction models such as ANN is the lack of end-user incorporation, especially in long-term predictions [32]. Predictions of elements such as growth in demand and effects on production cost are increasingly challenging because of the expert approach rather than a participatory approach.

3.1.3. Hybrid models

Both statistical and sensitivity-based models are critical in short-run price determination and prediction [33, 34]. Some of the best hybrid models include the ARIMA model used together with the radial-basis-function neural networks (RBFN). As discussed above, ARIMA gives the price estimate based on the time series and the moving average (MA) of the observed prices of the energy source in the discussion. For example, ARIMA can be used with a 12 kg LPG gas cylinder using the historical prices over one year. The RBFN applies the same premises but adds sensitivity to market forces like taxation, shortages, and factor prices. An aggregated price and MA for the hybrid estimates are used to predict and set future prices. The hybrid models of price estimation and price forecasting are common, with applications varying in terms of the models combined in price estimation and price prediction [34]. When using hybrid models, the prediction of energy prices often breaks down the variables that affect the price of energy into segments depending on the models making up the hybrid model. This model has been applied in different countries, including Zambia, Rwanda, and the Central African Republic.

In Zambia, due to increased externalities affecting energy demand, supply, and pricing, the Energy Regulations Board (ERB) applies the hybrid pricing strategy [35]. The country uses ARIMA and RBFN for short-term price setting for electricity and petroleum energy by the government. The Energy and Water Utilities Regulatory Act-2009 also allows the use of hybrid energy pricing strategies by allowing a combination of any acceptable strategies to set short-term energy prices in Tanzania [36]. The Energy and Water Utilities Regulatory Authority uses hybrid strategies to predict short-term electricity and petroleum prices in the country. The main challenge with the hybrid energy pricing models is their uncertainty consideration, making them hard to apply without consideration of both demand and supply externalities [37]. With emerging challenges, hybrid models have proved volatile given the externalities, making it necessary to provide platforms where energy can be understood at a level close enough to the users [38].

3.1.4. The hybrid iterative reactive adaptive (HIRA) price forecasting method

The short-term pricing models can only be used for energy in the short run and have numerous weaknesses even when used together. The time series methods attach the same value to all data, while the ANN methods attach more value to recent data [39]. However, there is no certainty on the value of each of these data types. The prices are less certain in highly differentiated markets where the price is volatile based on no specific factors.

The HIRA model is useful for both short-term and medium-term energy forecasting for prices of energy. The HIRA model includes the analysis phase and the forecasting phase. The analysis phase uses the data from other energy sources with more stable pricing, the historical data for pricing the energy source, and the parameters within which the energy price is forecasted. Based on the parameters analyzed at the analysis phase, the potential price per unit of the energy form under prediction and analysis is determined in the forecasting phase. The HIRA model is summarized in the step-by-step model (figure 2).

The analysis phase includes evaluating internal and external factors in the energy factors within the energy ecosystem for the source of energy under analysis. Internal factors include production, supply, and consumption of the energy source under analysis. For example, if the energy source under analysis is LPG, the internal factors for LPG are analyzed during the analysis phase. External factors and factors that are not directly connected to the energy sources are also analyzed. Such analysis can include political, economic, social, perception, legal, and regulatory factors. These factors may not be specifically related to the energy source under analysis but directly affect the energy because they generally affect the business environment. Input data is set into 24 datasets representing 24 h a day, while days are categorized based on whether they are weekdays or weekends. Analysis of the factors and prices is aggregated together to provide a predicted price level. The HIRA model can determine energy use for energy that can be broken in bulk [39]. For example, if a certain business wants to sell LPG in smaller quantities, the hourly charge can be determined using the HIRA model. The hourly charge can be determined by the equation below

$$P(T)_h = L(T)_h + N(T)_h.$$

$P(T)_h$ is the hourly rate that will be charged for the energy source. $L(T)_h$ is the linear price calculated as an average for a similar day, for example, the average of the prices on a Monday. $N(T)_h$ is the neural network price component determined during the analysis phase and using the short-term methods stated above.

The HIRA model is applicable across Africa to predict energy prices, although it is often used in predicting prices and other models. Predominantly, it is applied in Francophone African countries to predict daily prices to allow them to use the time series analysis from the predictions to predict long-term price fluctuations [34, 39]. Understanding the behavior of energy prices in different circumstances increases the accuracy of price determination. The HIRA models are used alongside the short-term prediction models with more comprehensive statistical applications like ARIMA because of their accuracy in using data [39]. While the HIRA model is good at using a procedure, the ARIMA model is good at the computation of the spot prices along the process.

3.2. Effect of price fluctuations energy pricing models

In energy pricing, one of the main challenges in SSA is price volatility due to numerous externalities that make price prediction and stability challenging [40]. The challenge of price volatility is high in SSA, making inflation a common occurrence and the concept of affordability less predictable [41]. Energy pricing considers price

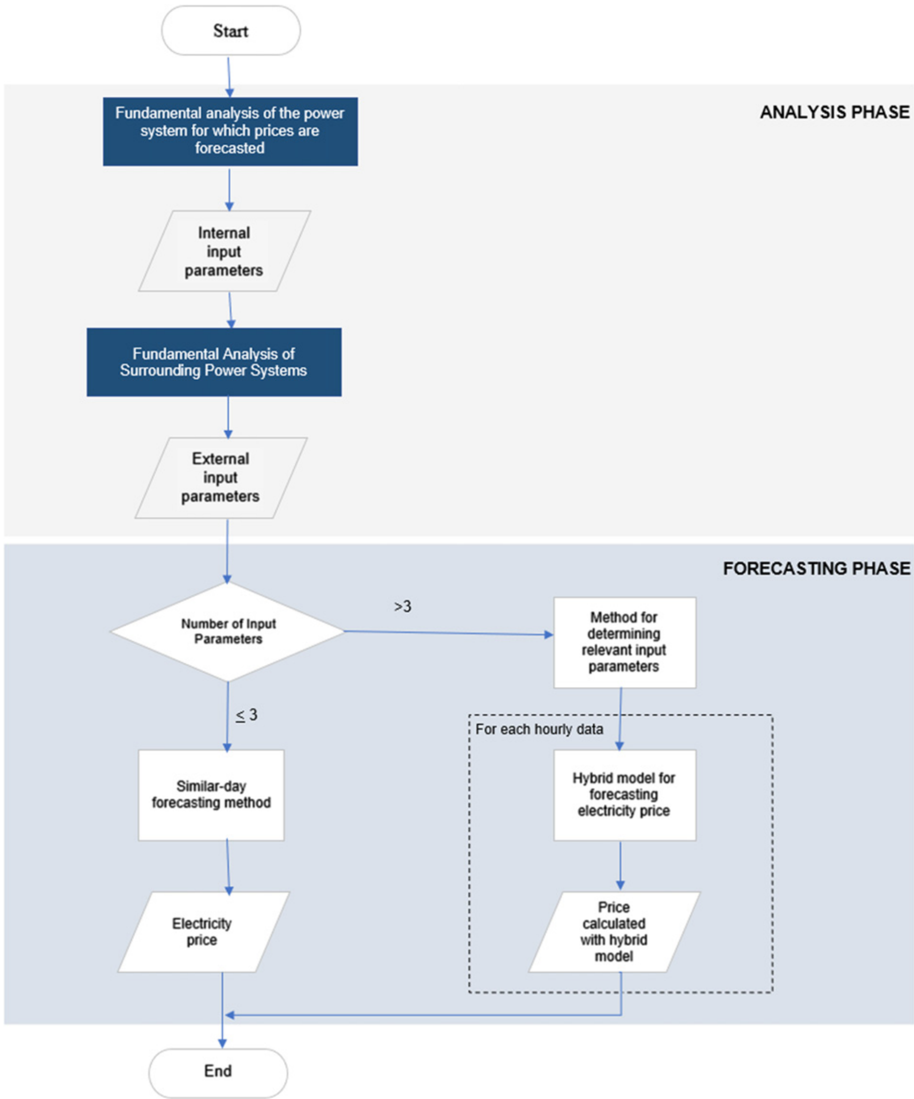

Figure 2. The flow chart showing steps in the HIRA model. Reproduced from [39]. CC BY 4.0.

fluctuations as critical elements of price estimates. Price fluctuations are the upward and downward changes in a product's prices because of predictable and unpredictable forces. Other researchers cite erratic supply, intermittency, and unreliable markets as possible causes of energy price fluctuations, yet there is no visible solution to solve this as part of certainty in energy pricing [42]. With such uncertainties, energy pricing can only be left to the government, developed to reduce the uncertainties by involving all the people or limiting the externalities.

Price fluctuation for energy sources (futures) can be studied and analyzed using either the daily logarithmic return of volatility duration average intensity [27]. Wang *et al* model the stochastic estimation for futures prices using statistical approaches to show the players in the market that affect short-term and long-term price fluctuations in different energy types. Future price fluctuations are critical because future prices need adjustment to the future fluctuations. The scientific models of price determination rely on accurate estimation of the future fluctuations, which can be estimated statistically and mathematically. The two-dimension stochastic interacting epidemic system (TDSIES), for example, models price fluctuations based on the small short-term players whose effects on price fluctuations are short-lived like the sellers and customers; and the long-term players whose impacts are more permanent and long term such as the producers and the government. Wang *et al* model the daily price fluctuations in stochastic formulae that reflect the short-term and long-term players' participation in the futures market for short-term and long-term price changes. The price fluctuation is defined using the formula below;

$$r\left(y\right) = \ln \wp\left(t\right) - \ln \wp\left(t-1\right), \quad t = 1, 2, \ldots, N.$$

Where; $\wp$ = the static price at any given time, t = time, $r(t)$ is the price fluctuation rate, ln is the natural logarithm.

The stochastic series represents the potential price fluctuations at any time. The determination of time depends on the analyst parameter. In the short run, it is the hours of estimation, while in the long run, it may represent the period in years. Therefore, volatility duration can be described as;

$$I\left(t\right) = \max\left\{T : \left|r\left(t+i\right)\right| > \left|r\left(t\right)\right|, i = 1, 2, \ldots, T\right\}, \quad t = 1, 2, \ldots, N-1 \quad \text{or;}$$

$$I\left(t\right) = \max\left\{T : \left|r\left(t+i\right)\right| < \left|r\left(t\right)\right|, i = 1, 2, \ldots, T\right\}, \quad t = 1, 2, \ldots, N-1.$$

The difference in the two formulae is the absolute value of the volatility trading factor represented by $\left|r\left(t-1\right)\right| > \left|r\left(t\right)\right| .r\left(t\right)$ reflects the difference in price between two trading days, while $I(t)$ defines the duration that an upward or downward trend in price lasts. Understanding $I(t)$ and $I(t)$ facilitate accurate data adjustment from trend analysis and ANN models. Therefore, price estimation models can analyze the potential of a price increase and decrease and the duration that such changes take before reverting to normal.

The price fluctuations and volatility of energy prices are among the main barriers to energy pricing in SSA. Energy prices are unstable, which makes analysis of the cost of energy challenging. There is a perception that offering electricity in Africa is expensive for electricity because of this volatility [43]. This is part of the larger challenge of providing electricity in the larger SSA context because prices vary more regularly, making costing and economic estimation a significant challenge [43]. Energy demand is an increasing need because of the growing SSA population [43]. The uneven interaction between demand and supply creates imbalances that increase price volatility. A model that accurately estimates the expected fluctuation in price to create an adjustment factor for the projected energy prices is necessary for energy price prediction and setting for households, small businesses, and the government.

3.3. Technology in energy price modeling in sub-Saharan Africa

Energy pricing has created major discussions on innovative ways that can help further energy commercialization, including the possibility of using production technology and market-based technologies to predict prices more accurately [44]. In SSA, commercialization of energy, including continued entry of privately owned businesses, makes it necessary to provide competitive pricing strategies to regulate market volatility [44]. However, these innovations have focused on energy production, increasing efficiency, and reducing production costs [45]. Although this has improved energy transitions, it has not achieved the desired pace of transitions, with energy prices for consumers continually hindering the uptake of renewable energy.

The level of technology in the energy sector in SSA has increased with the entry of profit-focused private businesses in energy investment [46]. Technological advancement includes product development and distribution technology investment, including mobile applications that combine different market forces to facilitate distribution [46]. With such advancements, pricing is certainly one of the elements that can be infused with technology for better pricing strategies and applications. Some of the technologically developing countries include South Africa, Kenya, Nigeria, Ghana, Rwanda, and Ethiopia. Leveraging the innovative and technological space in these countries is helpful for the incorporation of mobile technology in energy pricing, especially for domestic renewable energy sources and portable electricity.

4. Discussion

The results of the systematic literature review reveal three main concerns: (i) there are varied energy pricing models applied in SSA, but (ii) they are government controlled in most cases and focus on electricity and petroleum energy pricing, (iii) the households and small businesses are not involved across the value chain in price prediction and determination, and (iv) the energy pricing models are evolving with more technology infusion into energy in SSA making it necessary to create a participatory approach in energy pricing that incorporates technology and helps to account for externalities.

This discussion analyzes the results, relating them to their applicability in SSA. By incorporating energy price models commonly used in SSA and the effects of price fluctuations, the discussion session applies them to renewable energy, households, and businesses, which are the areas with major energy usage in SSA. Lastly, to make access to energy pricing information easier for people and businesses, this discussion section explores using technology to combine the energy pricing models, price fluctuations, and other technical factors for mobile applications access.

4.1. Commonly used energy pricing models in SSA and the existing gap

Linear, statistical, hybrid, and trend-based models are common in SSA energy pricing across different countries [20, 21, 27, 28, 33, 34, 39]. The results show that governments are often involved in energy pricing through parastatals or companies where the majority of the shareholding belongs to the government. The implication is a market dependent on the government and parastatals that offer wide pricing strategies expected to cater for the whole population and all externalities. The common energy pricing models include ARIMA, GARCH, hybrid models, ANN, and HIRA. Utility companies and agencies tasked with energy pricing apply these models, mainly to metered electricity energy sources and petroleum, the two most common energy sources prices by the governments and government agencies in SSA [20, 27, 35, 39]. These energy pricing models are used to forecast short-term prices except HIRA, which is used for long-term price forecasting.

The main strengths for all the pricing models are the familiarity within the agencies and the utility companies of their use. Within the government agencies that set these prices, there are illustrations and technical language showing the presence of the expertise to set and predict the energy prices at the expert level [21, 22, 35, 36]. Most of these models have also been used long enough within the companies to create familiarity and ample understanding. However, the results showed common weaknesses for the models, including lack of consumer participation [25], inadequate end user prediction and load challenges [32], and lack of proper consideration of externalities [42]. These challenges not only make pricing harder but also create more volatility in the market.

With the price fluctuations and uncertainty in market forces, investment of private businesses in the energy sector across SSA means that these models are bound to be used or ignored by the pricing strategies for these businesses depending on their ease of use. With the results showing that none of the models have ample participatory involvement and technology focused on end-users, each of the models can be applied better by incorporating a participatory approach and reach through mobile applications that would make pricing easier to regulate for the households and businesses. As discussed, the current energy pricing strategies in many SSA countries focus on metered electricity and petroleum as the primary government-controlled energy sources.

The conclusion from these models is that they are technical and easily understood by experts, who are currently involved in pricing at the energy utility companies and government parastatals. However, they lack visibility and consideration for the end-users and have a little consumer-based technological infusion. They also do not efficiently cover for the externalities and changing energy landscape with the entry of private businesses in the energy markets in SSA. Therefore, the price volatility of energy and the fact that the pricing for these energy sources is left to the market to legislate presents a challenge that can be resolved through a participatory approach that caters for externalities and considers historical information in energy price setting. Technology and pricing that includes technical formulas from the models fused with end-user and business input would aid better transitions and pricing for domestic renewable energy sources.

4.2. Energy price modeling with price fluctuation and externalities

The results have shown common energy price models used in Africa, including ANN, HIRA, hybrid models, and time series forecasting models like ARIMA and GARCH [20, 21, 27, 28, 33, 34, 39]. Each of these models is often used by the government and government agencies to offer some predictability to energy prices by predicting and setting short-term energy prices to avoid volatile price fluctuations. However, as discussed for each of the models, countries that apply them in SSA often apply them on metered electricity and petroleum-based energy sources, often controlled by the government through the energy parastatals and government-owned utility companies [20, 27, 35, 39]. The results have also shown that the investment by private companies in the energy sector, motivated by the continued drive towards sustainability and energy transitions to renewable energy in SSA, is likely to cause more price volatility and fluctuation [40]. This, coupled with other externalities such as intermittency, erratic supply, and unreliable markets, mean the energy price fluctuations are likely to be high in the absence of clear pricing guidelines that both the households and the businesses can understand.

Different market forces are incorporated when calculating price fluctuation, which may not be considered at face value by all businesses. The TDSIES, for example, uses short-term players, short-term actions, and short-term results to model price fluctuations. On the other side, the RBFN together with ARIMA model time series prices and factor in sensitivity to predict short-term prices. Such externalities can be put together in a technologically supported energy pricing platform to give accurate short-term forward prices. Other externalities can also be factored in the model, including market uncertainties, supply costs, locational factors, and seasonal factors.

In the long run, the HIRA model effectively determines the price for energy sources that may need procedural consideration, just like the hybrid models [34, 39]. The SSA economies are constantly evolving, which means different factors that might affect the energy prices, such as currency value, inflation, unemployment, GDP per capita, and economic growth, continue to emerge. Therefore, the hybrid and HIRA models are more effective and should be applied widely in price determination and price prediction for energy in the SSA countries, especially long-run price prediction. This would provide a framework for price determination and give clarity and flexibility while considering renewable energy price fluctuations. Energy prices are significantly volatile in SSA because the price fluctuation constant is not stable. However, even with such fluctuations, using HIRA and the hybrid models will offer significant stability in the price for renewables.

The main challenge of using the energy price models is their complexity, especially because they cannot be understood by people who are not experts or scholars in energy-related areas [21, 22, 35, 36]. Creating a participatory approach to pricing can help counter the majority of the energy externalities because all the stakeholders introducing and affecting these externalities can be included in the value chain. The conclusion from the results creates the need to infuse technology that is not only accessible but also easy to use to create understandable and easy to comprehend platforms for energy pricing that includes the externalities and fluctuations. Using technologically advanced platforms and models can create a better understanding of energy pricing. In an SSA energy market that is progressively having more private investments, this is an important step in facilitating price stability, price comparison, and moving closer to energy transition to renewable energy.

4.3. The nexus between mobile technology and energy price modeling

This research has shown that technology is infused in the energy price modeling but not one that is meant for the end-users or other external stakeholders. One of the main weaknesses for the energy utility companies and parastatals in the results above is their lack of customer-centered technology in their price modeling [20–23, 38]. The main challenge with using technology in energy pricing is the lack of precedence on using it to achieve the best results [47]. Despite this challenge, technology has proven effective in simplifying complex situations. The other challenge with all the models discussed in energy pricing is the lack of a participatory approach in energy pricing. Therefore, the customers and small businesses that are investing in the energy space should have a platform to understand the pricing models and contribute to their success in pricing. It can be deduced that the complexities of expert language, formulae, and applications of the energy pricing models should be simplified through technological platforms accessible to the people.

It can be further inferred that to make energy price modeling simple and easy to understand, the equations and formulae can be developed into simple mobile applications where customers key in simple inputs and get predicted prices as outputs. As Musango and Brent note in their research, technology is a strategic planning tool, which can be applied to strategic price forecasting for energy [48]. The statistical and nonlinear models of energy price forecasting such as ARIMA, GARCH, HIRA, and price fluctuations include complex formulae and statistical equations. For the average household and businessperson, equations and formulae are not a point of priority, which means simplification is the only approach. Technology in energy price determination and forecasting is not new as it has been applied in differential electricity pricing in South Africa [49]. Statistical modeling technology has also been used in pricing energy from dynamic, complex, and multi-phase micro-grids in SSA [50]. However, the mobile app technology recommended through this discussion is both interactive and analytical.

The statistical models rely on time series data in price prediction and price determination. The technology could be in the form of mobile applications and programs in which households and businesspeople can feed their price data over time. The technology should include daily or weekly updates. After a certain time that is considered statistically significant, the platforms or applications analyze the data to advise the businesses on their price range and the households on the prices they are likely to pay for their energy sources. Mobile app technology ensures that the businesses and stakeholders can be active participants in the price determination and price prediction for different forms of energy, create visibility for the renewables to improve the customers' decisions, and allow the energy markets to price all forms of energy.

According to our hypothesis, technology is the best way to include the community and businesses in incorporating the energy pricing models in energy pricing, especially for domestic renewable energy sources. Households and small businesses can be involved at the data stage and pricing stage. At the data stage, the households are involved in price recording and mapping to understand the market's seasonal and spot prices. The ARIMA and GARCH models rely on spot prices that are analyzed through a time series analysis to predict future prices. The HIRA model can also include ARIMA and GARCH models; hence, the households' involvement at this level produces data useful for all the statistical data. Household spot surveys can also help understand price fluctuations by developing an understanding of unexpected and unexplained price hikes. Price fluctuation forms an integral part of energy price modeling. Adjusting the prices and projections to the price fluctuation is important because it sets the ceiling and floor for the price, which controls the energy source's price variance. Such a participatory approach incorporated with technological applications is forecasted to yield faster and wider transitions to renewable energy among the people in SSA.

5. Lessons learnt from the review

The main lesson learnt from this review is the use of energy price modeling as one of the pathways to energy transitions in SSA markets. Several challenges have been identified to energy transitions to renewable energy in SSA, including price perceptions, energy access, unstructured energy markets, price volatility, and unreliable supply [51]. The challenge of energy access is progressively being resolved through the entry of private businesses in sustainable energy in Africa, including vendors of portable electricity, who could also solve the challenge of unreliable supply [52]. Renewable energy is perceived as expensive in SSA [53]. Energy price modeling is a simplified way of showing the households the price calculation process, the prediction of prices, and comparative pricing with unsustainable sources of energy such as charcoal and wood. Such comparisons are projected to ease the choice and enhance the easier transition to renewable energy in SSA.

To enhance these transitions, this literature review has established the need to use technology, including mobile application technology, to enhance the energy transitions in SSA. As discussed above, energy price models are increasingly complex and may only be understood at the expert level. From the literature, we conclude that making these models in a way that allows a participatory approach and incorporates the externalities can facilitate structured pricing. One of the main questions arising from this review is whether technology can be developed that takes different factors in price modeling and combines with custom factors in different unstructured markets in SSA to offer predictive prices for renewable energy sources. We conclude that, through understanding the prices in advance, the residents in settlements in SSA can compare these prices with their regular energy sources and make cost-based purchase decisions. This review predicts that such comparisons will speed energy transitions in these settlements.

The perception of price among members of the settlements in SSA means that awareness about the models used to price renewable energy can enhance energy transitions in these settlements. Awareness of these models will mean that people can increase their use in predictive pricing, which is an important aspect in enhancing energy transitions and the use of renewable energy. Creating knowledge areas informed by research and consultation with households and businesses in a transdisciplinary environment is an important aspect of energy transitions and research in SSA.

6. Conclusion

This paper set out to examine the energy pricing models that have been used across the SSA that can be applied to domestic renewable energy sources and used with increased involvement of the households as key stakeholders. Therefore, the hypothesis of this study was that energy price models are complex and scientific in nature, making them hard to understand for the customers and businesses; hence the use of technology to facilitate a participatory pricing approach to incorporate these models would enhance faster energy transitions in SSA. The main finding in this study is that statistical, nonlinear, and hybrid pricing models such as the HIRA, ARIMA, GARCH, and hybrid models are widely used in SSA and can be applied to renewables for households. They can be applied to different forms of energy used by households to involve the households in the pricing decision-making value chain as key stakeholders. Their involvement could also help them make better energy decisions, facilitating faster sustainable energy transitions. The discussion also presents technology as a viable way to ensure that energy price modeling can involve all stakeholders, including small businesses that often sell energy products to SSA households. Such technology includes web-based platforms and mobile applications into which the customers can feed information and get their energy prices or predicted prices.

The nascent energy markets in SSA can benefit from the increased adoption of energy pricing models across all forms of energy. Governments across the SSA have increasingly been the sole participants in energy pricing. This review found that they often focus on electricity and petroleum partly because of international trade and ease of control and management. However, electricity is not the widest used source of energy. With energy economics in SSA developing, price modeling for different forms of energy is palatable. Further, SSA has a high potential for producing renewable energy above metered electricity power, including wind, geothermal, solar, and biogas.

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Data availability statement

All data that support the findings of this study are included within the article (and any supplementary information files).

Appendix A. Energy access in SSA

	Sources of electricity production						Access to electricity
	Coal % of total 2015	Natural gas % of total 2015	Oil % of total 2015	Hydropower % of total 2015	Other renewable sources % of total 2015	Nuclear power % of total 2015	% of population 2015
Angola	0	0	46.8	53.2	0	0	42
Benin	0	0	94.4	4.1	1.5	0	37.7
Botswana	96.4	0	3.6	0	0	0	58.1
Burkina Faso							16.3
Burundi							8.6
Cameroon	0	6	17.9	75	1.1	0	58.7
Cabo Verde							87.1
The Central African Republic							24.1
Chad							7.7
Comoros							74.4
Congo, Dem. Rep.	0	0	0.1	99.7	0.1	0	16.4
Congo, Rep.	0	46.7	0	53.3	0	0	60.4
Cote dilvoire	0	78.1	5.2	15.5	1.2	0	62.6
Djibouti							57.5
Equatorial Guinea							66.3
Eritrea							45.7
Eswatini							65.8
Ethiopia	0	0	0	92.7	7.3	0	29
Gabon	0	46	10.2	43.2	0.6	0	89.6
Gambia							54.4
Ghana	0	38.8	0	50.9	0	0	75.7
Guinea							33.9
Guinea-Bissau							20.3
Kenya	0	0	12.5	39.2	48.3	0	41.6
Lesotho							31.8
Liberia							16.1
Madagascar							20.2
Malawi							10.8
Mali							37.6
Mauritania							39.5
Mauritius	39.4	0	37.8	4.1	18.7	0	97.3
Mozambique	0	12.8	0.8	86.4	0	0	24
Namibia	0.5	0	1.8	97.8	0	0	51.6
Niger	41.6	0	57.6	0	0.8	0	16.6
Nigeria	0	81.8	0	18.2	0	0	52.5
Rwanda							22.8
Senegal	0	4.2	83.6	8.6	1.8	0	60.5
Seychelles							100
Sierra Leone							19.7
Somalia							29.7
South Africa	92.7	0	0.1	0.3	1.9	5.5	85.5
South Sudan	0	0	99.4	0	0.6	0	18.4
Sudan	0	0	22.6	64.5	0	0	49.4
Tanzania	0	43.9	21.9	33.5	0.7	0	26.5
Togo	0	0	24.7	69.1	6.2	0	45.1
Uganda							18.5
Zambia	0	0	3	97	0	0	31.1
Zimbabwe	46.8	0	0.5	51.4	1.3	0	33.7
Sub-Saharan Africa	**50.6**	**9.5**	**4**	**20.5**	**2.4**	**3**	**39.3**

Appendix B. Systematic review summary

Reference	Key energy pricing contribution (with models found)	Referencing number
Han and Li (2019)	Comparison of forecasting energy consumption in East Africa Using the MGM, NMGM, MGM-ARIMA, and NMGM-ARIMA model	[19]
Nepal *et al* (2020)	Electricity load forecasting using clustering and s ARIMA model for energy management in building	[20]
EPRA (2021)	Tariff setting	[21]
ERA (2021)	Tariff adjustment methodology	[22]
Acheampong *et al* (2021)	Ghana's changing electricity supply mix and tariff pricing regime: implications for the energy trilemma	[23]
An *et al* (2020)	Trade war effects: evidence from sectors of energy and resources in Africa	[24]
Ma and Wang (2020)	Prediction of the energy consumption variation trend in South Africa based on ARIMA, NGM and NGM-ARIMA models	[25]
Kim *et al* (2019)	Short term electricity load forecasting for institutional buildings	[26]
Wang *et al* (2020)	Fluctuation and volatility dynamics of stochastic interacting energy futures price model	[27]
Anbazhagan and Kumarappan (2012)	A neural network approach to day-ahead deregulated electricity market prices classification	[28]
Sigauke and Chikobvu (2011)	Prediction of daily peak electricity demand in South Africa using volatility forecasting models	[29]
Fowowe (2014)	Modeling the oil price—exchange rate nexus for South Africa	[30]
Wang *et al* (2019)	Prediction of the energy demand trend in middle Africa—a comparison of MGM, MECM, ARIMA and BP models	[31]
Gebremeskel *et al* (2021)	Long-term evolution of energy and electricity demand forecasting: the case of ethiopia	[32]
Kaytez (2020)	A hybrid approach based on autoregressive integrated MA and least-square support vector machine	[33]
Ordóñez *et al* (2019)	A hybrid ARIMA–SVM model for the study of the remaining useful life of aircraft engines	[34]
ERB (2021)	Economic regulation- electricity pricing	[35]
EWURA (2009)	The energy and water utilities regulatory act-2009	[36]
Hafner *et al* (2018)	Energy in Africa: challenges and opportunities	[37]
Amir and Khan (2021)	Assessment of renewable energy: status, challenges, COVID-19 impacts, opportunities, and sustainable energy solutions in Africa	[38]
Cerjan *et al* (2019)	HIRA model for short-term electricity price forecasting	[39]
Wasseja and Mwenda (2015)	Analysis of the volatility of the electricity price in Kenya using autoregressive integrated MA model	[40]
Baraza (2021)	Counting the cost: is electricity affordable for Africa's non-residential consumers?	[41]
Emetere *et al* (2021)	Erratic electric power challenges in Africa and the way forward via the adoption of human biogas resources	[42]
Taneja (2018)	If you build it, will they consume? Key challenges for universal, reliable, and low-cost electricity delivery in Kenya	[43]
Amin *et al* (2021)	Does conventional energy pricing induce innovation in renewable energy? New evidence from a nonlinear approach	[44]
Conduah *et al* (2019)	Energy efficiency improvements in a microbrewery in South Africa	[45]
Opeyemi *et al* (2019)	Renewable energy, trade performance and the conditional role of finance and institutional capacity in sub-Saharan African countries	[46]
Herrero *et al* (2018)	Smart home technologies in everyday life: do they address key energy challenges in households?	[47]

Appendix C. Mathematical extraction and use for ARIMA and GARCH models

The ARIMA model is common in price prediction for electricity, where the prices are relatively volatile. The ARIMA model has three components. *The autoregression* (AR) identifies the change in a variable (the price of a form of energy) based on its own historic values [39, 54]. The AR variable is calculated by [21];

$$Y_t^* = \mu + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_t - p + \varepsilon_t$$

where; ε_t represents the error possible in the computation.

The integrated component (I) shows the differencing values achieved by subtracting the previous values' data values. For example, the price of a source of energy in February is subtracted from the price in January. Lastly, *the* MA incorporates the residual error from the AR and the observations (prices of energy) [21]

$$Y_t^* = \varepsilon_t - \theta_1 Y_{t-1} - \theta_2 Y_{t-2} - \cdots - \theta_p Y_{t-p}$$

where; ε_t is the possible error in the formula. t is time in years. Y represents a period is the price.

The integer value for each of these components is represented as a variable in the ARIMA model. P represents the number of lagged observations, d represents the number of times the raw observations are differentiated, *and* q represents the MA window [39, 55, 56]. A linear regression model is constructed from these variables to predict the future price. The ARMA formula (before adjustment with the I variable) is given by;

$$Y_t^* = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \theta_0 \varepsilon_t - \theta_1 Y_{t-1} - \theta_2 Y_{t-2} \ldots - \theta_p Y_{t-p} + \mu_t$$

$Y^*{}_t$ is the predicted price.

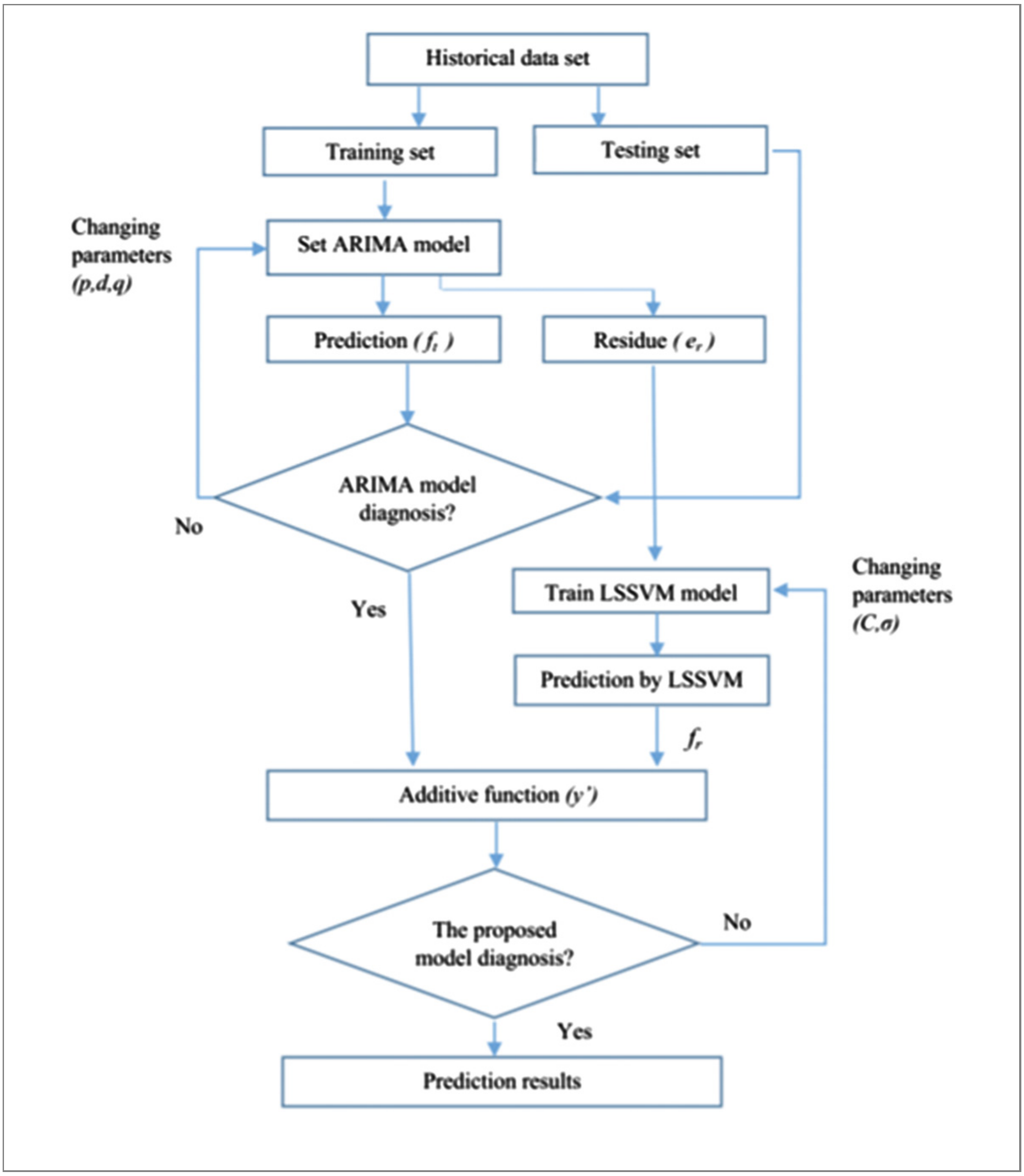
The GARCH model also applies time-series data but differs from ARIMA as it assumes that the variance error is serially autocorrelated. When the variance error is not constant (heteroskedastic variance error), GARCH is used. The GARCH model is used for prices that are extremely volatile [57]. The GARCH model can be calculated in Microsoft Excel and is defined by the following equation:

$$h_{t+1} - \omega + \alpha \varepsilon_t^2 + \beta h_t$$

where; h is the variance. ω is the residual squared. t is time. β are the empirical parameters determined by the maximum likelihood.

By calculating the variance and using the market trend, the price of a commodity such as energy can be predicted and, where necessary, set.

Appendix D. Electricity price prediction with ARIMA-LSSVM hybrid model (reprinted from [34], Copyright (2020), with permission from Elsevier.)



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