KAPSARC
مركز الملك عبدالله للدراسات والبحوث البترولية
King Abdullah Petroleum Studies and Research Center

Discussion Paper

# The Future of Residential Electricity Demand in Saudi Arabia and the Role of Energy Efficiency in the 2060 Net Zero Pledge



Mohammad Aldubyan

July 21, 2024 | Doi: 10.30573/KS--2024-DP26

## About KAPSARC

KAPSARC is an advisory think tank within global energy economics and sustainability providing advisory services to entities and authorities in the Saudi energy sector to advance Saudi Arabia's energy sector and inform global policies through evidence-based advice and applied research.

This publication is also available in Arabic.

## Legal Notice

© Copyright 2024 King Abdullah Petroleum Studies and Research Center ("KAPSARC"). This Document (and any information, data or materials contained therein) (the "Document") shall not be used without the proper attribution to KAPSARC. The Document shall not be reproduced, in whole or in part, without the written permission of KAPSARC. KAPSARC makes no warranty, representation or undertaking whether expressed or implied, nor does it assume any legal liability, whether direct or indirect, or responsibility for the accuracy, completeness, or usefulness of any information that is contained in the Document. Nothing in the Document constitutes or shall be implied to constitute advice, recommendation or option. The views and opinions expressed in this publication are those of the authors and do not necessarily reflect the official views or position of KAPSARC.

# Abstract

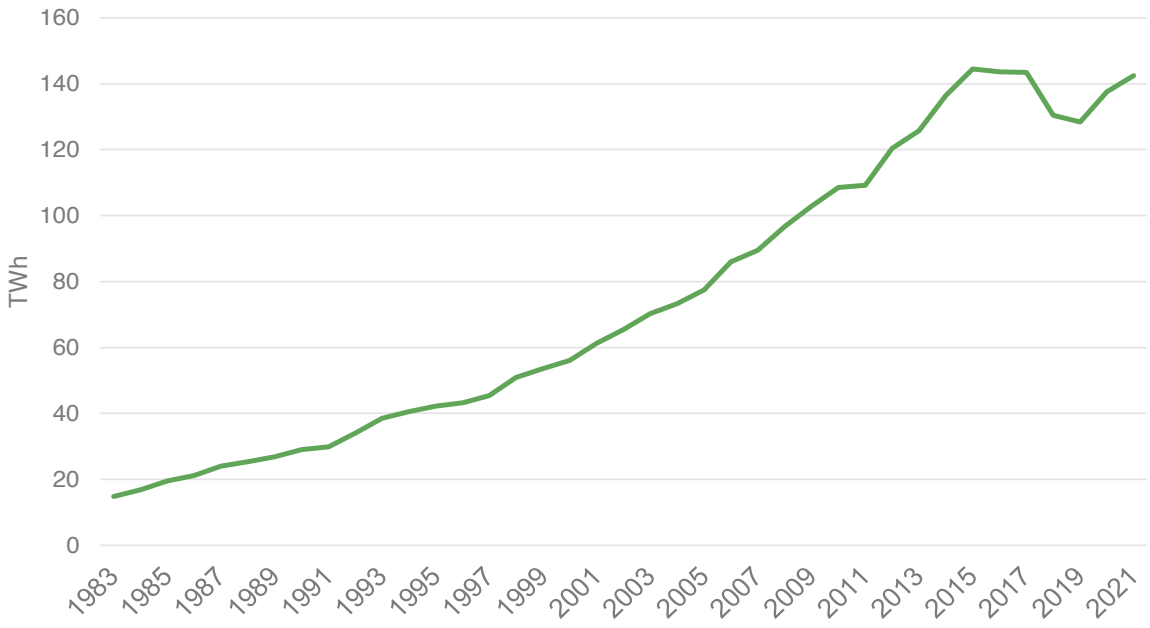
Saudi Arabia has set the ambitious goal to reach net zero by 2060, and reducing domestic electricity consumption and thus curbing greenhouse gas (GHG) emissions is critical. Since the residential sector is the biggest consumer of electricity in the Kingdom, understanding how its electricity consumption will evolve in the long term can help policymakers to design policies through which the sector can contribute effectively to that target.

The aim of this paper was twofold: (1.) forecasting the residential electricity consumption to 2060, and (2.) assessing the potential impact of energy efficiency (EE) on curbing electricity demand over the forecast period. We constructed a forecast model using the Autoregressive Integrated Moving Average (ARIMA) technique and historical residential electricity consumption data. We then built on this forecast to assess the potential impact of EE in curbing the electricity demand growth over the forecast period using a bottom-up building stock model tailored for Saudi Arabia. The EE assessment was divided into targeting future residential houses and renovating existing houses. The analysis showed that future electricity consumption is expected to pick up a steady upward trend over the next four decades. The EE assessment showed that tightening EE standards, specifically building insulation, air conditioning, lighting, and white good efficiencies, can reduce electricity consumption over the forecast horizon by 18% and 2060's consumption by 30%. This EE enhancement will enable 690 MtCO2 to be avoided over the next four decades and 39 MtCO2 of 2060's potential CO2 emissions.

# Introduction

The residential sector is the biggest electricity consumer in Saudi Arabia. In 2021, it accounted for 47% of total electricity consumption, with a total of 142.5 TWh by 8.4 million households (SERA 2022; GASTA2019). Since 1983, Saudi residential electricity consumption has witnessed a clear upward trend (except for a few years that we will discuss later). In 1990, as a reference point, the sector consumed 28.9 TWh, which amounts to approximately one fifth of the current consumption level (see Figure 1).

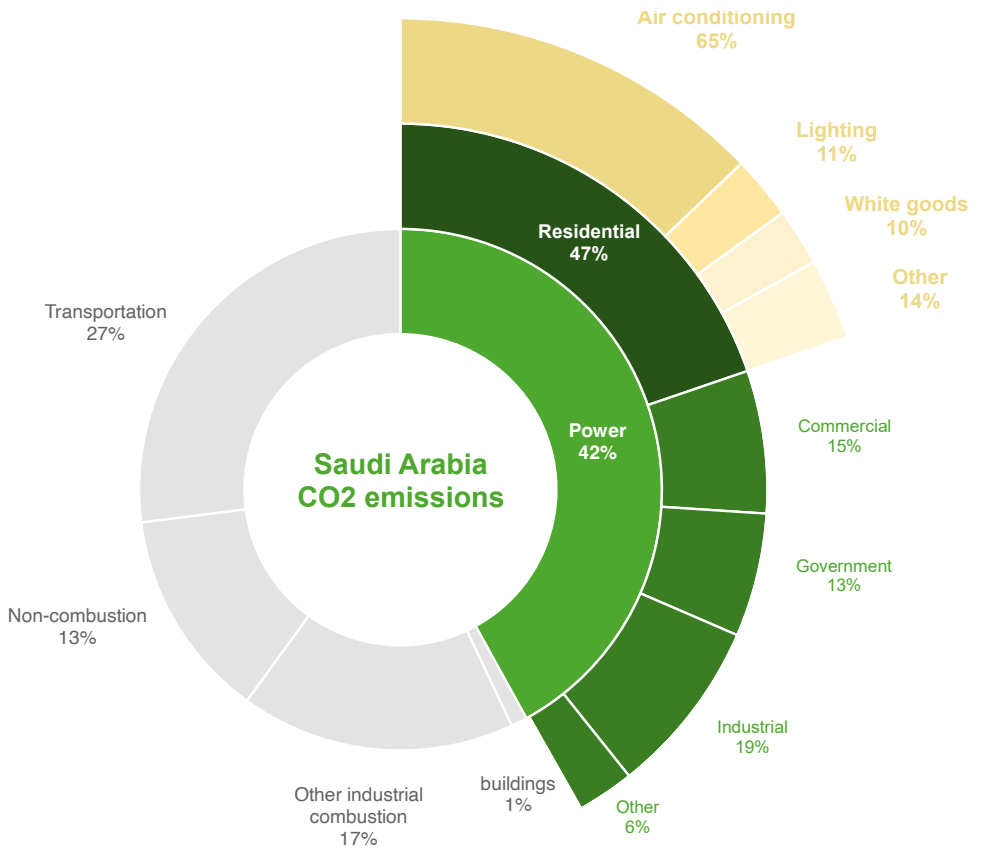
**Figure 1.** Historical residential electricity consumption.




*Source: SERA (2022)..*

To put this growth in a global context, global residential electricity final consumption grew by only 141% during the same period (IEA 2023). Fossil fuels are the primary source of electricity generation in the Kingdom, with around 99.7% of electricity generated from them (SERA 2021). It is also worth mentioning that power generation is responsible for around 42% of overall domestic CO2 emissions (Worldometer 2023) (see Figure 2). Thus, reducing electricity use intensity (EUI) can help to strike a balance between curbing domestic greenhouse gas (GHG) emissions and enhancing energy efficiency in order to achieve the Kingdom's national climate and sustainability goals. The residential sector is responsible for 47% of the total domestic electricity consumption in Saudi Arabia (SERA 2022).

**Figure 2.** KSA electricity consumption and CO2 emissions by sector and residential end-use (Worldometer 2023 and SERA 2022).




*Source: Worldometer (2023) and SERA (2022).*

The rest goes to commercial and government buildings, industry, and other consumers (Figure 2). Most of this demand, i.e., about 65%, goes to cooling (SEEC 2020).

In 2021, Saudi Arabia launched the Saudi Green Initiative (SGI), which aims to combine environmental protection, energy transition, and sustainability programs in order to reduce emissions, increase the use of green energy, and address climate change (SGI 2021). The SGI aims to reduce carbon emissions by 278 mtpa by 2030 through multiple streams, including investing in new energy sources and improving energy efficiency (SGI 2022). The goal of increasing energy efficiency implicitly aims at reducing EUI across all sectors, with a focus on the building sector as the biggest consumer of electricity.

This growth of residential electricity consumption in Saudi Arabia has been heavily driven by multiple factors. The impacts of these factors range from substantial to minimal, depending on the geographical, demographic, economic, and social aspects of the sector (Mikayilove et al. 2020). Although the goal of this paper goes beyond studying the impact of different factors on electricity consumption, it is still worth touching on the most critical factors shaping this electricity growth.

One of the factors that has been playing a critical role in shaping electricity demand in the Kingdom is the growing population. The Saudi population has been consistently growing at relatively high rates over the past three decades. It witnessed a 128% increase between 1990 and 2020, while the global population increased by only 46% during the same period (Worldometer 2023). This high population growth is due to high fertility rates as well as the increasing number of expatriates who live and work in Saudi Arabia.

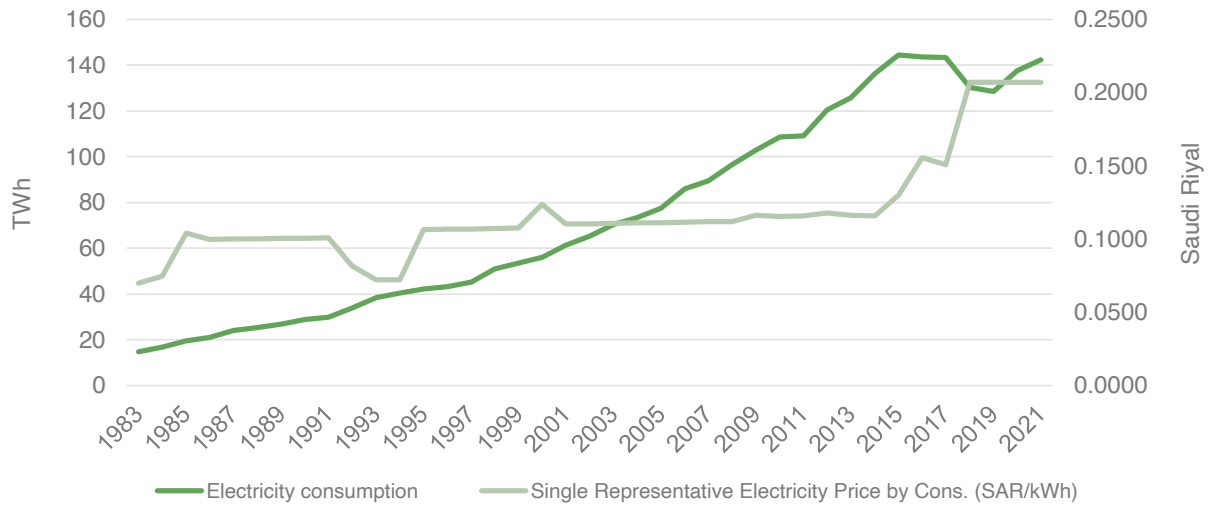
One of the reasons that overall electricity demand broke its upward trend between 2016 and 2019 was the mass exit of non-Saudi labor due to some major changes in expat levy policies (Aldubyan and Gasim 2021). The relationship between population and electricity consumption is found to be a one-way causality from population to electricity consumption (Schneider 2021). Age-distribution can also affect residential electricity demand as young and middle-aged individuals tend to consume more energy relative to senior people (Jo et al. 2020). According to GASTAT, 82% of Saudi Arabia's population is below 45 years old (GASTAT 2024).

The low price of residential electricity also plays a critical role in shaping consumption. Relatively low domestic electricity prices have been one of the influential drivers behind the residential electricity demand growth in Saudi Arabia. Lower electricity prices stimulate demand while higher prices not only encourage energy conservation but also incentivize investments in more efficient equipment and renewable energy. Saudi Arabia follows a fixed-rate pricing strategy for all sectors, and these prices are set by royal decrees. The residential electricity prices were kept almost constant from 1983 to 2014, except for a few changes (Figure 3). From 1983 to 2014, residential electricity prices hovered around 0.10 Saudi Arabian Riyal (SAR) per kilowatt-hour (kWh) on average (SEC 2023).

Over the past decade, however, electricity prices have been subject to several reforms, some of which were minor and a couple of which were major. In 2016, Saudi Arabia started implementing deferential energy price reforms, which are known as the first wave of domestic energy price reform in the Kingdom. In that year, the average price was increased from 0.13 to 0.15 SAR/kWh. Two years later, at the beginning of 2018, the second wave of energy price reforms was introduced by increasing the average electricity price even further to 0.21 SAR/kWh. These price reforms were part of Saudi Arabia's Fiscal Balance Program that aims to "sustain the status of public finances and achieve a balanced budget" (FBP 2018) under Saudi Vision 2030. Despite being beyond the scope of this paper, it is worth noting that low-income citizens have been provided with a financial support scheme to alleviate the impact of these price reforms in the Kingdom. In addition to the mass exit of expats mentioned above, the two price reform waves that took place in 2016 and 2018 were also, to some extent, part of reversing the upward trend of residential electricity consumption between 2016 and 2019.

Even though the increase in electricity prices has contributed to bringing the consumption rate down, increasing electricity prices has had a short-term impact on its demand (Aldubyan and Gasim 2021; Mikayilov et al. 2020). Many studies have shown that residential electricity consumption is price inelastic in Saudi Arabia (Aldubyan and Gasim 2021; Mikayilov et al. 2020; Diabi 1998). This inelastic behavior is partially due to the hot weather conditions in most regions and the need for heavy reliance on cooling, which consumes the vast majority of the electricity that is generated (Krarti et al. 2020).

**Figure 3.** Historical representative residential electricity rate vs. consumption.




*Source: SERA (2022) and SEC (2021).*

# Literature Review

Forecasting electricity demand is a crucial practice in predicting how electricity generation is most likely to evolve and, thus, which policies might be beneficial for managing future electricity demand. Robust electricity forecasts can help policymakers and operators improve supply stability as well as design better strategies for a more sustainable energy mix. Different forecasting techniques, including statistical and machine learning, have been developed and used to predict residential electricity consumption. Forecasting residential electricity demand depends on a multitude of factors. Some of these are predictable, such as weather conditions, while others are uncertain. This uncertainty can add a layer of difficulty to the forecast process.

There are many published studies and models that forecast residential electricity demand using statistical and machine learning techniques. Some studies apply univariate models, which use only historical electricity consumption data (Liu et al. 2020; Dong et al. 2016), while others depend on some explanatory variables, such as GDP, population, etc. (Tserkezos 1992; Son and Kim 2017). Gao et al. proposed a hybrid machine learning model that accounts for consumer behavior in forecasting residential electricity consumption through an internet search (Gao et al. 2021). They found that incorporating an internet search can improve forecasting accuracy. A joint forecasting model that combines the gray model (GM) and the logistic model was developed to forecast the electricity consumption of China from 2016 to 2020 (Liang and Liang 2017). Mohamed and Bodger (2005) proposed a variable asymptote logistic (VAL) model for forecasting electricity consumption in New Zealand, and they found that VAL has a lower forecasting error when compared to the logistic model. Mikayilov, Darandary, Alyamani, Hasanov, and Alatawi (2020) have projected the regional electricity consumption of Saudi Arabia and assessed the potential regional impact of price increases on the demand, and their projections show a continuous upward growth of demand even with a 5% increase in price.

Another approach to modeling future electricity consumption is by using Autoregressive Integrated Moving Average (ARIMA), which is a well-known time series forecasting analysis technique. In addition to its simplicity and flexibility, ARIMA models rely on very few assumptions, one of which is stationarity of the data. However, non-stationary time series can be made stationary through some techniques, such as log transformation or differencing. In general, constructing ARIMA models takes place in three stages: identification, estimation, and diagnostic (Box, Jenkins, and Reinsel 1976).

Abdel-Aal and Al-Garni (1979) developed an ARIMA model to forecast domestic monthly electricity consumption of the Eastern region of Saudi Arabia and compared its performance with some other regression-analysis and machine-learning models that have been developed previously for the same data. They found that ARIMA models are superior to the other two techniques. Fahmy et al. (2023) used frontier and ARIMA models to forecast the national electricity consumption of Saudi Arabia from 2020 to 2030 using the historical annual consumption, and they also compared their findings to three different studies that forecast national electricity consumption and highlighted the significant differences between these forecasts – namely, Soummane and Ghersi 2022, Al-Harbi and Csala (2019), and Almulla (2014). Another study projected the sectoral electricity consumption of Saudi Arabia using a general equilibrium model, and it found a slower electricity demand growth over the coming decade (Soummane and Ghersi 2022). Table 1 summarizes the reviewed literature for this study.

**Table 1.** Reviewed literature on forecasting electricity consumption.

| Reference | | Method | Data | Forecast horizon |
|---|---|---|---|---|
| Liu et al. (2020) | China | Holt-Winters (HW) method and Extreme learning machine (ELM) network | 1-minute interval from Dec. 2006 to Nov. 2010 | 15 minutes ahead |
| Dong et al. (2016) | USA | Artificial neural network (ANN), support vector regression (SVR), least-square support vector machine (LS-SVM), Gaussian process regression (GPR), and Gaussian mixture model (GMM) | 5-min interval | 1 hour and 1 day ahead |
| Tserkezos (1992) | Greece | Linear transfer function (LTF) method | Monthly | Comparing forecast with actual |
| Son and Kim (2017) | South Korea | Support vector regression and fuzzy-rough feature selection | Monthly, January 1991 and December 2012 | One-month ahead |
| Gao et al. (2021) | China | Extreme learning machine (ELM) | Monthly, January 2011 to December 2019 | Comparing forecast with actual |
| Liang and Liang (2017) | China | Hybrid modified gray and logistic | Annual, 2000 to 2015 | 2016 to 2020 |
| Muhamed and Bodger (2005) | New Zealand | Variable asymptote logistic (VAL) | Annual, 1984 to 1999 | 2000 to 2020 |
| Mikayilov and Darandary (2023) | Saudi Arabia | Structural time series | Annual, 1990 to 2021 | 2022 to 2030 |
| Abdel-Aal and Al-Garni (1979) | Saudi Arabia | ARIMA | Monthly, August 1987 to July 1993 | 12 months |
| Fahmy et al. (2023) | Saudi Arabia | Frontier and ARIMA | Annual, 1990 to 2019 | 2020 to 2030 |
| Soummane and Ghersi (2022) | Saudi Arabia | General equilibrium | No historical data | 2013 to 2030 |
| Al-Harbi and Csala (2019) | Saudi Arabia | | Annual, 2000 to 2018 | 2019 to 2040 |
| Almulla (2014) | Saudi Arabia | Model for Energy Supply Strategy Alternatives and their General Environmental Impacts (MESSAGE) | Annual, 1971 to 2011 | 2011 to 2050 |

Each forecasting technique has merits and weaknesses. What makes the ARIMA framework preferable over some of the others is that ARIMA models are easy to interpret, and in some cases, similar to our case, they only require historical data of the parameter of interest to generate a reliable forecast. In addition, an ARIMA framework requires only a few assumptions in order to generate a statistically significant forecast, as we describe in the methodology section of this paper. Thus, this analysis will employ an ARIMA framework to forecast Saudi residential electricity consumption.

In terms of assessing the potential impact of improving energy efficiency in the Saudi residential sector, there are many studies that investigate how different energy efficiency measures and policies may contribute to residential demand (Al-Homoud and Krarti 2021; Al-Tamimi 2017; Mujeebu and Alshamrani 2016; Belaid and Aldubyan 2021). Many other studies, on the other hand, conduct an analytical assessment to estimate the potential of enhancing energy efficiency in order to reduce electricity consumption and peak electricity demand. One study developed a bottom-up model to simulate Saudi residential electricity consumption and assess the potential impact of different energy efficiency programs (Krarti et al. 2020; Aldubyan et al. 2020). Another study assessed the potential effects of higher residential efficiency on electricity load profiles in Saudi Arabia by integrating an engineering-based model with an economic equilibrium framework (Matar 2016), and the results show that raising the average energy efficiency ratio (EER) from its 2011 average to EER 11 could have saved 255,000 barrels/day of crude oil in the power sector. The impact of different EEMs has also been assessed in order to estimate the potential reductions in electricity consumption in two Saudi regions, Riyadh and Qassim (Almushaikh and Almasri 2020). This study simulated the role of improving EE in the Saudi residential building sector on designing carbon neutral residential communities (Krarti and Aldubyan 2021).

However, the literature seems to lack combining long-term electricity forecasts with assessing the impact of EE on future residential electricity growth in Saudi Arabia. The only paper, as far as we are aware, that has forecast residential electricity consumption and assesses the potential impact of EE is the one by Soummane and Ghersi (2022). However, our analysis differs from this analysis in two main aspects. First, we aimed to forecast long-term residential electricity consumption (to 2060) in order to link it with Saudi Arabia's net zero target, while Soummane and Ghersi (2022) conducted a projection up to 2030. Second, we performed ARIMA modeling, while Soummane and Ghersi (2030) used a general equilibrium model.

# Methodology and Data

To establish the long-term residential electricity forecast and the impact of EE on curbing its growth, this analysis combines two different models – a statistical forecast model and a bottom-up building stock model. More specifically, we first constructed an ARIMA model and forecast the residential electricity consumption up to 2060, and we then estimated the potential reduction in future electricity consumption if different EE policies are implemented. The methodology of the forecast is described in detail in this section, while the bottom-up methodology is briefly described in this paper and can be found in Aldubyan et al. (2020) and Krarti et al. (2020).

## 1.1 Long-Term Electricity Forecast

As mentioned earlier, we used an Autoregressive Integrated Moving Average (ARIMA) model to forecast long-term residential electricity consumption in Saudi Arabia. The modeling process relies solely on the historical residential electricity consumption from 1984 to 2020 in order to forecast the horizon from 2021 to 2060. ARIMA is one of the most widely-used techniques in time-series forecasting. This approach relies on autocorrelation in the historical data to build a model and, thus, to generate a forecast (Hyndman and Athanasopoulos 2018). More specifically, ARIMA uses historical observations of three parameters in order to build a forecast model. These parameters are autoregressive (p), degree of first differencing (d), and order of moving average (q) (Hyndman and George 2018). The autoregressive part, AR(p), can be formulated as:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t$$

where p is the order of lagged value and ε is a white noise.

The moving average part, MA(q), can be written as:

$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q}$$

and ε is supposed to be white noise as well.

Thus, the combination of differencing with lagged values and lagged errors that we showed above produces the ARIMA model (Hyndman and Athanasopoulos 2018) as:

$$y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t$$

In addition, ARIMA models assume the historical data to be stationary. However, a trend of electricity consumption implies non-stationarity, which is clearly the case in our situation and in most electricity consumption data (Figure 3). As a remedy for non-stationary data, ARIMA models take differences between consecutive observations to fit a model instead of dealing with the observed data. We employ the Hyndman-Khandakar algorithm (Hyndman and Khandakar 2008) to identify the best ARIMA specifications (p, d, q) by combining unit root tests, Akaike Information Criterion (AIC) minimization, and Maximum Likelihood Estimation (MLH). The Hyndman-Khandakar algorithm determines differencing (d) by taking

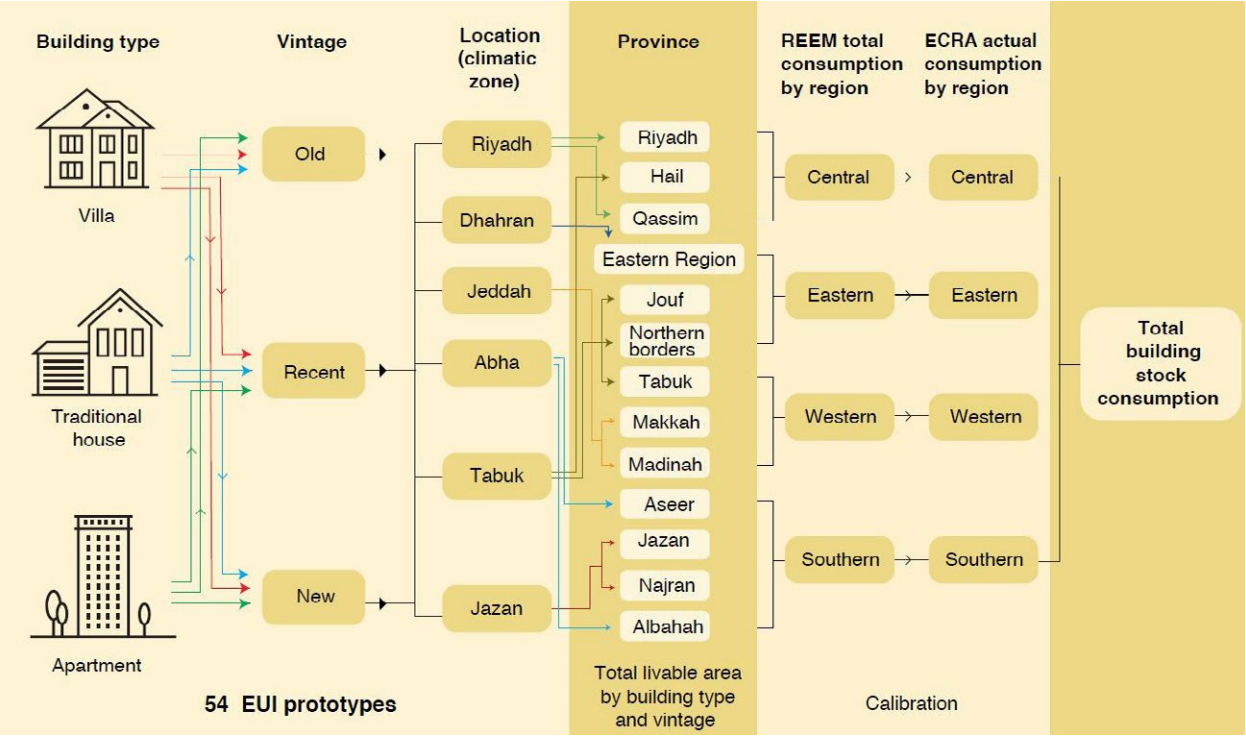
a sequence of differences and then testing for stationarity using the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al. 1992). The null hypothesis of this test is that the historical data are stationary. Thus, the Hyndman-Khandakar algorithm keeps increasing differencing until reaching stationarity that satisfies the KPSS test. After that, the values of p and q are determined based on the lowest AIC.

## 1.2 Energy Efficiency Impact Modeling

After forecasting residential electricity consumption, we utilize the Residential Energy Model (REEM) to assess the impact of different EE policies on future demand. REEM is a bottom-up model that simulates energy consumption in Saudi residential buildings from engineering and economic perspectives (Aldubyan et al. 2020; Krarti et al. 2020). It simulates the entire residential building sector by accounting for different building types, different vintages, and different weather conditions in Saudi Arabia. It then simulates different EE interventions to assess their impact on electricity consumption demand. REEM also accounts for behavioral implications of EE through estimating the rebound effect (Aldubyan et al. 2023). The following chart shows REEM's framework.

Assessing different EE policy on future housing electricity consumption might not be straightforward as future homes are likely to be different in terms of the characteristics that determine how they consume energy. In other words, future homes are expected to comply with newer building codes while most of the existing stock was built with lenient standards, especially buildings that were built many years ago. Thus, applying the same saving estimates of existing building stock to future stock might be unreasonably optimistic. This is where the merit of REEM emerges that distinguishes between different building vintages when estimating their demand and how they respond to different EE interventions. Since Saudi

**Figure 4.** REEM framework.



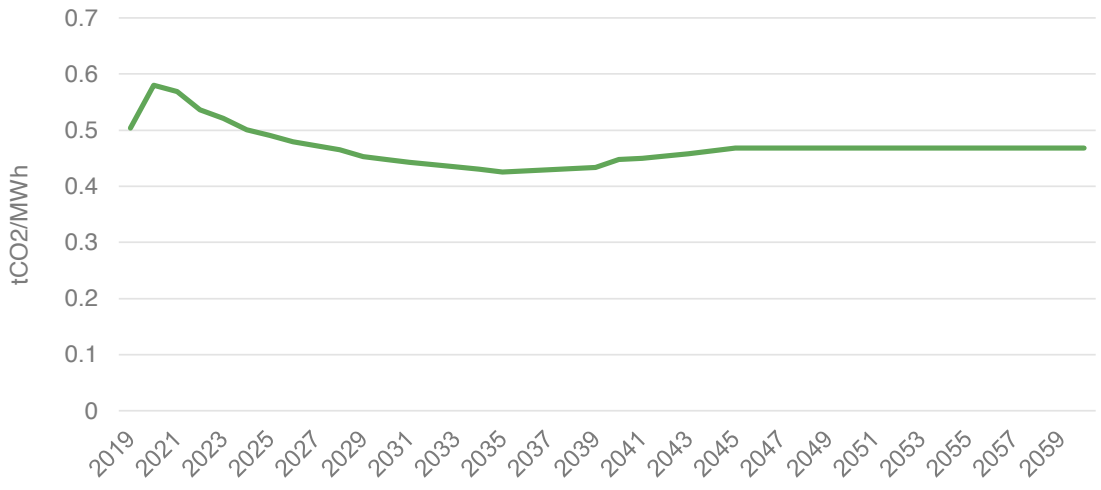

*Source: Aldubyan et al. (2020).*

Arabia has recently updated its residential building code with some stringent standards, this assessment assumes that future buildings will comply with these recent standards. More specifically, we assume that future homes will be similar in physical characteristics to new Saudi houses. REEM also allows for optimizing multiple EE policies in terms of energy savings and implementation costs as a function of building type, vintage, and geographical location (Krarti and Aldubyan 2022). This optimization analysis by REEM suggests that retrofitting existing stock with envelop insulation, having more efficient AC units (EER12 or higher), boosting lighting efficiency by 70%, and reducing air infiltration by 70% can achieve a 40% reduction in electricity consumption by 2060, i.e., around a 1% reduction annually. The model also suggests that future buildings can maintain a 0.5% improvement in efficiency and, hence, a reduction in electricity consumption annually, which can accumulate to a 20% reduction by 2060. This reduction can be achieved by enhancing lighting efficiency by 70% and white goods efficiency by 65%, and by reducing air infiltration by 70% throughout the forecasted horizon (Krarti and Aldubyan 2022). Our analysis assumes that future buildings would comply with the latest residential building codes and standards, which is an implicit assumption of the ARIMA model.

## 1.3 Assessing CO2 Emissions Reduction

The ultimate goal of this analysis is to estimate the long-term potential reduction in CO2 emissions due to energy efficiency policies and how that might contribute to Saudi Arabia's ambitious goal of reaching net zero by 2060. The potential reduction in CO2 emissions depends on an energy mix of the power generation throughout the forecast horizon. Saudi Arabia has set a target to displace liquid fuels to meet 50% of its electricity capacity from renewables, with the remaining 50% from natural gas. As a result, the power generation CO2 intensity is expected to witness a decline in the next few years. Therefore, it is critical to quantify how CO2 intensity would change over the forecast period in order to translate the impact of EE policies into a reduction in CO2 emissions. One study has explored future energy policy pathways for the power sector, among other sectors, in its research, and it estimates power sector CO2 emissions intensity up to 2045 using the King Abdullah Petroleum Studies and Research Center (KAPSARC) Energy Model (KEM), an equilibrium model that solves least-cost or highest-profit decisions for different sectors in the energy system (Matar et al. 2023; KAPSARC 2016). In the analysis, the Announced Policies Scenario (APS) was examined, which takes into account the exogenous imposition in which 50% of the electricity fleet will come from renewable sources while the remining 50% of the capacity will be from natural gas (Matar et al. 2023). We extend this power mix and CO2 emissions intensity to 2060 with an assumption that the 50% gas and 50% renewables pledge would continue beyond 2030 (Figure 5). We then utilize this scenario to convert our electricity forecast and, thus, the estimated EE impact into CO2 emissions.

**Figure 5.** CO2 emissions intensity of power generation in Saudi Arabia.




*Source: Matar et al. (2023).*

# Results and Discussion

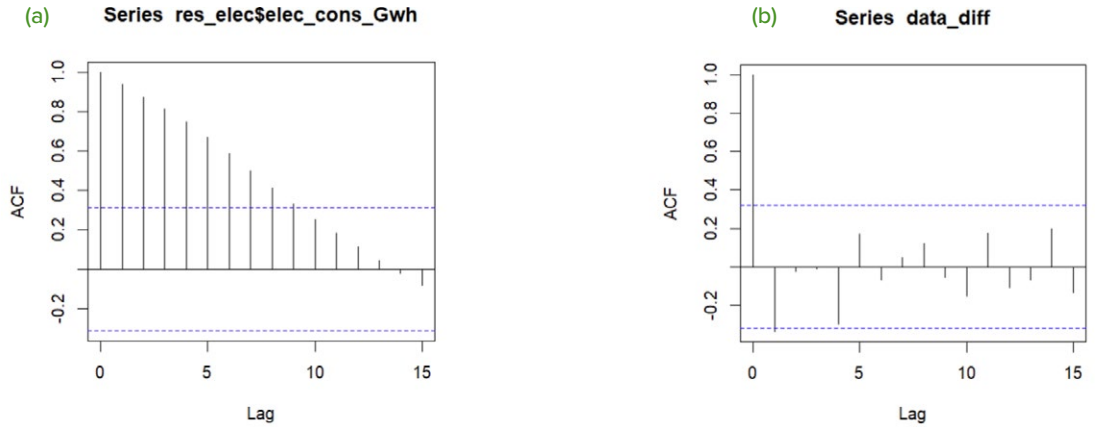
The results of this analysis are presented in this section. We start by showing the ARIMA model specifications, and we then present the long-term forecast of residential electricity consumption. After that, we conduct the necessary diagnostic tests of the specified model. Finally, we apply the set of energy efficiency policies mentioned in Section 3.2 to the forecast in order to assess how electricity consumption and its associated CO2 emissions can be reduced by 2060.

## 1.4 Model Specification

Due to the non-stationarity in the historical electricity consumption data, differencing the data is crucial. As mentioned in the methodology, the Hyndman-Khandakar algorithm specifies the best number of differences using the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test.

The algorithm suggests that our data needs second-order differencing to be stationary (d=2). Looking at the autocorrelation function (ACF) of original versus differenced data, we can see that taking the second-order difference has made the data stationary (Figure 6). The p-values of the KPSS (stationarity) test are 0.01 and 0.1 for non-differenced (a) and second-order differencing (b), respectively, indicating that we reject the null hypothesis of stationarity in the non-differenced and fail to reject it in the second-order differencing (b).

**Figure 6.** ACF before (a.) and after (b.) taking the second-order difference of the historical electricity consumption time series.




*Source: KAPSARC analysis.*

In addition to determining differencing, the Hyndman-Khandakar algorithm also estimates the autoregressive and moving average parts of ARIMA as AR(0) and MA(1), respectively. An AR(0) indicates that the model does not regress against itself, and the dependent variable, which is electricity consumption in our case, does not take historical data points as regressors. An MA(1) suggests that the model uses the previous forecast error as a regressor. Finally, the data will be differenced twice in order to obtain stationarity, which is the second attribute in the ARIMA specification. Thus, our model is ARIMA (0, 2, 1), and can be written as:

$$y''t=-0.75\varepsilon t-1+\varepsilon t$$

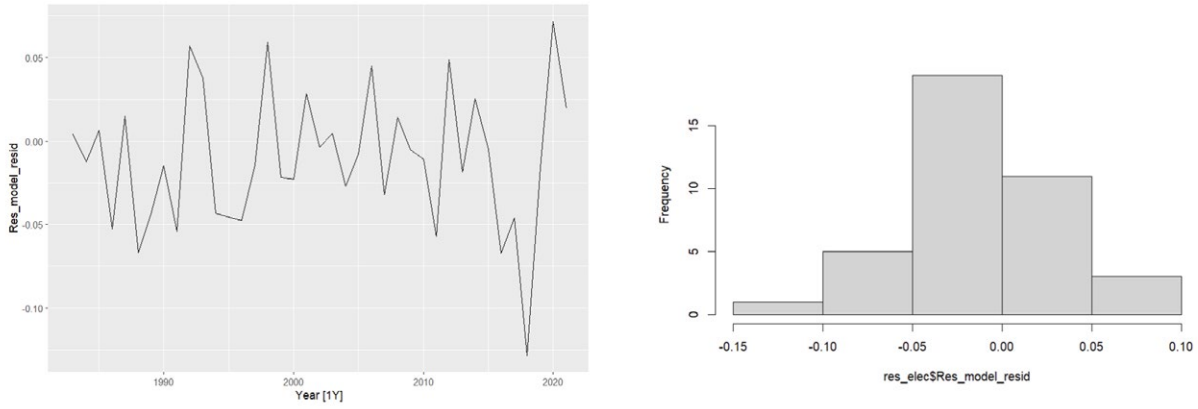
where y''t is the second-ordered differenced series and ε is an error term.

# 1.5 Diagnostic Tests

It is critical to run a diagnostic test to ensure the robustness of the specified model. For ARIMA models, normality and autocorrelation tests of the residuals are the most common diagnostic test. The residuals of the specified model are normally distributed around zero, as shown in Figure 7. Statistically, the Shapiro-Wilk test for normality (Shapiro and Wilk 1965) suggests that the residuals are drawn from a normally distributed population, with a p-value of 0.64.

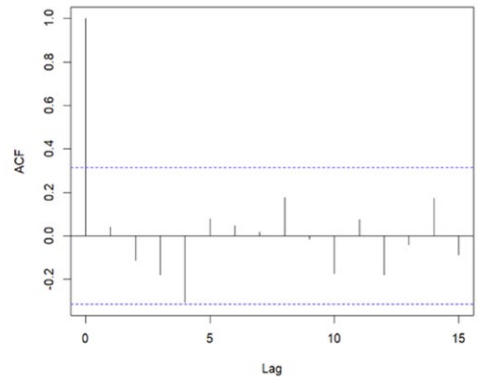
Due to differencing the data, the specified model shows no autocorrelation, as illustrated by the ACF test in Figure 8. With these tests, we can ensure the robustness of the specified model.

**Figure 7.** Normality test of the ARIMA(0, 2, 1) model.




*Source: KAPSARC analysis.*

**Figure 8.** ACF test of ARIMA(0, 2, 1)'s residuals.

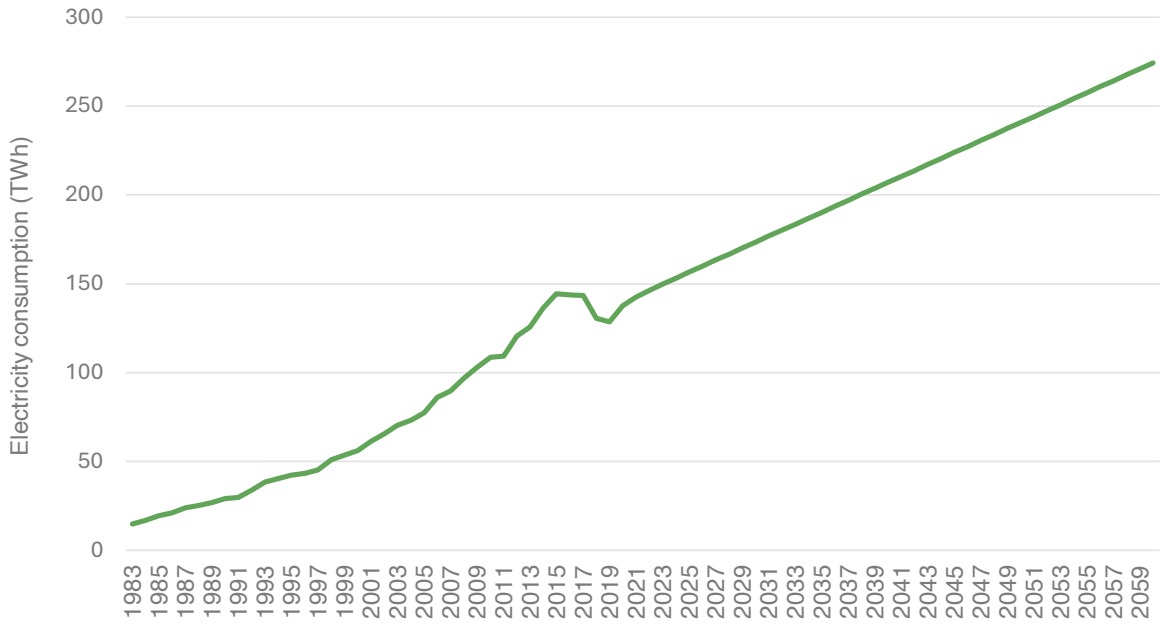



*Source: KAPSARC analysis.*

# 1.6 Electricity Forecast

After specifying the ARIMA model using the Hyndman-Khandakar algorithm and historical residential electricity consumption from 1983 to 2021, we conducted a long-term forecast from 2022 to 2060. As mentioned earlier, the reason behind choosing 2060 is that Saudi Arabia has set its net-zero emission target to be met in that year. The forecast shows that despite the disruption that residential electricity consumption witnessed during the last few years, the consumption is most likely to mimic the period from 1983 to 2015 (Figure 9). That is to say, the model suggests that residential electricity consumption is expected to double over the next 39 years. While this trend is expected, especially when we see the consistent growth over the pre-2015 period, it is important to highlight that this forecast assumes that all influential factors that are not part of the model, such as price and GDP, would maintain the same trends of the past, and that any exogenous intervention can change this forecast by pulling it up or making it flatter, depending on the direction of the intervention. For example, an abnormal increase in population growth and/or a reduction in real electricity prices should make the forecast steeper, while reductions in these two factors should bring future consumption down.

**Figure 9.** Long-term residential electricity consumption forecast for Saudi Arabia.



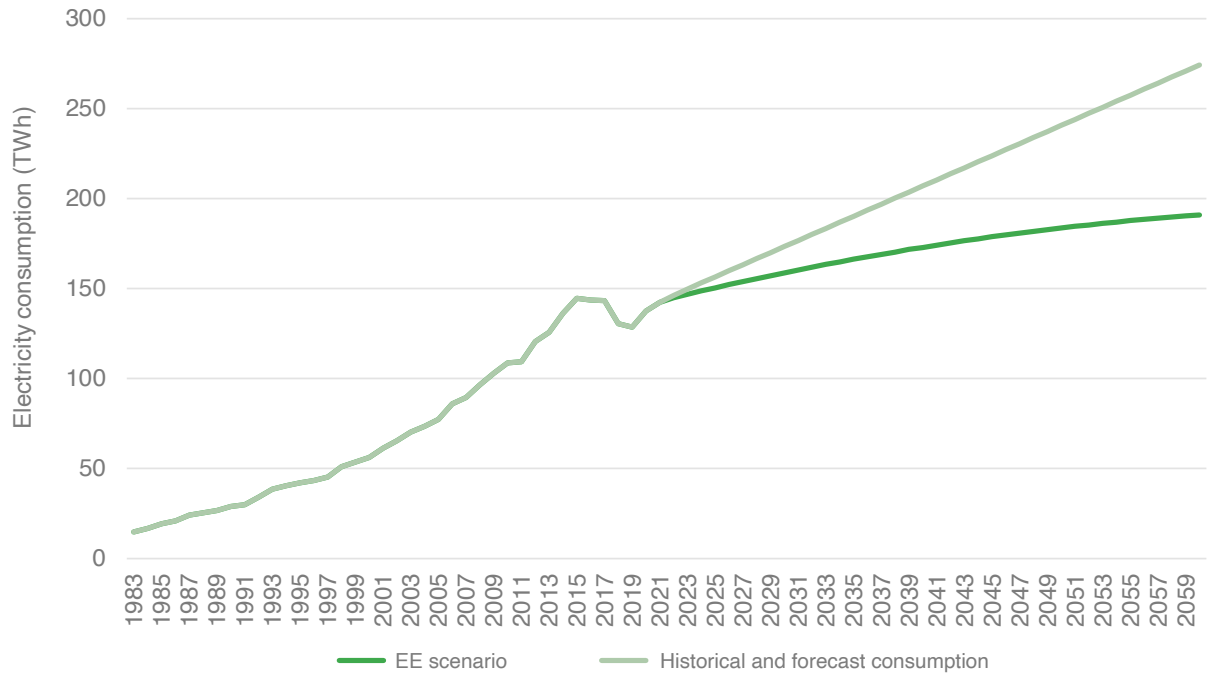

*Source: KAPSARC analysis.*

# 1.7 Potential Impact of Energy Efficiency on Electricity Consumption and Emissions

In this section, we estimate the impact of the optimized energy efficiency policies discussed earlier on the long-term residential electricity forecast. As mentioned before, we utilize REEM to evaluate how certain EE policies will reduce future consumption of existing stock and future stock.

Forecasting residential electricity consumption implicitly assumes an increase in the residential buildings. That is, the increase in electricity consumption is mainly due to an expansion in the building stock (future buildings). Thus, future electricity consumption can be seen and thus split into the consumption of existing buildings and future buildings. This disaggregation helps us to distinguish between energy efficiency programs applied to existing building stock versus future stock. As mentioned in Section 3.2, REEM suggests that among different EE policies, insulating a building's envelops, replacing AC unites with EER 12 or higher, improving lighting efficiency, and reducing air leakages of existing buildings would all reduce future consumption by 1% annually up to the year 2060. This increase in EE would result in a 40% cumulative reduction in electricity consumption by 2060. Future stock, in addition, would avoid 0.5% of its consumption annually if further improvements were achieved by boosting the efficiency of lighting and white goods and reducing air leakages. This annual reduction in consumption would add up to a 20% reduction in 2060. As a result, continuously improving existing stock and enhancing the Minimum Energy Performance Standards (MEPS) would reduce residential electricity consumption by up to 30% in 2060 – from the forecast 274 TWh to 190 TWh (Figure 10). Of the overall consumption, energy efficiency can help the residential sector to avoid around 1,497 TWh throughout the forecast period (the area between the two curves).

**Figure 10.** Potential reduction of Saudi residential electricity consumption achieved by targeted energy efficiency policies.

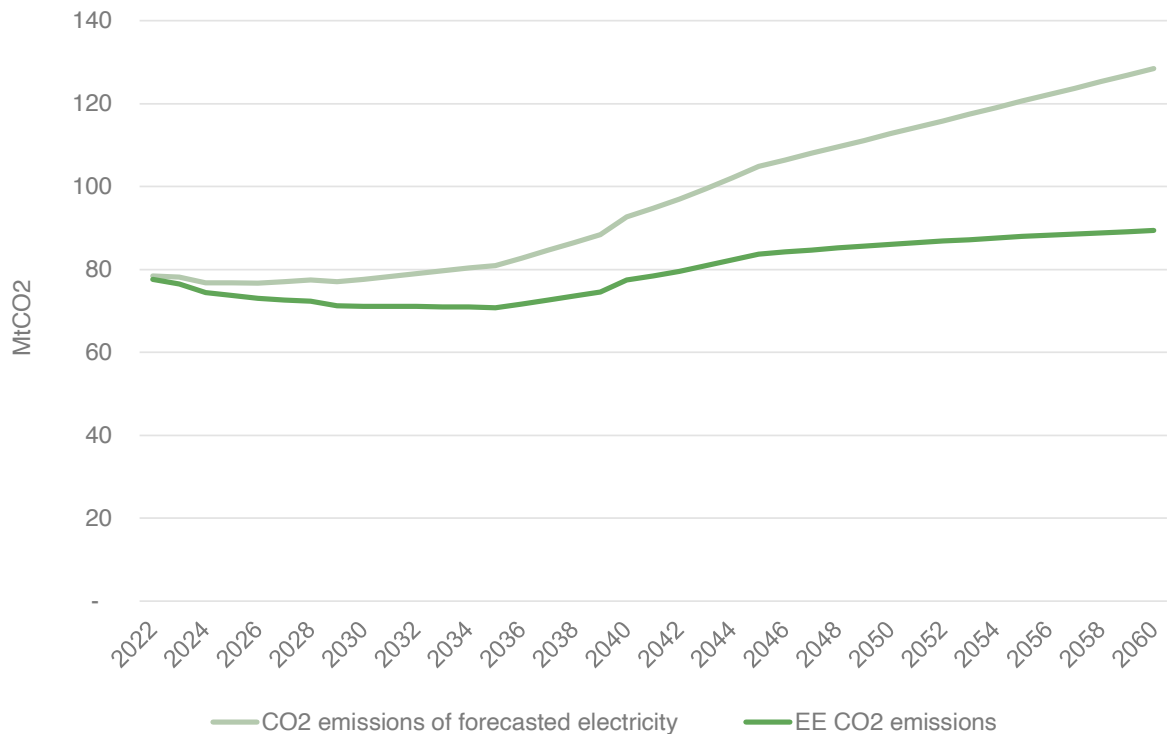



*Source: KAPSARC analysis.*

In fact, there are many EE measures and initiatives that can be implemented within the residential sector; however, we only assumed the most cost-effective EE measures. Thus, Saudi Arabia can even achieve further reductions if more stringent EE measures are rolled out. It is worth mentioning, though, that the potential reduction can be also magnified if Saudi Arabia performs regional-specific or even household-specific EE programs. This is because an effective EE program in one region might not be as effective in another, and a successful EE policy with some households is not necessarily successful with others. The effectiveness of any EE program depends heavily on the economic, demographic, climatic, and behavioral aspects of the targeted segment, to name a few.

Reducing emissions is one of the most critical goals of enhancing energy efficiency, besides other socio-economic benefits. More specifically, boosting the residential energy efficiency and reducing its CO2 footprint should pave the way for Saudi Arabia towards its 2030 target and net zero emissions by 2060. Our analysis shows that the optimized EE policies can reduce the residential sector's CO2 emission footprint by 18% over the forecast horizon – from 3,788 MtCO2 to 3,097 MtCO2. It can also curb 2060s CO2 emissions by 30% – from 128 MtCO2 to 89 MtCO2 (Figure 11). In the context of the Saudi Green Initiative that aims to reduce emissions by 278 Mtpa by 2030, these optimized EE policies, if implemented, can account for 12% of that pledge, which is equivalent to about 33 MtCO2 in 2030.

**Figure 11.** CO2 emissions of forecasted electricity consumption vs. EE scenario.




*Source: KAPSARC analysis.*

# Conclusion

It is critical to understand the major GHG emitters in Saudi Arabia in order to map out an effective framework towards the net zero target in 2060. The power sector has been the largest emitter in the Kingdom, and the residential sector has been responsible for almost half of the domestic power generation. Thus, predicting future electricity consumption would help policymakers in designing effective pathways that pave the way towards local climate initiatives and pledges, such as the Kingdom's target to have 50% of its domestic electricity capacity from renewables and the remaining 50% from natural gas by 2030, as well as its ambitious goal to reach net zero by 2060.

This analysis has constructed a long-term forecast for residential electricity consumption up to 2060, and it has assessed the impact of EE on flattening its growth. Using an ARIMA forecasting technique and historical data from 1983 to 2021, we forecast residential electricity consumption of the next 39 years (from 2022 to 2060). The forecast showed that residential electricity consumption will develop a consistent upward trend again after the disruption it witnessed over the last decade. It is expected to reach 274.3 TWh by 2060 if all influential factors, such as population growth, electricity prices, income, etc., maintain consistent growth. This growth is 92% of the consumption in 2021. Our analysis then utilized a published model to examine how EE enhancement can reduce that potential growth over time. We found that some optimized EE policies can flatten the consumption growth and reduce consumption by 18% over the forecast horizon. The potential reduction of 2060's consumption could be up to 30%. In terms of carbon emission reductions, these EE policies would be able contribute to 12% (33.3 MtCO2) of Saudi Arabia's pledge to cut emissions by 278 Mtpa by 2030. In addition, EE has the potential to reduce carbon emissions by 18% throughout the forecast horizon (690 MtCO2) and 30% of 2060's emissions (39 MtCO2).

# References


Abdel-Aal, R. E., and Ahmed Z. Al-Garni. 1997. "Forecasting Monthly Electric Energy Consumption in Eastern Saudi Arabia Using Univariate Time-Series Analysis." *Energy* 22, no. 11 (November): 1059–1069. https://doi.org/10.1016/S0360-5442(97)00032-7.

Aldubyan, Mohammad, and Anwar Gasim. 2021. "Energy Price Reform in Saudi Arabia: Modeling the Economic and Environmental Impacts and Understanding the Demand Response." *Energy Policy* 148, Part B (January): 111941. https://doi.org/10.1016/j.enpol.2020.111941.

Aldubyan, Mohammad, Moncef Krarti, and Eric Williams. 2020. "Residential Energy Model for Evaluating Energy Demand and Energy Efficiency Programs in Saudi Residential Buildings." Riyadh: King Abdullah Petroleum Studies and Research Center (KAPSARC). https://www.kapsarc.org/research/publications/residential-energy-model-for-evaluating-energy-demand-and-energy-efficiency-programs-in-saudi-residential-buildings/.

Aldubyan, Mohammad, Fateh Belaid, and Anwar Gasim. 2023. "The Rebound Effect in Residential Energy Demand: The Case of Saudi Arabia." Riyadh: King Abdullah Petroleum Studies and Research Center (KAPSARC). https://www.kapsarc.org/research/publications/the-rebound-effect-in-residential-energy-demand-the-case-of-saudi-arabia/.

Al Harbi, Fahad, and Denes Csala. 2019. "Saudi Arabia's Electricity: Energy Supply and Demand Future Challenges." In *2019 1st Global Power, Energy and Communication Conference (GPECOM)*, 467–472.

Al-Homoud, Mohammad S., and Moncef Krarti. 2021. "Energy Efficiency of Residential Buildings in the Kingdom of Saudi Arabia: Review of Status and Future Roadmap." *Journal of Building Engineering* 36 (April): 102143. https://doi.org/10.1016/j.jobe.2020.102143.

Almushaikah, AbdulRahman S., and Radwan A. Almasri. 2021. "Evaluating the Potential Energy Savings of Residential Buildings and Utilizing Solar Energy in the Middle Region of Saudi Arabia – Case study." *Energy Exploration & Exploitation* 39 (5): 1457–1490. https://doi.org/10.1177/0144598720975144.

Almulla, Youssef. 2015. "Gulf Cooperation Council (GCC) Countries 2040 Energy Scenario for Electricity Generation and Water Desalination." Master of Science Thesis EGI 2014: Mar-Sep 2014. KTH: Industrial Engineering and Management. https://www.diva-portal.org/smash/get/diva2:839740/FULLTEXT01.pdf.

Al-Tamimi, Nedhal. 2017. "A State-of-the-Art Review of the Sustainability and Energy Efficiency of Buildings in Saudi Arabia." *Energy Efficiency* 10 (5): 1129–1141. https://doi.org/10.1007/s12053-017-9507-6.

Belaïd, Fateh, and Mohammad Al Dubyan. 2021. "The Role of Residential Energy Efficiency in Shaping the Energy Transition in Saudi Arabia: Key Challenges and Initiatives." *IAEE Energy Forum: Fourth Quarter 2021*: 19–23.

Box, George E.P., Gwilym M. Jenkins, and Gregory C. Reinsel. 1976. *Time Series Analysis: Forecasting and Control*. Hoboken, New Jersey: Wiley.

Circular Carbon Economy National Program. "About Us." Accessed August 30, 2023. https://www.cce.org.sa/Pages/AboutUs.aspx.

Diabi, Ali. 1998. "The Demand for Electric Energy in Saudi Arabia: An Empirical Investigation." *OPEC Review* 22 (1): 13–29. https://doi.org/10.1111/1468-0076.00039.

Dong, Bing, Zhaoxuan Li, S.M. Mahbobur Rahman, and Rolando Vega. 2016. "A Hybrid Model Approach for Forecasting Future Residential Electricity Consumption." *Energy and Buildings* 117 (April): 341–351. https://doi.org/10.1016/j.enbuild.2015.09.033.

Fahmy, Marwa Salah ElDin, Farhan Ahmed, Farah Durani, Štefan Bojnec, and Mona Mohamed Ghareeb. 2023. "Predicting Electricity Consumption in the Kingdom of Saudi Arabia." *Energies* 16 (1): 506. https://doi.org/10.3390/en16010506.

Gao, Feng, Hong Chi, and Xueyan Shao. 2021. "Forecasting Residential Electricity Consumption Using a Hybrid Machine Learning Model with Online Search Data." *Applied Energy* 300 (October): 117393. https://doi.org/10.1016/j.apenergy.2021.117393.

General Authority for Statistics (GASTAT). 2019. *Population & Demography.* https://www.stats.gov.sa/en/1007-0.

Hyndman, Rob J., and Yeasmin Khandakar. 2008. "Automatic Time Series Forecasting: The Forecast Package for R." *Journal of Statistical Software* 27 (3): 1–22. https://doi.org/10.18637/jss.v027.i03.

Hyndman, Rob J., and George Athanasopoulos. 2018. *Forecasting: Principles and Practice*. Melbourne: OTexts.

IEA. "Electricity Consumption." https://www.iea.org/reports/electricity-information-overview/electricity-consumption.

Jo, Ha-Hyun, Minwoo Jang, and Jaehyeok Kim. 2020. "How Population Age Distribution Affects Future Electricity Demand in Korea: Applying Population Polynomial Function." *Energies* 13 (20): 5360. https://doi.org/10.3390/en13205360.

KAPSARC. "The KAPSARC Energy Model for Saudi Arabia: Documentation of the Model Build Called 'KEM-SA_v9.16'." [DATE] 2016." Riyadh: King Abdullah Petroleum Studies and Research Center (KAPSARC). https://www.kapsarc.org/wp-content/uploads/2016/11/KEM-SA_documentation_v9.16.pdf.

Krarti, Moncef, and Mohammad Aldubyan. 2022. "Peak Demand-Based Optimization Approach for Building Retrofits: Case Study of Saudi Residential Buildings." *Energy Efficiency* 15:69. https://doi.org/10.1007/s12053-022-10077-2.

Krarti, Moncef, Mohammad Aldubyan, and Eric Williams. 2020. "Residential Building Stock Model for Evaluating Energy Retrofit Programs in Saudi Arabia." *Energy* 195 (March): 116980. https://doi.org/10.1016/j.energy.2020.116980.

Krarti, Moncef, and Mohammad Aldubyan. 2021. "Role of Energy Efficiency and Distributed Renewable Energy in Designing Carbon Neutral Residential Buildings and Communities: Case Study of Saudi Arabia." *Energy and Buildings* 250 (November): 111309. https://doi.org/10.1016/j.enbuild.2021.111309.

Kwiatkowski, Denis, Peter C.B. Phillips, Peter Schmidt, and Yongcheol Shin. 1992. "Testing the Null Hypothesis of Stationarity Against the Alternative of a Unit Root: How Sure Are We That Economic Time Series Have a Unit Root?" *Journal of Econometrics* 54, no. 1-3 (October-December): 159–178. https://doi.org/10.1016/0304-4076(92)90104-Y.

Liang, Jie, and Yi Liang. 2017. "Analysis and Modeling for China's Electricity Demand Forecasting Based on a New Mathematical Hybrid Method." *Information* 8 (1): 33. https://doi.org/10.3390/info8010033.

Liu, Che, Bo Sun, Chenghui Zhang, and Fan Li. 2020. "A Hybrid Prediction Model for Residential Electricity Consumption Using Holt-Winters and Extreme Learning Machine." *Applied Energy* 275 (October): 115383.

Matar, Walid. 2016. "Beyond the End-Consumer: How Would Improvements in Residential Energy Efficiency Affect the Power Sector in Saudi Arabia?" *Energy Efficiency* 9:771–790. https://doi.org/10.1007/s12053-015-9392-9.

Matar, Walid, Noura Mansouri, and Evar Umeozor. 2023. "Energy Policy Pathways to Inform Climate Policy in Saudi Arabia." Riyadh: King Abdullah Petroleum Studies and Research Center (KAPSARC). https://www.kapsarc.org/research/publications/energy-policy-pathways-to-inform-climate-policy-in-saudi-arabia/.

Mikayilov, Jeyhun I., Fakhri J. Hasanov, Waheed Olagunju, and Mohammad H. Al-Shehri. 2020. "Electricity Demand Modeling in Saudi Arabia: Do Regional Differences Matter?" *The Electricity Journal* 33 (6): 106772. https://doi.org/10.1016/j.tej.2020.106772.

Mikayilov, Jeyhun I., Abdulelah Darandary, Ryan Alyamani, Fakhri J. Hasanov, and Hatem Alatawi. 2020. "Regional Heterogeneous Drivers of Electricity Demand in Saudi Arabia: Modeling Regional Residential Electricity Demand." *Energy Policy* 146 (November): 111796. https://doi.org/10.1016/j.enpol.2020.111796.

Mohamed, Zaid, and Pat S. Bodger. 2005. "A Variable Asymptote Logistic (VAL) Model to Forecast Electricity Consumption." *International Journal of Computer Applications in Technology* 22 (2): 65–72. https://doi.org/10.1504/IJCAT.2005.006937.

Mujeebu, Muhammad Abdul, and Othman Subhi Alshamrani. 2016. "Prospects of Energy Conservation and Management in Buildings – The Saudi Arabian Scenario Versus Global Trends." *Renewable and Sustainable Energy Reviews* 58 (May): 1647–1663. https://doi.org/10.1016/j.rser.2015.12.327.

Saudi Energy Efficiency Center (SEEC). 2020. "Introducing the New Requirements of Air Conditioners Standard SASO-2663 the Seasonal Energy Efficiency Ratio (SEER)". December 23.

Saudi Energy Efficiency Program. 2023. "Saudi Energy Efficiency Program." https://www.moenergy.gov.sa/en/OurPrograms/SPFEE/Pages/default.aspx.

*Saudi and Middle East Green Initiatives. "SGI Target: Reduce Carbon emissions by 278 MTPA by 2030: A Mission to Accelerate Saudi Arabia's Green Energy Transition and Mitigate the Impacts of Climate Change." https://www.greeninitiatives.gov.sa/about-sgi/sgi-targets/reducing-emissions/reduce-carbon-emissions/.*

Schneider, Nicolas. 2022. "Population Growth, Electricity Demand and Environmental Sustainability in Nigeria: Insights from a Vector Auto-Regressive Approach." *International Journal of Environmental Studies* 79 (1): 149–176. https://doi.org/10.1080/00207233.2021.1905317.

Shapiro, Samuel Sanford, and Martin B. Wilk. 1965. "An Analysis of Variance Test for Normality (Complete Samples)." *Biometrika* 52, no. 3/4 (December): 591–611. https://doi.org/10.2307/2333709.

Son, Hyojoo, and Changwan Kim. 2017. "Short-Term Forecasting of Electricity Demand for the Residential Sector using Weather and Social Variables." *Resources, Conservation and Recycling* 123 (August): 200–207. https://doi.org/10.1016/j.resconrec.2016.01.016.

Soummane, Salaheddine, and Frederic Ghersi. 2022. "Projecting Saudi Sectoral Electricity Demand in 2030 Using a Computable General Equilibrium Model." *Energy Strategy Reviews* 39 (January): 100787. https://doi.org/10.1016/j.esr.2021.100787.

Tserkezos, E. Dikaios. 1992. "Forecasting Residential Electricity Consumption in Greece Using Monthly and Quarterly Data." *Energy Economics* 14 (3): 226–232. https://doi.org/10.1016/0140-9883(92)90016-7.

Water and Electricity Regulatory Authority. 2021. *Annual Statistical Booklet for Electricity* 2021. https://sera.gov.sa/en/media-center/agency-publications.

Worldometers. 2023. "World Population by Year." https://www.worldometers.info/world-population/world-population-by-year/.

# About the Authors



**Mohammad Aldubyan**

Mohammad is a Fellow in KAPSARC's Climate & Sustainability program. His research focuses on energy efficiency in buildings, energy demand, and energy modeling. He is currently leading the Residential Energy Model (REEM), which simulates residential energy demand and estimates the impact of energy efficiency programs on Saudi Arabia's housing sector. Mohammad holds an M.Sc. in Renewable and Clean Energy from the University of Dayton, Ohio, and an M.Sc. in Economics from Purdue University, West Lafayette.

# About the Project

The Climate and Sustainability program advises the Kingdom on how to achieve its sustainability and climate targets. It does so by producing state-of-the-art national, regional, and global climate-energy-economic models, analysis, and insights. These focus on climate economics, climate change policies, and environmental sustainability.




www.kapsarc.org