How Would Real-time Electricity Pricing Affect the Saudi Power Sector in the Long-run?

Walid Matar[1]

Abstract

This paper shows the effects of real-time electricity pricing (RTP) on the long-run marginal costs of power generation in Saudi Arabia. To do this, it links a multi-sector energy system model with a residential electricity use model. The energy system model contains an economic power dispatch optimization component. The residential framework embeds households, whose decisions are governed by microeconomic principles, in a physical building energy model. The analysis entails liberalizing fuel prices for the power utilities and setting the dynamic prices of electricity equal to the long-run marginal electricity supply costs. The electricity prices are solely offered to households. The key takeaways from this analysis are:

- RTP, a form of dynamic electricity pricing, reduces the variability of the marginal costs for Saudi power utilities throughout the day.
- Lowered capital spending by the Saudi power sector results from RTP and consequently lower power loads. Moreover, the curtailed investment in power plants would more than cover the costs of residential smart meter replacements.

Keywords: Real-time electricity pricing; Saudi Arabia; energy efficiency; energy system model; price-based demand response

[1] King Abdullah Petroleum Studies and Research Center (KAPSARC). PO Box 88550 Riyadh, Saudi Arabia, 11672. Tel.: +966536004253. Email address: walid.matar@kapsarc.org. Declarations of interest: none.

1. Introduction

Saudi Arabia recently began replacing conventional analogue electricity use meters with digital meters for residential customers. Argaam (2019) reports that the total cost of replacement is 9 billion Saudi riyals. The cost is being wholly covered by the Saudi Electricity Company (SEC). Once this change is complete, SEC will have simpler billing operations, access to time-of-use (ToU) power load information, and in the scope of this paper, the ability to charge time-varying electricity rates. Dutta and Mitra (2017) classified static and dynamic electricity pricing into the categories broadly shown in Table 1. As discussed by Yang et al (2018), dynamic prices comprise a category of price-based demand response tools that power utilities may exercise.

Table 1 – Electricity pricing schemes (based on Dutta and Mitra, 2017)

Pricing scheme	Brief description
Flat tariffs	A single electricity price throughout time.
Tiered tariffs	Prices scale with the quantity of electricity use in every billing period. Different quantity tiers are applied regionally.
Seasonal tariffs	Static electricity prices in each seasonal period.
Time-of-use (ToU) tariffs	Time-varying rates that are fixed to incentivize customers to shift their load to certain times of the day.
Critical peak pricing	A dynamic electricity price that is highest during the peak load segment.
Real-time pricing (RTP)	A dynamic electricity price that is reflective of the marginal cost of supply.
Peak time rebates	Rebates that are provided to customers for electricity use below a pre-determined quantity.

A ToU electricity pricing scheme may be preferred by local electricity regulators as a first foray into dynamic pricing. Assumed ToU tariffs for residential customers were previously analyzed in the Saudi context by Matar (2017, 2018, 2019, 2021). Since Saudi Arabia has no previous experience with dynamic prices, those analyses were not empirical in nature. As a continuation of past ToU price studies, the purpose of this paper is to discuss the effects of real-time electricity pricing on the Saudi power suppliers. Particularly, their marginal costs of power generation, which depend on their fuel use and power capacity investment decisions. Real-time pricing (RTP) varies throughout the day based on the marginal cost of electricity supply.

To this end, the paper makes use of the KAPSARC Energy Model (KEM) and a residential electricity use framework. The core version of KEM is an equilibrium model that consists of six energy or energy-intensive sectors in the Saudi economy (KAPSARC, 2016). One of those six sectors is electric power generation. It also represents four regions within Saudi Arabia. For power generation, each modeled day in KEM contains eight load segments due to its temporal aggregation. This means the model produces eight electricity marginal costs per day per region. A single marginal cost is an average of the prices for a few hours during the day. The residential electricity use paradigm, which is linked to the electric power sector, entails the merger of microeconomics and a conventional building energy model (Matar, 2021). It ultimately outputs power load curves for the residential sector. Contingent on welfare maximization, the load curves are a product of households' behavioral adjustments and/or energy efficiency purchases. This way, the demand functions and the associated price elasticities are implicitly determined in the framework. Through the linkage, this paper looks at the long-run marginal costs of power generation and delivery[2] at the fuel prices offered to power plants at the market prices of 2017.

Much of the literature on time-varying electricity pricing studies the subject from the point of view of the consumer (e.g., Allcott, 2011; Faruqui et al, 2012; Faruqui et al, 2013; Herter et al, 2013). It focuses on experimental studies and surveys of residential customers. The next section provides an in-depth look at past studies on dynamic electricity prices, and what insights may be obtained in the context of this study. Then, the methods and energy pricing scenarios are fleshed out. After discussing the results, the paper summarizes the findings in the conclusion.

[2] The term 'delivery' means generation, transmission, and distribution.

2. Time-varying electricity pricing

In basic economic theory, pricing of a good is deemed efficient when its marginal cost of supply is equal to the marginal value of its demand (Dewees, 2001). Generally, the short-run marginal costs of electricity generators are used to instantaneously decide who generates to satisfy the demanded power load. If the electricity price is fixed, the constant response is shouldered by the power suppliers. Conversely, wholesale and retail electricity markets attempt to ensure economic efficiency by having both the quantities supplied and demanded adjust based on an equilibrium price that is discovered concurrently. In this case, the highest marginal generation cost equals the highest marginal value of demand. When it comes to electricity, this dance is performed constantly throughout the day. Due to the electric power load variation and the lack of widespread electricity storage, the short-run marginal costs, and thus the equilibrium prices, vary from time point to another. In practice, however, most regions do not have a market where suppliers and consumers can quickly respond to differing loads or prices throughout the day.

In regulated settings, electricity may still be priced to reflect costs of electricity generation, transmission, and distribution. The regulated prices may be cost-reflective for all consumers, or be priced in a way that does not reflect the true costs for a particular customer group. This has been the case in the Gulf Cooperation Council (GCC), where electricity prices have been time-invariant and cross-subsidized between the consumer segments. For instance, households and schools in GCC countries have been paying below-cost rates, whereas other consumer segments, particularly the government, have been paying above-cost. For example, ECRA (2018) reports that the average electricity cost-of-service[3] in Saudi Arabia was 5.44 US cents per kWh. The same report states that in 2017, the government electricity tariff was fixed at 8.53 US cents per kWh, the industrial tariff was 4.80 US cents per kWh, and the residential tariff started at 1.33 US cents per kWh for the first 2 MWh of use per month.

[3] The cost to serve is comprised of electricity generation, transmission, distribution, consumption of capital, and capital expenses.

Various studies have shown that higher economic efficiency can be achieved by moving to dynamic prices. For instance, Faruqui et al (2012) discuss the tradeoff between risk and reward for the consumer of time-varying pricing schemes. In their paper, reward is defined as the potential to save money, and the risk is exposure to potential price volatility. Their illustration starts with flat tariff scheme and culminates with RTP. They find that making electricity prices more variable with time generally improves the reward but also increases risk. This relationship is envisaged to be non-linear in nature, where the risk increases at a higher pace than the reward as prices move closer to RTP.

Faruqui and Sergici (2010) report that in the 2000s, regulators in the United States were investigating if and to what extent customers' electricity demand responded to dynamic electricity prices. To this end, a collection of 15 nationwide experiments that tested ToU pricing and critical peak pricing were surveyed. Their results were highly variable, depending on the extent of price increase and whether consumers had enabling technologies to substitute or shift electricity use.

Allcott (2011) studies the effects of the first experimental program in the United States to test hourly RTP on households. He finds that households responded in the short-run by conservation, or through behavioral adjustments, during the peak hours. They did not, however, shift their electricity use to off-peak hours.

Around that time, Faruqui et al (2013) studied the price response of residential customers in Michigan to peak time rebates and critical peak pricing. Those two electricity pricing schemes deviate from RTP, but are still examples of dynamic prices. They utilized constant elasticity of substitution (CES) functions to estimate customers' aggregate price elasticities. Specifically, the extent to which they responded by shifting loads from peak to off-peak and daily own-price elasticities. The authors estimated the same substitution elasticities (of -0.11) and daily elasticities (of 0.00) for both pricing cases.

Moreover, the experimental study presented by Herter et al (2013) shows that households in California, who signed up for the time-varying electricity rate, helped the power utilities save over 20% to 50% on their peak loads than those who chose to stick with the tiered electricity price. Those households reduced their electricity bills in the summer. Of course, those are the results for select regions at a given point in time.

These past surveys or experiments of dynamic electricity pricing programs confirm theoretical outcomes of power load reductions when consumers face higher prices. The confirmation of theory goes hand-in-hand with this study's method, as discussed in the next section.

3. Method

This paper links two models:

- KEM: An energy system equilibrium model developed for Saudi Arabia.
- The residential electricity use model in which a household is embedded in a physical building energy model. Its data calibration is based on household surveys conducted by the Saudi General Authority for Statistics. Detailed data inputs are provided by Matar (2021).

Essentially, the residential electricity use model outputs the power load curve information based on its determined behavioral adjustments and/or energy efficiency purchase. The residential power load curve is added to those of the other consumer segments. The energy system model outputs the operational decisions of the power system in meeting that load demand. The linkage entails iterating between the two models until both the load curves and the electricity prices converge. The electricity prices used in the paper are the marginal costs of power generation and transmission. This pricing scheme is termed RTP from here on out.

Both models characterize four regions of Saudi Arabia as illustrated in Figure 1. The regions are based on the operating areas of SEC. They have varying socio-economic and climatic attributes.

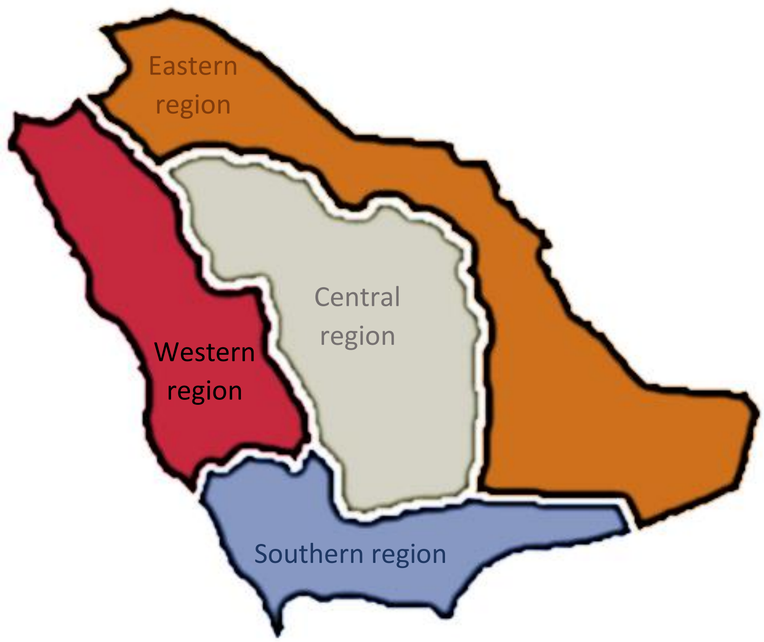

Figure 1 – The four Saudi regions as represented in KEM and the residential electricity model (source: KAPSARC, 2016)

3.1 The KAPSARC Energy Model

KEM is a multi-sector energy system model for Saudi Arabia (KAPSARC, 2016). Shown by Figure 2, it consists of six energy or energy-intensive sectors. They are: electricity, cement production, petrochemical and fertilizers, water desalination for municipal water use, oil and natural gas extraction and transport, and oil refining. The model characterizes the operational and investment decisions of each of those sectors. Each sector aims to either minimize its own cost or maximize its own profit. The power generation sector in particular is formulated to minimize costs to meet power load demand. The model disaggregates Saudi Arabia into four regions that are consistent with the operating areas of the Saudi Electricity Company (SEC). KEM's data inputs are detailed by Matar and Anwer (2017) and Matar and Shabaneh (2020) for 2015. Those data are used for the purpose of this analysis.

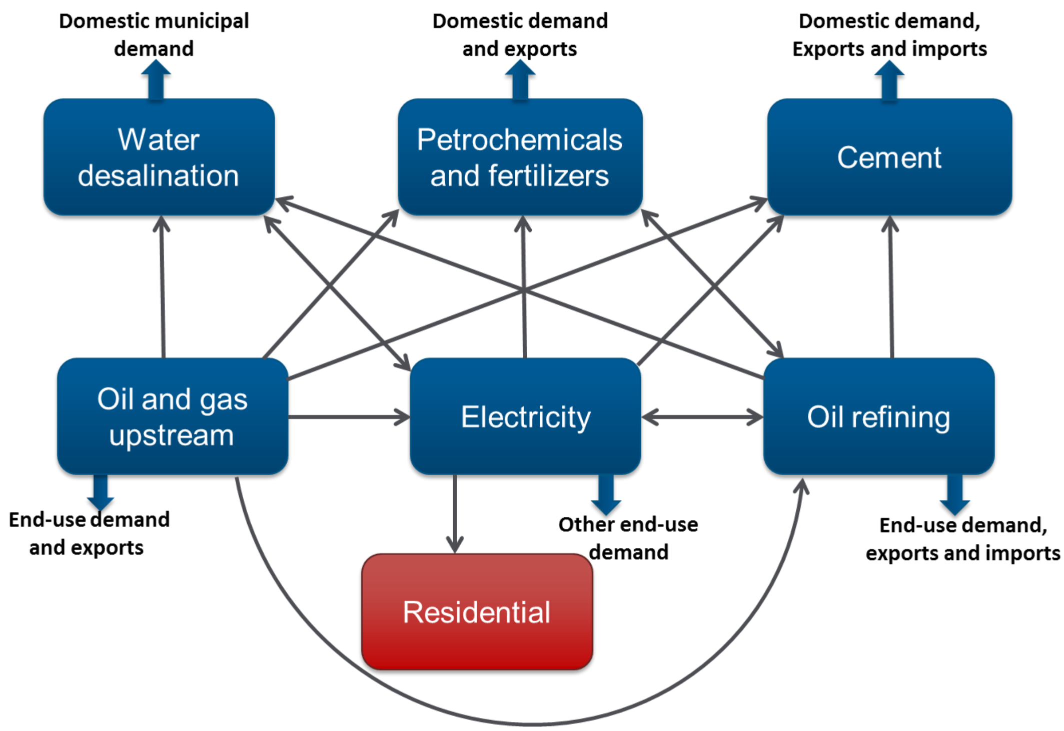

Figure 2 – The KAPSARC Energy Model (source: KAPSARC, 2016)

The power generation sector covers all existing technologies in the Saudi power system. In addition, prospective technologies that Saudi Arabia may deploy, like nuclear power and solar thermal power, are also incorporated for potential investment. To keep the model size tractable, it makes operational decisions for representative weekdays and weekends in the summer, winter, and an intermediate seasonal period for each region. Furthermore, it discretizes each of those days into eight load segments. It outputs the long-run marginal costs for those load segments. A single marginal cost is an average of the costs for a few hours during the day.

The chronological power load curves are determined by the residential electricity use model. Those power loads then inform the load demand that the power generation has to meet. The power sector then makes the appropriate operational and plant investment decisions in the long-run. The term “long-run” is defined as the steady state that happens at some point in the future.

The operational decisions include the levels of chronological fuel use, which would change as the households respond to changing electricity prices by altering their loads. Other sectors, like the oil refining industry, may subsequently change their operations.

3.2 The residential electricity use model

Figure 2 shows, at a high-level, the residential electricity use model is linked to the power generation sector of KEM. The residential model itself is described by Matar (2018, 2019, 2021). The residential component merges the physical laws that govern energy flows in a dwelling with the microeconomic fundamental by which economists study household decision-making. Households' decisions are guided by a utility function that measures their welfare or satisfaction (Johansson, 1991). The electricity consumption variables in the utility function are defined by a physical building energy model. The basic structure of the framework is shown by Figure 3. It essentially internalizes a household's responsiveness to price. A detailed description of data calibration and input is provided by Matar (2021).

The physical component characterizes the conductive, radiative, and convective forms of heat that are transferred into and out of the air inside a thermal envelope. It resembles commercial building energy models in that respect, except it was designed from the bottom up to be linked with KEM, and to facilitate further development for the purposes of energy economics research. It incorporates the sensible and latent heat gains or losses as a result of air exchange between indoor and outdoor air, windows, lighting, and internal elements like occupancy and appliances. The total hourly power load is the sum of the direct uses of light bulbs and appliances, the power required to run the supply and return fans of the air-handling units, and the power draw from the refrigeration cycle of the air conditioners. The power used by the refrigeration cycle is directly related to the amount of heat transferred into and out of the interior to achieve the desired indoor temperature and relative humidity settings. The physical component allows for the analysis of specific energy efficiency measures.

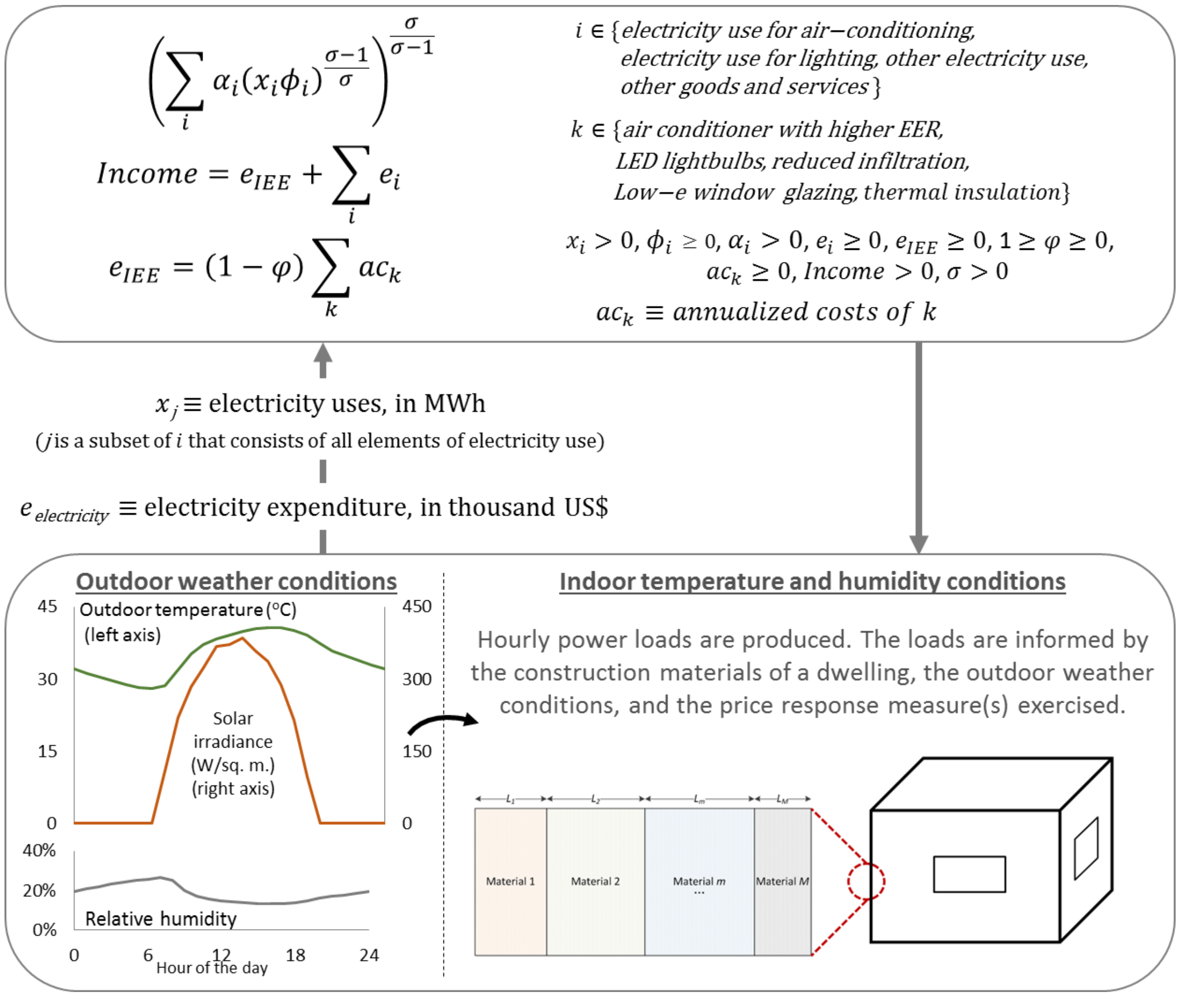

Figure 3 – The residential physical-microeconomic framework (source: Matar, 2021)

The levels of energy use that are determined in the physical component are fed to the microeconomic component. There, a constant elasticity of substitution (CES) utility function is used, as shown by the top-most formulation in Figure 3. While the substitution elasticity is fixed, the own-price elasticity of the goods' demand is allowed to vary based on the expenditure shares. x_i are the electricity uses by service, in megawatthours (MWh), and ϕ_i are adjustment factors that estimate the utility gained by the installation of energy efficiency measures. In other words, ϕ_i adjust any decreased use of electricity due to energy efficiency by modifying $x_i\phi_i$. A more detailed description of ϕ_i is provided by Matar (2021). The consumption of other goods and services is determined in monetary terms. Furthermore, the price of other goods and services is set to unity.

α_i are the preferences, and they sum to unity for all i. The households were calibrated to have preference shares for electricity ranging between 0.5% and 35%. The preference share depends on the region and household income, as explained later. This calibration was performed by starting at a near-zero electricity preference setting, and slowly raising that preference until the households no longer responded behaviorally to the 2017 electricity tariffs. The preference share devoted to electricity is further disaggregated to its various components. The analysis uses estimates based on the 2011 consumption shares reported by Faruqui et al (2011) for a household in Saudi Arabia. These metrics are shown in Table 2. The preference share of other goods and services is 100% minus the electricity preference share. Finally, σ is the elasticity of substitution, and the calibrated value is 0.9.

Table 2 – Estimated electricity use breakdown for a household in Saudi Arabia

Electricity end use	Shares of electricity consumption (%)
Cooling	70
Lighting	5
Other	25

Source: estimated by the author from Faruqui et al. (2011)

In the budget constraint, $Income$ is the households' average annual income by region. It is based on the average 2017-2018 income of a household in each region reported by the General Authority for Statistics (2018), as shown in the Appendix. The total household population is broken up into two income classifications: low- and high-income. The income levels associated with each region are tabulated in the Appendix. e_i are the annual expenditures on electricity and other goods and services. Expenditure on electricity may be computed based on hourly prices or Saudi Arabia's present progressive, or tiered, pricing structure.

e_{IEE} is the annualized investment and maintenance cost required for a particular energy efficiency measure. The analysis only includes the expenditure on higher energy efficiency measures in the income constraint, as its effects in the form of lower electricity use appear in the utility function. Also, φ, which specifies the level of subsidy provided by another firm or government, is set to zero here.

The features and costs of the energy efficiency measures, k, incorporated in this analysis are detailed by Matar (2021). The costs vary due to the climate and typical dwelling characteristics in each region. The costs are annualized using an individual's discount rate that is consistent with the findings of Hausman (1979), Harrison et al (2002), and Bruderer Enzler et al (2014). They estimate average discount rates for individuals of around 30%. In contrast, Alberini et al (2013) estimate a range of discount rates for individuals of 1.5 to 3%; below those that are usually used by private firms.

4. Fuel and residential electricity pricing in the analysis

Fuel prices in 2020 are set by the government (ECRA, 2020a). Oil prices offered to power utilities deviate from their corresponding international market levels. Natural gas, which is not traded internationally and therefore not affected by external prices, is priced below its marginal cost of production (Matar and Shabaneh, 2020). These prices produce low marginal costs of power generation, and do not signal the investment in more energy efficient or renewable technologies. The current average electricity tariff reflects the current low costs of electricity service (ECRA, 2020a).

Recent analyses looked at the effects of fuel price liberalization (Matar and Anwer, 2017; Matar and Shabaneh, 2020). The government has plans to raise fuel prices to better match international benchmarks (Saudi Vision 2030, 2017). Thus, this paper looks at the long-run marginal costs of power generation and delivery at the fuel prices offered to power plants at the market prices of 2017. Although this analysis fully liberalizes oil prices, previous analyses have shown that the energy system would displace oil for alternative generation technologies at well below the 2017 market prices (Matar et al, 2016; Matar and Anwer, 2017). The model will invest in new power capacity based on these fuel prices.

The reference case examines the residential electricity tariffs that were applied in 2017 in Saudi Arabia. This is because the residential electricity use model is calibrated to 2017 for data availability reasons. Shown in Table 3, The Electricity & Co-generation Regulatory Authority (ECRA, 2016) details the 2017 electricity tariffs. The tariffs were revised in 2016 and did not change again until 2018. That is when the tariffs were last changed as of the end of 2020.

Table 3 – 2017 and 2018 residential electricity tariffs in Saudi Arabia (ECRA, 2016; ECRA, 2018)

<table>
<tr><th rowspan="2">Monthly electricity use</th><th colspan="2">Electricity tariff (Halalah per kWh)</th></tr>
<tr><th>2017</th><th>2018</th></tr>
<tr><td>Up to 2 MWh</td><td>5</td><td rowspan="3">18</td></tr>
<tr><td>More than 2 MWh and up to 4 MWh</td><td>10</td></tr>
<tr><td>More than 4 MWh and up to 6 MWh</td><td>20</td></tr>
<tr><td>More than 6 MWh</td><td>30</td><td>30</td></tr>
</table>

The other electricity pricing case studied is the RTP, which is only applied to households. As shown in Table 4, residential electricity use constituted nearly half of total 2019 electricity use in Saudi Arabia. Real-time prices are the long-run marginal costs of power delivery throughout time. They are determined by the linkage of KEM and the residential model as the marginal electricity costs at the supply and demand equilibria. The loads demanded by households are impacted by the electricity price charged. Several iterations are needed between the two models to converge upon an equilibrium state. Hence, electricity prices in the RTP case will be presented in the results section.

Table 4 – Electricity use by consumer segment in Saudi Arabia from 2017 to 2019 (sources: Saudi Arabian Monetary Authority (SAMA), 2019; SEC, 2020)

Consumer segment	Electricity use share (%)		
	2017	2018	2019
Residential	50	45	46
Industrial	16	18	18
Commercial	17	16	16
Governmental	13	15	14
Other	4	6	6

5. Results and discussion

The energy amounts contained in the fuels used by the power sector are shown in Figure 4. There are two fuel price cases shown: the administered fuel prices and liberalized fuel prices. The administered fuel price case is joined with only the 2017 electricity prices just to highlight the present fuel mix. As a consequence of fuel price liberalization, the electric power sector utilizes more natural gas and invests in renewable power capacity relative to the status quo. The current use of oil becomes excessively costly in the long-run. For the case in which fuel prices are liberalized, 2017 electricity pricing and RTP are analyzed. Principally, the difference between the fuel use results of the administered and liberalized fuel prices is consistent with Matar et al (2016, 2017), Matar and Anwer (2017), and Matar and Shabaneh (2020).

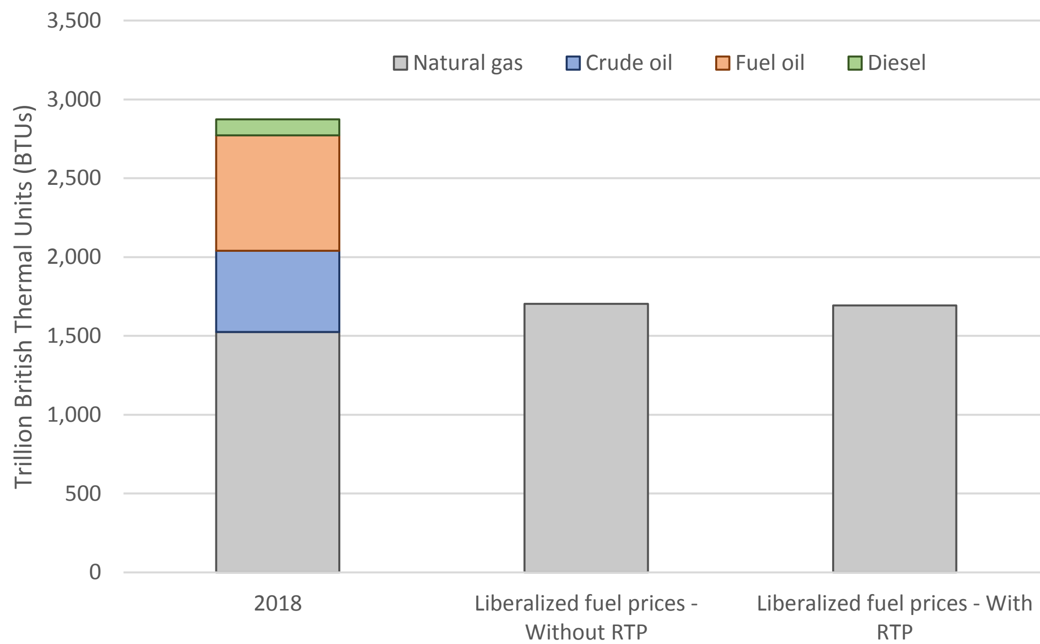

Figure 4 – Fuels used for power generation in the long-run in the status quo and with liberalized fuel prices (source: ECRA (2019) for 2018 data; model results for liberalized fuel price scenarios)

Compared to the fuel use of 2018, raising oil prices to the market levels would of course displace the use of oil by less costly options. Those options come in the form of higher energy efficiency, reverse osmosis plants, and renewable technology. The adoption of these technologies results in higher natural gas allocation for power generation (Matar and Anwer, 2017). The investments are shown for the power system in Figure 5. In this environment with or without RTP, around 1,700 trillion British Thermal Units (BTUs) of natural gas are used. The use of natural gas is slightly lower when RTP is applied.

The use of natural gas is similar in both liberalized fuel price scenarios. This is because the model first makes use of natural gas, and then when gas supply is exhausted, the next least-cost option is sought to meet remaining power load. In this case, that option happens to be renewable power technologies. Although the natural gas use in both fuel price liberalization scenarios is similar, the investment story begins to contrast the effects of RTP on power generation. The power plant capacity additions for each fuel price liberalization variant are shown by Figure 5. Without RTP, the sector would build 33 GW of solar photovoltaic (PV) plants and 31 GW of natural gas-fired combined cycle plants. With households charged the equilibrium real-time prices, PV capacity additions fall to 17 GW. That is around a half of the additions of a case that charges the 2017 electricity prices. Combined cycle capacity falls to 24 GW. In all, around $24 billion in capital expenditure would be avoided. With RTP applied, the power load demanded does not decrease below the point where only natural gas can be used to satisfy it. The resulting demand response can help the power utility recoup the $2.4 billion (9 billion Saudi riyals) it has spent to overhaul residential electricity meters.

Figures 6 and 7 present the long-run marginal power production costs for all four regions of Saudi Arabia. They show the costs in the summer and winter without and with RTP. Once deployed, PV is typically first in the merit order as it has a zero marginal generation cost. Thus, in the cooler winter months when power loads in Saudi Arabia are lower than in the summer, the marginal costs during the late morning and early afternoon periods can fall to zero. This is due to the PV capacity deployed to meet summertime demand.

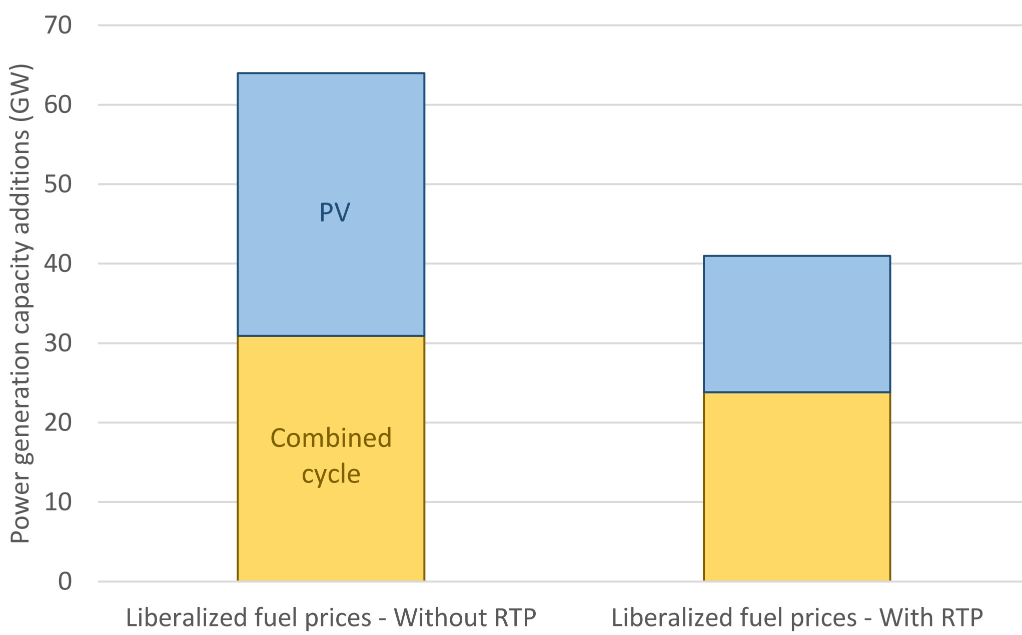

Figure 5 – Investment in new power plants in the long-run when fuel prices are liberalized, without and with RTP (source: model results)

With RTP in place, the households' power loads diminish, which in turn lowers the investment in PV. The power loads during the peak period would be lowered. The reduction in PV capacity would result in a flatter 'duck curve'[4] in the summer. This means the power system experiences lower ramping up and down of thermal power plants and a higher trough in the summer daytime portion of the load curve. Lower PV investment with RTP applied would reduce or eliminate the occurrence of zero prices during winter.

All this means is that the power system's marginal supply cost does not hit the low lows and high highs with RTP. Relative to just fuel price liberalization, the consumer in this instance would benefit from a more stable electricity price during the year. The key takeaways from this section are:

- In the long-run, real-time electricity pricing would reduce the variability of the marginal costs in the power generation sector.
- During the summer, RTP would be lowest during or surrounding the system peak (ECRA, 2020b). This may result in unwanted load shifting to the peak load segment.

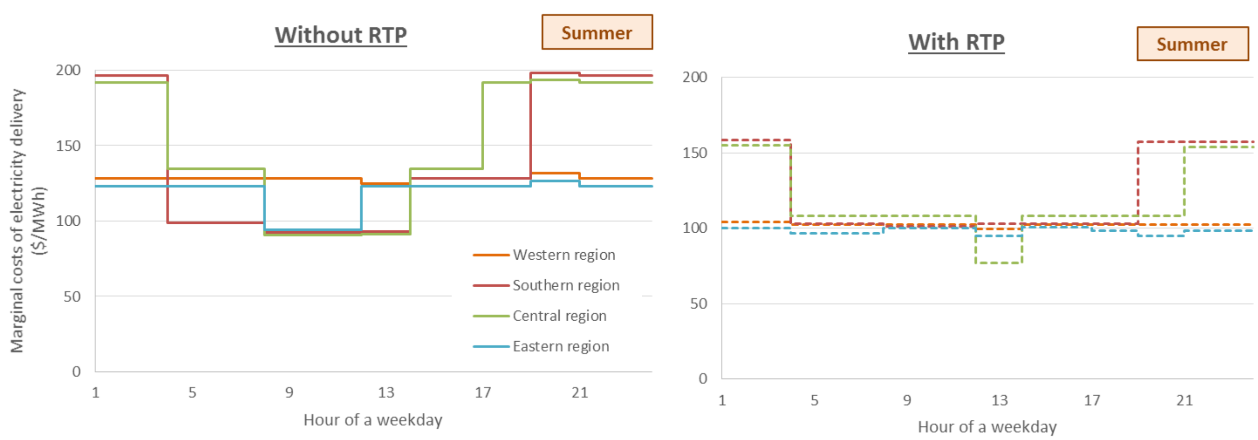

Figure 6 – The long-run marginal costs of electricity delivery on a summer weekday after liberalizing fuel prices, without and with RTP (source: model results)

[4] A duck curve is a term coined by the California Independent System Operator. It stems from the work of Denholm et al (2008), which signifies the effects of PV on the residual load curve throughout the day.

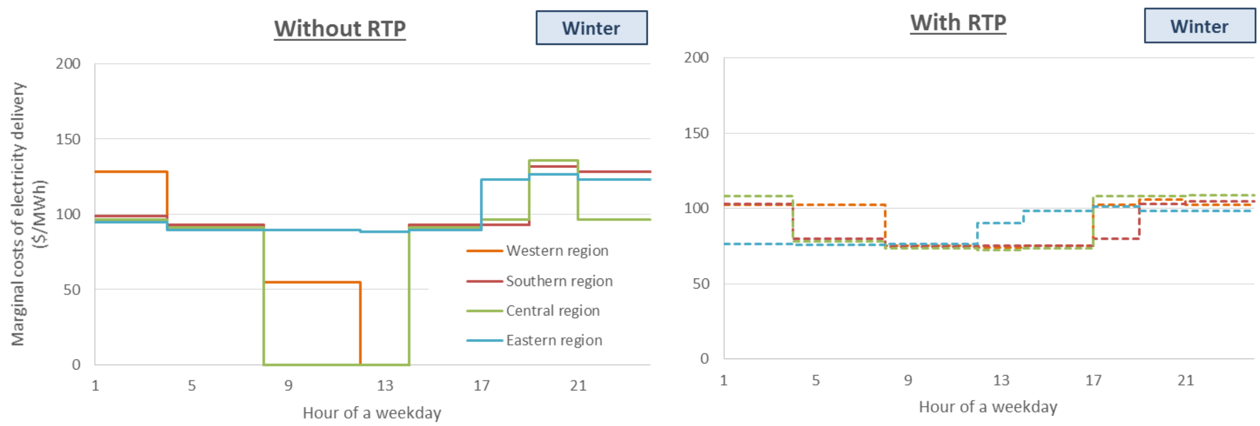

Figure 7 – The long-run marginal costs of electricity delivery on a winter weekday after liberalizing fuel prices, without and with RTP (source: model results)

Although the focus of this paper is on power supply, the results reveal the underlying reasons behind the lower electricity demand and the stabilizing the marginal costs. Looking at the end-consumer's response to higher electricity prices with RTP, the residential modeling framework shows that households both behaviorally adjust and invest in energy efficiency in the long-run. The measures adopted reduce the cooling load of the dwellings; thereby having the greatest reduction of power load during the middle of the day.

The response measures that are exercised are not the actual measures that would be exercised. They are, however, indicative of how households would respond. For one thing, energy efficiency options are constrained in our model. For another, the analysis is performed for archetypical dwellings; whereas households are heterogeneous. The response here is similar to Matar (2021) entails buying more-efficient air conditioners, lighting, and weatherizing the dwellings. Also, behavioral adjustment is exercised by raising the thermostat settings in the summer, spring, and fall. Table 5 shows how the model results vary between low- and high-income households' responses to RTP.

Table 5 – Response measures exercised by households under RTP (source: model results)

Household dwelling type and region(s)	The resulting difference in response between high- and low-income households
Villas in the south	Both high- and low-income households purchase more efficient air conditioners, weatherize their homes, and replace lightbulbs. Both household groups also adjust the thermostats in the summer, spring, and fall, and lower lighting use. High-income households comparatively raise the thermostat set-point during the summer peak more than low-income households.
Apartments in the south	Exhibited energy efficiency purchases are the same as those for “Villas in the south”. The behavioral response is similar, with the only exception being low-income households are the ones who raise the thermostat set-point during the supper peak more so than high-income households.
Apartments in the west	Exhibited energy efficiency purchases are the same as those above. The difference in behavioral response comes about from low-income households raise the thermostat set-point in the spring and fall. Whereas high-income households do not.
Traditional houses in the south, central, and east	Energy efficiency purchases are the same in both groups. Low-income households, unlike high-income ones, also respond by raising the thermostat set-point in the spring and fall. In the southern area, high-income households also respond in the spring and fall but not as starkly.

For example, in all but the western region, low-income households in apartments react more drastically by setting their indoor temperatures higher than the base case in the spring and fall seasons. Their high-income counterparts do not adjust their thermostats in the spring and fall. This is mostly the case, as those with higher income would have higher disposable income after electricity prices are raised. The responses described in Table 4 are relative to the base case with 2017 electricity prices, where households do not react behaviorally or purchase higher energy efficiency at all.

6. Conclusion

This study explored the potential effects of real-time electricity pricing on the power generation sector's operations in Saudi Arabia. This analysis provides insights into the potential effects of such an electricity pricing scheme in a liberalized fuel pricing environment. To this end, it presents linked multi-sector energy and residential electricity use models.

The residential model embeds households, whose decisions are governed by microeconomic principles, within a physical building energy model. Energy flows in these dwellings adhere to physical laws, such as the law of energy conservation. The analysis disaggregates households into low- and high-income households living in archetypical villas, apartments and traditional houses. Different regions within the country are considered separately to account for their particular socioeconomic and climate characteristics.

RTP is specified as the time-varying long-run marginal cost of supplying electricity in the liberalized fuel pricing environment. RTP is offered solely to households; the electricity prices charged to other consumer segments remain unchanged. Even so, the use of RTP has pronounced effects on overall load demand.

This analysis provides two key takeaways. First, RTP reduces the intraday variability of the marginal costs to Saudi power utilities relative to the case without RTP. When fuel prices are liberalized, RTP is higher than 2017 electricity prices, and power loads decrease in turn. Lower power loads lead to reduced investments in power plants in the long run. This reduction includes lower solar PV capacity additions to the Saudi power system. Given the lack of energy storage, reduced PV capacity additions mitigate the wide variation in the daytime and nighttime marginal costs of production. Lower PV capacity also mitigates the thermal plants' ramping requirement.

Secondly, the curtailed investment in power plants in the RTP scenario more than covers the cost of residential smart meter replacements. Total investments over time are estimated to be about

$24 billion lower in the RTP scenario. By comparison, the actual cost of smart meter replacements for all residential customers is estimated to be $2.4 billion.

References

Alberini, Anna, Silvia Banfi, and Celine Ramseier. 2013. Energy Efficiency Investments in the Home: Swiss Homeowners and Expectations about Future Energy Prices. The Energy Journal 34: 49-86.

Allcott, Hunt. 2011. Rethinking real-time electricity pricing. Resource and Energy Economics 33: 820-842.

Argaam. 2019. Saudi Electricity awards SAR 9 bln smart meter project to local, Chinese firms. Accessed June 22nd, 2020: https://www.argaam.com/en/article/articledetail/id/1335418.

Bruderer Enzler, Heidi, Andreas Diekmann, and Reto Meyer. 2014. "Subjective discount rates in the general population and their predictive power for energy saving behavior." Energy Policy 65: 524-540.

Denholm, Paul, Robert Margolis, Milford. 2008. Production Cost Modeling for High Levels of Photovoltaics Penetration. Technical Report NREL/TP-581-42305.

Dewees, Donald N. 2001. Price and Environment in Electricity Restructuring. University of Toronto: 9.

Dutta, Goutam, and Krishnendranath Mitra. 2017. A literature review on dynamic pricing of electricity. Journal of the Operational Research Society 68: 1131-1145.

ECRA. 2016. Electricity Tariff. ECRA Fourth Edition, April 2016.

ECRA. 2018. Activities and Achievements of the Authority in 2017. 128, 153, 154. (Arabic release)

ECRA. 2019. Annual Statistical Booklet For Electricity & Seawater Desalination Industries 2018. Electricity & Cogeneration Regulatory Authority: 151.

ECRA. 2020a. Activities and Achievements of the Authority in 2018. 66, 133. (Arabic release)

ECRA. 2020b. Annual Statistical Booklet for Electricity and Seawater Desalination Industries 2019: 37.

Faruqui, Ahmad, and Sanem Sergici. 2010. Household response to dynamic pricing of electricity: a survey of 15 experiments. Journal of Regulatory Economics 38: 193-225.

Faruqui, Ahmad, Ryan Hledik, Greg Wikler, Debyani Ghosh, Joe Prijyanonda, and Nilesh Dayal. 2011. “Bringing Demand-side Management to the Kingdom of Saudi Arabia.” The Brattle Group: 40.

Faruqui, Ahmad, Ryan Hledik, and Jennifer Palmer. 2012. Time-Varying and Dynamic Rate Design. The Brattle Group: Global Power Best Practice Series. 17-18.

Faruqui, Ahmad, Sanem Sergici, and Lamine Akaba. 2013. Dynamic pricing of electricity for residential customers: the evidence from Michigan. Energy Efficiency 6: 571-584.

General Authority for Statistics. Household Expenditure and Income Survey 2018. (2018): 110.

Harrison, Glenn W., Morten I. Lau, and Melonie B. Williams. 2002. “Estimating individual discount rates in Denmark: a field experiment.” American Economic Review 92(5): 1660-1617.

Hausman, Jerry A. 1979. Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables. Bell Journal of Economics 10(1): 33-54.

Herter, Karen, Vikki Wood, Shelley Blozis. 2013. The effects of combining dynamic pricing, AC load control, and real-time energy feedback: SMUD'S 2011 Residential Summer Solutions Study. Energy Efficiency 6: 641-653.

Johansson, Per-Olov. 1991. An Introduction to Modern Welfare Economics. New York: Cambridge University Press.

KAPSARC. 2016." The KAPSARC Energy Model for Saudi Arabia: Documentation of the model build called 'KEM-SA_v9.16.'" Accessed January 16, 2020. https://www.kapsarc.org/wp-content/uploads/2016/11/KEM-SA_documentation_v9.16.pdf.

Matar, Walid, Frederic Murphy, Axel Pierru, Bertrand Rioux and David Wogan. 2017. Efficient Industrial Energy Use: The First Step in Transitioning Saudi Arabia's Energy Mix. Energy Policy 105: 80-92.

Matar, Walid, Rodrigo Echeverri and Axel Pierru. 2016. The Prospects for Coal-fired Power Generation in Saudi Arabia. Energy Strategy Reviews 13-14: 181-190.

Matar, Walid. 2016. Beyond the end-consumer: How would improvements in residential energy efficiency affect the power sector in Saudi Arabia? Energy Efficiency 9(3): 771-790.

__________. 2017. A look at the response of households to time-of-use electricity pricing in Saudi Arabia and its impact on the wider economy. Energy Strategy Reviews 16: 13-23.

__________. 2018. Households' response to changes in electricity pricing schemes: bridging microeconomic and engineering principles. Energy Economics 75: 300-308.

__________. 2019. A household's power load response to a change in the electricity pricing scheme: An expanded microeconomic-physical approach. The Electricity Journal 32: article number 106644.

__________. 2021. Residential energy efficiency investment and behavioral response under different electricity pricing schemes: A physical-microeconomic approach. International Journal of Sustainable Energy 40: 1-21.

Matar, Walid, and Murad Anwer. 2017. Jointly reforming the prices of industrial fuels and residential electricity in Saudi Arabia. Energy Policy 109: 747-756.

Matar, Walid, and Amro M. Elshurafa. 2018. Electricity transmission formulations in multi-sector national planning models: an illustration using the KAPSARC Energy Model. Energy Reports 4: 328-340.

Matar, Walid, and Rami Shabaneh. 2020. Viability of seasonal natural gas storage in the Saudi energy system. Energy Strategy Reviews. (forthcoming)

Saudi Arabian Monetary Authority (SAMA). 2019. Annual Statistics 2018.

Saudi Electricity Company (SEC). 2020. Financial results for the fiscal year ended 31 December 2019. 2.

Saudi Vision 2030. 2017. Fiscal Balance Program: Balanced Budget 2020. 38.

Yang, Changhui, Chen Meng, and Kaile Zhou. 2018. Residential electricity pricing in China: The context of price-based demand response. Renewable and Sustainable Energy Reviews 81: 2870-2878.

Appendix – Description of income classifications used in the analysis

The distribution of income in society is often measured using the Gini coefficient. The latest regional Gini coefficient data for Saudi Arabia were published by The General Authority for Statistics (GAStat) (2018); the data collection was part of a survey that started in early 2017 and ended in early 2018. Figure A1 shows the cumulative regional distributions for two groups. The groups are classified as low- (y_1) and high-income (y_2). A condition that the cumulative income share of the second group is equal to or higher than that of the first group is also stipulated. These two equations or inequalities are used to solve a system of two equations and two unknowns for each region. Equation A1 represents a discrete formulation for the Gini coefficient that resembles a Lorenz curve.

$$Gini = 3 - \frac{4y_1+2y_2}{y_1+y_2} \quad \text{(A1)}$$

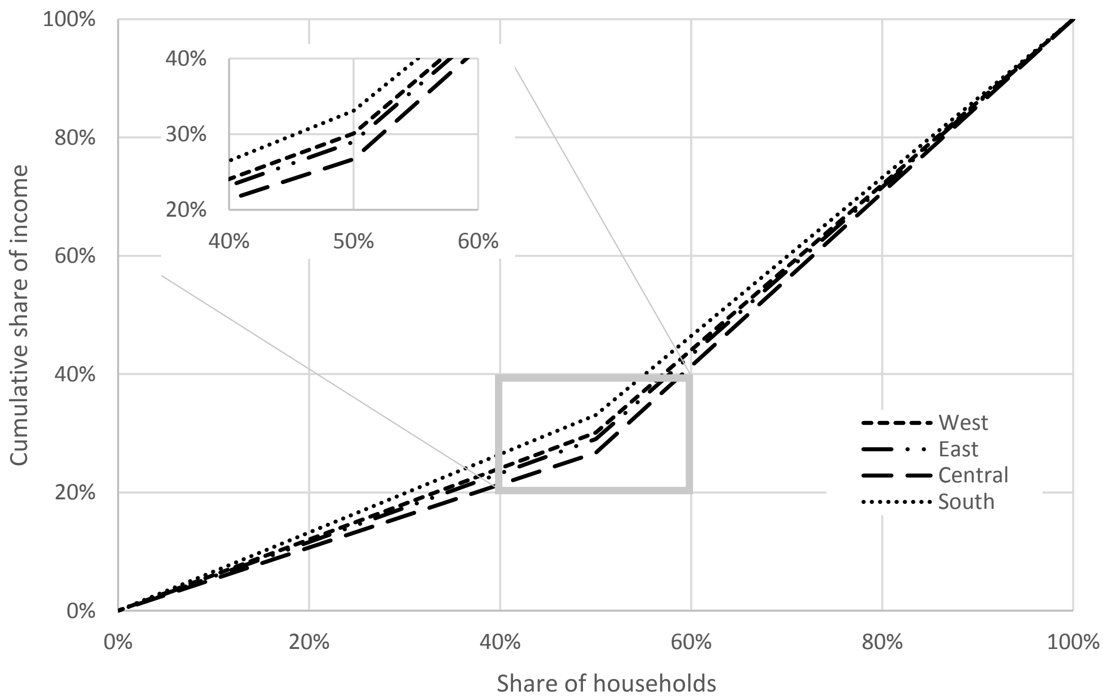

Figure A1 – Income distribution among households (source: GAStat, 2018; KAPSARC analysis)

The cut-off point between the low- and high-incomes groups is the 50% mark. This analysis estimates the average monthly incomes in the two areas above and below the 50% mark. They are shown in Table A1.

Table A1 – Average monthly income levels in each group by region (KAPSARC analysis)

Region of Saudi Arabia	Low income (US dollars)	High income (US dollars)
Central	6,525	17,914
Western	6,646	15,434
Southern	7,266	14,685
Eastern	8,340	20,419