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Households' Demand Response to Changes in Electricity Prices: A Microeconomic-Physical Approach

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Key Points

Energy economists are interested in how a change in electricity prices prompts a response by way of end-user power demand. It is difficult to estimate price elasticities statistically if historical prices are low and change infrequently, especially in the short run. This paper extends a previous analysis by Matar (2018) that explored the merger of a residential building energy model and a utility maximization component by incorporating more demand-reducing measures within a utility-maximization framework for households. The framework is informed by the physical equations that govern how electricity is consumed. The measures considered are:

- Independently adjusting the thermostat set-point in the spring and fall, and during the peak and off-peak hours in the summer.
- Turning off lights.
- Switching off consumer electronics.

We have calibrated the physical component for a dwelling in Saudi Arabia. Domestic electricity tariffs in the – tiered – progressive pricing structure were partially raised in 2018. In addition to those increases, the response to other electricity pricing schemes is analyzed: time-of-use and real-time prices. We show that for a household with a low preference for electricity, the 2018 price increases do warrant an adjustment in indoor temperature in the hot summer months and lower electricity use for consumer electronics. Since we adopt a dwelling in Saudi Arabia, the response measure that is most exercised is thermostat set-point adjustments. A subdued response is found for households that have adopted higher energy efficiency or have a high preference for electricity.

Summary

Price-based demand response is a subset of demand-side management (Yang et al. 2018). Energy prices may rise if they were previously subsidized by the government, if production costs rise, or if policymakers want to design prices that induce certain behavior; however, rises can also adversely affect industrial competitiveness and social welfare. Therefore, it is important to better understand the drivers of customers' demand in the case of electricity price changes.

This paper further studies the role of physical factors in the household's decision-making process when faced with an electricity price change. This paper is an extension of a previous analysis by Matar (2018) that explored the merger of a building energy model and a utility (a measure of satisfaction) maximization component. It demonstrated this approach for a residence in the central region of Saudi Arabia, which typically has an hourly power load profile that is dominated by electricity use for air conditioning in the summer. It examined one price response measure, which combined the adjustment of the thermostat set-point over multiple seasons.

This paper maintains the same calibration as the residential building energy model described above, and expands on it to cover other measures that a household may be willing to exercise. Those measures influence the solution of the physical component directly and indirectly. For instance, if lighting power draw is lowered, then the cooling load would also decline.

This analysis avails the household with higher flexibility in seasonal and time-of-day indoor temperature adjustments. In addition, we include the ability for the household to turn off lights and reduce the hourly use of consumer electronics in an incremental fashion. Matar (2018) reported that households with a low preference for electricity would raise the thermostat setting by 0.5 to 2.5 degrees Celsius (°C), depending on the alternative price scheme implemented. We explore whether the addition of more demand-reducing measures will lower the need to raise indoor air temperature.

The method allows flexibility in setting the electricity price scheme. The approach incorporates progressive pricing schemes, time-of-use (TOU) pricing, and real-time pricing (RTP), and the household's income. We explore the effects of higher energy efficiency on the household's decisions in conjunction with the various electricity pricing schemes. We look at higher air conditioning efficiency, reduced infiltration, and more efficient lighting, both individually and together.

A household in Saudi Arabia that has a low preference for electricity would adjust the thermostat by 1 °C in the summer for the price change that took place in 2018. If TOU prices were imposed that have higher administered electricity prices during the system peak period, it would adjust the set-point by 1 °C during the off-peak hours, and by 1.5 °C during peak hours in the summer; no response is observed in other seasons. RTP would generate the greatest response, as it exhibits the highest price deviations from the base case. We additionally found no response in the form of lighting usage, but there is reduced use of consumer electronics. Alternatively, a high-preference household does not respond to any pricing schemes used in this study.

Moreover, higher energy efficiency lessens the households' reaction to higher electricity prices. This supports the idea that energy efficiency – in conjunction with price-based demand response – is desirable in anticipation of an electricity price increase.

Past Studies on Price-based Electricity Demand Response

A great amount of empirical literature exists on households' response to electricity price changes. It mainly revolves around price elasticities that are computed based on historical information. For example, Campbell (2018) recently estimated short- and long-run price elasticities for Jamaica, based on data from 1970 to 2014. He uses a co-integration technique to find a long-run value of -0.82. Schulte and Heindl (2017) apply a quadratic expenditure system to estimate own- and cross-price elasticities for various goods, including electricity, in Germany. They find own-price elasticity of -0.43. Atalla and Hunt (2016) use a structural time series model, and conversely find that some countries in the Gulf Cooperation Council (GCC) have zero price elasticities in the short- and long-run.

Specifically for Saudi Arabia, Al-Faris (2002) estimates a short-run price elasticity of -0.04. Atalla and Hunt (2016) estimate a constant aggregate price elasticity for Saudi Arabia in the short- and long-run, both of which are -0.16. These values show that households in Saudi Arabia have historically exhibited less responsiveness to electricity prices than those in other countries. Using the statistically-estimated price elasticity found by Atalla and Hunt (2016), Matar and Anwer (2017) assess the effects of different residential electricity prices on the Saudi energy system.

Electricity prices have not changed frequently and/or electricity expenditures have constituted a minor share of households' expenditure to matter in several countries. Saudi Arabia, as with the rest of the GCC countries, is a prime example of that; as described in the next section. An issue that arises with empirical price elasticity estimates for a given region is when a price change lies outside of past variation. In South Africa, for example, real prices declined slightly from the 1980s until the late 2000s as a result of inflation, but have since risen significantly (Deloitte 2017). In these cases, a statistical approach to analyzing the own-price effects on electricity demand has been limiting.

Other papers take a real-world experimental approach. Reiss and White (2005) assess how short-run electricity demand varied for a sample of households in California as a result of different electricity prices. They found that 44% of sampled households did not change their electricity usage behavior, while the remainder exhibited own-price elasticities that ranged from just above 0 to -2. Also, Faruqui and Sergici (2010) conducted a survey to summarize experimental studies from 1996 until 2007. The price elasticity results of those studies affirm the conceptual finding of Reiss and White (2005), namely that some customers do not react to price changes. The range that Faruqui and Sergici (2010) posit is not as wide. Faruqui and Sergici (2010) also found that critical-peak pricing with enabling technologies (e.g., automated control of certain appliances) leads to double the load reduction during peak periods than a case without these technologies.

Furthermore, the paper authored by Youn and Jin (2016) presents a novel study for two reasons. First, it incorporated the effects of outdoor temperature on the household's decision-making using a utility-maximization principle. Second, it analyzed a specific electricity pricing scheme that is difficult to model econometrically. Matar (2018) extended upon that rationale by incorporating a physical simulation of energy use by households to inform the utility function, and expanding the electricity pricing schemes that could be studied, ranging from progressive pricing schemes to hourly schemes. Given the high share of electricity use devoted to cooling in Saudi Arabia, the paper looked only at thermostat set-points. In this paper, we include other price response measures in a hybrid utility-maximizing and physical residential electricity use simulation framework.

Other authors have linked a physical residential simulation to electricity prices. McKenna and Keane (2015) and Yoon et al. (2014) relate electricity prices to the indoor temperature setting, using an algorithm that is detached from the economic rationale that drives a utility-maximizing agent; the former paper uses a simplified physical electricity use model. Earlier, Braun (2003) was closer in his representation, although the rationale used for the indoor temperature set-points was cost-minimization. Recently, Krarti et al. (2017) merged a building energy model with a cost-minimization component to assess energy efficiency investment options and indoor conditions for households in Saudi Arabia. While the dual problem of a utility-maximization problem is formulated as minimizing cost, the dual problem must contain the utility in the constraints (i.e., what is the minimum cost to achieve a certain level of satisfaction?). This utility constraint is not found in typical cost-minimization problems, and in fact, not contained in the algorithms applied by McKenna and Keane (2015), Yoon et al. (2014), Braun (2003), and Krarti et al. (2017).

Methodology

Our approach entails the merger of the physical equations that govern a household's hourly loads and a utility maximization problem. It is an expanded form of the version used by Matar (2018), and more information on the calibration of the electricity use component is provided in the Appendix. Matar (2018) proposed this method, but one of its limitations was that only one price response measure was considered. Only adjustments to the indoor thermostat for the summer, spring, and fall all together were variable. That price response measure was sufficient for proposing the methodology but was constraining.

Figure 1 illustrates how we extend upon that analysis for n different measures, denoted by M_j, from M_1 to M_n. The utility of the household is plotted against those measures. The axis for the utility can be viewed as coming out perpendicularly with respect to the paper. Matar (2018) graphically shows the solution discovery process for one price response measure. As this is a graph of n+1 dimensions, however, it is difficult to show the solution discovery process on paper. In this analysis, the five measures that households can exercise in response to a price change, j, are:

- Varying the indoor thermostat set point in the summer, with an option of raising the temperature during peak hours by 0.5 °C compared to other hours in the day.

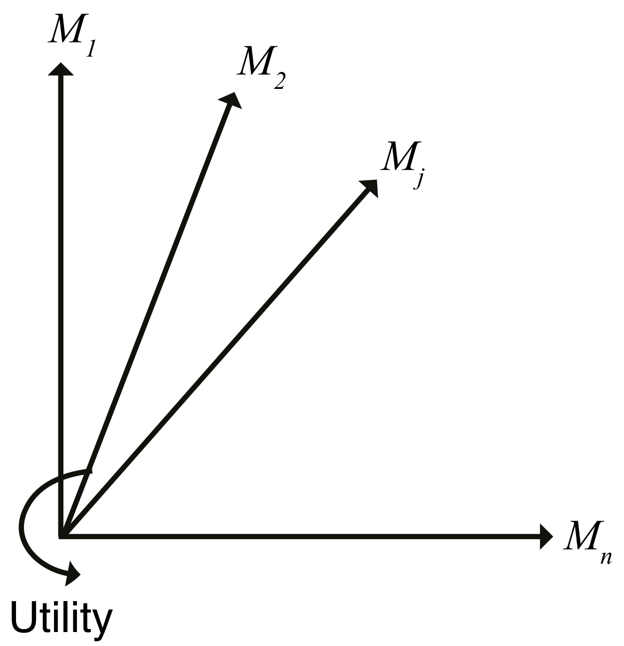
- Independently varying indoor thermostat set points in the spring and fall.

- Turning off lights, using the illumination requirement of the habitable area as a proxy.

- Switching off consumer electronics.

We take into account that changing lighting and appliance usage affects the heat gained by the indoor zone. So, turning off lights, for example, contributes not only to lower direct electricity use, but also lower air-conditioning loads.

Figure 1. The utility function is dependent on n variables.



Source: KAPSARC.

Moreover, since we have more measures that impact the household's electricity consumption, we disaggregate the utility function used by Matar (2018) into i components. It is approximated by a Cobb-Douglas function and its components in Equations 1-5. x_i represent the various electricity consumption quantities related to the measures in megawatthour (MWh), previously denoted by j. The untouched, or remaining, electricity consumption is also expressed in MWh, and the level of expenditure on other goods and services is expressed in monetary terms. The price of other goods and services is set to unity. α_i are the Cobb-Douglas preferences, and they sum up to unity for all i.

Although we do not directly solve a maximization problem, it is worth pointing out that a strict utility maximization problem using a Cobb-Douglas functional form should restrict the electricity price elasticity to -1. Matar (2018) showed that linking the building energy model with a microeconomic component results in price elasticities that deviate from -1, which means this linkage is approximated; both the quantity of and expenditures on electricity are derived from the building energy model. Matar (2018) showed the price elasticities were not constant under different electricity pricing schemes.

Relaxing the Cobb-Douglas form to a constant elasticity of substitution (CES) function still results in a restricted own-price elasticity, based on the assumed constant elasticity of substitution and share coefficients, although different from -1. Future work will explore alternative utility functional forms in place of Cobb-Douglas or CES functions, ones that can accommodate changing behavior through seasons and with respect to different prices. Transcendental logarithmic (translog) functions are generalizations of the Cobb-Douglas form and may also work as an approximation of this issue (various approximations are described by Christensen et al. 1975; Hayes 1986). Translog functions still exhibit restrictions in setting preference parameters (Jorgenson and Lau 1975), and we would have to consider estimating them econometrically.

$P_{AC_{season,hours,daytype}}$ are the hourly loads by air conditioning equipment by season and day type. We consider two types of day: weekends/holidays and weekdays. Similarly, $P_{lighting_{season,hours,daytype}}$ and $P_{CE_{season,hours,daytype}}$ are the hourly loads stemming from the use of lighting and consumer electronics. $Dayinseason_{season,daytype}$ are the number of days in each season by type. Δt is the hourly resolution during the day, which in our model is taken as unity.

$$Utility = \prod_i x_i^{\alpha_i} \tag{1}$$

$$x_{AC} = \sum_{season,hour,daytype} P_{AC_{season,hour,daytype}} Dayinseason_{season,daytype} \Delta t \tag{2}$$

$$x_{lighting} = \sum_{season,hour,daytype} P_{lighting_{season,hour,daytype}} Dayinseason_{season,daytype} \Delta t \tag{3}$$

$$x_{CE} = \sum_{season,hour,daytype} P_{CE_{season,hour,daytype}} Dayinseason_{season,daytype} \Delta t \tag{4}$$

$$x_{other\ electricity} = \left[E_{electricity} - \left(x_{AC} + x_{lighting} + x_{CE}\right)\right]_{initial} \tag{5}$$

To calculate $x_{other\ electricity}$, the total contribution of electricity use by air conditioning, lighting, and consumer electronics are subtracted from the total electricity use ($E_{other\ electricity}$), all computed in the base case. $x_{other\ electricity}$ is unchanged across all electricity pricing scenarios.

Because of the number of independent variables introduced by our utility function, the computational procedure differs from the one used by Matar (2018). Matar (2018) used the point at which the marginal utility turns negative as the trigger to stop the solution discovery process. This minimized the time it took the model to run in the case of a single load reduction measure. In this case, however, we have to perform the computation for all possible combinations of the demand-reducing measures.

The model then identifies the point at which the maximum utility value is obtained. All results, including the value of indoor temperature, lighting requirements, and annual electricity costs, will be shown for that point.

For consumer preference shares, α_i, we adapt similar values used by Matar (2018) for the high and low electricity preference scenarios, as defined in Table 2; we want to directly compare the results of this analysis with those from that paper. We have to further disaggregate the electricity used for cooling, lighting, operating consumer electronics, and other uses from the electricity expenditure share. We use the consumption shares as a proxy from the electricity expenditure share; the shares were reported by Faruqui et al. (2011) for a household in Saudi Arabia in 2011. We realize this is a rough estimate as consumption shares with progressive tariffs may not represent expenditure. Table 3 shows these metrics.

There is also the household's budget constraint, as shown by Equation 6. Income is the annual household income in thousands of dollars. Income has been set to $34,314 based on the average household income in Saudi Arabia (Central Department of Statistics and Information (CDSI), 2013). The index m represents two categories of goods: total electricity, and other goods and services. Although we have electricity divided by end-use in the utility function, we can aggregate total electricity for budgetary purposes. The calculation of the annual electricity expenditure and the electricity pricing policies are articulated in the following section.

$$Income = \sum_m e_m \qquad (6)$$

Figure 2 illustrates the linkage between the physical and economic components. This procedure is performed iteratively due to computational issues that arise from the bilinear features of the building energy equations.

Table 2. Consumer preference share scenarios for a household.

	Low	**High**
Preference share for electricity (percent)	10	20
Preference share for other goods and services (percent)	90	80

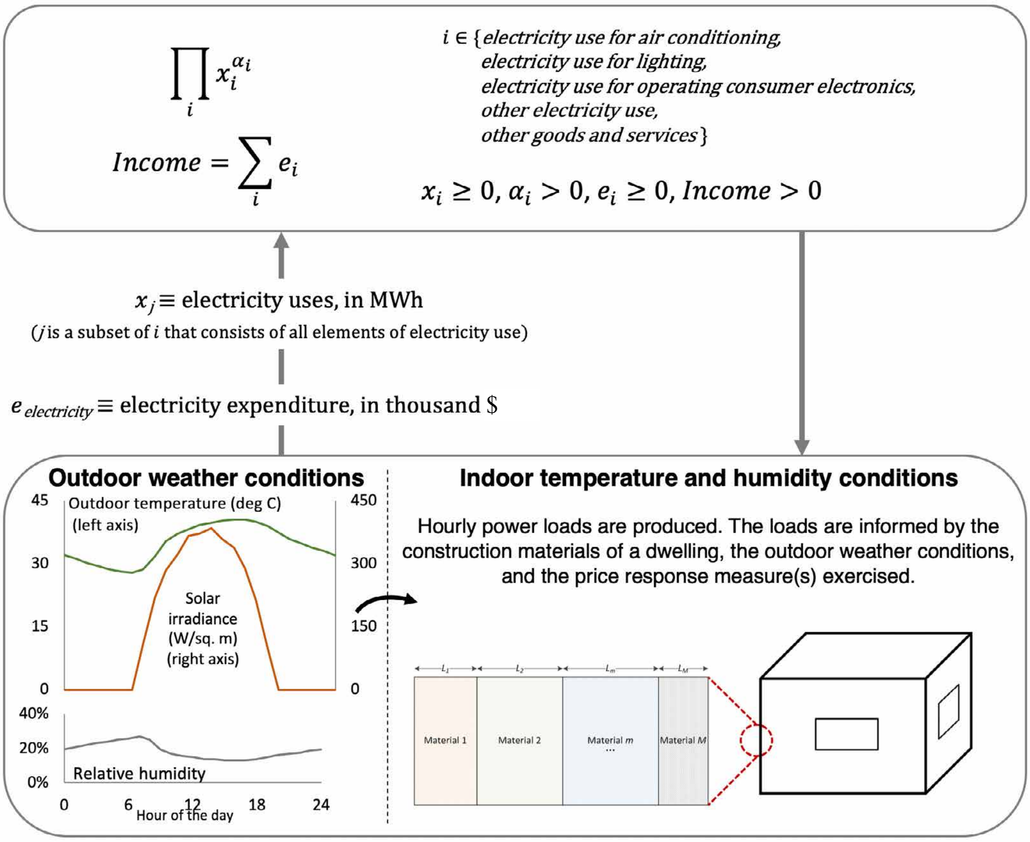
Source: Author's assumptions.

Table 3. Estimated electricity use breakdowns for a household in Saudi Arabia.

Electricity end-use	Shares of electricity consumption (percent)
Cooling	70
Lighting	5
Consumer electronics	3
Other	22

Source: Authors' estimation using Faruqui et al. (2011).

Figure 2. The coupling of the microeconomic and engineering methodologies.



Source: KAPSARC.

Policy Scenarios

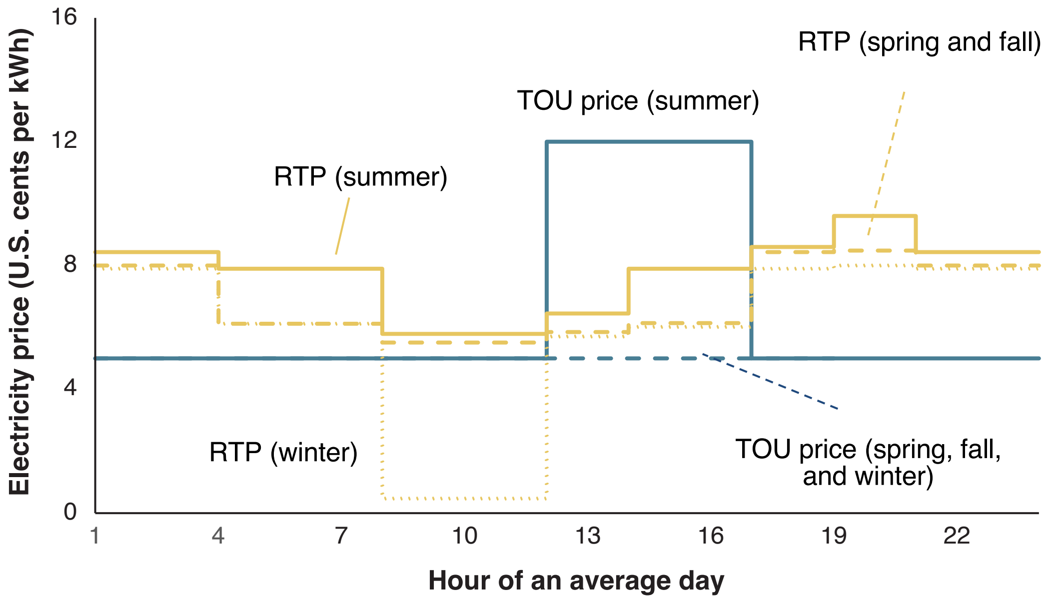
Electricity pricing

In addition to base pricing, which replicates the 2017 electricity pricing scheme implemented in Saudi Arabia, several alternative electricity pricing scenarios are chosen for this analysis. The first is the revised electricity tariffs introduced in Saudi Arabia in 2018. The second and third scenarios, termed RTP and TOU pricing, highlight the capabilities of this framework to handle hourly prices. Table 1 and Figure 3 define the four scenarios. These scenarios are also policies that the regulator may choose to impose if meters capable of reading hourly consumption are installed. TOU electricity prices impose a higher price when the overall system experiences its peak; typically in the summer months between noon and 5 p.m.

RTP takes seasonal hourly long-run marginal electricity generation and delivery costs for the central region of Saudi Arabia from the KAPSARC Energy Model (KEM) (KAPSARC 2016). Specifically, the deregulated fuel prices and dynamic electricity pricing scenarios are derived from Matar and Anwer (2016). KEM produces long-run marginal costs of electricity delivery when it is run in a steady-state fashion. Its output assumes a perfectly competitive energy system. Given that we are only applying this price to a single household, it would not have significant equilibrium effects that could influence the marginal costs.

When fuel prices were deregulated in 2015, the power system received the price signal to install 38 gigawatts (GW) of photovoltaic (PV) solar power generation, convert capacity of open-cycle gas turbines to more efficient combined-cycle power plants, and build some nuclear power plants (Matar and Anwer 2016). The real-time prices shown in Figure 3 take this sequence of events into account. The deployment of PV is responsible for the lower marginal cost of delivery at midday. As would be expected, the highest cost of production is during the hot summer months, and the lowest cost is during the cooler winter months when demand for air conditioning is minimal. Further details on the inputs and the results of KEM are found in Matar and Anwer (2016).

Figure 3. Household electricity pricing in real-time pricing (RTP) and time-of-use (TOU) pricing scenarios.



Sources: source for TOU pricing: KAPSARC analysis; source for RTP: Matar and Anwer (2017).

We discretize a 24-hour day into eight – non-uniform – load segments in KEM, while the residential model put forward in this analysis discretizes a day into hourly segments. So the output of KEM has to be aligned with its hourly counterpart.

Electricity expenditures for the base pricing and 2018 pricing cases are shown by Equations 7-8.

$$e_{electricity} = \sum_{season} \left[\left(f + \sum_{\substack{b \\ only\ if \\ d_b \le c_{season}}} (d_b - d_{b-1})\pi_b + \sum_{\substack{b \\ only\ if \\ d_b > c_{season}\ and \\ (d_b - c_{season}) < (d_b - d_{b-1})}} (c_{season} - d_{b-1})\pi_b \right) \cdot months_{season} \right] \tag{7}$$

Where c_{season} are the total electricity consumed in each season in kilowatt-hours (kWh),

$$c_{season} = Number\ of\ days_{season} \sum_{hour} P_{hour,season} \Delta t \tag{8}$$

f represents the fixed monthly price paid by the customer for the meter-reading. We calibrate this parameter using sample electricity bills from the Saudi Electricity Company, which state a $4 per month charge. d_b are the upper quantity levels of each consumption bracket, b.

π_b are the electricity tariffs for each consumption bracket in the scheme; these tariffs may be made the same for all brackets, which would resemble a flat tariff structure. $months\ season$ are the number of months in each seasonal period, and $Numberofdays_{season}$ is the number of calendar days in a season. The model differentiates monthly consumption and electricity expenditures between weekdays and weekends, but the equations show them for a single day type to avoid convoluted notation.

We show the same metric for the TOU pricing and RTP cases in Equations 9-10. $TOU_{hour,summer}$ and $RTP_{hour,season}$ are the hourly prices, in dollars per kWh. The TOU pricing and base pricing schemes replicate the cases used by Matar (2018) so they may be directly compared across both papers; the other cases do not.

$$e_{electricity} = \sum_{hour} TOU_{hour,summer} c_{summer} + \sum_{\substack{season \\ all\ seasons\ except\ summer}} \left[\left(f + \sum_{\substack{b \\ only\ if \\ d_b \le c_{season}}} (d_b - d_{b-1})\pi_b + \sum_{\substack{b \\ only\ if \\ d_b > c_{season}\ and \\ (d_b - c_{season}) < (d_b - d_{b-1})}} (c_{season} - d_{b-1})\pi_b \right) \cdot months_{season} \right] \tag{9}$$

$$e_{electricity} = \sum_{(hour,season)} RTP_{hour,season} c_{season} \tag{10}$$

Energy efficiency cases

One of the advantages of this methodology is that we can explicitly represent energy efficiency measures. We look at three measures in this analysis, first applied independently of one another, and then one scenario in which they are all applied together:

- Improved energy efficiency ratio (EER) of the air conditioning units.
- High adoption of light-emitting diodes (LED).
- Reduced infiltration rates.

The air conditioning EER in the residential model is calibrated based on the Saudi market survey conducted by AMAD for Technical Consultation and Laboratories (2011); its value is 7 British thermal units per watt-hour (Btu/Wh). Higher EER means higher efficiency of the refrigeration cycle used by the air conditioner. We raise the EER to 11.5 Btu/Wh, the minimum value imposed for new air conditioners sold in Saudi Arabia in 2015 (Saudi Energy Efficiency Center 2014).

Moreover, we set the shares of lighting technologies in the residence based on import data obtained from the former Central Department of Statistics and Information, now known as the General Authority for Statistics. The technology share for 2011 is estimated to have comprised 42% incandescent bulbs, 36% linear fluorescent bulbs, 12.5% halogen bulbs, and 9.5% compact fluorescent bulbs.

In the case of high adoption of LED bulbs, the lighting used by the household is made exclusively of LEDs. Such bulbs in the model are categorized as having an efficacy of 80 lumens per watt (W), and a power rating of 20 W per bulb. We concede, however, that the choice of lighting may be dependent on the usage level: It may be cost-effective, for example, to install less expensive, less energy efficient, yet shorter-lasting bulbs where the bulbs would have a low utilization rate.

Lastly, the infiltration levels are characterized by the mixing of outdoor and indoor air. They are expressed by how many air changes per hour (ACH) are taking place in the air-conditioned zone; higher ACH means more infiltration. We approximate the infiltration levels in the base case to be 0.70 ACH for a house in the central region, as calibrated by Matar (2016). We stipulate that infiltration is reduced to 0.25 ACH for the higher-efficiency case. This reduction may be achieved through sealing cracks between walls and doors and windows.

Given that we have electricity pricing and energy efficiency scenarios, Table 4 summarizes the 20 cases that we look at in this analysis for a household with the low and high preferences for electricity.

Table 4. Summary of analyzed scenarios (dark gray: the base case; light gray: alternative scenarios).

		Electricity pricing cases			
		Base pricing	2018 pricing	TOU pricing	RTP
Energy efficiency cases	**No added energy efficiency measures**	Base case			
	Higher EER				
	LED adoption				
	Reduced infiltration				
	Combined efficiency measures				

Source: KAPSARC.

Model Results and Discussion

The solution discovery process cannot be visualized on paper, as the graph would contain six dimensions. However, we added a feature in the code to output the combination of response measures that result in the maximum utility. They are separately shown in sub-section 6.2.1 for the low-electricity preference case. At optimality, both preference cases produce the same electricity consumption as results from other end-uses across energy efficiency scenarios, as shown in Table 5. The base case, with base electricity pricing and no added energy efficiency, does not result in any demand response.

Electric power loads

The area under the hourly load curves for a given day constitutes electricity used in watt-hours (Wh) during the day, but the hourly loads (in W) are important when time-based pricing is implemented. In Figures 4 and 5, the total load curves in the summer and the spring and fall are displayed for the various electricity pricing scenarios. The loads pertain to no added energy efficiency measures, and they correspond to the maximum utility derived in each scenario. The 2018 pricing scenario yields a shifted load curve in the summer compared to base pricing. The shape of the curve hints at a thermostat adjustment in that season. The loads in the spring and fall are only shifted during the nighttime period, which signals that only appliance usage is changed.

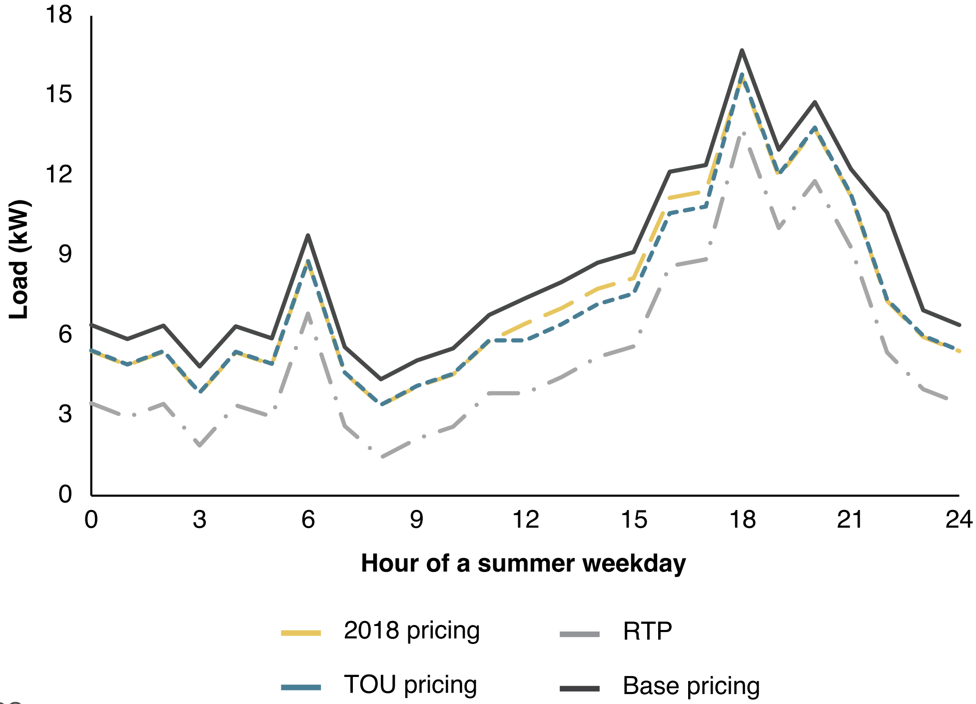
The TOU pricing case does warrant a greater response than 2018 pricing in the summer. The response is observed by lower loads during the peak hours – from 12 p.m. to 5 p.m. – during the summer months. The largest response arises when the household is faced with RTP. This makes sense, as it represents the largest electricity price change from base pricing. When faced with RTP, the household adjusts the desired indoor temperature in the summer and turns off appliances and/or lights in all seasons.

Table 5. Electricity uses other than for air conditioning, lighting, and infiltration.

	Preference case	No added energy efficiency measures	Higher EER	LED adoption	Reduced infiltration	Combined efficiency measures
Electricity use (MWh in the year)	Low	13.0	13.9	13.1	14.4	14.9
	High	13.0	13.9	13.1	14.4	14.9

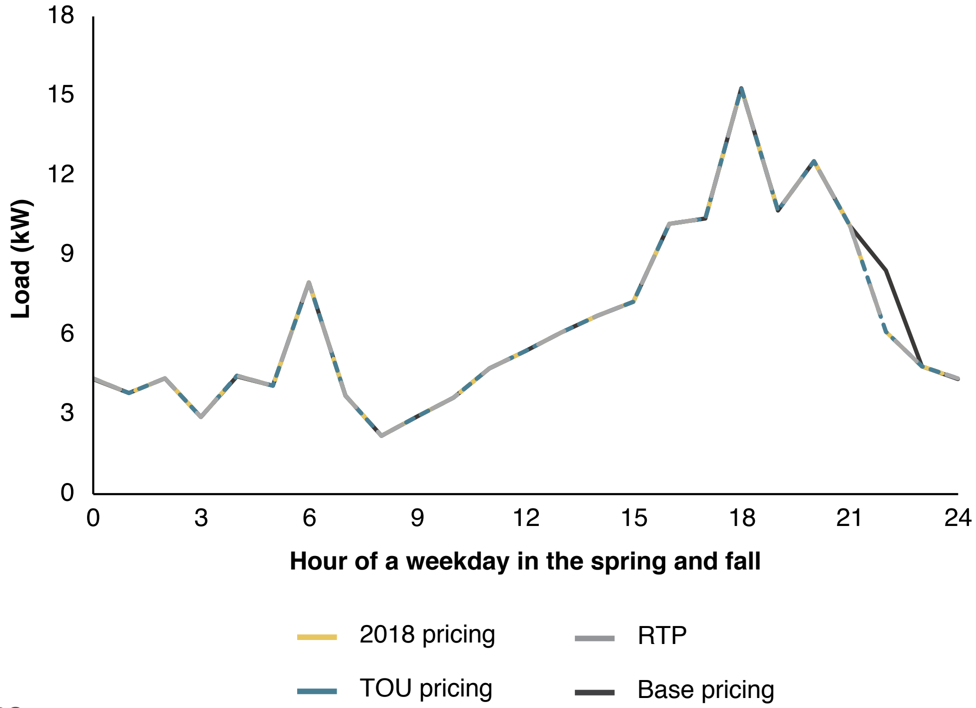
Source: KAPSARC.

Figure 4. Diurnal load curve on a summer weekday for all electricity pricing cases and no added energy efficiency (low preference for electricity).



Source: KAPSARC.

Figure 4. Diurnal load curve on a summer weekday for all electricity pricing cases and no added energy efficiency (low preference for electricity).



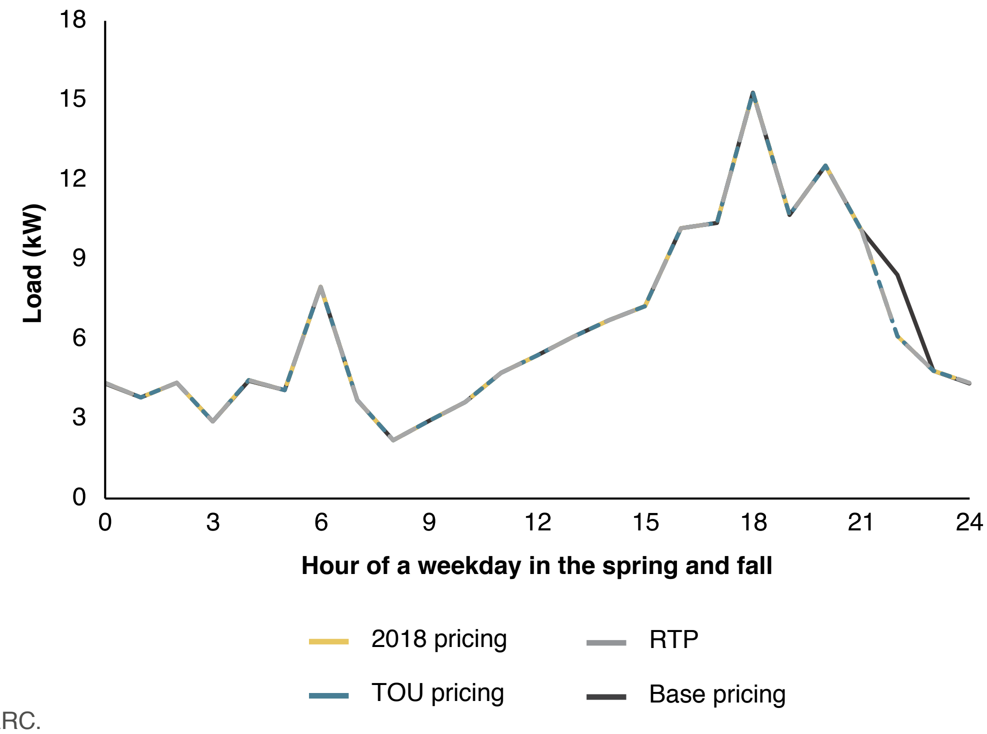
Source: KAPSARC.

Settings of energy use reflecting short-run electricity price response

Household with a low preference for electricity

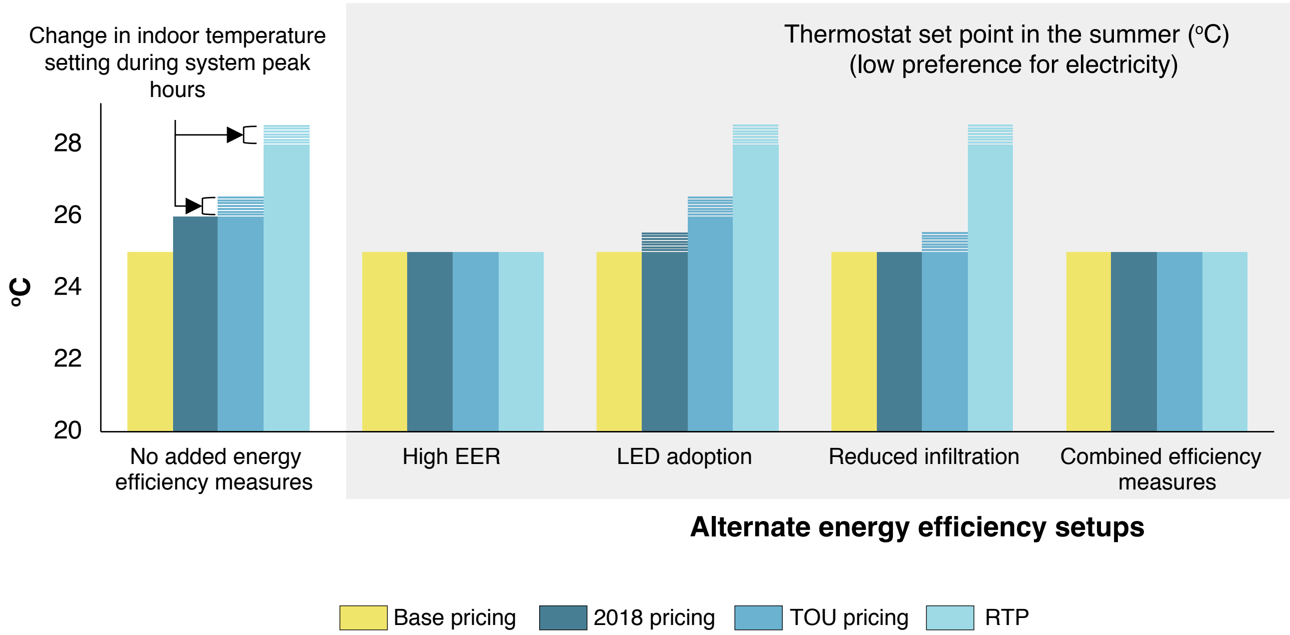
Air conditioning use varies the most when electricity prices change; this is because thermostat set points have the greatest weight, as shown in Table 3. For no added energy efficiency measures, the alternative electricity pricing cases, and a low-electricity-preference household, the range of indoor temperature adjustment at optimality is found to be between 1 °C to 3 °C in the off-peak summer hours; this is shown in Figure 6. No load shifting occurs in the spring and fall, as Figure 7 shows. The peak hours during the summer show higher indoor temperature settings of 0.5 °C above the off-peak hours only in the TOU pricing and RTP cases. In the previous analysis, the on-peak thermostat setting was 1 °C higher with this price applied. That is lower than the 1.5 °C deviation found in this paper in the peak hours of the summer months, but higher than the spring and fall findings. Matar (2018) combined the thermostat adjustment of the three seasonal periods into one measure, whereas this analysis distinguishes this metric between seasons.

Figure 5. Diurnal load curve on a spring or fall weekday for all electricity pricing cases and no added energy efficiency (low preference for electricity).



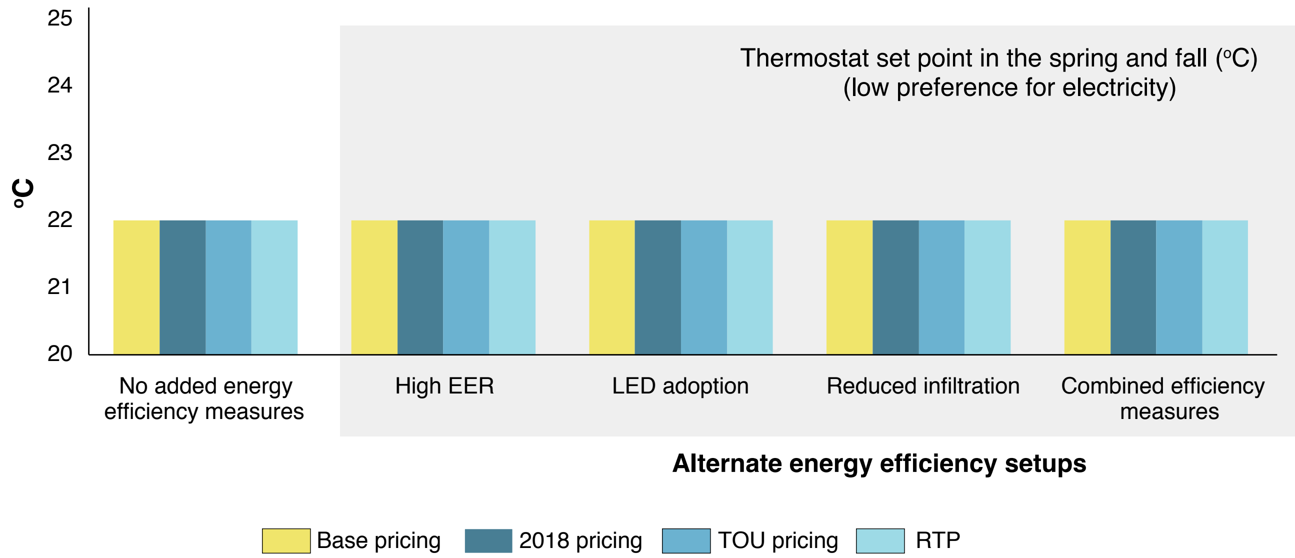
Source: KAPSARC.

Figure 6. Indoor thermostat set points in the summer at the optimal utility value, for a household with a low preference for electricity.



Source: KAPSARC.

Figure 7. Indoor thermostat set points in the spring and fall at the optimal utility value, for a household with a low preference for electricity.



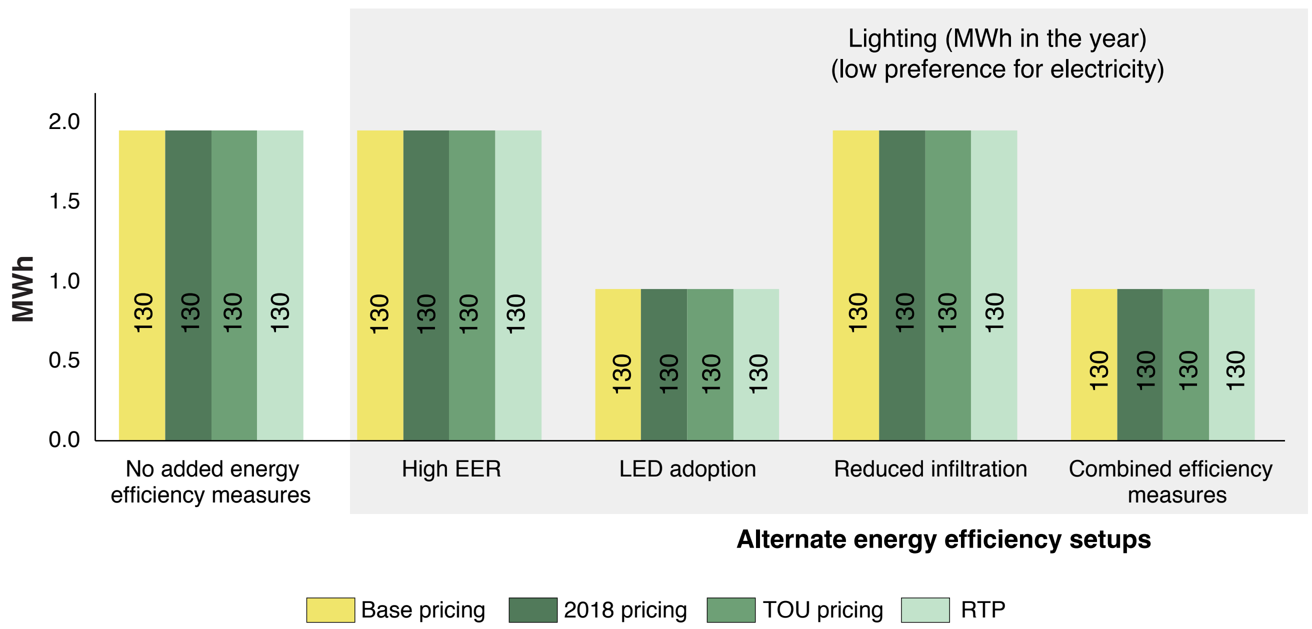
Source: KAPSARC.

At worst, some higher energy efficiency measures do not individually alter the behavior of the households, in terms of making thermostat adjustments. Some efficiency measures, like a higher air-conditioning EER or reduced infiltration rates, do warrant a more subdued response to 2018 pricing and TOU pricing. For example, under the defined TOU price, the thermostat is adjusted by 1 °C in the off-peak hours in the summer and by 1.5 °C during the peak with no energy efficiency measures. However, the household with higher EER would not raise the thermostat setting at all, and only raise it by 0.5 °C in peak hours with solely reduced infiltration.

Reducing infiltration by sealing cracks between walls and doors or windows is a low-cost measure. Yet, it would have significant effects on the price response and households' expenditure behavior. LED bulb adoption, another relatively low-cost option, would induce a lower response with 2018 pricing imposed. Replacing air conditioners with more energy efficient units can take place over the long-run (more than one year), but it can generate the greatest price response effects.

Figure 8 shows the amounts of electricity used to power on lights for each case, in MWh. The optimal lighting requirement associated with the energy use, in lumens (lm) per m^2, is written on the individual columns. We have tested many luminosity increments between 130 lm per m^2 and a lower value, but the model would not find a higher household utility with a lower value. The only reductions in lighting use come from installing LED bulbs, as opposed to solely a response to electricity price.

Figure 8. Electricity used for lighting at optimal utility value, for a household with a low preference for electricity (values in columns are in lumens per square meter).



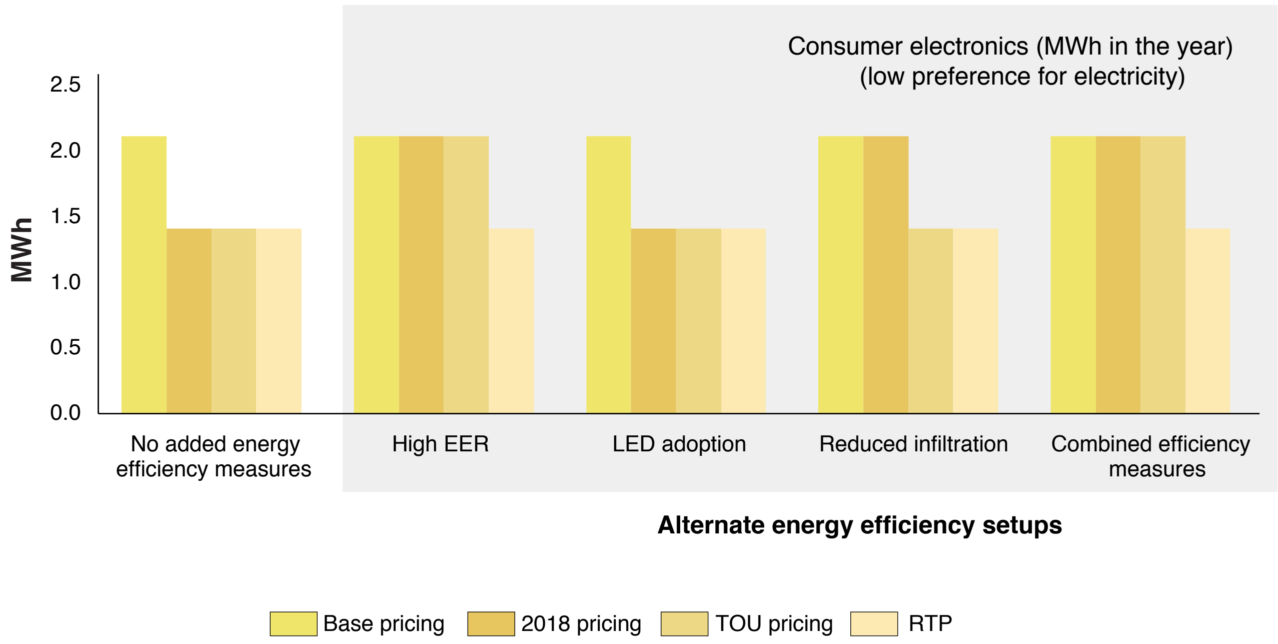
Source: KAPSARC.

Figure 9 illustrates how the household would turn off consumer electronics as a result of the different pricing schemes, shown in MWh. By default, RTP yields the greatest response, and a moderate response is found with 2018 pricing and TOU pricing. When infiltration is reduced, or LED lighting is adopted, households do turn off their consumer electronics, but this behavior is limited. Higher EER or the combination of all energy efficiency measures show no response, minus the RTP case.

Households with a high preference for electricity

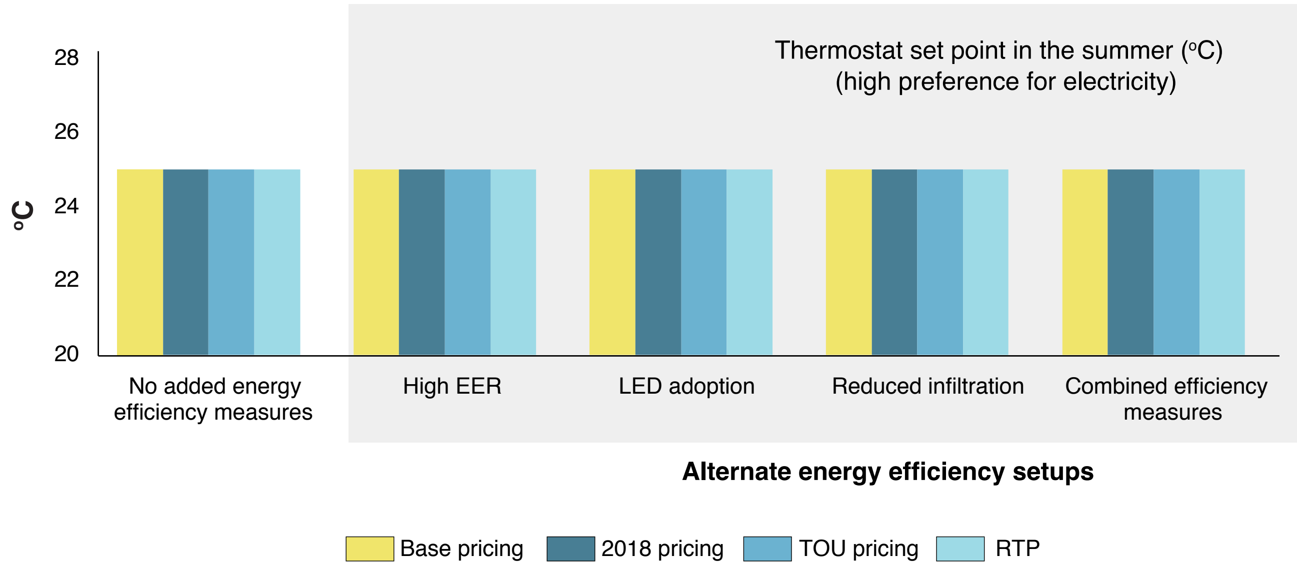
Households with a high preference for electricity do not respond to any of the changed electricity pricing cases. Furthermore, real-time prices do not cause any changes to households operating consumer electronics. This is shown in Figures 10 and 11. The thermostat setting in the spring and fall and the use of lighting do not vary across electricity pricing and energy efficiency cases for those households with a high preference share for electricity. In the spring and fall, the indoor temperature setting is 22 °C throughout, and the lighting use resembles the data shown in Figure 8. In this preference case, households exhibit less willingness to change electricity use patterns.

Figure 9. Electricity consumption for consumer electronics at optimal utility value, for a household with a low preference for electricity.



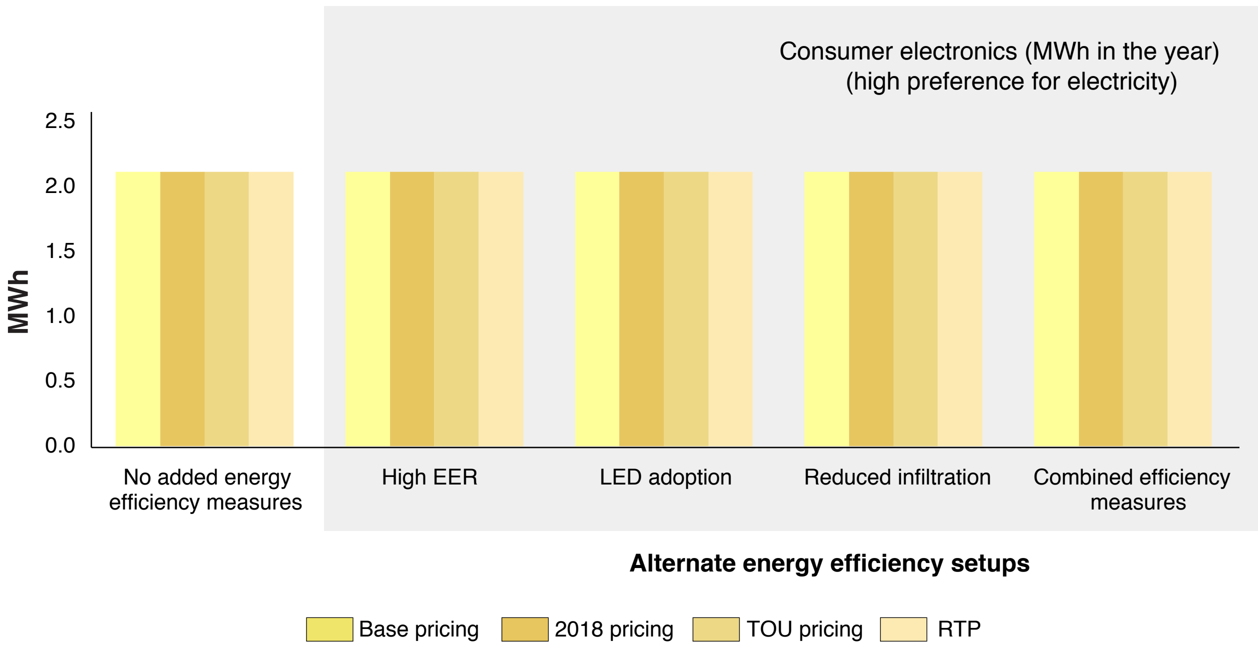
Source: KAPSARC.

Figure 10. Indoor thermostat set points in the summer at the optimal utility value, for a household with a high preference for electricity.



Source: KAPSARC.

Figure 11. Electricity consumption for consumer electronics at optimal utility value, for a household with a high preference for electricity.



Source: KAPSARC.

Average electricity price

Table 6 shows the average electricity prices paid in each case by a household with a low electricity preference during the year; they are computed by Equations 7-10. One interesting feature of these results is the higher average price paid by the household with LED adoption and TOU pricing. This is attributed to the fact lighting is used at night, which corresponds to the lower tariff in the scheme.

Table 7 shows average prices for a household with a high electricity preference. They are equivalent or a little higher than those of a low-electricity-preference household for base pricing, 2018 pricing, and TOU pricing. This makes sense given their limited price response. However, RTP produces equivalent or lower average prices for the high electricity preference case. The real-time prices are lowest during the middle of the day and highest at night. The higher electricity use for cooling attributes more weight for the lower price hours. The high-preference household spends more money on electricity than a household with a low electricity preference under an RTP policy, but the average unit price is lower.

Table 6. Average electricity price at optimal utility value for a household with a low electricity preference (U.S. cents per kWh).

		Electricity pricing cases			
		Base pricing	2018 pricing	TOU pricing	RTP
Energy efficiency cases	**No added energy efficiency measures**	3.6	4.9	6.9	8.3
	Higher EER	2.5	4.9	6.9	8.2
	LED adoption	3.5	5.0	7.0	8.3
	Reduced infiltration	3.5	5.1	6.8	8.2
	Combined efficiency measures	2.5	4.9	6.8	8.2

Source: KAPSARC.

Table 7. Average electricity price at optimal utility value for a household with a high electricity preference (U.S. cents per kWh).

		Electricity pricing cases			
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Energy efficiency cases	**No added energy efficiency measures**	3.6	5.1	7.0	8.2
	Higher EER	2.5	4.9	6.9	8.2
	LED adoption	3.5	5.1	7.0	8.1
	Reduced infiltration	3.5	5.1	6.8	8.2
	Combined efficiency measures	2.5	4.9	6.8	8.2

Source: KAPSARC.

Conclusion

Matar (2018) introduced a methodology to assess a household's electricity price response computationally. The framework calls for hybridizing a microeconomic representation that considers how a household chooses among a group of expenditure items in order to maximize its satisfaction, and a physical electricity use simulation. It argued that indoor conditions that are influenced by outdoor weather conditions, and the construction of the residential enclosure were important in a household's decision-making process. This paper expanded the methodology of Matar (2018) to account for more price response measures that the household could exercise. Namely, distinguishing between seasons and hours (peak hours versus off-peak hours) in setting the thermostat set point, turning off lights, and shifting or turning off consumer appliances.

Although this papers assesses different electricity pricing scenarios and energy efficiency measures for the most part, we find consistency between the two analyses for TOU pricing. Ultimately, air conditioning use exhibits the greatest response to these scenarios because we have calibrated the model to a household that primarily uses electricity for cooling. Still, the increased flexibility of distinguishing seasons and hourly periods in a day, and the options to reduce electricity use for lighting and consumer electronics, yielded a more developed methodology that can be used for a household in any region.

A household in Saudi Arabia that has a low preference for electricity would adjust the thermostat by 1 °C in the summer for the price reform enacted in 2018. If TOU prices were imposed with higher administered electricity prices during the system peak period, it would adjust the set-point by 1 °C during the summer off-peak hours, and by 1.5 °C during summer peak hours; no response was observed in other seasons. RTP would generate the greatest response, as the price deviations from the base case are highest in this scenario. We additionally found no response in lighting usage across all scenarios for this specific preference setting, but the use of consumer electronics was reduced. Alternatively, a high-preference household does not respond to any pricing schemes studied.

Furthermore, higher energy efficiency lessens the households' reaction to higher electricity prices. This is especially true in the case of low-electricity-preference households. Higher air-conditioning EER yields the greatest effects, to a point where the households would not have to adjust their thermostats or their usage of consumer electronics as electricity prices change. The onset of LED lighting shows a more subdued response for 2018 pricing in terms of summer cooling load, while reduced infiltration causes no response at all or more restraint when 2018 pricing and TOU pricing are applied, respectively. This supports the idea that higher energy efficiency should precede higher electricity prices.

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Appendix – Modeling Residential Electricity Use

Description of the residential electricity use component

Matar (2016) describes the electricity use model and its validation. The model characterizes the conductive, radiative, and convective forms of heat that are transferred into and out of the air inside a thermal envelope. In this respect, it resembles commercial building energy models. However, it was designed from the bottom up to link with the KAPSARC Energy Model, described by KAPSARC (2016), and to facilitate its further development for the purposes of energy economics research. Such development includes adding the utility maximization component used in this paper.

The conductive heat transfer through the multi-material walls and roof of the envelope is calculated using a transient one-dimensional diffusion equation. This equation relates the hourly outdoor temperature, humidity, and solar radiation conditions, the construction materials of the residence, and the hourly temperatures of the indoor surfaces. The indoor surface temperatures are then used in calculating the heat gain within the overall indoor air calculations.

The model also incorporates the sensible and latent heat gains or losses as a result of air infiltration or exfiltration, windows, lighting, and internal elements such as people and appliances. The total hourly power load is calculated as the sum of the direct uses of light bulbs and appliances, the power used by the supply and return fans of the air-handling unit, and the power draw from the compressor of a vapor-compression refrigeration cycle used by the air conditioner. The power used by the refrigeration cycle is the cooling load divided by the unit's coefficient of performance.

Parameterization of the residential electricity use model

The residential electricity use component is calibrated for a typical villa in the central region of Saudi Arabia. ASHRAE Standard 55-2010 is used to calibrate the acceptable indoor temperature conditions based on ranges for thermal comfort. The thermostat set points are 25 ^{o}C, 22 ^{o}C, and 21 ^{o}C for the summer, spring and fall, and winter, respectively.

Other data specific to the central region of Saudi Arabia are partially gathered from the Saudi census, carried out by the former Central Department of Statistics and Information (CDSI) in 2010. The construction materials for a villa and the size of an average household are obtained from the CDSI's census, and the size of the residence in Saudi Arabia is estimated based on the habitable area per occupant figures from Al-Harigi et al. (2004).

AMAD for Technical Consultation and Laboratories (2011) estimated air conditioner efficiency and the domestic light bulb market, and the import data was gathered by the CDSI. The usage times of indoor lighting are specified such that lights are turned on from sunset to 10 p.m. Outdoor lighting only accounts for direct use and does not contribute to the internal heat gain. The appliance use schedule is assumed due to lack of data; thus we see spikes in the power load profile in Figures 4 and 5. The refrigerator is used continuously throughout the year.

Hourly solar irradiation, outdoor dry-bulb temperature, and relative humidity data for the city of Riyadh are acquired from the National Renewable Energy Laboratory (NREL) (2017). The direct normal irradiance is used to compute the solar irradiation incident on each surface of the residence.

About the Author

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Walid Matar is a research fellow at KAPSARC who is working on energy systems models; particularly the KAPSARC Energy Model, and satellite projects such as the residential electricity use and passenger transportation models. Walid holds an M.Sc. in mechanical engineering from North Carolina State University and a B.Sc. in the same field from the University of South Carolina.

About the Project

The aim of this project is to develop a framework to analyze households' price response to any electricity pricing scheme, especially in regions where historical data are unavailable or insufficient. The framework combines physical and microeconomic principles. The physical side governs the electricity used throughout the day to satisfy services that people desire, while the microeconomic side imposes a normative utility function for the household to represent its satisfaction. While the present paper uses output from the KAPSARC Energy Model (KEM), future work will entail a formal linkage between KEM and the residential model with price response, and the addition of energy efficiency purchases and incentives.

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