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Electric Vehicle Deployment and Carbon Emissions in Saudi Arabia: A Power System Perspective

Amro M Elshurafa and Nawaz Peerbocus

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Highlights

A power system model for Saudi Arabia was built to quantify the carbon emission implications of deploying electric vehicles (EVs) within the Kingdom. The model represented the four operating regions in the Kingdom as segmented by the electricity regulator.

The model simulated 18 scenarios. These scenarios stemmed from varying the number of EVs deployed, the efficiency of internal combustion engine vehicles (ICEVs), the efficiency of EVs, and the time of charging.

The marginal emissions method was used to quantify the incremental emissions that would result from charging the EV batteries.

On average, deploying 100,000 EVs (nearly 0.67% of Saudi Arabia's passenger vehicle fleet) in place of the same number of ICEVs would result in a net carbon emissions reduction of 0.36%, a ratio of approximately 1 to 0.5.

In the worst-case scenario, net emissions would increase if the most efficient ICEVs were replaced with the least efficient EVs.

The time of charging EV batteries does not have a material effect on EV emissions because the marginal generator, for the most part, remains the same in all regions.

Summary

Although battery electric vehicles (EVs) are emission-free at the tailpipe, the energy mix that provides electricity to charge EVs is generally not. Ideally, it is desirable to charge EVs from a low- or no-carbon energy source so that the emissions avoided by switching from internal combustion engine vehicles (ICEVs) outweigh the incremental emissions from the power used to charge the EVs. To that end, this paper quantifies the net carbon emissions associated with EV deployment in Saudi Arabia by considering the country's energy mix. The authors built a model characterizing the Saudi power system, and a total of 18 different scenarios were simulated using the marginal generation emissions method.

The scenarios varied the driving ranges, EV efficiencies and time of charging for passenger transportation. The model also ran best- and worst-case scenarios. On average, for each 1% of the passenger vehicle fleet replaced by EVs, fleet emissions fall by 0.5%; in the best-case scenario, emissions fall by 0.9% for each 1% of the fleet replaced. The worst-case scenario, however, results in a net increase in emissions. Furthermore, given that the marginal generator for most regions of the Kingdom does not vary, the effects of charging EVs during peak or off-peak times has little effect on net emissions. The latter observation indicates that time-of-use pricing would currently be ineffective in promoting emission reductions.

Introduction

It was established decades ago that the energy transition is driven by a desire to decarbonize energy supplies by switching to renewable energy sources (Leach 1992) and reduce energy demand by increasing energy efficiency practices (Morris and Pehnt 2014). The broad policy drivers that stand behind energy transitions are energy security (Jonsson et al. 2015), economic growth and job creation by establishing renewable industries (Dai et al. 2016), and combating the adverse environmental effects of burning fossil fuels (Balsalobre-Lorente et al. 2018).

The appeal of cleaner technologies is their environmental benefits. Fossil fuels produce greenhouse gases (GHGs) and particulate matter, harmful to the environment and human health. According to the International Energy Agency (IEA), global energy-related carbon dioxide (CO_2) emissions totaled 32.6 gigatonnes in 2017 (IEA 2018). The power generation and transportation sectors are the two largest energy-related CO_2 emitters, with a share of 42% and 25%, respectively.

Governments globally are encouraging the development of renewable energy technologies to reduce power sector-related carbon emissions (Dogan and Seker 2016; Mittal et al. 2016; Squalli 2017; Van Vuuren et al. 2017). They are also providing incentives for the uptake of electric vehicles (EVs) to reduce carbon emissions in the transportation sector (Moro and Lonza 2018; Teixeira and Sodré 2016; Wolfram and Lutsey 2016). There are two main categories of EV: (1) battery EVs that rely purely on electricity stored in a battery to drive an electric motor, and (2) hybrid EVs powered by electric and internal combustion motors working in tandem. This paper only focuses on the first type of EV.

With the exception of a few jurisdictions, such as Norway and Sweden, the uptake of EVs has been modest. They compete with incumbent technology, i.e., the long-established internal combustion engine vehicle (ICEV). The main challenges impeding the rapid uptake of EVs relative to ICEVs include higher retail costs and/or total cost of ownership (Letmathe and Suares 2017; Lévay, Drossinos, and Thiel 2017; Weldon, Morrissey, and O'Mahony 2018), the lack of ubiquitous infrastructure (i.e., charging stations) (Lorentzen et al. 2017; Lucas et al. 2018), shorter driving ranges, resulting in the so-called 'range anxiety' (Adepetu and Keshav 2017; Jung et al. 2015), and long charging times (Bonges III and Lusk 2016; Richard and Petit 2018).

Although the EV industry is evolving and addressing these challenges, most mainstream projections do not see EVs as the prevailing transportation technology in the coming 20 years. In its 2018 Energy Outlook, BP projected that only around 15% of the 2 billion vehicles that it forecast to be on the road by 2040 would be electric. The price of ICEVs is falling and their efficiency is improving, meaning that EVs have to compete with a moving target.

While, in contrast with an ICEV, an EV is emissions-free on the road, it is necessary to calculate the net carbon emissions associated with the use of EVs by understanding the energy mix of the electricity used to charge the EV. Ideally, the energy used to charge EVs should come from a low- or no-carbon source. However, if the energy mix is 'dirty,' it is possible that a greater deployment of EVs could result in higher net emissions than those generated by ICEVs. Many studies have considered the link between EVs and the country's energy mix. They have found that EV deployment does not necessarily translate into a reduction in GHG emissions (Casals et al. 2016; Faria et al. 2013; Jochem, Babrowski, and Fichtner 2015). One study found that deploying EVs in Taiwan would reduce CO_2 emissions but increase sulfur dioxide emissions (Li et al. 2016).

Introduction

This paper quantifies the effects of deploying EVs in Saudi Arabia on the country's carbon emissions by analyzing the energy mix behind the Kingdom's electricity supply. We developed a power model for Saudi Arabia using the commercially available software package, PLEXOS, and studied different EV adoption and charging scenarios. The scenarios were created in such a way that upper and lower limits of emissions could be quantified, providing policymakers with realistic boundaries to calibrate their expectations. We found that, on average, for each 1% of the passenger vehicle fleet converted from ICEVs to EVs, fleet emissions would fall by 0.5%. In the best-case scenario, emissions would fall by 0.9% for each 1% of the fleet converted to EVs. The worst-case scenario, however, results in a net increase in emissions. Our results indicate that a careful EV roll-out policy is needed to ensure that EVs do indeed attain the desired objectives (Rahman et al. 2017).

This paper only focuses on the link between EVs and Saudi Arabia's energy mix. It does not consider the complete life cycle of the vehicle, the battery, or any of its other components. This paper is not a life cycle assessment (LCA) study (Hache et al. 2019). It is a partial well-to-wheel (WTW) study as it does not consider the emissions associated with finding, extracting and transporting the primary fuel (Moro and Lonza 2018). While LCAs are important and insightful (Onat et al. 2017), they are beyond the scope of this paper. This paper assumes that charging stations and other infrastructure that support EV deployment are readily available.

Review and Motivation

Quantifying emissions

At first glance, deploying EVs seems a plausible way of reducing carbon emissions in the transportation sector. However, the net effect on the environment is directly linked to the energy mix that provides the required electricity to charge the batteries used by EVs. Ideally, it is desirable that the emissions avoided by driving an EV instead of an ICEV should outweigh the emissions stemming from the power sector. This concept forms the foundation for numerous studies and is also the backbone of the analysis conducted in this paper. Two methods are used to estimate carbon quantities emitted by the power sector: the first is based on average emissions, and the second is based on marginal emissions.

As the name suggests, the average emissions estimation bases its calculations on the overall carbon emitted in kilograms of CO_2 (kg·CO_2) by the sector normalized by the total power generated in kilowatthours (kWh). As such, an average emissions factor, possessing the units of kg·CO_2/kWh, is used to quantify how much carbon would be emitted from an additional kWh generated by the sector. In the case of EV deployment, the power sector would have to provide additional energy for EV charging purposes.

Calculating net emissions via the average estimation method has the advantage of being easy and practical, which makes it especially attractive for high-level studies (Moro and Lonza 2018). For example, the average emissions method has been used to estimate emissions in the Irish context, and it was found that 50–75% of emissions from private cars would continue to be outside the reach of electrification (Smith 2010). Other studies also rely on average emissions to study pollutants and their effects on human health (Requia et al. 2018). A further study used the average emissions method to compare the impacts on carbon emissions of deploying EVs within Europe, but also coupled it with a Monte Carlo simulation to model the probability of different outcomes (Casals et al. 2016). Teixeira and Sodré assessed the carbon emissions impact of replacing a conventional fleet of taxis with EVs in Brazil using the average method, but also used several averages to account for alternative energy mixes (Teixeira and Sodré 2016). Analyzing emissions from a global perspective using average emissions has also been done (Woo, Choi, and Ahn 2017).

Despite its practicality, the average method has limitations – it is an oversimplification of the power system's response to the incremental loads that occur. Assume, hypothetically, that a utility generates half of its electricity from a nuclear reactor (which is carbon-free) and the other half is generated from coal (which produces approximately 1 kg·CO_2/kWh). Using the average method, an additional kWh generated would result in 0.5 kg of CO_2. However, realistically the nuclear reactor would be serving as the base load and the additional kWh needed would be met by the marginal generator, i.e., the coal plant. Hence, the actual carbon emissions resulting from this hypothetical case would be 1 kg·CO_2/kWh, not 0.5 kg·CO_2/kWh (Thomas 2012).

The average method does not take into account a number of factors that affect the actual emissions that would result from deploying EVs. The energy mix may change through the seasons and even through the same day (Thomas 2012), and as the mix changes, so does the marginal generator. In larger countries the mix can also vary from one region to another, and the average emissions method may not be able to capture these regional differences. In the United States (U.S.) emissions may vary by as much as 22% due to regional differences in the energy mix and ambient temperatures (Yuksel and Michalek 2015). Similarly, one can easily imagine how the time of charging also affects the level of emissions from the power sector (McLaren et al. 2016). Hence, several papers have addressed this issue. Hoehne and Chester, for example, proposed an optimized scheduling method to minimize carbon emissions (Hoehne and Chester 2016). An enhancement to the average emissions method exists and is known as a weighted average emission, where a weighting of the energy mix based on time of day (Rangaraju et al. 2015) is incorporated in the calculation (Jochem, Doll, and Fichtner 2016).

The marginal emissions method, on the other hand, is capable of addressing the emissions implications of EV charging with more granularity. Depending on how detailed the description of the power system is, the spatial and temporal details can be captured. Given this advantage, many researchers have adopted the marginal emissions method to quantify net emissions resulting from EV deployment. In the U.S., for example, and using the marginal method, it was found that EVs would increase GHG emissions by approximately 7% compared with hybrid vehicles (Thomas 2012). Another study, again for the U.S., concluded that restricting EV charging to off-peak hours would result in higher total emissions (McLaren et al. 2016). The latter finding may seem counterintuitive at first glance, but depending on the fuel mix and fuel prices, the peak marginal generator may be less carbon-intensive than the off-peak marginal generator. The marginal method has also been utilized to study emissions in the United Kingdom (Hawkes 2010), Germany (Jochem, Babrowski, and Fichtner 2015), and the Netherlands (Van Vliet et al. 2011).

Because the marginal emissions method is more accurate, the GHG Protocol stipulates that analysts should use it over the average emissions method (Broekhoff 2005). However, a major challenge in adopting the marginal emissions method is that it requires significant data coupled with complex modeling (Nealer and Hendrickson 2015) when neither is necessarily immediately available or affordable. It is for these two reasons that the average method is generally considered more accessible.

The Saudi context

The intention of this paper is to quantify the net emissions impact of introducing EVs in Saudi Arabia in view of the country's power mix. Hence, it is important to provide an overview of the Saudi power sector to help decide on the most appropriate quantification method to use, based on what has been explained in the previous section.

According to the Electricity and Cogeneration Regulatory Authority (ECRA), the Kingdom's electricity regulatory body, the country has four operating regions: Eastern, Central, Western, and Southern. As is widely known, the eastern part of the Kingdom is the oil- and gas-rich region, and hence nearly all of the power generation in the Eastern region is fueled by gas. Similarly, over 70% of the power in the Central region is met by gas. The Western and Southern regions, by contrast, are heavily dependent on liquid fuels for power generation.

In 2017, 54% of Saudi Arabia's electricity was generated from gas. The remainder was mainly met by crude oil and heavy fuel oil (HFO), and a small portion from diesel. As regards transmission line connectivity between the regions, the Central region is connected to both the Eastern and Western regions, and the Southern region is connected to the Western region. The total available generation capacity stood at around 80 gigawatts (GW) in 2017 (ECRA 2017), the total consumption in the Kingdom was slightly less than 300 terawatthours (TWh), and the peak load was 62 GW.

A notable observation about the power sector in the Kingdom is that the peak loads in both the Central and Southern regions are higher than each region's generation capacity, as Table 1 shows. From an operational viewpoint, this fact means that the available capacity in other regions would shoulder any deficit.

The Central and Western regions contain nearly two-thirds of the population (Table 2). However, the peak load and energy consumption patterns do not fully correlate with the demographic patterns. The Eastern region, despite having only half as many people as either the Central or Western regions, has a peak load of 20 GW, as shown in Table 1, and a comparable energy consumption, as shown in Table 2. The high energy consumption prevailing in the Eastern region, relative to the population, is because most of the Kingdom's industrial sector and manufacturing facilities are located there.

Table 1. Peak loads and available generation capacity in Saudi Arabia, 2017.

Region	Peak load (GW)	Available capacity (GW)
Eastern	20	23
Central	20	16
Western	19	21
Southern	6	4

Source: ECRA (2017).

Table 2. Population and energy consumption in Saudi Arabia.

Region	Population (million)	Population (%)	Energy consumption (TWh)
Eastern	5.637	17.8	82
Central	10.074	31.7	91
Western	11.297	35.6	97
Southern	4.734	14.9	28

Sources: GaStat (2016) and ECRA (2017).

Due to hot and arid summers, loads during the summer increase drastically to cater for air-conditioning needs. The load during the summer is around 60 GW compared with 35 GW during the winter. Clearly, this difference has dispatch implications (i.e., determining the marginal generator) and consequently has carbon emission implications as well.

The above observations about the Kingdom's power sector can be summarized in the following four points: (1) The energy mix differs significantly between regions; (2) sizable electricity transfer occurs between regions; (3) the demographic distribution is not uniform; and (4) a large load variation exists between the summer and winter. Associating these observations with the objective of this paper, to assess net carbon emissions from EV deployment, it can immediately be concluded that using the average emissions method would skew the results considerably. Assuming that most EV deployment occurs in the Western region, for example (where generation is dominated by liquid fuel), using the average emissions method instead of the marginal emissions method would underestimate carbon emissions from EVs. Conversely, if most of the EV deployment occurs in the Eastern region (i.e., generation is dominated by natural gas), then the average emissions method would overestimate emissions. Hence, based on the contrast between the average and marginal emissions method calculations, and keeping in mind the intent of this paper, we have opted for the marginal emissions method.

Method and Assumptions

Thus far, we have established that the convenience and accessibility of the average emissions method comes at the expense of accuracy, while the marginal emissions method provides a more precise quantification of emissions, subject to greater data and modeling requirements.

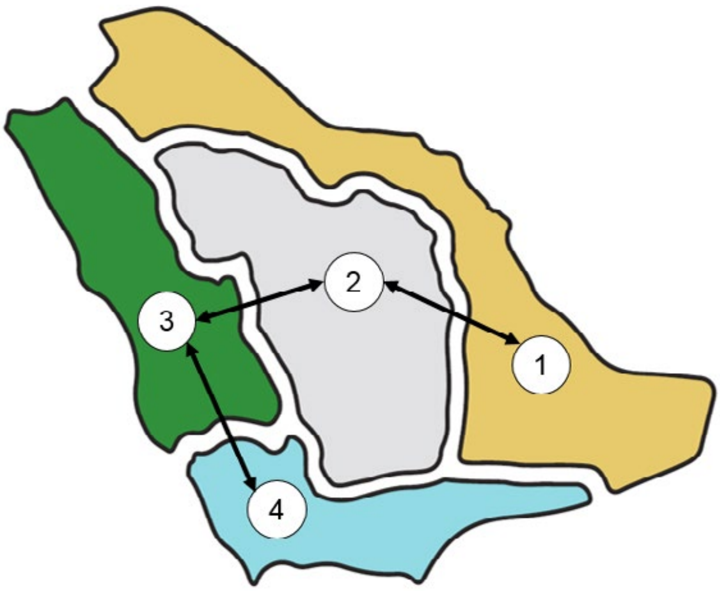
To assess the avoided emissions from EV use, several assumptions have to be made relating to, among others, the fuel efficiency of ICEVs, the efficiency of EVs, and driving ranges. Furthermore, to assess the marginal emissions that would result from greater power demand on the grid, the load profile, energy mix, time of charge, and fuel carbon content have to be known. In the next section, we discuss the methodology and assumptions, and the modeling we performed.

The Saudi power model

In order to quantify carbon emissions, we developed a power model for Saudi Arabia. The Kingdom was divided into four operating regions as per ECRA's, and each was represented by one node, as shown in Figure 1. More nodes in each region could have been used to represent the power sector more accurately. This may be necessary for studies concerned with power-centric topics, such as optimal power flow studies, for example. However, for the purposes of this paper, a single node per region strikes the right balance between model size/complexity and accuracy.

Around 1,000 generators were represented, aggregated by technology and fuel. The generation technologies that exist in the Kingdom are combined cycle, gas turbines, steam turbines, and diesel generators. The fuels used are natural gas (GAS), crude oil (CRD), heavy fuel oil (HFO), and diesel (DSL). The fuel shares and fuel prices were calibrated for 2017. The heat rate for each generation technology, which is a measure of generator efficiency, is summarized in Table 3. The heat rate of generators and the carbon content of

Figure 1. The four operating regions of Saudi Arabia.



Notes: Node 1 = Eastern region; node 2 = Central region; node 3 = Western region; node 4 = Southern region. The arrows depict transmission line connectivity and possible power flows.

fuels are fundamental parameters that need to be known in order to estimate carbon emissions.

As mentioned, the operating regions are connected by existing transmission infrastructure, as indicated in Figure 1. The line connecting the Central and Eastern regions has a capacity of 5.2 GW; the line connecting the Central and Western regions has a capacity of 1.2 GW; and the line connecting the Western and Southern regions has a capacity of 1.5 GW (Rioux et al. 2017). The resistance and reactance losses of the power flow were modeled on per-unit basis. Table 4 summarizes the fuel prices in Saudi Arabia for the power sector in 2017 and the emission factors associated with each fuel. Note that the emission factor values do differ across several reports by a few percentage points.

Table 3. Heat rates of thermal plants as used in the model (Matar and Anwer 2017; Rioux et al. 2017).

Generator technology	Fuel	Heat rate (BTU/kWh)
CC	GAS	9,213
	OIL	9,676
GT	GAS	13,237
	OIL	13,860
	DSL	12,150
ST	GAS	8,804
	OIL	9,446
	DSL	8,952
DSL	DSL	13,000

Notes: BTU = British thermal units; CC = combined cycle; DSL = diesel; GT = gas turbine; GAS = natural gas; OIL = HFO or crude; ST = steam turbine.

Table 4. The carbon emission factors of fuels and fuel prices used in the model.

Fuel	CO_2 emissions factor (kg/GJ)	Fuel price ($/MMBTU)
GAS	56.1	1.250
CRD	75	1.144
HFO	75	0.600
DSL	74.1	2.410

Sources: Zijlema (2018); Elshurafa and Matar (2017).

Notes: CRD = crude oil; kg/GJ = kilograms per gigajoule; MMBTU = million British thermal units.

EV deployment and energy requirements

As EVs are deployed, the grid will have to supply additional energy for battery charging. Clearly, the additional energy needed depends, among several other factors, on the deployment rate and distances traveled. These two parameters in particular are deserving of a dedicated research undertaking. Arriving at deployment rates and distances traveled should ideally be done through tailored studies that consider consumer perceptions of EVs against ICEVs, and consumer driving patterns and habits. However, such an endeavor is beyond the scope of this paper. Instead, we have studied different deployment scenarios and traveled distance scenarios to capture the impact of EV deployment on carbon emissions.

Globally, the share of EV sales varies widely. For example, in 2018 around 30% of all vehicle sales in Norway were EVs and nearly 18% were hybrids. Across the U.S., EV sales also varied from below 1% to above 5% in 2018. Given that the retail price of EVs is still considered relatively high compared with ICEVs of the same class, it is not a surprise to learn that these sales numbers were backed by various types of policy support. Saudi Arabia has around 15 million passenger cars on the road, and in 2017 nearly 685,000 cars were sold in the country (Statista 2019). Keeping in mind the global EV uptake levels, three deployment scenarios of 25,000, 50,000, and 100,000 EVs, representing roughly 3.5%, 7%, and 14% of annual car sales, were studied. While the 14% scenario can be viewed as aggressive, it was deliberately chosen to assess how a high deployment level would affect carbon emissions.

The other important parameter that significantly affects carbon emissions in Saudi Arabia is the distance traveled by vehicles. Gasoline consumption in the Kingdom totaled 32.97 billion liters (L) in 2017 (MAAAL 2018). Based on this level, average upper and lower limits of kilometers driven were calculated using highest and lowest ICEV efficiency: a small 4-cylinder sedan ICEV requires 0.06 L per kilometer (km), whereas an 8-cylinder sport utility vehicle (SUV) requires 0.15 L/km. The upper and lower limit of total kilometers driven in the Kingdom, therefore, is easily calculated as 549.5x109 km and 219.8x109 km. Because there are 15 million cars in the Kingdom, the annual distance traveled per car ranged between 14,653 km and 36,633 km.

Different EV models also have different efficiencies. By consulting various specification sheets, we concluded a representative range of high and low efficiencies to be from 0.09 kWh/km to 0.20 kWh/km. Using these efficiency values, coupled with the distance traveled per car and the number of cars deployed, we calculated the additional energy the grid would need to supply.

At a minimum, assuming 14,653 km are traveled annually by 25,000 EVs at an efficiency of 0.09 kWh/km, the grid would have to provide an additional 32,970 megawatt hours (MWh) annually. At the other extreme, deploying 100,000 EVs that travel 36,633 km with an efficiency of 0.20 kWh/km translates into an additional 732,667 MWh, which the grid would have to supply each year. The remaining scenarios are summarized in Section 3.4. The least additional energy required would stem from a scenario where ICEVs are least efficient (i.e., least kilometers driven) and EVs are most efficient (i.e., least kWh required). Conversely, the maximum energy requirement would result from a scenario where ICEVs are most efficient (most kilometers driven) and EVS are least efficient (most kWh required).

It is worth noting here that the efficiencies reported by manufacturers of ICEVs and EVs serve as typical values. City or highway driving conditions significantly affect the driving range for both types of vehicle. Furthermore, the ambient temperature and the use of air conditioning and/or heaters while driving also affect the driving range, but the effect is more pronounced in the case of EVs. In view of the countless combinations of possible driving behaviors and patterns, the use of the upper and lower ranges provided gives some insight into the best- and worst-case scenarios.

Charging and impact on load

Charging points capable of charging EV batteries can typically be categorized according to their charging speed: rapid, fast, and slow units. These are rated at ~50 kW, 7–22 kW, and 3 kW respectively. Tesla's network offers a supercharging point rated at 120 kW. Rapid or supercharging networks are not as widely available as the other types and can be used only with vehicles that possess rapid charging capability (Morrissey, Weldon and O'Mahony 2016). Despite that, even in the extremely unlikely event that all EVs under the highest deployment rate scenario (i.e., 100,000) connect to the grid to charge at a rate of 50 kW, the generation capacity of the grid would still be able to cater for this additional load (i.e., 100,000 cars x 50 kW/car = 5 GW), and the reserve requirements would still be met. However, this is just a hypothetical case used to stress-test the assumptions and ensure they are reasonable.

The previous section arrived at the incremental amount of electricity that would be needed during one year if EVs were deployed. If the average emissions method were used, then the additional carbon emissions that would result from EV deployment could now be calculated. However, as stated earlier, in this paper we use the marginal emissions method to quantify net emissions. As a result, the incremental amount of electricity alone is not enough; we also need to know when the charging is taking place, the duration of the charging session (it is not necessary to charge the battery fully), and the charging point capacity.

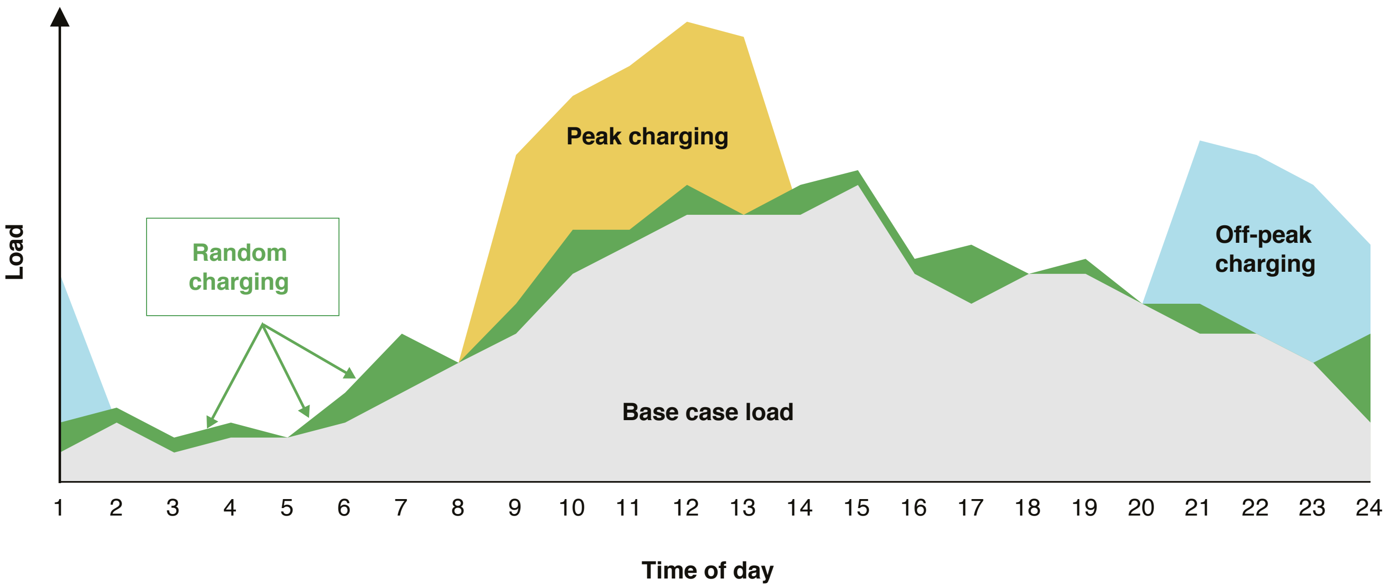
However, arriving at the charging patterns, akin to driving patterns, is a problem that warrants a separate study, given their stochastic nature (Amini, Kargarian, and Karabasoglu 2016). Indeed, several research papers have examined the topic of driving and charging patterns to arrive, for example, at optimal charging strategies (Wei, Liu, and Mei 2016) and optimal charging station placement (Shahraki et al. 2015), or to synergize EV and photovoltaic deployment (Chaouachi et al. 2016). The complexity of the problem grows quickly if time-of-use pricing or incentives to charge at certain times are introduced as policy support mechanisms to influence or somewhat control charging times (Kim, Kwak, and Chong 2017). Remember, however, that the intent of this paper is not to deduce driving patterns or consumer attitudes toward EVs – the objective is to quantify net emissions from EV deployment.

Hence, similar to what was carried out in the deployment section, this section studies a number of charging time scenarios (Sun et al. 2015), keeping in mind the marginal emissions method of calculation. Two scenarios present themselves as pertinent to the study, namely restricting all the charging to peak times, and restricting all charging to off-peak times. These two categories have been adopted previously (Mullan et al. 2011) because they are potentially representative of two extreme cases of carbon emissions resulting from EV deployment. A third scenario, which lies between these two extremes, is one where charging occurs at random times (Islam, Mithulananthan, and Hung 2018).

Recall that the Kingdom has four operating regions, each with an EV load profile that we refer to as a base case, i.e., no EV deployment yet. Because three scenarios are considered with respect to charging, i.e., peak, off-peak, and random, three new load profiles are examined and compared with the base case. Furthermore, the distribution of EV cars deployed follows the Kingdom's demographic distribution, as shown in Table 2. Consequently, the additional load to be supplied by the grid also follows the population distribution. For example, because 17.8% of the Saudi population resides in the Eastern region, it is assumed that 17.8% of the EVs deployed will be in that region and, hence, also the incremental load.

To explain the impact of EV deployment on the load profile more clearly, Figure 2 shows a conceptual schematic, provided for illustrative purposes, to describe visually the three load profiles simulated. The base case load profile, i.e., the scenario where no EVs are deployed, is shown in gray. The load profile for peak charging is shown in yellow, where the charging in this scenario is restricted to between 9:00 a.m. and 1:00 p.m. Similarly, the blue shaded area corresponds to the off-peak charging scenario, and is restricted to between 9:00 p.m. and 1:00 a.m. Finally, the random charging load profile is shown in green and, as the name suggests, charging can occur at any time. Note that for the random charging scenario, it is statistically possible to have no cars being charged at any given moment. In such a case, the load profiles of the random charging scenario and base case scenario coincide. The plot in Figure 2 is for illustrative purposes and is not drawn to scale. Nonetheless, it is worth mentioning that the yellow, blue and green shaded areas should all sum to the same amount. Furthermore, the sizes of these colored areas correspond with the number of EVs deployed.

Figure 2. A conceptual schematic of the load profile for the base case contrasted with the three other scenarios: peak charging (yellow), off-peak charging (green), and random charging (blue).



Notes: The shaded regions in yellow, blue and green represent the additional load needed to meet EV charging requirements. These three colors have the same area because they all correspond to the same load, albeit met at different times. As more EVs are deployed, the area of these colored regions increases. The figure is for illustrative purposes only and is not drawn to scale.

Summarizing scenarios

As discussed, the scenarios presented above serve as upper- and lower-limit case studies. Three main variables contribute to the number of scenarios that are simulated. These variables are:

- The number of EVs deployed, for which three scenarios have been chosen.
- When these EVs are charged, for which three scenarios have been chosen.
- The efficiencies of the EVs and ICEVs, for which two scenarios have been chosen for each type of vehicle.

Hence, there are 18 different possible combinations, translating into 18 scenarios to be studied. Table 5 summarizes these scenarios.

Table 5. Summary of scenarios simulated.

Factor to be varied	Number of scenarios	Overview of scenario	Total number of scenarios
EV deployment level	3	Low: 25,000 Medium: 50,000 High: 100,000	18
Load profile, i.e., when charging occurs	3	Peak Off-peak Random	
Incremental load to be satisfied based on EV and ICEV efficiencies	2	Low: EV at 0.09 kWh/km and ICEV at 0.15 L/km High: EV at 0.20 kWh/km and ICEV at 0.06 L/km	

Results and Discussion

This section discusses the results of a single year, using exogenous hourly load profiles for each region. The model was run using the heat rates, fuel prices and transmission line capacities outlined in Section 2. The load profiles include both power and water sector loads, and the model was run in least-cost dispatch mode. Initially, and to obtain the results for the base case, the model was run assuming that no EVs are deployed. In the base case the total carbon emissions from ICEVs were 252 million tonnes, translating into around 840 gtCO_2/kWh. These results are consistent with a previous study on carbon emissions for Saudi Arabia, which indicated that carbon emissions from ICEVs totaled 249 million tonnes (Wogan, Carey and Cooke 2019).

Results from scenarios – Emissions

The deployment scenario, efficiency of vehicles and time of charging ultimately all translate into a unique profile for each region in each of the scenarios created. Table 6 presents a summary of the results for each scenario. Note that the results represent the incremental emissions in the power sector only due to EV deployment – not net emissions. For example, on this basis, a medium EV deployment scenario of 50,000 cars, with low incremental load (i.e., 65,940 MWh), and assuming peak charging, results in additional power sector emissions of 56,976 tonnes of CO_2 compared with the base case (i.e., no EVs deployed).

As can be seen in Table 6, the incremental carbon emissions in the power sector are highest under the off-peak scenario and are lowest in the random charging scenario. These results can be explained by highlighting the role that marginal generators play in each region. Because the energy needs of the Western and Southern regions are virtually all met by liquid fuels, the time of charging has no effect on their carbon emissions because the marginal generator will always be liquid-fired. For the Eastern region, the marginal generator is always gas.

In the Central region, however, 30% of the energy is supplied by liquids and hence the marginal generator could be either liquid- or gas-fired depending on the load. At off-peak times, the marginal generator would use liquid fuel. At peak times, the additional energy required in the Central region would be met from gas-fired plants and/or through the transmission connection with the Eastern region. The energy transmitted from the

Table 6. Incremental CO_2 emissions in the power sector in tonnes resulting from the 18 scenarios simulated.

Deployment scenario	Incremental load (based on ICEV and EV efficiency scenarios)	Time-of-charging scenario		
		Peak	Off-peak	Random
Low (25,000 EVs)	Low (32,970 MWh)	28,480	28,689	28,403
	High (183,166 MWh)	158,399	159,515	157,976
Med (50,000 EVs)	Low (65,940 MWh)	56,976	57,388	56,948
	High (366,333 MWh)	316,799	319,018	316,306
High (100,000 EVs)	Low (131,880 MWh)	114,021	114,821	113,886
	High (732,667 MWh)	634,222	638,278	632,977

Eastern region to the Central region would have originated from gas. As such, the peak charging scenario (i.e., gas satisfying the marginal kWh) would result in lower emissions in the Central region (and the Kingdom as a whole) compared with the off-peak charging scenario.

While the marginal generator emissions method can explain why the peak charging scenario results in lower emissions compared with the off-peak scenario, the differences between time-of-charging scenarios are small, all other things being equal. The reason for these close results is due to (1) the nature of the energy mix, and (2) the nature of EV deployment as assumed. Note that 50% of the population resides in the Eastern and Central regions, and both regions are primarily powered by gas, while the other 50% of the population resides in the Western and Southern regions, both powered by liquids. Apart from the Central region, there is little difference between the emissions of the marginal unit of power at peak and off-peak times of all the regions. Furthermore, the flows of energy between regions, as per the model, did not fundamentally change the energy mix of any region. Moreover, the Central region, where the marginal generator role becomes pronounced, had 31% of the deployed EVs. The difference in carbon emissions would be greater if a larger number of EVs were deployed in the Central region.

Table 6 summarizes the incremental carbon emissions that result from EV deployment. To assess net emissions, the avoided carbon emissions also have to be quantified. According to the European Union Energy Portal smaller ICEVs emit around 0.1 kg/km of CO_2, whereas larger SUVs can emit 0.4 kg/km or even higher. In this paper, we have adopted this range and assume that the deployed EVs fully substitute ICEVs in number and driving range. Because time of charging did not significantly affect the incremental carbon emissions, the scenarios can now be reduced from 18 to six. These six scenarios represent best-case and worst-case scenarios with respect to carbon emissions. In the best-case scenario (i.e., the greatest reduction in carbon emissions), the highest-emitting ICEVs are removed from the road and replaced with the most efficient EVs. Conversely, the lowest-emitting ICEVs are removed from the road and replaced with the least efficient EVs in the worst-case scenario (the lowest reduction in carbon emissions).

The best- and worst-case scenarios are summarized in Table 7. Note how the best-case scenarios result in a reduction in overall emissions. These cases correspond to situations where the entire ICEV fleet to be retired comprises SUVs, replaced by the most efficient EVs. On the other hand, the worst-case scenarios result in an overall increase in emissions (numbers shown in red). The latter corresponds to a situation where only small ICEVs were taken off the road and replaced by the least efficient EVs. With this analysis, the upper and lower limits of net carbon emissions should help policymakers set realistic targets now that the potential of EVs to reduce emissions has been quantified.

Although informative, the best- and worst-case scenarios are unlikely to occur given that they lie at two extremes. A more realistic scenario is provided in Table 7, where we adopt the median incremental load and an ICEV emission factor of 0.25 kg·CO_2/km. A reduction in net emissions would be achieved under this median scenario. For example, replacing 25,000 ICEVs with EVs would avoid around 67,000 tonnes of emissions. One advantage of summarizing the results as shown in Table 7 is that it implicitly provides a sensitivity analysis. The upper and lower limits provide boundaries of what EVs can contribute with respect to reducing emissions. Furthermore, even if a lower average emissions factor for ICEVs is used (say, 0.2 kg·CO_2/km), the net result would still be a net reduction in emissions.

Table 7. Net emissions in tonnes calculated as the difference between incremental CO_2 emitted due to additional power generation caused by EV deployment and avoided emissions resulting from ICEVs taken off the road.

Deployment scenario	Incremental load scenario (based on ICEV and EV efficiency scenarios)[(1)]	Incremental CO_2 emitted from power sector[(2)]	Avoided CO_2 emissions from retiring ICEVs and deploying EVs[(3)]	Net emissions
Low (25,000 EVs)	Low (best-case scenario)	28,524	-146,530	–118,006
	Median	93,577	-160,269	–66,692
	High (worst-case scenario)	158,630	-91,583	67,692
Med (50,000 EVs)	Low (best-case scenario)	57,104	-293,060	–235,956
	Median	187,239	-320,538	–133,299
	High (worst-case scenario)	317,374	-183,165	134,209
High (100,000 EVs)	Low (best-case scenario)	114,243	-586,120	–471,877
	Median	374,701	-641,075	–266,374
	High (worst-case scenario)	635,159	-366,330	268,829

(1) 'Low' represents the best-case scenario; 'High' represents the worst-case scenario; 'Median' represents a realistic midpoint.

(2) Average values were calculated from Table 6.

(3) Parameters used for 'Low': 14,653 km for kilometers driven and 0.4 kg·CO_2/km for ICEV emission factor. Parameters used for 'High': 36,633 km for kilometers driven and 0.1 kg·CO_2/km for ICEV emission factor. Parameters used for 'Median': 25,643 km for kilometers driven and 0.25 kg·CO_2/km for ICEV emission factor.

Results from scenarios – Revenues

This section summarizes the net revenues that would result in each scenario from the additional energy sold due to EV deployment. The costs applied do not include capacity costs, transmission costs, or any other costs – they only represent the fuel component. The fuel cost for the base case was found to be $3.773 billion.

The results are shown in Table 8. We used 2017 electricity prices, and as shown, EV deployment will always result in positive net revenues for the grid, despite the relatively low energy prices that were prevalent in Saudi Arabia at the time. Electricity prices are currently higher compared with 2017, which means that revenues are expected to be even higher. An additional median annual revenue of $3.2 million would be generated in the low deployment scenario, and this revenue can reach as high as $22 million in the best-case scenario. All things equal, the EV deployment would result in a higher capacity utilization of the generation units, especially if charging occurs during off-peak times. The latter means that the unit operating cost for the industry would decrease.

Table 8. Net revenues in U.S. dollars, calculated as the difference between incremental fuel costs that the grid will incur and the incremental revenue that the grid will collect from additional energy sales for EV charging.

Deployment scenario	Incremental load borne by grid (based on ICEV and EV efficiency scenarios)[1]	Incremental fuel cost[2]	Incremental revenue[3]	Net revenue
Low (25,000 EVs)	Low	595,505	1,582,560	987,055
	Median	1,948,676	5,187,264	3,238,589
	High	3,301,846	8,791,968	5,490,122
Med (50,000 EVs)	Low	1,188,397	3,165,120	1,976,723
	Median	3,897,226	10,374,552	6,477,326
	High	6,606,055	17,583,984	10,977,929
High (100,000 EVs)	Low	2,378,074	6,330,240	3,952,166
	Median	7,804,758	20,749,128	12,944,371
	High	13,231,441	35,168,016	21,936,575

(1) 'Low' represents the best-case scenario; 'High' represents the worst-case scenario; 'Median' represents a realistic midpoint.

(2) Results as calculated from the energy model.

(3) Sales of energy assumed at a conservative price of 0.18 SAR/kWh, which is equivalent to 0.048 $/kWh. This value was deduced based on the tariff prices in Saudi Arabia during 2017. Governmental tariff: 0.32 SAR/kWh; industrial tariff: 0.18 SAR/kWh; residential tariff: tiered at 0.05, 0.10, 0.20, 0.30 SAR/kWh for 1–2,000, 2,001–4,000, 4,001–6,000, 6,001+ kWh consumption levels, respectively. Residential customers owning EVs will likely be paying bills at the higher tiers; commercial tariff: tiered at 0.16, 0.24, 0.30 SAR/kWh for 1–4,000, 4,001–8,000, 8,001+ kWh consumption levels, respectively. Commercial customers will likely be paying bills at the higher tiers.

Discussion and policy implications

The analysis shows that deploying EVs would result in a net reduction in carbon emissions, as detailed in Table 7. However, recall that 32.97 billion liters of gasoline were consumed in 2017. At an average tailpipe emissions factor of 2.29 kg/L, the total CO2 emissions resulting from passenger transportation was around 75 million tonnes. While the net emissions in Table 7 may be viewed as small compared with the total emissions, it is important to consider these numbers in the context of the number of EVs deployed in place of ICEVs.

If 25,000 EVs were deployed, the median case shows that a net 67,000 tonnes of carbon would be avoided (Table 7); this translates into a 0.089% emissions reduction. At first glance, this number may seem small. However, it is important to note that 25,000 vehicles represent only around 0.17% of the 15 million ICEVs on the road. In other words, replacing 0.17% of the fleet resulted in a 0.089% emissions reduction. The same calculation can be performed for the other scenarios to conclude that: (1) on average, replacing 1% of the ICEV fleet with EVs would result in a 0.5% carbon emissions reduction; (2) in the best-case scenario, replacing the same 1% would result in a 0.9% carbon emissions reduction; and (3) the worst-case scenario would result in a net increase in emissions.

These high-level numbers are applicable as long as the deployed number of EVs is small. As the share of EVs becomes significant, the dynamics of the grid and its operation would change significantly, and a new analysis with appropriate assumptions should be carried out to assess the implications.

Focus EV deployment on Eastern region initially

Saudi Arabia has embarked on an energy transition as part of Saudi Vision 2030. Aligned with this vision, significant changes are occurring and challenging the status quo. One of these changes is the introduction of the Saudi Corporate Fuel Efficiency (CAFE) Standard, which aims to improve the Kingdom's overall fuel efficiency with respect to passenger vehicles to 19 km/L by 2025 (AAWSAT 2019). The main driver behind the CAFE standard is to reduce fuel consumption and carbon emissions (Zirogiannis et al. 2019). As with most transition policies, CAFE will require time to be implemented. Saudi Arabia could choose to deploy EVs in the Eastern region initially, given that it is powered by gas, which is considerably less carbon-emitting than liquid fuels. As the fuel mix in other regions evolves to become more environmentally friendly in the near future, more aggressive EV deployment could occur in these remaining regions. However, coupling EV deployment in the Eastern region could complement the implementation of the CAFE standard throughout the Kingdom to contribute to greater carbon emission reductions.

Synergize the deployment of renewables and EVs

The Kingdom has announced that it intends to build nearly 60 GW of renewables by 2030 (40 GW of which will be solar photovoltaic), and this capacity will be deployed throughout the country. Rolling out an EV deployment strategy that, in particular, focuses on the Western and Southern regions and is aligned with the renewables deployment plan could ensure that EVs help maximize the reductions in carbon emissions. As discussed earlier, these regions are reliant on liquid fuels, which dilutes the desired impact of EVs. If, however, a reasonable amount of renewables is deployed in the Southern and Western regions, their marginal generation will transform from being highly polluting to carbon-free. With such a coordinated policy, renewables can provide two distinct advantages: reduce the reliance on liquid fuels and maximize the benefits of EV deployment. Note that the notion here is to synergize utility-scale deployment of renewables with EV deployment. Microscale charging stations powered by renewables are also possible (Yan, Zhang, and Kezunovic 2019).

Time-of-use pricing implications

Charging customers different rates at different times of the day, known as time-of-use pricing (TOUP), has been a common practice in many countries since well before the advent of EVs. The rationale behind adopting TOUP is essentially to incentivize consumers to shift some of their activities from peak to off-peak times, thereby economizing on the use of peak-time electricity, reducing costs and reducing stress on the electrical grid. In addition to relieving stress on the grid, TOUP can be designed to give customers the incentive to charge their EVs at times when the marginal generator is least polluting (Nilsson, Stoll, and Brandt 2017). But these two goals may not be complementary in certain countries.

In the Saudi context, the marginal generator in the Eastern region is always gas-fired, whereas the marginal generator in the Western and Southern regions is always liquid-fired. Hence, in the latter regions, even if the EV owner shifts the time of charging to off-peak in response to TOUP implementation, it will not contribute to reducing carbon emissions, although it would promote EV charging during off-peak times to benefit the grid. Notably, TOUP in the Central region has the potential to reduce emissions and to relieve stress on the grid. TOUP policies should be designed to reflect the underlying cost structure of the energy supply mix, while also taking into account the emissions reduction objectives of the pricing scheme.

Using the average emissions method for approximation

Section 2 contrasted in detail the differences between the average and marginal methods for quantifying emissions. It was concluded that the average emissions method is easy to implement but provides a less accurate estimate, whereas the marginal emissions method provides a more accurate estimate but has higher data and modeling requirements. Based on the modeling results, it was found that the marginal generator in the Eastern region (and mostly for the Central region as well) is gas. Similarly, the marginal generator for the Western and Southern regions is liquid-based, even considering the energy transfer that occurs between these two regions.

As such, using an average emissions factor for the Eastern and Central regions would provide a quick and reasonable estimate for policymakers when considering EV deployment in these regions. The same line of reasoning also applies to utilizing an average emissions factor for the Western and Southern regions. While the average emissions method cannot be a substitute for the marginal emissions method, because the Eastern/Central regions are separate from the Western/Southern regions, the average method can be useful for quick verification or initial policy screening exercises before more detailed modeling occurs. As the energy mix evolves in the Kingdom, whether by technologies changing or increases in energy imports and exports between regions, using the average emissions method (despite aggregating the heat rate of plants) can be used as an indicator of changing emissions.

Effect of temperature on EV driving ranges

EV manufacturers provide driving specifications based on moderate temperatures. However, at high or low temperatures battery capacities and charging/discharging behaviors change, impacting driving ranges, efficiency (Yuksel and Michalek 2015) and the expected lifetimes of the batteries. Furthermore, high or low temperatures trigger the use of heating or air conditioning to control cabin temperatures, once again resulting in a reduced driving range (Kambly and Bradley 2015). In Saudi Arabia, temperatures are generally high for most of the year. As such, it is important from a policy and power generation perspective to correct for the environment in which EVs will be operating so that the energy requirements are not significantly over- or underestimated. The analysis conducted herein accounted for such a consideration by using a worst-case efficiency scenario for EVs. In other words, using a high kWh/km figure is representative of an EV with low efficiency, or an average efficiency that would account for the negative temperature effects on EV performances.

Conclusion

The main contribution of this paper has been to quantify, using a power sector model, the net carbon emissions that would result from deploying EVs in Saudi Arabia. While EVs are emissions-free at the tailpipe, the energy that is required to charge the batteries powering the EVs may not be so. The actual impact of net emissions depends on the underlying generation mix in the power sector.

There are two widely accepted methods to assess incremental carbon emissions in the power system that stem from deploying EVs: the average emissions method and the marginal emissions method. The former offers practicality but provides only an approximation of emissions, while the latter provides a more accurate representation of emissions but requires considerable modeling and data. In this paper, we used the marginal method, despite the additional effort required, as the GHG Protocol requires its use for policy analysis.

Based on the modeling performed, we found that deploying EVs in the Kingdom would, on average, result in a net decrease in carbon emissions. Given the energy mix (as of 2017), if 100,000 ICEVs (i.e., 0.667% of the 15 million cars on the road), for example, were replaced with 100,000 EVs, then carbon emissions would decrease, on average, by around 0.35%, or 266x103 tonnes. As a rule of thumb, and at low levels of deployment only, one can assume that each 1% of ICEVs replaced with EVs would reduce emissions by 0.5%. By extension, if the entire passenger car fleet was changed to EVs, then fleet emissions would theoretically halve on average, i.e., fall by 35 million tonnes. However, if not done carefully, rolling out EVs in Saudi Arabia may actually result in a net increase in emissions if the most efficient ICEVs are replaced with the least efficient EVs.

There is a push to increase the efficiency of Saudi Arabia's power system and to rely less on liquid fuels. Furthermore, the Kingdom plans to deploy a large amount of renewables. If renewable energy policies are considered simultaneously with EV deployment policies, the social and economic returns may be amplified. In particular, renewables deployment in the Western and Southern regions of the Kingdom would result in the marginal generator for EV charging becoming carbon-free. Such a transition achieves two objectives: replacing liquid fuels and hence reducing carbon emissions, and further enhancing the role that EVs would play in emissions reduction.

Finally, and keeping in mind the energy mix and energy flows between regions within the Kingdom, we found that the time of charging EV batteries does not have a material effect on emissions reduction. Although the load profiles are affected because additional energy has to be generated to charge batteries, the marginal generator for the most part remains the same in all regions. This suggests that TOUP design needs to consider the underlying local cost structure of the energy supply mix while also taking into account the emissions reduction objectives of the pricing policy.

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About the Authors

Amro M. Elshurafa

Amro is a Research Fellow working on energy transitions. His research interests include power system modeling, solar PV techno-economics, and hybrid microgrid design and optimization. The author of 40+ papers and reports and the inventor of several patents, he holds a Ph.D. in engineering complemented thereafter with an MBA in finance.

Nawaz Peerbocus

Nawaz is the program director for Energy Transitions and Electric Power. Before joining KAPSARC, he was chief economist at the Saudi Electricity Company (SEC) where he led the strategic transformation project and advised on strategic planning issues. Prior to SEC, Nawaz was director of market strategy at Enbala, and senior economist at the Ontario Independent Electricity System Operator in Canada.

About the Project

We attempt to quantify the effects of deploying EVs in Saudi Arabia on the country's carbon emissions by analyzing the energy mix behind the Kingdom's electricity supply. We developed a power model for Saudi Arabia using the commercially available software package, PLEXOS, and studied different EV adoption and charging scenarios. The scenarios were created in such a way that upper and lower limits of emissions could be quantified, providing policymakers with realistic boundaries to calibrate their expectations.