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Electric vehicle deployment and carbon emissions in Saudi Arabia: A power system perspective

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ABSTRACT

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 desired to charge EVs from a low- or no-carbon energy source to ensure that the emissions avoided from driving EVs outweigh incremental emissions resulting from the power sector. To that end, this paper quantifies the net carbon emissions associated with EV deployment in Saudi Arabia by considering the energy mix. A model characterizing the Saudi Power System was built, and a total of 18 scenarios were simulated using the marginal generation emission method. The scenarios varied driving ranges, EV efficiencies, and time of charging for passenger transportation. Situations representing best- and worst-case scenarios were also run. On average, for each 1 % of EV deployed, emissions would reduce by 0.5 %, while at the best-case scenario emissions reduce by 0.9 %. The worst-case scenario, however, results in a net increase in emissions. Further, given that the marginal generator for the most part in the various regions of the kingdom does not change, it was found that adopting a time-of-use pricing mechanism would not promote emission reduction.

1. Introduction

Governments, globally, are resorting to 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), and resorting to electric vehicles (EV) to reduce carbon emissions in the transportation sector (Glitman et al., 2019). However, with the exception of a few jurisdictions like Norway and Sweden for example, the uptake of EVs globally has been modest. EVs are competing with an incumbent technology, i.e. the internal combustion engine vehicle (ICEV), which has been in existence for over a century. The main challenges impeding rapid uptake of EVs thus far include (relative to ICEVs): high retail cost and/or total cost of ownership (Letmathe and Suares, 2017; Lévay et al., 2017; Weldon et al., 2018), lack of ubiquitous infrastructure (i.e. charging stations) (Lorentzen et al., 2017; Lucas et al., 2018), shorter driving range which results 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).

While an EV on the road is carbon-free compared to an ICEV, it is necessary to consider the energy generation mix present in the particular country to assess net carbon emissions (McLaren et al., 2016). Ideally, it desired that the energy that will charge the EV is generated by a low- or no-carbon source. However, if the energy mix is highly-polluting, then it is possible that EV deployment would result in more emissions compared with ICEV. Many studies have been conducted and have considered the link between EVs and the energy mix, and it was found that EV deployment does not necessarily translate in a reduction in GHG emissions (Casals et al., 2016; Faria et al., 2013; Jochem et al., 2015). In one study that was performed in the context of Taiwan, it was found that EV deployment would reduce CO_2 emissions but increase SO_2 emissions (Li et al., 2016). More examples will follow in the next section.

In this paper, the effects of deploying EVs in Saudi Arabia on carbon emissions is quantified by considering the power system (i.e. energy mix) providing electricity to the kingdom. We develop a power model[1] for Saudi Arabia, and analyze different EV adoption and charging scenarios. The scenarios were created in such a way that upper and lower limits of carbon emitted would be quantified to provide policymakers with realistic boundaries to manage expectations. Results indicate that careful EV roll out policy is to be well-articulated to ensure that EVs indeed attain the desired objectives (Rahman et al., 2017). Note also that this paper is not a life cycle assessment (LCA) study (Hache et al., 2019), and assumes that charging stations and infrastructure requirements that support EV deployment (Palomino and Parvania, 2019) are

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[1] The model was built using the commercially available software package, PLEXOS: www.energyexemplar.com.

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readily available.

2. Review and motivation

2.1. Quantifying emissions

At a first glance, the deployment of EVs seems as a plausible solution to reduce carbon emissions in the transportation sector. As mentioned, 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 desired that emissions avoided from driving an EV outweigh incremental emissions stemming from the power sector. Broadly, there are two ways that are used to estimate carbon quantities that are 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 emission estimation bases its calculations on the overall carbon emitted (kg·CO_2) by the sector normalized by the total power generated (kWh). As such, an average emission 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 rather easy and practical, which is 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 will continue to be outside the reach of electrification (Smith, 2010). Other studies also rely on average emissions for studying pollutants and their effect on human health (Requia et al., 2018). Another study used the average emission method to compare impacts of deploying EVs on global warming within Europe (Casals et al., 2016).

Despite its practicality, the average method has limitations as it is an oversimplification of the power system's response to incremental loads. In our context, the average method does not take into account a number of factors that affect the actual emissions that would result from deploying EV including temporal (Thomas, 2012) and geographical variations. In the USA, emissions may vary by as much as 22 % due to regional differences in the energy mix and ambient temperature (Yuksel and Michalek, 2015). Similarly, one can easily imagine how the time of charging also affects the emissions resulting from the power sector (McLaren et al., 2016).

The marginal emission method, conversely, is capable of addressing the emission 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 emission method to quantify net emissions resulting from EV deployment in the US (McLaren et al., 2016; Thomas, 2012), UK (Hawkes, 2010), Germany (Jochem et al., 2015), and the Netherlands (Van Vliet et al., 2011).

Because the marginal emission method is more accurate, the GHG Protocol requires that analysts should use it over the average emission method (Broekhoff, 2005). However, a major challenge in adopting the marginal emission method is that it requires significant data coupled with complex modeling (Nealer and Hendrickson, 2015).

2.2. The Saudi context

According to the Saudi Electricity and Cogeneration Regulatory Authority (ECRA), there are four operating regions: Eastern, Central, Western, and Southern. As well known, the eastern region of the kingdom is the oil-and-gas rich region. Hence, demand in the eastern region is fully met by gas. Similarly, over 70 % of the demand in the central region is met by gas. The western and southern regions, however, are heavily dependent on liquids.

In 2017, 54 % of demand was satisfied by gas. The remaining portion was mainly met by crude oil and heavy fuel oil (HFO), and a small portion of diesel. In terms of transmission line connectivity, the eastern region is connected to the central region, the central region is connected to the western region, and the western region is connected to the southern region. The total available generation capacity was around 80 GW (ECRA, 2017), the total consumption was 300 TW h, and the peak load was 62 GW.

Table 1
A summary of peak loads and available generation capacity in Saudi Arabia for 2017 (ECRA, 2017).

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

It is worth mentioning that the peak loads in both the central and southern regions are higher than the generation capacities available in those regions (Table 1). From an operational viewpoint, this means that the available capacity in other regions shoulders any capacity deficit.

Demographically, the central and western regions contain nearly two-thirds of the population. However, the peak load and energy consumption patterns do not fully correlate with these demographic patterns. The eastern region, despite having only half as many people compared with either the central or western regions, has a peak load of 20 GW (Table 1) and comparable energy consumption (Table 2). This high energy consumption prevailing in the eastern region, relative to the population, is because most of the industrial sector of the kingdom is located in the eastern region.

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

The above observations about the Saudi power sector can be summarized in four points: (1) the energy mix differs significantly between regions, (2) sizable energy transfer occurs between regions, (3) the demographic distribution is non-uniform, and (4) a large load variation exists between summer and winter. Associating these observations with the objective of this paper, it can be immediately concluded that using the average emission method will skew results considerably. Hence, based on the contrast that was provided above between the average and marginal emission method calculations, and keeping in mind the intent of this paper, the marginal emission method will be adopted.

3. Method and assumptions

3.1. The Saudi power model

A power model for Saudi Arabia was developed and calibrated for the year 2017. The kingdom was divided into four operating regions as per ECRA, and each region was represented by one node (Fig. 1). More nodes in each region could have been used to represent the power

Table 2
Population (GASTAT, 2016) and energy consumption in Saudi Arabia (ECRA, 2017).

Region	Population (Million)	Population percentage (%)	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

Fig. 1. The four operating regions of the kingdom. The eastern region (node 1), the central region (node 2), the western region (node 3), and the southern region (node 4). The arrows depict transmission line connectivity and possible power flows.

sector more accurately. However, for the purposes of this paper, a single node per region strikes the right balance between model size/ complexity and accuracy.

Around 1000 generators were represented, aggregated by technology and fuel. The generation technologies that exist in the kingdom are combined cycle plants (CC), gas turbines (GT), steam turbines (ST), and diesel. The fuels used are natural gas, crude oil, heavy fuel oil (HFO), and diesel. The heat rate for each generation technology is summarized in Table 3.

As mentioned, the operating regions are connected with existing transmission infrastructure as per Rioux et al. (2017). The fuel prices in Saudi Arabia for the power sector in 2017 along with the emission factors associated with each fuel are summarized in Table 4.

3.2. EV deployment and energy requirements

As EVs are deployed, the grid will have to supply additional energy for battery charging purposes. This additional energy needed depends, among several other factors, on the deployment rate and on distances travelled. These two parameters in particular are deserving of a dedicated research undertaking that considers consumer driving patterns and habits (Dua et al., 2019). However, such an endeavor is beyond the scope of this paper. Instead, different deployment scenarios and travelled distance scenarios will be considered.

Globally, the share of EV sales varies widely. For example, around 30 % all vehicle sales in Norway are EVs, and nearly 18 % are hybrids.

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

Generator Technology[a]	Fuel[a]	Heat Rate (BTU/kWh)
CC	GAS	9213
	OIL	9676
GT	GAS	13,237
	OIL	13,860
	DSL	12,150
ST	GAS	8804
	OIL	9446
	DSL	8952
DSL	DSL	13,000

[a] CC: Combined Cycle, GT: Gas Turbine, ST: Steam Turbine, DSL: Diesel, GAS: Natural Gas, OIL: HFO or Crude.

Table 4
The carbon emission factors of fuels (Zijlema, 2018) and fuel prices (Elshurafa and Matar, 2017) used in the model.

Fuel	CO_2 Emission Factor (kg/GJ)[a]	Fuel Price ($/MMBTU)
GAS	56.1	1.250
CRD	75	1.144
HFO	75	0.600
DSL	74.1	2.410

[a] Emission factors vary between sources by a few percent.

Across the US states, EV sales varied also from below 1% to above 5% in 2018. Given that the retail price of EVs is still considered relatively high compared with same-class ICEVs, it is not surprising to learn that these sales numbers were policy-supported. In Saudi Arabia, the number of vehicles on the road is around 15 million, and in 2017, there were nearly 685,000 vehicle sold (Statista, 2019). Hence, 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 impact carbon emissions.

EV-related emissions are heavily dependent on the distance travelled by vehicles. Gasoline consumption in Saudi Arabia totaled 32.97×10^9 liters in 2017 (MAAAL, 2018). Based on this, average upper and lower limits of kilometers driven could be calculated using highest and lowest ICEV efficiency: a small 4-cylinder sedan ICEV requires 0.06 L/km, whereas an 8-cylinder sport utility vehicle (SUV) requires 0.15 L/km. The upper and lower limits of total kilometers driven in the kingdom, then, is easily arrived at to be 549.5×10^9 km and 219.8×10^9 km. Because there are 15 million cars in the kingdom, the annual distance traveled per car would range between 36,633 km and 14,653 km. To simplify the modeling, we assume here that EVs perfectly substitute ICEVs.

Different EVs possess different efficiencies also. By consulting various specification sheets, a reasonable range to be used to describe high and low efficiencies is between 0.09 kW h/km and 0.20 kW h/km respectively. Using these efficiency values, coupled with the distance traveled per car and the number of cars deployed, the additional energy to be supplied by the grid can be calculated.

At a minimum, assuming 14,653 km are travelled annually by 25,000 EVs at an efficiency of 0.09 kW h/km, the grid will have to provide an additional 32,970 MW h. On the other extreme, deploying 100,000 EVs that travel 36,633 km with an efficiency of 0.20 kW h/km translates to an additional 732,667 MW h to be supplied by the grid. The least additional energy required would stem from a scenario that considers ICEVs that are least efficient (i.e. least kilometers driven) and EVs that 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).

The efficiencies reported by manufacturers for ICEVs and EVs serve as typical values. City or highway driving conditions significantly affect the driving range for both types of vehicles. Further, idling time, ambient temperature, and the use of air conditioning and/or heater while driving also affects the driving range, but the effect is more pronounced in the case of EVs. Because of the countless combinations of possible driving behaviors and patterns, the use of the upper and lower ranges provide insight to best and worst-case scenarios.

3.3. Charging and impact on load

EV charging points, with respect to speed, can be typically categorized to rapid, fast, and slow units, and are rated at ∼50 kW, 7 kW – 22 kW, and 3 kW, respectively. A super-charging point rated at 120 kW is offered by Tesla's network. Nonetheless, rapid or super-charging networks are not as available as the other types and can only be used with vehicles that possess rapid charging capability (Morrissey et al., 2016). Despite that, even at the extremely unlikely scenario that all EVs, in the highest deployment rate scenario (i.e. 100,000), connect to the grid to charge at a rate of 50 kW at the same time, the generation capacity of the grid would still be able to cater for this additional load (i.e. 100,000 cars x50 kW/car = 5 GW), and reserve requirements would still be met as well.

The previous section arrived at the incremental amount of energy that would be needed during one year if EVs were deployed. Now, it is necessary to know *when* the charging is taking place, the duration of the charging session (it is not necessary to fully charge the battery), and the charging point capacity.

But arriving at the charging patterns, akin to driving patterns, is a problem that warrants a separate study given their stochastic nature (Amini et al., 2016). Indeed, several research papers have examined the topic of driving and charging patterns to arrive for example at optimal charging strategies (Wei et al., 2016) or optimal charging station location placements. The complexity of the problem grows quickly if time-of-use pricing or incentives to charge at certain times is introduced as a policy support mechanism to influence or somewhat control charging times (Kim et al., 2017). Remember however, the intent of this paper is not to analyze driving patterns or consumer attitudes towards EV – the objective is to quantify net emissions from EV deployment.

Hence, similar to what was done in the deployment section, a number of charging time scenarios (Sun et al., 2015) will be studied keeping in mind the marginal emission method of calculation. Two immediate scenarios pose themselves as pertinent to the study, namely restricting all the charging to take place during peak-times, and restricting all the charging to take place during off-peak times; These two categories have been adopted previously (Mullan et al., 2011) because they are representative of the extreme cases in terms of carbon emissions that would result from EV deployment. A third scenario, which lies between these two extremes, is one where the charging occurs at random times (Islam et al., 2018).

Recall that there are four operating regions in the kingdom, each with a load profile which we will refer to as a base case, i.e. no EV deployment yet. Because three scenarios will be considered with respect to charging, i.e. peak-charging, off-peak, and random charging, three new load profiles will be examined and compared with the base case. Further, the distribution of EV cars deployed will abide by the demographic distribution as shown in Table 2. Consequently, the additional load that will be supplied by the grid will also follow the population density. As an 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 the eastern and, hence, equally the incremental load.

To explain the impact of EV deployment on the load profile more clearly, Fig. 2 is provided, where a conceptual schematic is shown for illustrative purposes to visually describe the three load profiles that will be simulated. The base case load profile, i.e. the scenario where no EVs are deployed, is shown in grey. The load profile for peak-charging is shown in yellow, where the charging in this scenario was restricted to occur between 9:00am to 1:00pm. Similarly, the blue shaded area corresponds to the off-peak charging scenario, and was restricted to take place between 9:00pm to 1:00am. Finally, the random charging load profile is shown in green and as the name suggests, the charging can occur at any time. Note that for the random charging scenario, it is statistically possible to have no cars being charged in any given moment. In such a case, the load profile of the random charging scenario and base case scenario would coincide. The plot in Fig. 2 is provided 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. Further, the larger the number of EVs deployed, the larger the area of these shaded regions would be.

3.4. Summarizing scenarios

As discussed, the scenarios presented above serve as upper- and lower-limit case studies. Three main factors contribute to the number of scenarios that will be simulated; these factors are: (1) how many EVs are deployed, and three scenarios were chosen; (2) when these EVs are charged, and again three scenarios were chosen; (3) what the efficiencies of the EVs and ICEVs are to arrive at the additional energy that the gird needs to supply, and typical efficiencies representing high and low efficiencies (i.e. two efficiencies) for both types of vehicles were chosen. Hence, 18 different combinations are possible translating to 18 scenarios to be studied. Table 5 summarizes these scenarios.

4. Results and discussion

The results are discussed in this section for a single year using exogenous hourly load profiles for each region. In the base case, assuming no EVs are deployed total carbon emissions from the power sector were 252 million tons, translating to a rate of around 840 g·CO_2/kWh. These results are consistent with previous studies (Wogan et al., 2019).

4.1. Results from scenarios – emissions

The deployment scenario, efficiency of vehicles, and time of charging ultimately all translate to a unique profile for each region in each of the scenarios created. In Table 6, the summary of the results are shown for each scenario. Note that the results represent the incremental emissions that have resulted from EV deployment, not total emissions. As an example, at a medium EV deployment scenario of 50,000 cars, with low incremental load (i.e. 65,940 MW h), and assuming peak charging, there will be an additional 56,976 tons of CO_2 emitted compared to the base case (i.e. no EVs deployed).

As can be seen, from Table 6, the incremental carbon emissions are highest in 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. For the western and southern

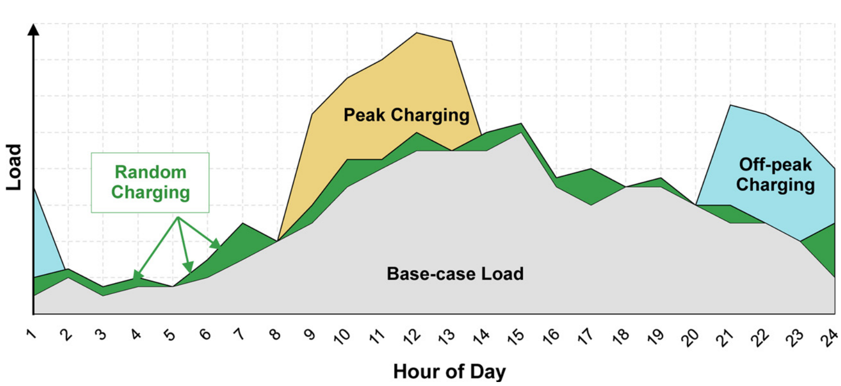

Fig. 2. A conceptual schematic of the load profile for the base case contrasted with the three other scenarios: peak charging (yellow), off-peak charging (blue), and random charging (green). The shaded regions in yellow, blue, and green represent the additional load required to meet EV charging requirements. These three regions also possess the same area because they all correspond to the same load (but met at different times). As more EVs are deployed, the area of these shaded regions increases. The figure is for illustrative purposes only and is not drawn to scale. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Table 5
Summary of scenarios to be simulated.

Factor to be Varied	Number of Scenarios	Overview of Scenario	Total Number of Scenarios
EV deployment levels	3	Low: 25,000 Med:50,000 High:100,000	18
Load profiles, i.e. when charging occurs	3	Peak Off-peak Random	
Incremental load to be satisfied based on EV and ICEV efficiency	2	Low: EV at 0.09 kW h/km and ICEV at 0.15 L/km High: EV at 0.20 kW h/km and ICEV at 0.06 L/km	

Table 6
Incremental CO_2 emissions in tons 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 MW h)	28,480	28,689	28,403
	High (183,166 MW h)	158,399	159,515	157,976
Med (50,000 EVs)	Low (65,940 MW h)	56,976	57,388	56,948
	High (366,333 MW h)	316,799	319,018	316,306
High (100,000 EVs)	Low (131,880 MW h)	114,021	114,821	113,886
	High (732,667 MW h)	634,222	638,278	632,977

regions, because their energy needs are virtually all met by liquid fuels, the time of charging does not have an effect on carbon emissions as the marginal generator will always be a 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 will be met from gas-fired plants and/or through the transmission connection with the eastern region. The energy transmitted from the 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 well) compared to the off-peak charging scenario.

While the marginal generator emissions method can explain why the peak charging scenario results in lower emissions compared to the off-peak scenario, it is noted that the differences between all scenarios, as related to time of charging, is small. The reason for these close results is due to (1) the nature of the energy mix and (2) the nature of EV deployment as it was 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, and both regions are powered by liquids. In other words, 50 % of the EVs that are deployed are charged by gas and the other half are charged by liquid fuels. Further, 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 bigger if a larger number of EVs are to be deployed in the central regions.

Table 6 summarized the additional carbon emissions that result from EV deployment. To assess net emissions, the avoided carbon emissions have to be also quantified. According the European Union Energy Portal[2], smaller ICEVs emit around 0.1 kg/km of CO_2, where larger SUVs can emit 0.4 kg/km or even higher. In this paper, it is assumed that the EVs deployed fully substitute ICEVs in number and driving ranges. Because time of charging did not significantly affect the incremental carbon emissions, the scenarios now can 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. most reduction in carbon emission), the most emitting ICEVs are removed from the road and replaced with the most efficient EVs. Conversely, the least emitting ICEVs are removed from the road and replace with the least efficient EVs in the worst-case scenario (least 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 (numbers shown in green). These cases correspond to situations where all the ICEV fleet to be retired is SUVs, and was 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 these two categories analyzed, the upper and lower limits of carbon emissions helps policymakers set realistic targets now that the potential of EVs in reducing 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 the median incremental loads and an ICEVs emission factor of 0.25 kg·CO_2/km were used. At this median scenario, a reduction in net emissions would be achieved. For example, if 25,000 EVs were deployed, and replaced ICEVs, then around 67,000 tons of emissions would be avoided. 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. Further, even if a lower average emission factor for ICEVs was used (say 0.2 kg·CO_2/km), the net result would still be a net reduction in emissions.

4.2. Results from scenarios – costs

Similar to what was performed above, we summarize here the net revenues that would result in each scenario from the additional energy sold due to EV deployment. The costs mentioned herein 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.

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

[2] Available at: https://www.energy.eu/car-co2-emissions/

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

Deployment Scenario	Incremental load scenario (based on ICEV and EV efficiency scenarios)[a]	Incremental CO_2 emitted from power sector[b]	Avoided CO_2 emissions from retiring ICEVs and deploying EVs[c]	Net Emissions[d]
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
Medium (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

[a] '**Low**' represents the best case scenario; '**High**' represents the worst case scenario; '**Median**' is represents a realistic midpoint.
[b] Average values were calculated from Table 6.
[c] 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.
[d] Numbers in green represent net reduction in emissions, while numbers in red represent net increase in emissions.

Table 8
Net revenues in US 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 gird (based on ICEV and EV efficiency scenarios)[a]	Incremental fuel cost[b]	Incremental revenue[c]	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**
Medium (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**

[a] '**Low**' represents the best case scenario; '**High**' represents the worst case scenario; '**Median**' is represents a realistic midpoint.
[b] Results as calculated from the energy model.
[c] 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. Explicitly: 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 1–2000, 2001–4000, 4001–6000, 6001+ 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 1–4000, 4001–8000, 8000+ kWh consumption levels, respectively. Commercial customers will likely be paying bills at the higher tiers.

4.3. Discussion

The analysis shows that deploying EVs would result in a net reduction in carbon emissions. However, recall that there were 32.97 billion liters of gasoline consumed in 2017. At an average tailpipe emission factor of 2.29 kg/L, then the total CO_2 emissions resulting from *passenger transportation* was around 75×10^6 tons. While the net emissions compared to the total emissions may be viewed as small, it is important to view these numbers with respect to the number of EVs deployed which have replaced ICEVs.

At 25,000 EVs deployed for example, the median case shows that a net 67,000 tons of carbon would be avoided as shown in Table 7; this amount translates to a 0.0.9 % emission reduction. At a first glance, this number may seem small. However, it is important to note that 25,000 vehicles represent around 0.17 % only of the 15 million ICEVs on the road. In other words, replacing 0.17 % of the fleet resulted in a 0.0.9 %. The same calculation can be performed for the rest of the scenarios to conclude that: (1) on average, deploying 1 % of EVs would result in a 0.5 % carbon emission reduction, (2) in the best case scenario, deploying 1 % of EVs would result in a 0.9 % carbon emission reduction, and (3) the worst case scenario would result in a net increase in emissions.

4.3.1. Focus EV deployment on Eastern region initially

Saudi Arabia has embarked on an energy transition journey as part of its Vision 2030. In alignment 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 intends to improve the overall fuel efficiency of the kingdom 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 simultaneously carbon emissions (Zirogiannis et al., 2019). As with most transition policies, they require time to be implemented. Saudi Arabia may choose to start building EV infrastructure in the eastern region in the initial stages of deployment since the eastern region is powered by gas, which is considerably less carbon-emitting compared to liquid fuels. This is not to say that other regions should not deploy EVs. Rather, it suggests a gradual roll-out program for infrastructure. As the fuel mix in other regions evolves to become more environmentally-friendly in the near future, more aggressive EV deployment can occur in the remaining regions.

4.3.2. Synergize deployment of renewables and EV

The kingdom has announced that it intends to build nearly 60 GW of renewables by 2030 (40 GW of which will be solar photovoltaics), and this capacity will be deployed throughout the kingdom. Rolling out an EV deployment strategy in the western and southern regions in particular that is aligned with the renewable deployment plan can ensure that EVs provide maximum benefit in terms of reducing carbon emissions. As discussed earlier, the western and southern regions are reliant on liquid fuels, which dilutes the desired impact that EVs can have. If, however, a reasonable amount of renewables is deployed in the southern and western regions, the marginal generation in these regions will transform from being highly polluting to being carbon-free. With such a coordinated policy view, renewables can provide two distinct advantages: reduce reliance on liquid fuels and maximize attained benefits from EV deployment.

4.3.3. 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 well before the advent of EVs. The rationale behind adopting TOUP is to essentially incentivize consumers to shift some of their activities from peak times to off-peak times thereby economizing on the use of electricity, reducing cost, and reducing stress on the electrical grid (Levin, 2019). For EV purposes, in addition to relieving stress on the grid, TOUP incentivizes customers to charge their EVs during times where the marginal generator is least polluting (Nilsson et al., 2017). But these two goals may be competing in some countries. In the Saudi context, the marginal generator in the eastern region is always gas, whereas the marginal generator in the western and southern regions is always liquid-fired. Hence, in these regions, even if the EV owner shifts the time of charging to off-peak times due to a TOUP implementation, that will not contribute to reducing carbon emissions, but would aid in promoting charging of EVs to off-peak times to benefit the grid. However, the TOUP in the central region has the potential to both reduce emissions and relieve stress on the grid - this is because of the underlying energy mix during peak and peak hours in the central region. TOU pricing 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.

4.3.4. Effect of temperature on EV driving ranges

EV manufacturers provide the driving specifications at typical temperatures. However, at high or low temperatures, the battery capacity and dis/charging behavior changes which translates to affecting the driving range, i.e. efficiency (Yuksel and Michalek, 2015) and the expected lifetime of the battery. Further, high or low temperature triggers the use of heating or air conditioning to control the cabin temperature which once again results in reducing the driving range (Kambly and Bradley, 2015). In Saudi Arabia, the temperatures rise well above 40 degrees Celsius for most of the summer months. As such, it is important, from a policy and power generation perspective, to correct for the environment that EVs will be operating in so that the energy requirements are not significantly over- or underestimated. The analysis conducted herein accounted for such consideration by using a worst-case scenario efficiency for EVs.

5. Conclusion

It was 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 15 million cars on the road) for example were replaced by 100,000 EVs, then carbon emissions would decrease, on average, by around 0.35 %, or 266×10^3 tons. As a rule of thumb, and at low levels of deployment only, one can assume that each 1% of EV deployed can reduce emissions by 0.5 %. In other words, if the complete passenger car fleet was changed to EVs, then the emissions would reduce, on average, to half, i.e. reduce by 35 million tons. If not done carefully, however, introducing EVs in the kingdom may actually result in a net increase in emissions if the most efficient ICEVs are replaced with the least efficient EVs.

In Saudi Arabia, there is a push to increase the efficiency of the power system and to rely less on liquid fuels (Timmerberg et al., 2019). Further, 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, renewable deployment in the western and southern regions of the kingdom would result in transforming the marginal generator for EV charging purposes to becoming carbon-free. Such a transition achieves two objectives: replacing liquid fuels and hence reducing carbon emissions, and augmenting the role that EVs would play in emission reduction even further.

Finally, and keeping in mind the energy mix and energy flows between regions within the kingdom, it was found that the time in which EVs would be charged does not have a material effect on emissions reduction. Although the load profiles are affected because additional energy is to be generated to charge batteries, the marginal generator for the most part remains the same in all regions. In other words, time-of-use pricing cannot be deemed as an effective tool to promote reducing emissions, though it can still be used to release some stress on the power system by shifting charging to off-peak times.

Disclaimer

The views expressed in this paper are those of the authors and do not necessarily represent the views of their affiliated institutions.

Declaration of Competing Interest

None.

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