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King Abdullah Petroleum Studies and Research Center

How Firm Capacity and Forced Outage Rate Assumptions of Renewables Impact Capacity Expansion Model Results

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Key Points

The undergoing energy transition relies heavily on the deployment of renewables such as solar photovoltaic (PV) and wind power for the generation of electricity. These variable and intermittent resources would modify power systems' reliability compared to the situation where electricity is generated by conventional dispatchable power plants. It is also important to accurately capture their contribution to resource adequacy in long-term expansion planning. This discussion paper assesses how varying the firm capacity (FC) and forced outage rate (FOR) assumptions of renewable energy (RE) impact capacity expansion models (CEM). Eight scenarios that vary the FC and FOR, RE share targets, and annual RE uptake were run on a power system model of Saudi Arabia. Assuming a relatively high FC and a relatively low FOR favors renewables (i.e., Optimistic-RE), while the opposite disfavors them (i.e., Pessimistic-RE). Compared with optimistic RE assumptions, the pessimistic RE assumptions result in significant increases in costs, emissions, and battery storage deployment of up to 11%, 17%, and 41%, respectively. However, no observable patterns were found for resource adequacy. Quantifying the extent to which FC and FOR of RE technologies, which are considered heavily weather-dependent, impact investments in the power sector provides valuable insights for policymakers as the world moves forward more aggressively with RE deployment to reduce emissions and combat climate change.

To better prepare the power system to transition to more renewable sources, variable and intermittent sources of electricity should be carefully modelled in capacity expansion models (CEM). Results from CEM are sensitive to reliability assumptions of solar PV and wind.

Assumptions considered for the firm capacity and the forced outage rate of solar PV and wind influence electricity generation costs, carbon dioxide (CO_2) emissions and battery storage deployment. For our case study of Saudi Arabia until 2030, we observed an increase up to 11%, 17% and 41% respectively when considering pessimistic assumptions compared to optimistic ones.

The paper identifies no noticeable patterns for how the FC and FOR assumptions could impact reliability performances. Indeed, varying the FC and FOR of renewables can change or maintain the reliability status of regions (when viewed in isolation), with no observable order.

The results presented in this paper reaffirm the importance of collecting accurate RE-specific weather data to support effective RE deployment, as this can help avoid significant over- or under-investment.

Introduction

The power generation sectors of many countries are undergoing a transformation through the deployment of renewable energy (RE) to address climate change issues. Saudi Arabia, for example, intends to retire liquid fuels in its power mix and develop its renewable capacity to meet its 50% renewable target by 2030 (Vision 2030 2022; Saudi & Middle East Green Initiatives 2023).

Similar to any technology, RE has strengths and weaknesses. On the plus side, renewables enjoy near-zero marginal generation cost, require no fuel, and emit no carbon during operation. On the other hand, renewables are inherently variable and intermittent in nature as their output is dependent on the weather. While utilities have succeeded in dealing with demand variability for decades, renewables add a dimension of supply variability that must be considered during planning and operations. As the share of RE increases, so does the challenge of maintaining the reliability of its supply. Energy storage and network development can contribute to smoothening the output of renewable technologies and thus help in integrating more RE into power systems (Santos et al. 2017).

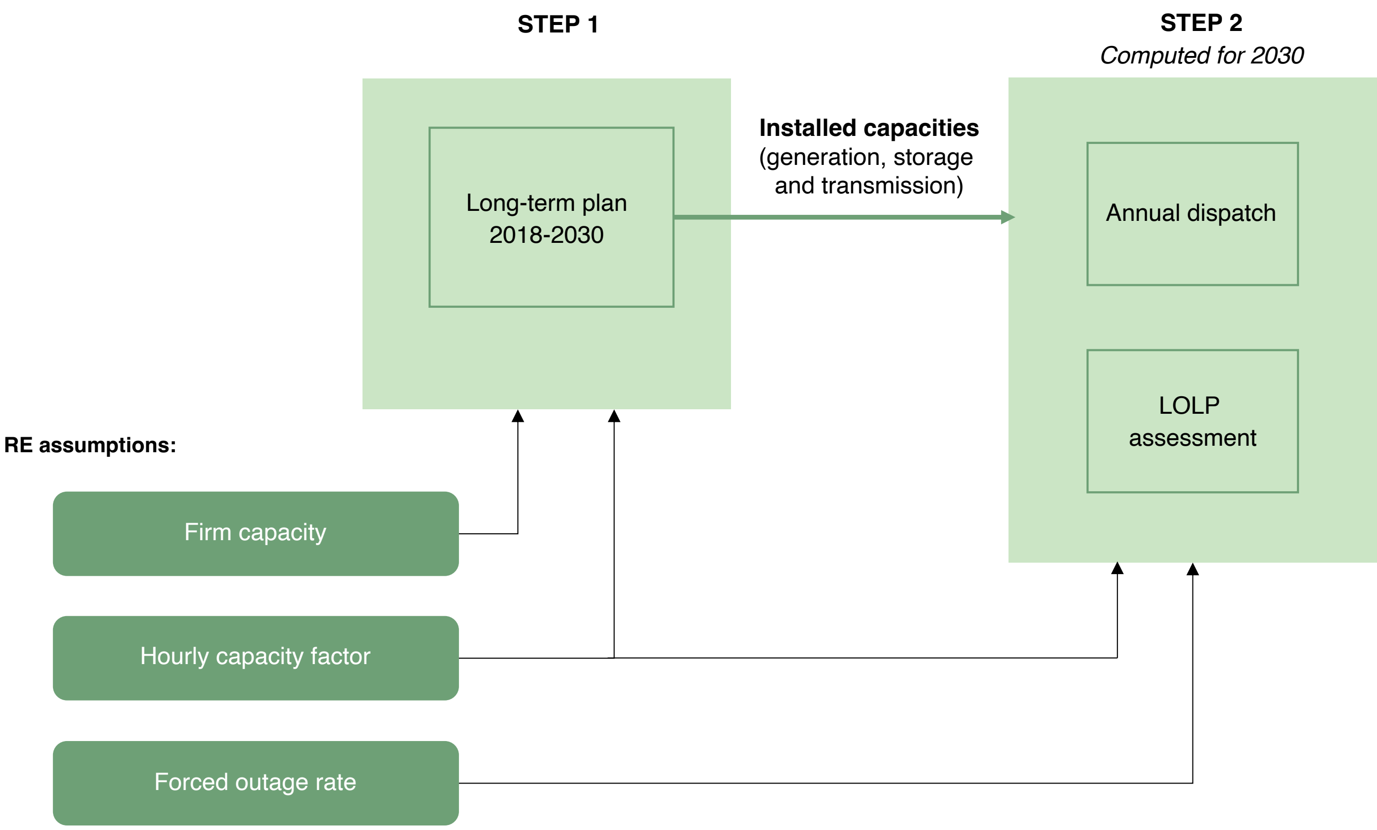
Given that weather data is crucial for effective RE deployment, we see that several countries around the world have already started collecting RE-specific weather data. However, inadequate data exist in many regions, including the Middle East and North Africa (MENA), for example. Despite these data challenges, policymakers have already started to plan the transition of the power system toward renewables.

This paper assesses the extent to which weather- and reliability-dependent assumptions for RE affect long-term expansion planning. The results reaffirm the importance of collecting accurate RE data. Our modeling framework focuses on the effects of firm capacity (FC) and forced outage rate (FOR) assumptions from the results of a Saudi Arabian capacity expansion model (CEM) that extends until 2030. The remainder of the paper proceeds as follows. The second section presents the method, the model and the eight scenarios considered for Saudi Arabia. The third section provides and discusses the main results. Finally, the paper concludes with the key observations from the Saudi case study.

Method, Model, and Scenario Description

We follow a two-step method to assess the impacts of varying the values of the FC and FOR, as illustrated in Figure 1. First, we compute the evolution of the Saudi power mix (including generation, storage, and transmission) until 2030 via a CEM. Second, we assess the resource adequacy of the installed power generation mix in 2030. The FC assumption is used for planning purposes (step 1 in Figure 1), to arrive at the installed capacities. In step 2 (see Figure 1), the FOR is used to assess resource adequacy in 2030 through the loss of load probability (LOLP).

Figure 1. Presentation of the two-step method.



Source: Authors.

Firm Capacity and Forced Outage Rate Definitions

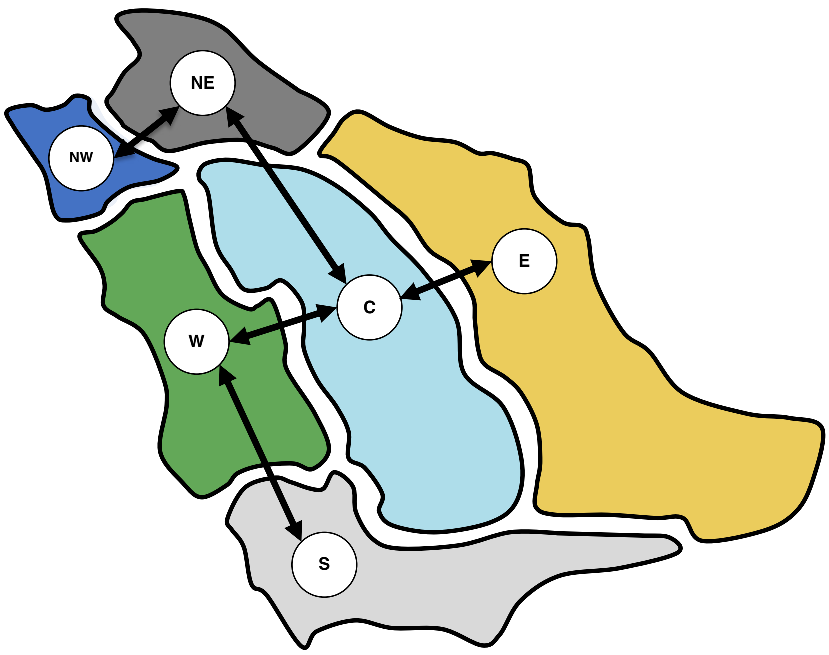
The FC has been defined in Sepulveda et al. (2018, 2404) as the capacity "that can be counted on to meet demand when needed in all seasons and over a long duration", and in Zachary, Wilson, and Dent (2022) as the "capacity which is always available to supply the energy needed up to a given constant rate." While its definition varies in the literature,[1] FC can generally be viewed as the capacity guaranteed to be available when required, and thus available to meet the resource adequacy requirement (Brouwer et al. 2014).

The FOR is defined as the percentage of time when a power plant is unable to generate electricity (NERC 2022). Generally, the FOR relates to mechanical failures. However, for RE (especially wind), mechanical failures are not the sole cause of unplanned outages, and it is necessary to expand the concept to consider weather-related failures, as suggested in Milligan and Porter (2005).

Model and Main Assumptions

We use the KAPSARC Power Model, which was built using the commercially available software PLEXOS.[2] The model describes six Saudi regions along with the existing transmission interconnection, as illustrated in Figure 2, calibrated to 2018 data. Our model was used in previous publications (Elshurafa and Peerbocus 2020; Elshurafa et al. 2021; Soummane et al. 2022). We obtain the solution for the 2018-2030 horizon via mixed-integer linear programming, and the reliability in 2030 is assessed using the PASA module of PLEXOS with daily resolution.

Figure 2. The six Saudi regions, as defined by the Saudi Electricity Company, and associated existing transmission interconnections.



Source: Authors.
Note: C = central region; E = eastern region; NE = northeastern region; NW = northwestern region; S = southern region; W = western region.

Similar to Elshurafa et al. (2021), we assume that Saudi peak load will increase from 62 gigawatts (GW) in 2018 to 75 GW in 2030, with the annual energy consumption reaching 444 terrawatthours (TWh). For a detailed description of the demand projections, one can refer to Soummane and Ghersi (2022).

Investment decisions on power plants, storage and network capacity are allowed from 2022 and beyond, but we consider the evolution of the Saudi power sector from 2018 (the year the model was calibrated to) to 2022 based on the publicly available data. Investment decisions are allowed for generation technologies (gas, PV, wind, concentrated solar power, nuclear, and batteries with four hours of storage) and transmission lines. We include the publicly announced RE projects in the Kingdom, which total 4.5 GW of solar PV and 1.3 GW of wind power. We also assume that oil-based power plants will be fully retired by 2030.

For transmission, we include the transfer capacity between the northwestern (NW) and western (W) regions to be commissioned in 2026. We allow the transfer capacity of existing lines to increase (see Figure 2) or the building of new lines between regions that are not currently connected (i.e., eastern (E)-northeastern (NE); central (C)-NW; C-southern (S) and eastern (E)- S). The additional transmission capacity is allowed in steps of 1 GW, with a maximum of 2 GW per interconnector from 2022-2030.

The capital and operating costs used are the same as those used in Elshurafa et al. (2021), except that the gas price is assumed to increase to US$ 2 per million British thermal units (MMBtu) from 2026, with the overnight transmission costs set at US$ 330,000 GW per kilometer (km) (The World Bank 2021).

We set a 10% capacity reserve margin (Saudi Electricity Company 2011) to be met by FC (not installed capacity), for every region. The FC of thermal generation is equal to its nameplate capacity, while the FC of renewables is as shown in Table 1. An hourly operating reserve has to be satisfied regionally (Mills 2017; KACARE 2018).

We initially modeled two cases, which would reach RE shares of 25% and 50% of electricity generated in 2030, without RE building constraints. The case using 25% renewables for electricity generation in 2030 fits approximately with public announcements (Vision 2030 2022; Saudi & Middle East Green Initiatives 2023), whereas the 50% target is more ambitious and used to assess the sensitivity of our results to RE penetration. We observed that RE is commissioned in 2030 to meet the electricity share constraint, i.e., RE is not gradually deployed before 2030 because of its high costs compared to other conventional technologies. To smoothen the representation of RE development and obtain more realistic results, another set of simulations was performed with a maximum RE capacity that could be deployed annually.

Scenarios Simulated

We assess the implications of varying three main assumptions: being optimistic or pessimistic regarding renewable energy in terms of FOR and FC, the maximum RE capacity that could be built annually, and the share of RE in total electricity consumption by 2030.

Optimistic-RE and Pessimistic-RE

FC and FOR are key parameters to model solar PV and wind power in a CEM. FOR is considered in a broader sense than what is generally intended for thermal generation units, i.e., FOR for PV and wind encompasses both mechanical failures and weather, similar to Milligan and Porter (2005). The literature suggests that wind turbines can provide 5% to 25% of FC (Tuohy and O'Malley 2011; Brouwer et al. 2014) and that the FOR is in the range of 50%-80% (Milligan and Porter 2005; Das and Basu 2020). For solar PV, the FC and FOR appear to range between 10%-30% and 10%-30%, respectively (Basu 2020; Das and Basu 2020). Table 1 summarizes the FOR and FC values considered for PV and wind for the Optimistic-RE (Opt-RE) and Pessimistic-RE (Pes-RE) scenarios. The firm capacity for PV is only available during daytime hours, whereas the firm capacity for wind is assumed to be throughout the day.

For all other conventional dispatchable units, we assume an FC of 100% and a FOR of 5%, according to the range found in the literature (Najjar and Abu-Shamleh 2020).

Table 1. Summary of scenarios FC and FOR assumptions.

Technology	FC		FOR	
	Pes-RE	Opt-RE	Pes-RE	Opt-RE
Solar PV	10%	30%	30%	10%
Wind	5%	25%	80%	50%

Note: The FOR for RE considers both mechanical availability and intermittency related to weather conditions.
Source: Authors.

Annual building constraint

This sensitivity analysis relates to how much RE can be built in a single year. In the unconstrained scenario, the model is free to build as much RE as is needed. However, in the constrained scenario, we limit the maximum annual possible builds of PV and wind to 6 GW each in the 25% RE scenario and 12 GW in the 50% RE scenario, respectively.

RE share of consumption

We test two RE targets for 2030: 25% and 50%. The RE target is implemented as a percentage of the electricity generation rather than power capacity.

Summary of scenarios

We have two variations for three main parameters, totaling eight scenarios. Table 2 names and summarizes these scenarios.

Table 2. Summary of scenarios simulated.

Scenario nlumber	Share of RE	FC and FOR assumptions	RE building constraints
S1	25%	Opt-RE	No
S2	25%	Pes-RE	No
S3	25%	Opt-RE	Yes
S4	25%	Pes-RE	Yes
S5	50%	Opt-RE	No
S6	50%	Pes-RE	No
S7	50%	Opt-RE	Yes
S8	50%	Pes-RE	Yes

Source: Authors.

Results and Discussion

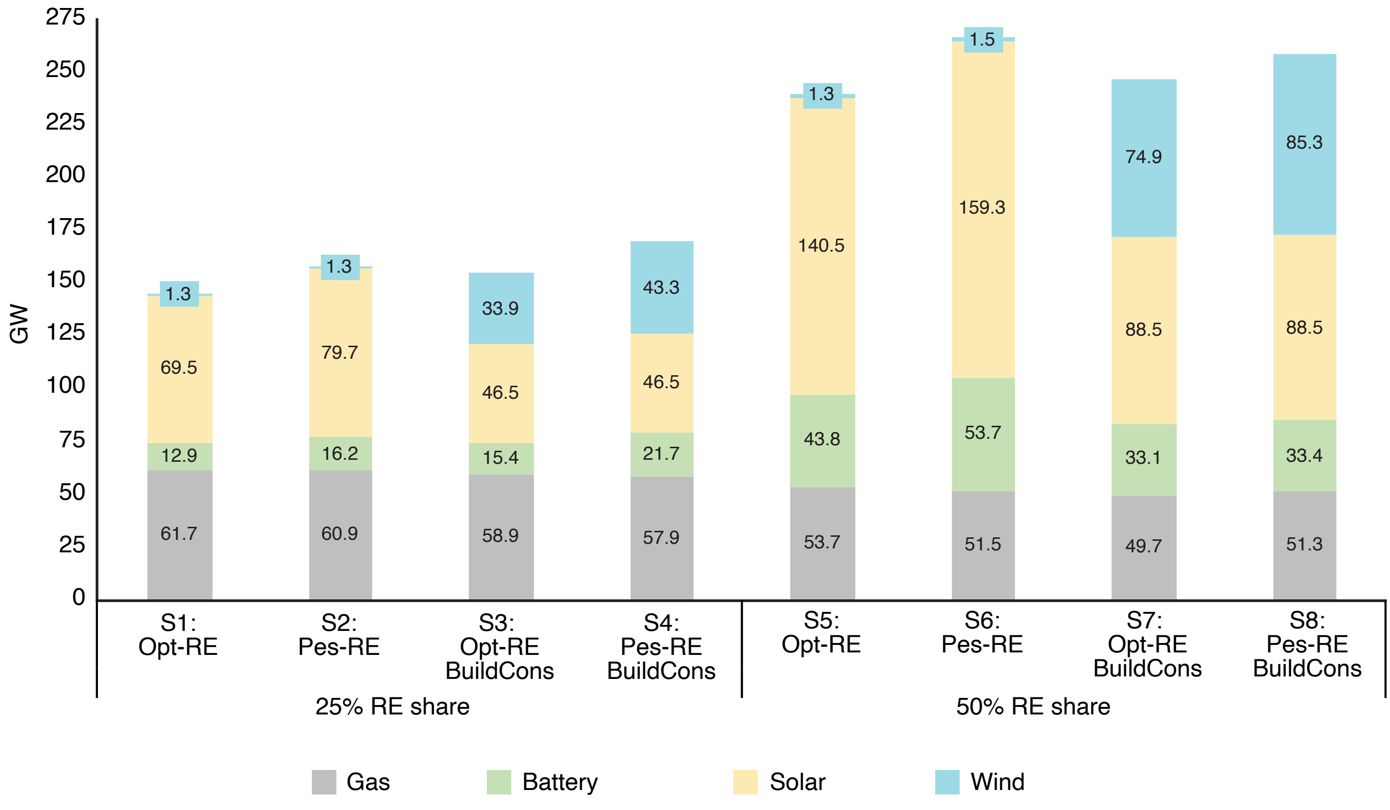
Technology Builds

Figure 3 shows the total cumulative capacity that would be installed in 2030 by technology obtained with our model in step 1 (see Figure 1). There are three insights that we would like to discuss.

First, we see that wind energy is still uneconomic compared with PV. In all scenarios without a build constraint, wind is hardly built and PV dominates deployment, supported by considerable storage. This trend is in line with observations from Breyer et al. (2022). Note that the 1.3 GW of wind power in the scenarios without annual building constraints (S1, S2, S5 and S6) corresponds to the capacity already announced and assumed to be deployed, i.e., does not come from the optimization model. Moreover, in the scenarios with annual building constraints (S3, S4, S7 and S9), the constraint on solar builds is binding, i.e., the maximum allowed solar capacity is deployed and wind is then used by the model to meet the renewable target. In other words, the solar capacity observed in these scenarios directly results from the annual building constraint imposed on solar power.

Second, we observe a difference in solar PV builds in the Opt-RE and Pes-RE (S1 vs. S2 and S5 vs. S6), which highlights the importance of estimating accurate FC and FOR for RE to avoid under- or

Figure 3. The total cumulative capacity built in GW for each of the eight scenarios by 2030.



Source: Authors.
Note: S = scenario; BuildCons = annual capacity building constraints.

over-investing in RE and unserved energy. Low FC assumptions for RE (i.e., Pes-RE scenarios) lead to more solar PV capacity in 2030. This situation occurs not only because of the cost difference between wind and solar, but also because electricity demand varies significantly between day and night, making it necessary to build considerable PV capacity to meet morning demand. At night, however, the available gas/storage/wind capacity is adequate to meet demand.

Third, we see that in the 50% scenarios the model opts to build considerable storage and little gas to handle the significant amount of overgeneration (i.e., minimize curtailment or dumping). Significant storage capacity is added to the system from 2026 to cope with RE variability. When RE penetration increases from 25% to 50%, storage capacity increases by 53% (S8 compared with S4) to 240% (S5 compared with S1).

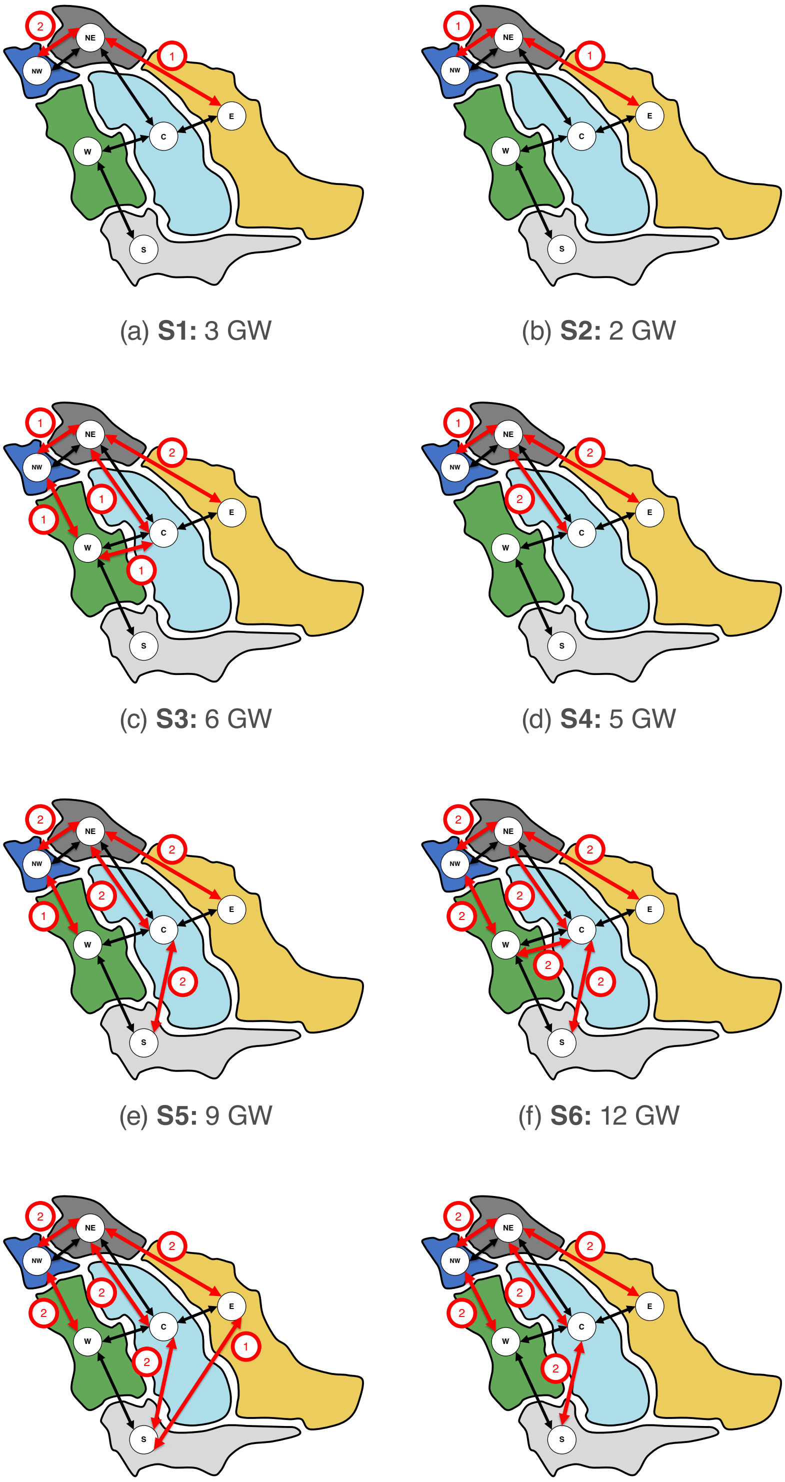
As expected, RE development leads to a decrease in carbon dioxide emissions over the simulated period (see Appendix). Compared with a business-as-usual scenario[3] where no RE target is set, annual emissions of the power sector are reduced over the simulated period 2018-2030 by roughly 30% in the 25% RE scenarios (S1 through S4), and by 44%-52% in the 50% RE scenarios (S5 through S8).

Transmission Builds

Figure 4 summarizes the network in 2030 based on all eight scenarios and specifies the new transmission builds (in red). Unsurprisingly, the maximum transmission interconnection capacity among all scenarios (i.e., 12 GW) is observed in scenario S6, which is also the scenario where the maximum RE capacity was deployed (see Figure 3). The model never chooses to build additional capacity between the central and eastern regions. The line that joins these regions has a capacity of 6.2 GW. However, all other existing lines have significantly smaller capacities.

Compared with the Opt-RE scenarios, we find that the model handles the additional RE builds with either additional battery deployment and/or additional transmission builds, as expected. For example, we see that in scenario S2, fewer transmission lines are built, but more battery capacity is deployed than in S1. No Pes-RE scenarios had both fewer lines and smaller battery capacities than the Opt-RE cases.

Figure 4. The transmission network in 2030 for all scenarios.



(a) **S1:** 3 GW

(b) **S2:** 2 GW

(c) **S3:** 6 GW

(d) **S4:** 5 GW

(e) **S5:** 9 GW

(f) **S6:** 12 GW

(g) **S7:** 11 GW

(h) **S8:** 10 GW

Source: Authors.

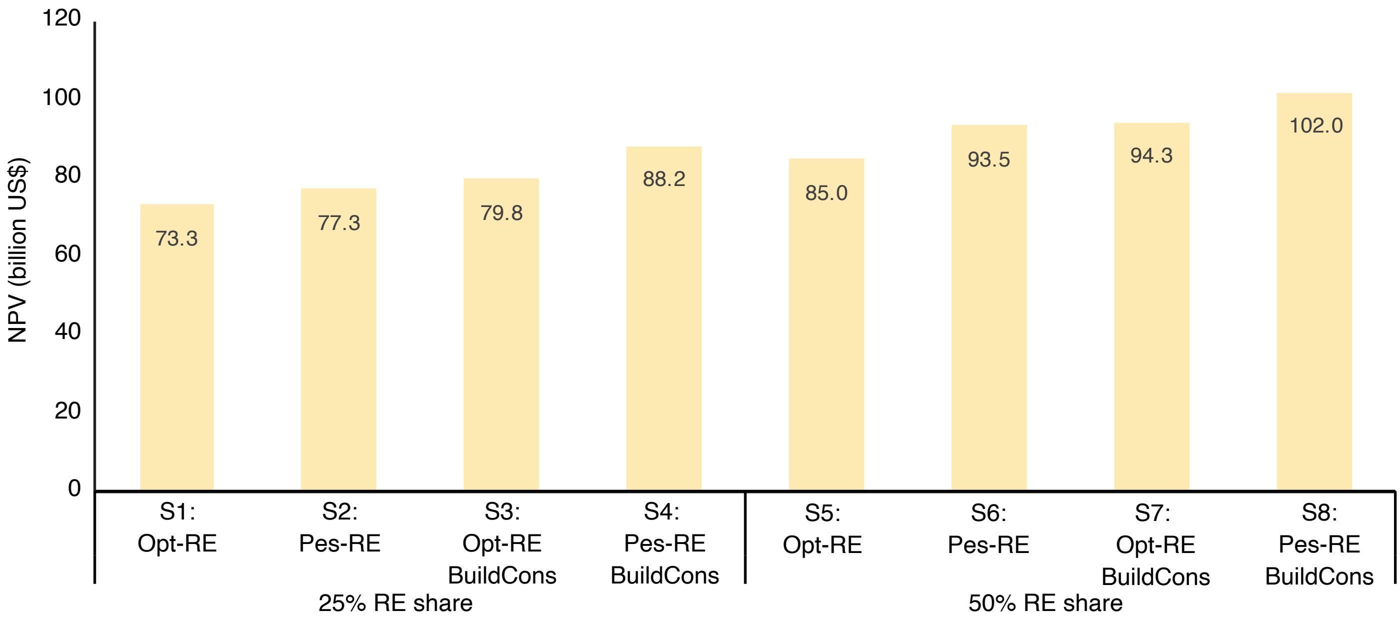
Note: The new transmission lines built are represented in red, and the number in the circle indicates the capacity of the added lines (in GW). The line that is planned to be built between the western and the northwestern regions is not shown for brevity.

Power System Costs

Investment decisions in the power sector are not solely driven by cost optimization. In many instances, decisions can be driven by policy considerations, including environmental concerns, for example. The net present value (NPV) of the costs for all scenarios is provided in Figure 5, using a discount rate of 5%. First, it shows that all Pes-RE scenarios result in a higher NPV than their Opt-RE counterparts. This increase in the costs of the Pes-RE scenarios compared with their Opt-RE counterparts ranges between 5% and 11%, which is considerable. Second, considering an annual RE build constraint also increases the NPV by a factor of 9%-15% compared to the counterpart with no annual build constraint. This additional cost is explained by the significant wind power deployed in these scenarios (which is less economic than solar in our case) to meet the renewable target, despite the bidding constraint on solar capacity.

Scenario 8 (50% RE with Pes-RE assumptions and an annual build constraint) results in the highest NPV of all the scenarios considered here, and represents approximately a 39% increase compared with a business-as-usual scenario where no RE target is set.

Figure 5. The net-present value (NPV) (5% discount rate) of the cost over the period 2018-2030 for all scenarios in billion US$, which includes all generation costs, storage costs, and investment annuities of new transmission lines.



Source: Authors.

Resource Adequacy

We assess the resource adequacy of the system through the loss of load probability (LOLP), which is defined as the probability that the available generation fails to meet the demand. Regional resource adequacy indices could be viewed through two lenses: (1) assessing the resource adequacy of each region, assuming that each region is a standalone geographical entity, and (2) assessing the resource adequacy of each region while incorporating the power than can be imported from neighboring regions through the available transmission interconnectors.

Our results show that the resource adequacy targets for all regions, considering power imports from neighboring regions, are met (i.e., the LOLP is less than 0.06%). However, here, we focus on the LOLP targets of the regions in isolation, which is an indicator focused on in the Saudi power sector.

Table 3 presents the estimated LOLP in 2030 for each region considered in isolation.[4] The target loss of load expectation, as indicated by the Saudi regulator, is five hours per year (KACARE 2018), which translates to a LOLP target of 0.06%. Hence, in Table 3, LOLP values are highlighted in green if they are below 0.06% and highlighted in red otherwise.

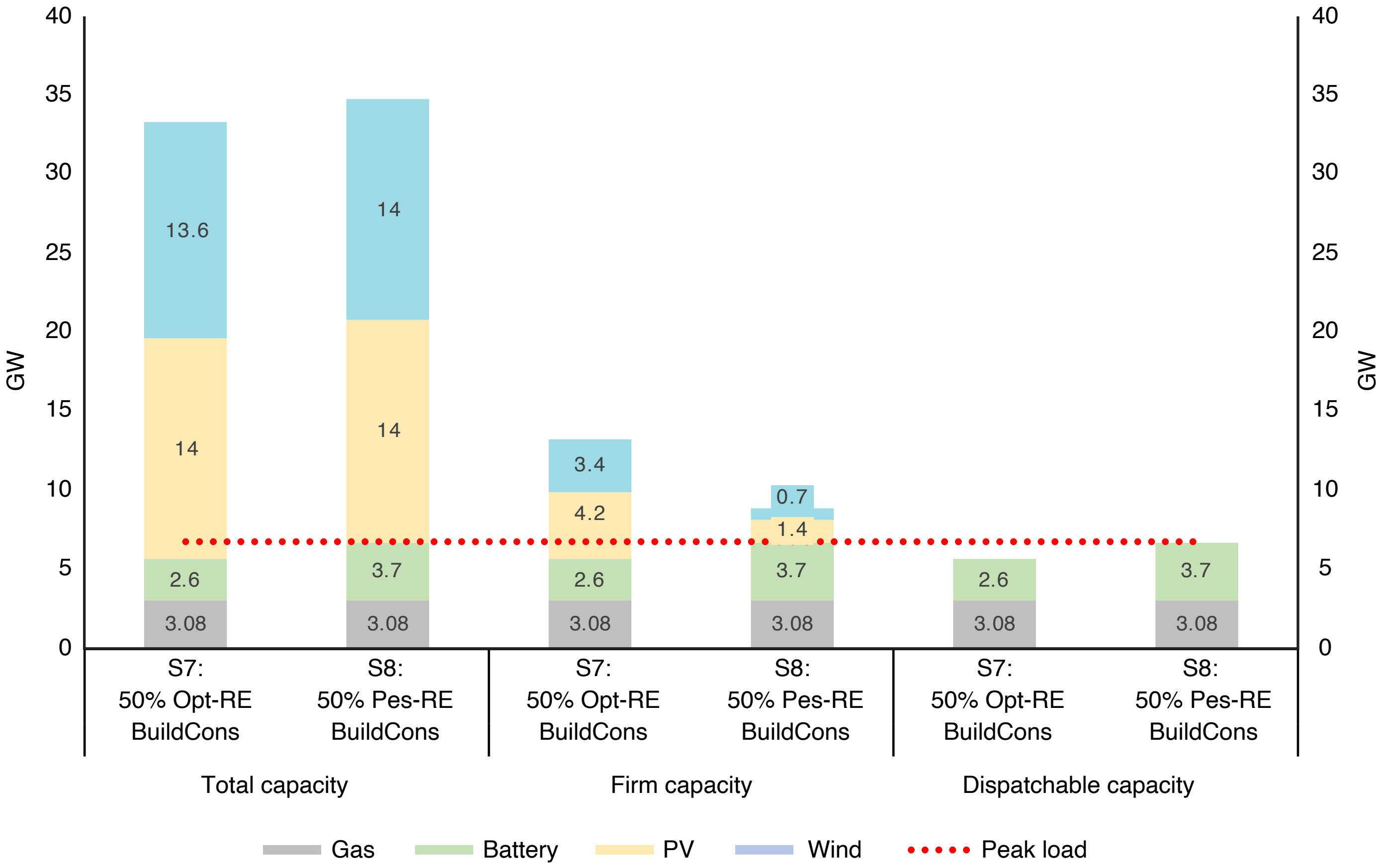
From Table 3, we see that no trend can be observed. A region could meet the LOLP target in an Opt-RE scenario but not in the Pes-RE scenario (e.g., the NW region in S1 and S2), or vice-versa (e.g., the W region in S3 and S4). Further, a region could simultaneously meet the LOLP targets in both Opt-RE and Pes-RE scenarios (e.g., the S region in S5 and S6), or simultaneously meet neither LOLP targets in both variations (e.g., the NE region in S1 and S2).

Table 3. Isolated-region LOLP values (%) in 2030, as simulated by the model.

Scenarios	Regions					
	C	E	NE	NW	S	W
S1: 25% Opt-RE	0.59	0.45	0.16	0.00	0.00	0.32
S2: 25% Pes-RE	0.00	0.00	0.56	0.07	0.00	0.00
S3: 25% Opt-RE BuildCons	0.80	0.35	0.00	0.00	1.44	0.50
S4: 25% Pes-RE BuildCons	0.34	0.77	0.03	0.49	0.03	0.05
S5: 50% Opt-RE	0.69	0.08	0.00	0.00	0.00	2.80
S6: 50% Pes-RE	1.22	0.00	0.00	0.00	0.00	0.27
S7: 50% Opt-RE BuildCons	2.24	0.00	0.00	0.00	6.67	7.31
S8: 50% Pes-RE BuildCons	0.00	0.00	0.00	0.00	0.00	0.00

Source: Authors.

Figure 6. Total built capacity, total firm capacity, and total dispatchable capacity in the southern region in 2030.



Source: Authors.
Note: The firm capacity is calculated based on the FC assumptions presented in Table 1 and 100% firm capacity for thermal units and batteries. The dispatchable capacity excludes renewables.

One of the highest LOLP values calculated in Table 3 is 6.67% for the southern region in S7. We take a closer look at this value in Figure 6, which presents the total installed capacity in the southern region by 2030, the consequent firm capacity considering the FC assumptions (see "Technology Builds," above), and the total dispatchable capacity, which excludes RE capacity.

As highlighted in Figure 6, installed capacity in S7 is around 33 GW, whereas firm capacity is around 13.3 GW, and total dispatchable capacity is only around 5.68 GW. Comparing the latter value to the regional peak load (6.78 GW) explains the LOLP of 6.67%. Indeed, the RE capacity has a high FOR and is unable to handle the 1 GW difference between the dispatchable capacity and the regional peak load observed in S7 while meeting the LOLP target. The dispatchable capacity appears to be slightly higher in scenario S8 (6.78 GW) than in S7, which, when added to the RE capacity, is sufficient to meet the regional peak load of 6.79 GW with a good level of reliability. Thus, the LOLP target is met in S8.

Similar trends were found in other regions. We reiterate that the LOLP values provided herein represent values for the regions in isolation. The LOLP values for all regions, while incorporating the transmission capacity from neighboring regions, are all within the allowed range.

Conclusion

In this paper, we quantified the extent to which varying the FC and FOR values of RE technologies would impact the modeling results of a capacity expansion modeling exercise. We find that variations in the FC and FOR values can have significant impacts on long-term power generation plans. Explicitly, and with Saudi Arabia as a case study, assuming pessimistic values for FC and FOR results in an increase of 11%, 17%, and 41% in electricity generation costs, emissions, and battery storage deployment, respectively, compared with assuming optimistic values.

As far as the impact of varying FC and FOR on reliability, no noticeable patterns were observed: The reliability status of regions (when viewed in isolation) can change or stay as they are with no observable patterns. Overall, this paper's results reaffirm the importance of collecting accurate RE-specific weather data to support effective RE deployment, as this can avoid significant over- or under-investment.

Endnotes

[1] The term 'load carrying capability' is used in Garver (1966), while 'capacity value' can be found in Milligan and Porter (2005) and Keane et al. (2010), and 'capacity credit' in Dent, Keane, and Bialek (2010) and Voorspools and D'haeseleer (2006).

[2] https://www.energyexemplar.com/plexos. This study was carried out with PLEXOS version 8.300.

[3] We have run a counterfactual business-as-usual scenario where no RE target was set for 2030, while keeping all other assumptions identical (including oil retirement by 2030).

[4] The LOLP was estimated in PLEXOS with daily resolution. This choice was motivated by the balance between accuracy and the time required to obtain a solution

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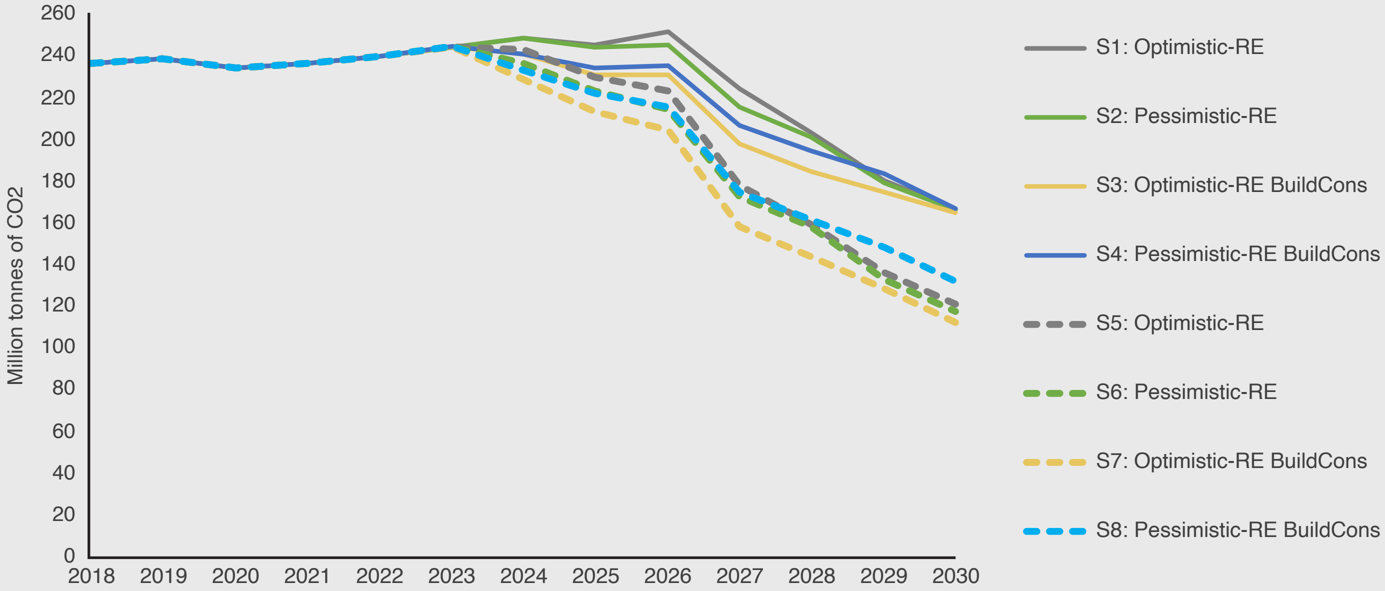
Appendix

Figure A1. Total power sector carbon emissions in million tonnes until 2030 for all scenarios.



Source: Authors.

Figure A1 shows the carbon emissions for each scenario. As expected, all scenarios result in a reduction in emissions compared with the base year 2018. The emission reductions are considerable in all 50% RE scenarios (i.e., S5 through S8).

In the 25% RE scenarios (S1 through S4), the total emission values in 2030 are similar at around 165 million tonnes. However, in the 50% scenarios (S5 through S8), the variation is larger, with S8 having in the most emissions.

Notes

About the Authors

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Amro is a fellow at KAPSARC with over 20 years of experience in energy and technology garnered on three continents. His research interests lie in renewable energy policy, power systems modeling, net-zero power, and hybrid microgrid design and optimization. He has led and executed several national modeling initiatives both at the distributed and utility scales. Some aspects of his research have been adopted by BP in creating their seminal annual statistical review. Credited with 50+ papers and patents, he holds a Ph.D. in Electrical Engineering and an MBA in Finance.

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Marie is a research lead in the Utilities & Renewables program at KAPSARC. Her current research focuses include power system modeling and market designs for energy transitions. Prior to joining KAPSARC, Marie worked on long-term and short-term electricity market design, transmission grids at the European scale and smart-charging opportunities for electric vehicles. Marie holds a Ph.D. in Economics from Dauphine University, PSL (France), an M.Sc. in Environmental and Energy Economics from École des Ponts ParisTech (France) and an M.Sc. in Engineering from ENSTA Institut Polytechnique de Paris (France).

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Frank is an engineer, energy policy analyst, and program director for the Utilities & Renewables program at KAPSARC. Prior to joining KAPSARC, Frank was a research professor at the School of Planning and Public Policy at Rutgers University and director of the Rutgers Energy Institute. He has conducted original and applied research in the areas of electric power system modeling, clean energy policies, and climate change for government agencies, energy companies and research institutions. He has also worked as an economic consultant and nuclear engineer. He earned his doctorate from the Massachusetts Institute of Technology.

About the Project

The undergoing energy transition heavily relies on the deployment of renewables such as solar photovoltaic (PV) and wind power for the generation of electricity. These variable and intermittent resources would modify power systems' reliability compared to the situation where electricity is generated by conventional dispatchable power plants. This project contributes to an understanding of how solar PV and wind should be modeled and how results from long-term planning are sensitive to these assumptions. This understanding helps to define their deployment and ensure a reliable and resilient power system.