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King Abdullah Petroleum Studies and Research Center

Achieving Renewable Energy Targets Without Compromising the Power Sector's Reliability

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About KAPSARC

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Key Points

Without proper measures and modifications, replacing as little as 5% of conventional generation with renewable energy sources can severely deteriorate a power system's reliability.

To avoid any disruptions, conventional reserves are needed even in power systems with overbuilt renewable generation. Renewable generation alone cannot economically achieve reliability targets.

Conventional generation failures are sensitive to temperature. Thus, models that link generation failures with temperature provide more realistic system reliability estimates.

Temperature is closely linked with both reduced generation from renewables and increased demand. This is to be put into consideration when deploying renewables in the Kingdom given its hot climate.

Understanding the correlations among demand, renewable generation and temperature is vital for reliably operating a power system and transitioning to renewable energy sources. The specific relationship between these factors is unique to each power system and must be quantified to accurately study power system reliability.

Summary

Saudi Arabia's Ministry of Energy has set ambitious renewable energy goals. Although the Kingdom's current energy mix is dominated by conventional energy (>95%), it aims to draw 50% of its energy from renewable sources by 2030. Currently, the Kingdom enjoys very high solar photovoltaic potential, and it is also well positioned for wind generation. Thus, studying the reliability of highly renewable power systems and the impact of converting conventional generation to renewable energy is of paramount importance. The latter analysis is important because temperatures in the Kingdom are often high for a considerable portion of the year.

Given this context, we propose improvements to the probabilistic modeling of power systems with a high share of renewables. Specifically, we model wind turbine availability states to forecast wind farms' power generation and adjust generators' forced outage rates (FORs) based on temperature. We also use a resource adequacy model to inform a detailed load flow analysis. We implement these improvements using the Monte Carlo method to calculate the loss of load probability (LOLP) and expected unserved energy (EUE) metrics. We report the impacts of these improvements on these metrics. Our proposed methods can be used to better guide system operators in maintaining system reliability as they transition to renewable energy sources.

We find that these model enhancements can significantly impact the reliability metrics of a power system with a high share of renewable energy. Specifically, we find the following results:

> The simulation of wind turbine failures increases the LOLP by 7.5%, with a negligible impact on EUE.

> Adjusting FORs based on temperature increases the LOLP by 36% and increases EUE by 5%.

> When the two scenarios are combined, the LOLP increases by 60% and EUE increases by 14%.

In particular, higher temperatures impact outage rates. Temperature is highly correlated with demand, and renewable energy sources are highly variable. Taken together, these findings highlight the need to maintain adequate conventional reserves regardless of energy targets. Failing to do so will severely compromise the power system's reliability.

Introduction

The share of renewable energy sources (RES) in power systems is growing rapidly (Staffell and Pfenninger 2018). However, some types of RES, such as wind and solar photovoltaics, are characterized by inherent intermittency and the inability to provide some crucial ancillary services. Thus, reliability concerns are also growing (Bremen 2010; Engeland et al. 2017; Kroposki 2017). It is widely accepted that power systems can generally accommodate small shares of RES with negligible impacts on operations. As the share of RES becomes significant (e.g., above 50%), however, the flexibility, stability and reliability of a power system becomes a genuine concern (IEA 2017). This study therefore focuses on power system reliability, with an emphasis on systems whose RES shares are large.

To gauge the reliability of a power system, we consider the loss of load probability (LOLP) and expected unserved energy (EUE). These metrics are among the most used indices for evaluating a power system's reliability (Al-Shaalan 2019; Fazio and Hua 2019). We incorporate the impacts of wind turbine failures and temperature in our calculations of the reliability indices. Doing so allows us to better evaluate the reliability of power systems with very high shares of RES (i.e., above 50%). We then augment these results with a load flow analysis to evaluate the extent to which these enhancements impact the reliability indices. Based on these enhancements to the model, we find that the reliability indices may vary by as much as 35%.

A. The Saudi context

Saudi Arabia is extremely well positioned to benefit from its wind and solar resources. It is ranked sixth globally in terms of solar energy potential, with an average of 8.9 hours of sunshine per day. Its average daily horizontal irradiation is 5,600 watthours per square meter. In terms of wind resources, it ranks 13th globally, with average onshore wind speeds of 6-8 meters per second (Saudi Arabia General Investment Authority 2018). Despite this wealth of renewable energy potential, however, the Kingdom's current energy mix is almost entirely conventional (i.e., over 99%). It depends on natural gas and liquids for energy production.

Recently, the Kingdom outlined ambitious goals to cut back on liquid fuels and achieve a 50% renewable power system by 2030 (Saudi Press Agency 2021). However, because RES can impact reliability, these plans must be studied carefully to ensure that the power system's reliability is not compromised. By analyzing a system that closely resembles the Kingdom's proposed targets, we can anticipate pain points and devise consistent, accurate instruments to evaluate its reliability.

Moreover, in the Saudi context, it is important to consider the role of temperature in the power system. The Kingdom uses most of its electricity to satisfy the demand for air conditioning, which is highly dependent on the temperature. However, wind and solar energy sources are adversely affected by higher temperatures, and conventional generation's failure rate tends to increase with temperature as well. Temperature therefore has a compound effect on reliability, as it both increases demand and decreases generation. Thus, we also include temperature and its effect on outages in our analysis. We aim to quantify its impact on the reliability of power systems with high RES shares.

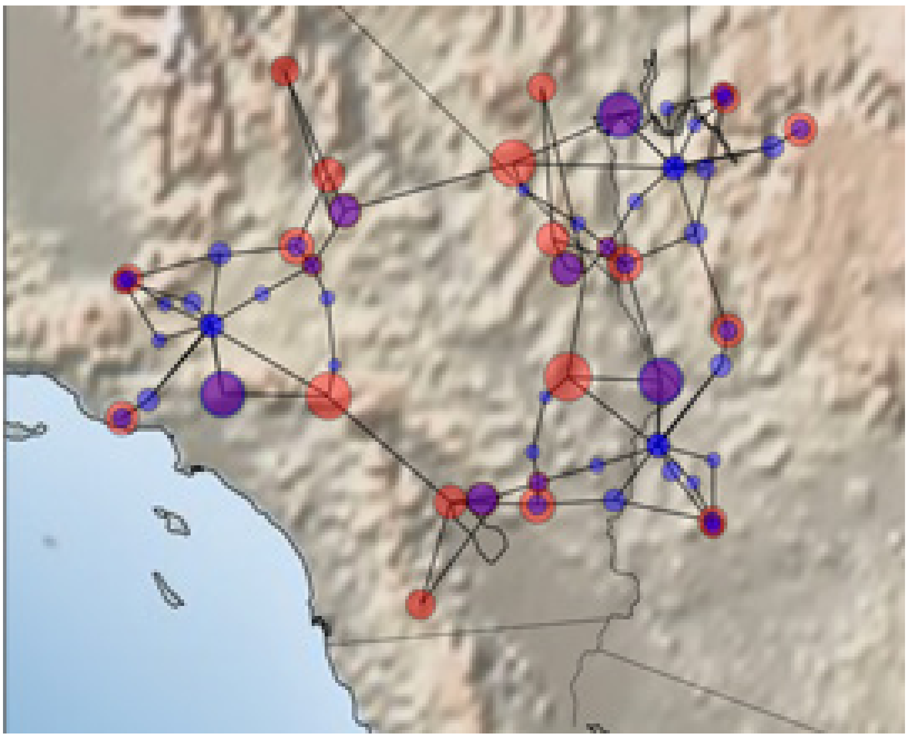
Methodology

A. Model

We use the Reliability Test System-Grid Modernization Lab Consortium (RTS-GMLC) as the model power system for our analysis (Barrows et al. 2020). This system features a modern generation fleet with many natural gas generators and renewable generation, which comprises over 50% of conventional generation in the system. The RTS-GMLC incorporates 157 generators spread over three areas with a mix of conventional generation and RES. The total generation capacity of the RTS-GMLC is 14.5 gigawatts (GW). Of this capacity, 5.2 GW come from RES, including 2.5 GW from wind and 2.7 GW from solar resources.

To better understand the effects of our model enhancements on the system's underlying reliability, we consider several metrics in our analysis. We define the LOLP as the probability that at least one shortfall event occurs in any given year. A shortfall event occurs when demand is higher than generation for any single hour. The LOLP does not reflect the magnitude or duration of a loss of load event. Thus, we also use two other metrics: the loss of load expectation (LOLE) and the loss of load hours (LOLH). These metrics are given in units of days per year and hours per year, respectively (North American Reliability Corporation 2018). Finally, to gauge the severity of loss of load events, we use the EUE, defined as the average unserved energy per shortfall event.

Figure 1. Node map of the RTS-GMLC, showcasing its location in the southwest United States and the system elements.



Source: Barrows et al. (2020).

B. Enhancement 1: Simulation of wind turbine failure states

Each wind farm comprises many wind turbines, and each turbine has a non-negligible failure rate (Spinato et al. 2009). We model the four wind farms in the RTS-GMLC as clusters of individual turbines, each with its own independent forced outage rate (FOR). We select a turbine model from the National Renewable Energy Laboratory (2020) and take wind speed data from Draxl et al. (2015). With these inputs, we create a generation profile for wind for the year 2020. We then simulate the availability states of each turbine in the four wind farms. Summing the generation of the turbines in each wind farm gives the total hourly wind farm generation.

C. Enhancement 2: Temperature-adjusted FOR

Generator failure is correlated with temperature (Murphy, Sowell, and Apt 2019). Moreover, both demand and RES generation depend on temperature (Felder 2004; Lledó et al. 2019; Staffell and Pfenninger 2018). Thus, temperature's effect on conventional generator availability should be quantified to better gauge its overall impact on system reliability. Common practice in the industry is to use winter and summer adjustments (North American Reliability Corporation 2012). In contrast, Murphy, Sowell, and Apt (2019) use historical generator outage data to calculate temperature correlation coefficients for different types of generators. We propose using similarly calculated temperature coefficients to adjust the FORs of generator units throughout the simulation.

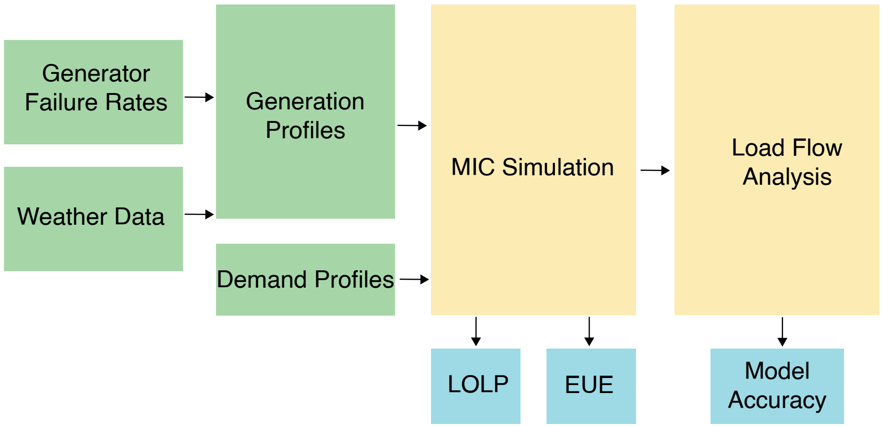
D. Resource adequacy informs the detailed load flow analysis

Conducting a load flow analysis of a large power system over a full year is computationally expensive. Including this analysis in the Monte Carlo (MC) simulations that we use would exhaust computational resources further. Conversely, a resource adequacy model can be evaluated in a fraction of the time required for a full load flow analysis. With our model, we can identify the parameters that lead to the highest risk of load supply failure. Then, we perform detailed load flow analyses using the generation availability states from the resource adequacy model. We reserve these detailed analyses for cases that are close to shortfalls, which we term 'close-call' events.

E. Impact of increasing the RES share on reliability

We study the effect of increasing the share of RES on a system's reliability. We model this increase by reducing the generation capacities of all conventional generators in the system proportionally to their share of generation. We correspondingly increase the generation capacities of RES using a similar method. Thus, we can study the impact of replacing conventional generation with RES. We can also estimate the necessary level of RES to replace a given amount of conventional generation to maintain the same LOLP.

Figure 2. Block diagram of the modeling methodology.



Note: Inputs are green, modeling steps are orange and outputs are blue.

Source: Authors.

Results And Discussion

A. Modeling setup

In our model, we consider four scenarios:

Scenario 1: Base, no enhancements enabled.

Scenario 2: Turbine failure states enabled.

Scenario 3: Temperature-adjusted FORs enabled.

Scenario 4: Both turbine failure states and temperature-adjusted FORs enabled.

We run all scenarios for five separate demand profiles. The base demand profile is sourced from the RTS-GMLC time-series dataset. To study the impacts of increased or decreased loads on the system, we also create four other demand profiles. These profiles are created by scaling the base profile in increments of 15%. Two demand profiles are lower than the base, and two are higher. We use the same demand profiles in each scenario. We calculate the reliability metrics for each scenario following the process explained earlier.

B. Results

Table 1 shows the reliability metrics for the four scenarios for the base and +15% demand profiles. The system experiences no loss of load events in any scenario if demand is below the base level. This result is due to the general overprovisioning of the RTS-GMLC, as Barrows et al. (2020) mention. We find that the simulation of turbine failure states increases the LOLP by 7.5%. The temperature adjustment increases the LOLP by 36%, and the combined turbine failure simulation and temperature adjustment increases the LOLP by 62%.

For the base demand profile, the LOLP, LOLE and LOLH are equal. In this profile, a loss of load event occurs in at most one hour in each simulated year. As demand increases, however, multi-hour events may occur within a single day, and single-hour events may occur on multiple days in a simulated year. The standard reliability target for a system is one loss of load event every 10 years, or an LOLE of 0.1 days per year. Thus, these results indicate that the system as evaluated is well equipped at the base demand profile and in all scenarios. However, the results for higher demand profiles demonstrate the system's sensitivity to fluctuations in demand. A detailed analysis of the results shows that hours with minimal to no renewable generation primarily drive this greater occurrence of shortfall events.

Figure 3 shows the correlation matrix of wind farms and demand in the RTS-GMLC dataset as a heat map. The figure also includes typical meteorological yearly temperature data for the location, taken from Sengupta et al. (2018). The shortfall hours are aligned with higher demand in the dataset, namely hours with low wind production and higher temperatures. For this reason, we find a minimal impact on the EUE when simulating the failure states of wind turbines.

Table 1. Reliability metrics results.

Demand	Scenario	LOLP	LOLE (days/year)	LOLH (hours/year)	EUE (MWh/hour)
Base	Base	0.0017±0.0001	0.0017±0.0001	0.0017±0.0001	118.5392±5.3982
	Turbine	0.0019±0.0001	0.0019±0.0001	0.0019±0.0001	119.6778±6.5306
	Temp	0.0024±0.0001	0.0024±0.0001	0.0024±0.0001	124.468±4.5754
	Turbine + Temp	0.0027±0.0001	0.0027±0.0001	0.0027±0.0001	134.8118±6.3649
+15%	Base	0.8171±0.001	1.5799±0.0029	1.6637±0.0035	179.2337±0.3657
	Turbine	0.8468±0.0011	1.7424±0.003	1.8382±0.0033	179.6649±0.2464
	Temp	0.8618±0.001	1.8218±0.0037	1.9289±0.0044	183.6544±0.6048
	Turbine + Temp	0.886±0.0008	1.9994±0.0032	2.124±0.0035	183.788±0.3332

Source: Authors.

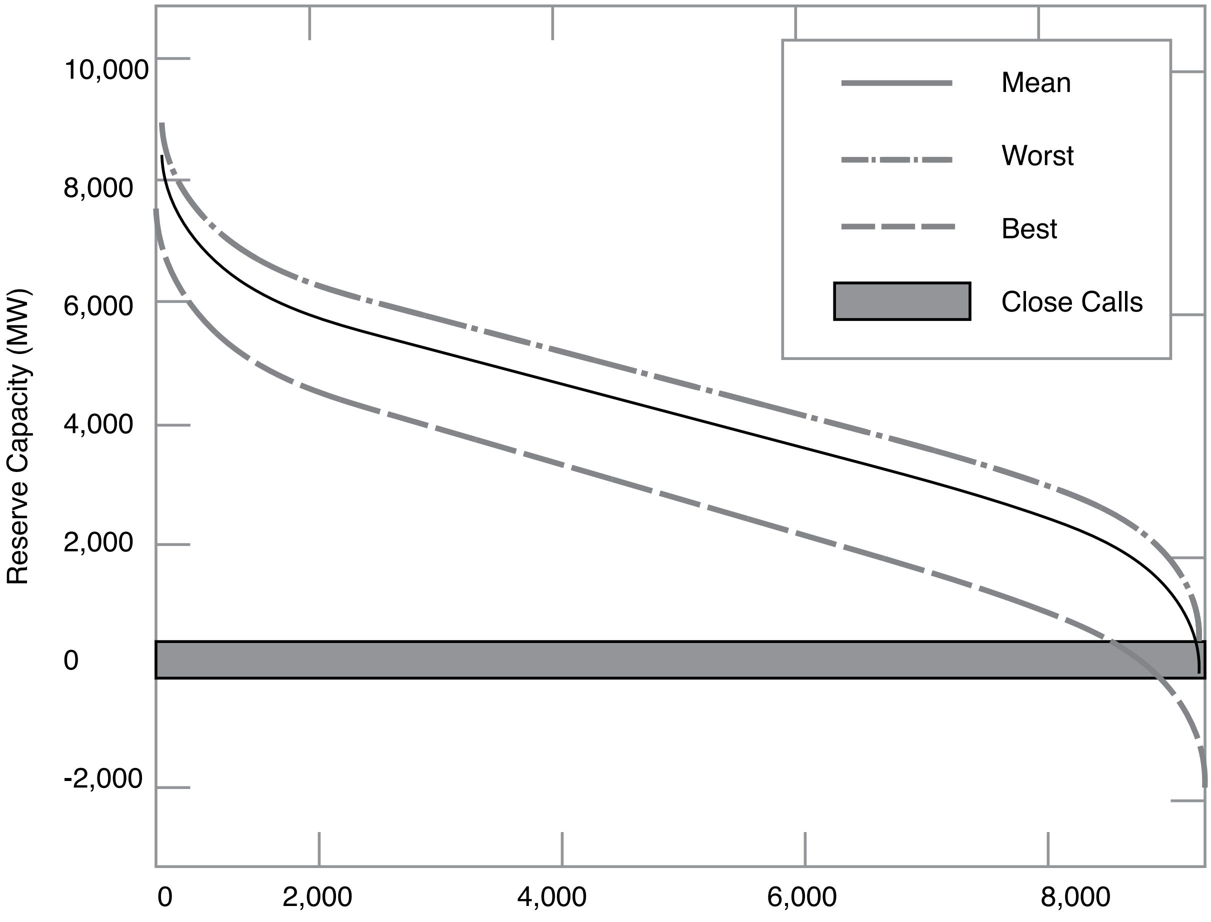
Figure 3. Correlation heat map of demand and wind resources alongside temperature.

	309_WIND_1	317_WIND_1	303_WIND_1	122_WIND_1	Total Wind	Total Load	Temperature
309_WIND_1	1.00	0.72	0.75	0.64	0.82	-0.31	-0.25
317_WIND_1	0.72	1.00	0.61	0.87	0.93	-0.34	-0.31
303_WIND_1	0.753	0.61	1.00	0.59	0.83	-0.28	-0.22
122_WIND_1	0.64	0.87	0.59	1.00	0.91	-0.33	-0.31
Total Wind	0.82	0.93	0.83	0.91	1.0	-0.36	-0.31
Total Load	-0.31	-0.34	-0.28	-0.33	-0.36	1.00	0.50
Temperature	-0.25	-0.31	-0.22	-0.31	-0.31	0.50	1.00

Source: Authors.

Figure 4 shows the distribution of hours by reserve capacity as well as our cutoff for 'close-call' events. These events lie between those that we consider to be shortfall events and those that we find to be safe events with high confidence. Using the less-constrained resource adequacy method to pinpoint problematic conditions for further analysis can reduce computation time while retaining a high level of accuracy. The close-call margin can be adjusted dynamically to either reduce the run time or increase the accuracy of the results.

Figure 4. Reserve capacity graph with mean, worst case and best case reserve capacities at each hour across all MC simulations and the threshold for close calls.

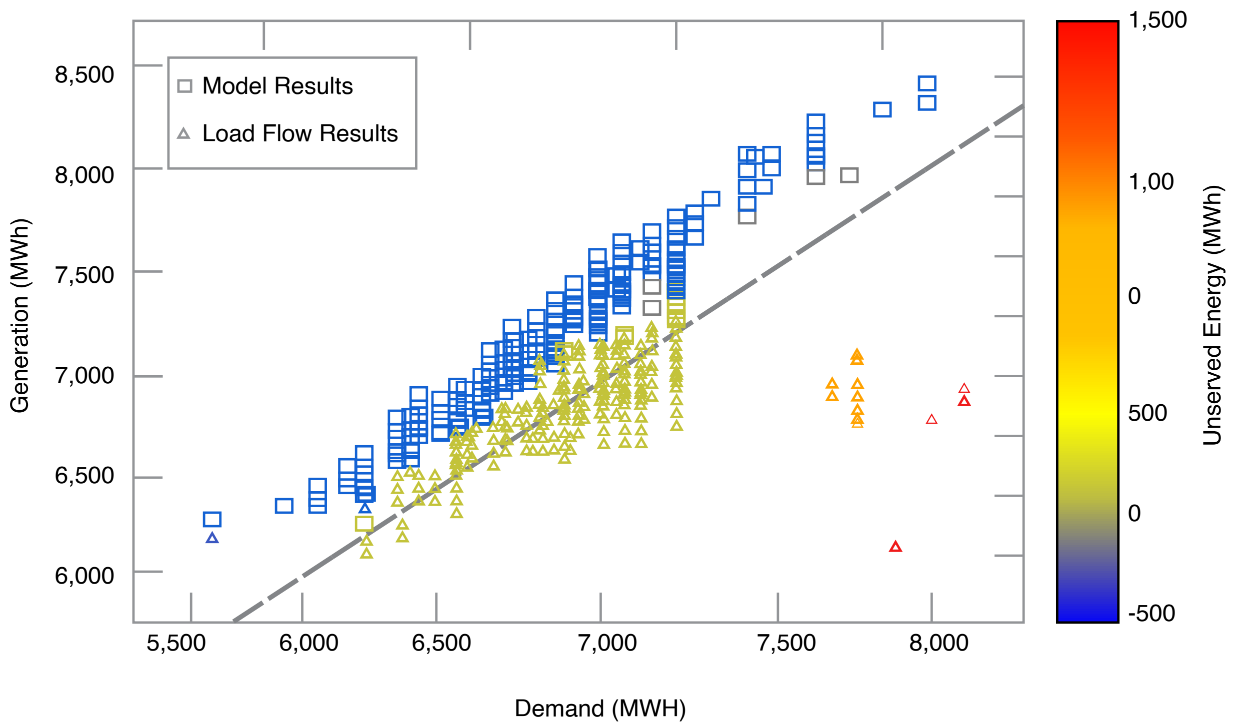


Source: Authors.

Results and Discussion

We conduct a load flow analysis for these close-call hours using the pandapower tool (Thurner et al. 2018). The results are shown in Figure 5. Additionally, Table 2 compares accuracies at different close-call margins for the base scenario.

Figure 5. Close-call analysis results.



Note: The graph shows the model results alongside load flow results at the close-call margin of 500 megawatt hours (MWh). The results below the dashed line constitute shortfalls. The color of each datapoint is based on the difference between generation and demand at that point.

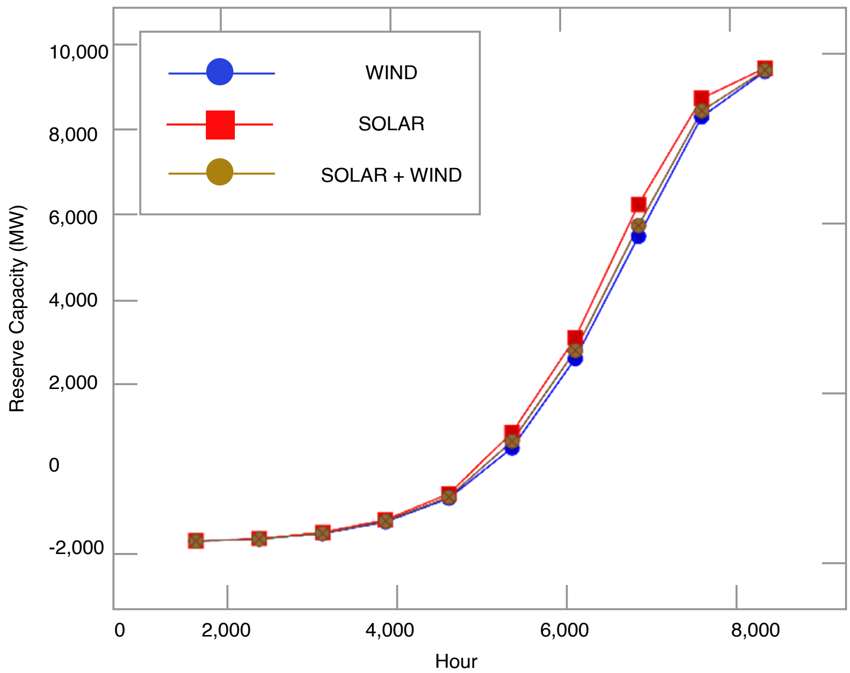
Source: Authors.

Table 2. Close-call analysis results.

Margin (MWh)	Close Calls (Hours)	Load Flow Shortfalls (Hours)	Marginal Model Accuracy (%)	Cumulative Model Accuracy (%)
100	24	20	17.77	17.77
200	60	40	44.44	33.33
300	130	62	68.57	52.31
400	282	93	79.61	67
500	574	144	82.53	74.91

Source: Authors.

Figure 6. LOLP of the RTS-GMLC when conventional capacity is increasingly replaced with renewable capacity, with total capacity remaining fixed.



Source: Authors.

Figure 6 shows the effect of increasing the percentage of RES while keeping total installed capacity constant on the LOLP of the RTS-GMLC. We increase the capacity of renewables from its initial level in increments of 1% of total installed capacity. When we replace conventional generation with wind resources, the system's reliability degrades quickly. This finding is expected given wind generation's lower capacity factor relative to the conventional generators that it is replacing (Lledó et al. 2019).

Conclusion

In this study, we proposed several enhancements to models of power system reliability to capture the impact of renewables. We find that simulating the failure states of wind turbines is a useful enhancement. This extension of the model is particularly valuable when the reliability of turbines and their subassemblies degrades, which can occur with age. In the base scenarios, the simulation of turbine failure states increases the LOLP by 7.5%. The impact on the EUE is less significant owing to temperature-related factors. The adjustment of conventional generators' FORs increases the LOLP by 36% and the EUE by 5%.

Our method can be used to simulate operational temperature ranges. Thus, it can capture existing failure scenarios, such as the 2021 Texas blackouts (Busby et al. 2021). In the case of turbines, which are not protected against cold weather, the FORs can be increased when temperatures go outside the safe limits. Thus, failure rates can be defined for specific temperature ranges. This method can also be used to simulate differing turbine-specific failure rates if the variability of component failure rates is known in advance. Other cases, such as updated turbine technologies and newer models, can be handled similarly.

This method can also be used to model failures at extremely high temperatures in the Kingdom. However, applying these methods to the Kingdom requires knowledge of failure temperature correlation coefficients. Historical outage data and readily available historical temperature data are necessary to calculate these coefficients.

Another issue that arose during this study is the potential for transmission networks to cause shortfall events. When decentralized or distributed RES is introduced, the load on transmission networks designed exclusively for conventional generation will increase. Transmission network studies and upgrades are therefore also necessary in understanding the impacts of the renewable energy transition.

Finally, future work will include assessing common-cause failure states of wind resources and the correlation between wind and other renewables.

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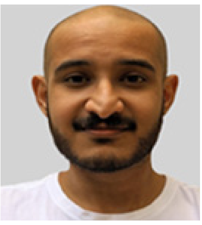
Notes

About the Authors



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Nezar is an engineer with a bachelor's degree in electrical engineering from King Saud University. He interned with the Energy Transitions and Electric Power team at KAPSARC, working on power system modeling and probabilistic reliability analysis. His prior experience includes solar system modeling and deployment and microcontroller programming.

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Frank is an engineer, energy policy analyst and Program Director for Energy Transitions and Electric Power. Prior to joining KAPSARC, Frank was a Research Professor at the School of Planning and Public Policy at Rutgers University. He served as Director of the Rutgers Energy Institute and Director of the Center for Energy, Economics and Environmental Policy. In those roles, he conducted original and applied research. His research areas were electric power system modeling; clean energy policies; and climate change for academic foundations, government agencies and energy utilities. He has also worked as an economic consultant and nuclear engineer.

Amro Elshurafa

Amro is a research fellow at KAPSARC with nearly 20 years of experience in the fields of energy and technology across three continents. His research interests are renewable energy policy, power systems modeling, and hybrid microgrid design and optimization. He has led and executed several national modeling initiatives on both the distributed and utility scales. Credited with over 40 papers and several patents, Amro holds a Ph.D. in electrical engineering and an MBA in finance.

About the Project

This project analyzes the ramifications for power system reliability of converting a large share of conventional generation to renewable energy in the Saudi power sector. Our research stems from the Saudi government's recent announcements that the Kingdom will fully rely on gas and renewables for power in the future.

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