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RESEARCH ARTICLE

Impact of Loads and Photovoltaic Uncertainties on Cascaded Failure in Transmission Networks of Future Power Grids

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ABSTRACT The increase investment of renewable energy resources (RESs) into power systems, such as solar photovoltaics (PVs), introduces additional uncertainty in transmission line loading. This uncertainty adds challenges to cascading failure analyses of power systems especially in future power scenarios of high penetration of RESs. In this paper, cascaded failures of power systems caused by the sequence tripping of transmission lines in the presence of RESs (mainly PV systems) is analyzed. By studying the lost power and the line failure probability, the potential impact of integrating more RESs on cascaded failures is investigated. In this regard, the uncertainties of RESs are examined by adding PV systems probability distribution function that reflects the solar irradiance for a typical day.A transmission-boosting approach is proposed in this paper to minimize the impact of failure risk to mitigate the possibility of the cascaded failure caused by the increased penetration of RESs. This paper presents a systematic approach to mitigate the risk of cascading failures via reconducting of transmission lines. Simulation studies for different penetration scenarios of PV systems have been carried out to test the impact on the cascaded failure and to validate the proposed transmission-boosting approach. The results in this paper imply that the increase in penetration of PV systems in the power grid would increase the potential of both cascaded failure risk and occurrence. In addition, the results have shown the efficacy of the proposed transmission-boosting approach in minimizing the cascaded failure risk when implemented. The findings have been validated using the modified version of the IEEE 39-bus test system modeled and simulated in Matlab.

INDEX TERMS Cascaded failures, photvoltaic energy systems, steady-state analysis, transmission-boosting.

I. INTRODUCTION

Cascading failures of power systems have been analyzed extensively in the literature, defined as a sequence of outages initiated by one or more disturbances that may lead to a large blackout. A large blackout may be defined as an unplanned electricity service disruption lasting more than 5 minutes and impacting at least 300 MW of demand or 50,000 customers [1]. An exogenous event may initiate the cascaded failure process, which leads to dependent events, described as a sequence of events earlier in the power system that causes a blackout. These dependent events include overloading of transmission lines, generator rotor dynamics instability, or even voltage collapse [2]. The

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initiating or exogenous event may cause dependent events that may lead to a blackout. From a timeline point of view, the cascading process can be divided into two phases [3]: slow and fast. The slow phase can extend from several minutes up to hours. The cascade then escalates quickly from tens of seconds to milliseconds for the fast phase, where transmission lines overload propagation and power system dynamics related to the frequency and voltage stability are present. A similar observation was reported in [4], where the authors analyzed the acceleration in cascading outage records. Differences arise between extreme and common cascades in terms of acceleration. Common cascades showed a more modest acceleration. Accounting for a stochastic model based on power flow redistribution, the authors in [5] developed a model that captures the cascading failure propagation. Also, the authors in [6] presented an algorithm that finds collections of n-k contingencies which initiate large cascading failures in power systems. The developed algorithm which was verified by simulations is found faster than the random search algorithm. It is worth noting that, the authors developed an AC power flow algorithm to simulate cascading failures that are publicly available. Similarly, in [7], the authors combined a random chemistry algorithm with outage probabilities to estimate the overall risk of large cascading failures. The authors in [8] analyzed the cascading failure process severity based on historical and simulation data where uniform and non-uniform probability distributions were considered for the initial line trips in the simulation for the cascading failure. The authors in [9] presented a method to construct a Markovian influence graph that described failure propagation. It was reported that the outage probabilities of a given component depend on the outages that happened in the prior generation. Simulations of a given system can construct the influence graph. On the other hand, the authors in [10] analyzed a series of blackout data. They offered insights into blackout risk, the nature of cascading failure, critical points' significance and occurrence, and the complex system dynamics of blackouts. A power law distribution has been observed in blackout data and was reproduced in blackout models of power systems. The topological behavior in cascading failure propagation has been also studied in several works [11]. In [12], the authors analyzed the topological structures that may prevent failure from spreading. The propagation of transmission line failures was analyzed using a network graph structure by the authors in [13] and [14]. Their findings were presented in two scenarios: one where the post-contingency network stays connected and another where the failure propagation causes the network to split into multiple islanding networks.

RESs are expected to take a significant share of power generation globally. In fact, RESs have already registered high share levels in many countries. One of the most used and salient examples of RESs is PV systems. Despite the advantageous characteristics of grid-connected PV systems, the extensive penetration levels of such sources might also cause some challenges and issues, such as increasing the system's vulnerability to external events that may cause cascaded failure. Few studies on the cascading failure of power systems with RESs can be found in the literature. For instance, the authors in [15] employed a graph-based approach using a thermal-inertia-based cascades model to analyze power system vulnerability to cascading failures considering RESs in the power system network. Their results showed that with increasing uncertainty levels of the RESs, the power systems' vulnerability to cascading failures increases. The authors in [16] provided benchmarking for cascading failure models. Potential test buses that can be used for cascading failure analysis with high penetration of RESs were also introduced. In addition, the authors [17] developed a model to simulate cascading failures of power systems, which included frequency control dynamical processes. The authors analyzed the difference between synchronous machine-based generation nodes and power electronics-based generation nodes, interfacing RESs. Simulations showed that increasing the renewable energy penetration would potentially lead to an increase in the risk of power outages. The authors in [18] proposed a cascading failure risk quantification framework in power systems with high penetration of RESs. They developed a dynamic model that has the ability to capture the frequency-related dynamics during the cascading failure. An approach to simulate cascading failures in power systems based on the thermal stability of transmission lines outage and automatic power balance has been proposed in [19]. The simulation approach was then used to analyze the impact of wind energy integration. Their findings showed that wind generation uncertainty severely affects grid vulnerability to cascading overloads. The authors in [20] analyzed the grid vulnerability to cascading failures under high penetration of wind energy systems. The analysis was carried out using a dedicated model developed by the authors incorporating AC power flow. It was shown that the developed model produced comparable results to historical data on power outages as well as other existing methodologies. However, these studies have not considered the impact of solar generation. On the other hand, few works have tried to account for the impact of solar PV generation on the cascaded failure. The authors in [21] studied the variability of solar generation farms, where they modeled the output power's probability distribution function (pdf) using three methods; Analytical, non-sequential Monte Carlo, and sequential Monte Carlo. The results showed that the three methods have comparable results. The authors did not evaluate cascading failures with the presence of solar generation. The authors in [22] proposed a real-time risk assessment for cascading failures for power systems with high penetration of RES. Fault graph chains were fitted through nonlinear mapping with the risk indicators of the cascading failure. The nonlinear mapping was done through cascaded graph neural networks, which include convolutional neural network (GCN) layers and multi-layer perceptron (MLP) layers. However, neither the type of RESs nor the uncertainties have been studied in detail.

Several strategies have been implemented to increase the power transfer capacity of existing transmission lines. The authors in [23], [24] and [25] dealt in more depth with the physical details of the transmission tower and the conductor material of the transmission line to increase the power transfer capacity with practical applications and case studies on transmission lines and power grids. The authors in [26] laid out several strategies to mitigate the risk of cascading failure and blackouts. While reconductoring was not analyzed, improving other physical aspects of transmission lines was discussed. Several policymakers have discussed options to increase power lines capacity to improve the modern power grid with a high percentage of RES against outages [27]. To our knowledge, no paper introduced a systematic approach to mitigate the risk of cascading failures via reconductoring of transmission lines similar to the approach presented in this paper, which provides a vital tool for grid planners and operators.

This paper aims to provide a better insight into the impact of PV systems on cascading failures of power systems, mainly transmission networks. More specifically, the future power scenarios where PV systems are highly integrated. For this purpose, the stochastic nature of the RESs (i.e., PV systems) and the loads are considered in the same quasi-steady state simulation setup. Line outage probabilities were calculated under the same uncertainties as above. The simulations considered three scenarios: Scenario 1-A, where the power system is considered without PV systems, which represents a base scenario without any PV systems. Scenario 2-A, where PV systems are replacing typical generation buses. Scenario 3-A, where PV systems replace more generation buses than Scenario 2. Simulation results are also verified with a dynamic simulation. In addition, a framework to mitigate the impact of increased penetration levels on the failure risk is proposed by boosting the power capacity of the most vulnerable transmission lines. The impact of boosting the vulnerable lines is analyzed with simulations under the same three scenarios above.

The remainder of the paper is organized as follows: Section II discusses the uncertainties of power systems through the uncertainties of the Renewable energy sources and the uncertainties of the loads. Section III discusses two methodologies that are used for cascading failure analysis. Section IV presents the simulation results. Finally, Section V presents the conclusions of this work.

II. POWER SYSTEMS UNCERTAINTIES

Modern power systems have different uncertain parameters originating from various reasons. The deregulation of power systems, the introduction of RESs, and other factors shaping modern power systems have introduced new types and increased the uncertainties of power systems. Sources of uncertainties can be classified into technical and economic parameters [28]: Technical parameters are divided into topological and operational parameters of the power grid, economic parameters such as decisions related to small business sectors, cost of production, uncertainty in fuel supply, etc.. At the same time, the uncertainties handling approaches can be divided into three categories: a probabilistic approach, a possibilistic approach, and a hybrid probabilistic-possibilistic approach [29]. The global proportion of RESs in the energy supply is anticipated to grow significantly. Among these, PV systems will remain a central position within the RES blend. These sources are frequently characterized as intermittent. This concern requires attention due to its potential effects on several aspects of power system networks such as reliability and stability particularly during periods of extensive RESs integration. Depending on the context of the study, the variability of PV-based RESs can be described with the aid of the probability distribution function (pdf) in case of studying the power systems' performance at different times of the day and different seasons of the year.

A. LOADS AND PROBABILISTIC MODELLING

Loads on power system networks are changing throughout the day and throughout the months as well. If at a given location, loads were measured hourly for 24 hours during the winter and the summer [30], then a daily load profile will be obtained as shown in Fig. 1 (a). Loads uncertainty can be modeled as a Gaussian probability distribution function (PDF) as shown in the following equation [29].

$$PDF(S) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{(S-\mu)^2}{2\sigma^2}} \tag{1}$$

where S denotes power drawn by the load, σ, and μ denote standard deviation and mean of the power. Fig. 2 (b) shows a Gaussian distribution of a load with a mean of 1 MW and a variance of 0.15 of the mean.

B. PV SYSTEMS

PV energy generation depends on the solar irradiance at the location of the installed PVs energy resources. Solar irradiance changes during the day and the seasons of the year. Fig. 1 (b) shows solar irradiance at a specific location measured for 24 hours for two particular days for two seasons. In this work, the output generated power is modeled in Watt from PV system based on Kernel (PDF), which was obtained from hourly solar irradiance data of the east Amman region, Jordan, recorded for three years. The generated power in Watt is calculated based on the following mathematical model [21]:

$$P = \begin{cases} P_{rated} \dfrac{G_t^2}{G_{std} R_c}, & \forall G_t \in [0, R_c) \\ P_{rated} \dfrac{G_t}{G_{std}}, & \forall G_t \in [R_c, G_{std}] \\ P_{rated}, & \forall G_t \in (G_{std}, \infty) \end{cases} \tag{2}$$

where P denotes the output power of the PV system, P_{rated} is the rated power of the PV system, G_t is the solar irradiance in W/m^2, G_std is the solar irradiance in the standard environment, R_C is a certain irradiance point usually set as 150 W/m^2. Fig. 2 (a) shows the Kernel based PDF of the

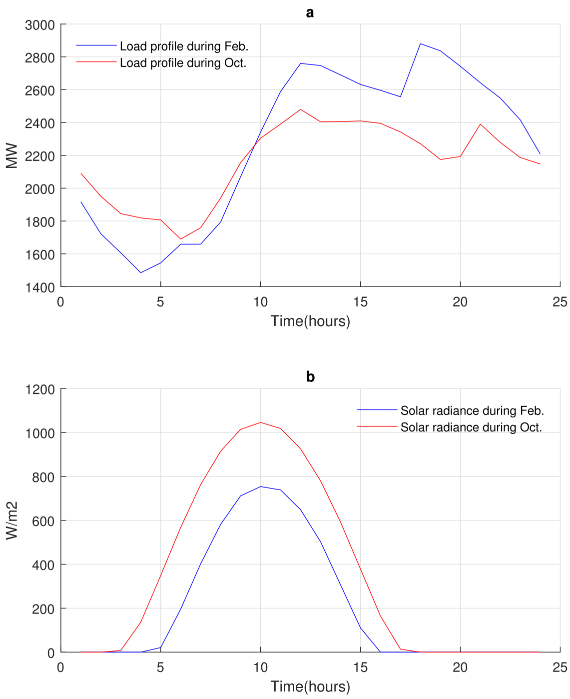

FIGURE 1. **(a) Hourly load profile, (b) Solar irradiance profile.**

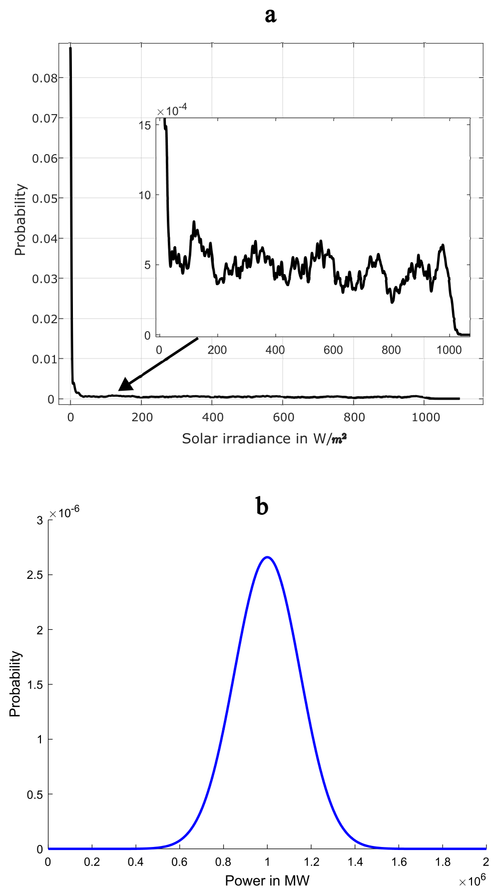

FIGURE 2. **Probability distribution characteristics for: (a) solar irradiance, and (b) load profile.**

solar irradiance of the data used in this paper, and Fig. 2 (b) shows a normal PDF of unit load of 1 MW.

III. METHODOLOGY

A. CASCADED FAILURE ANALYSIS

As mentioned earlier in the introduction, the cascading failure process can be divided into two main phases, slow and fast, where complex mechanisms are involved in each of these two cascading failure phases. The work in this paper analyzes the beginning of the fast phase process when transmission lines trip successively due to overloading. This tripping sequence may eventually lead to power systems stability issues, such as voltage collapse or dynamic instability. The tripping sequence may stop at some point, impacting only a small area, or may propagate and lead to a blackout. A statistical analysis of the impact of uncertainties of both the loads and the PV systems connected to the transmission system will be done. Simulations will be conducted based on two models, which will be discussed next, using a case study to examine the impact of high PV penetration on the risk of cascading failures in power systems.

In the first model, stochastic model introduced in [5] is analyzed, which is based on the DC load flow model. The power injection at the system nodes is defined by $P(t) = [G(t)^T, -L(t)^T]$, for generators $G(t)$ and loads $L(t)$, with a mean (μ_P) and Covariance (C_P) defined as follows.

$$\mu_P = \begin{bmatrix} -\mu_g \\ -\mu_l \end{bmatrix}, C_P = \begin{bmatrix} \Sigma_{gg} & \Sigma_{gl} \\ \Sigma_{lg} & \Sigma_{ll} \end{bmatrix} \tag{3}$$

where the subscript l denoted loads and g generation. The line flows mean (μ_l) and covariances (C_F) are defined as: $\mu_l = \sqrt{(y_t)}\ (\tilde{A}_t^T)^{-1}\mu_P(t)$ and $C_F(t) = \sqrt{(y_t)}(\tilde{A}_t^T)^{-1}C_P(t)(\tilde{A}_t^T)^{-1}\sqrt{(y_t)}$. Where (μ_l) and (C_F) are line flows mean and covariance, A is the line-node incidence matrix, $\tilde{A} = \sqrt{y}A$, $\tilde{A}$ is the weighted line node incidence matrix. y is lines admittance array. It follows that variance $\sigma_l = \sqrt{(C_F(l,l))}$. Then define the normalized distance of the line flow to overload threshold a_l as

$$a_l = \frac{F_{lmax} - \mu_l}{\sigma_l} \tag{4}$$

where F_{lmax} is the line capacity. It follows that the line failure probability $P_l(t)$ at a given step in terms of the Q function can be calculated as follows. $P_l(t) \approx Q(a_l)$, where

$$Q(a_l) = \int_{a_l}^{\infty} \frac{e^{\frac{-t^2}{2}}}{\sqrt{2\pi}}\, dt \tag{5}$$

Relation 5 gives an insight into the impact of adding RES to a given power system. The procedure for calculating the line failure probabilities is presented in Algorithm 1.

In the second model, a quasi-stead-state simulation tool (ACSIMSEP) developed in [6] and [7] is used to simulate the cascading failure process under the same conditions that

Algorithm 1 Lines Failure Probability Calculations

Require: choose a power system case study
Ensure: Calculate P_l
1: Apply $N-2$ contingency
2: Update power system incidence matrix
3: Calculate Covariance matrix
4: Calculate a_l using Eq. 4
5: Calculate P_l using Eq. 5

model 1 in this paper was subjected to for the following three uncertainties: 1- the N-2 contingencies, 2- The load uncertainties and 3- PV system uncertainties for power system networks that contain such sources. The simulation tool employed is based on AC power flow model with a function that enables a separate calculation of each island if the line tripping resulted in islands. Each island can perform separate AC power flow, enabling rebalance of that island by ramping up or down generators to match the loads within a specific time and at ramp rate limits. If generation ramp-up is insufficient to supply the loads, then load shedding is implemented. If overloads remain in the network after the rebalance, overloaded lines will trip after a time delay to simulate an overcurrent relay. It is worth mentioning that ACSIMSEP model is similar in design to the OPA model [31]. In our simulations, it didn't have the rebalance functionality for the implemented RES. Rebalance was only considered for typical generation units. Algorithms 1 and 2 describe the overall simulation setup, where Monte Carlo simulations (MC) were performed considering the same uncertainties for the two models.

Algorithm 2 Overall Simulation Setup

Require: Power system case study (Scenario 1)
1: Replace some generation units with PV; Scenario 2
2: Replace some generation units with PV; Scenario 3
3: for t $\leq$ number of MC simulations
  Assign uncertainties for loads based on Eq. 1
  Assign uncertainties for PV based on Eq. 2
  Assign random N-2 Contingencies
4: end for
5: for t $\leq$ number of MC simulations
  Calculate probabilities using Algorithm 1
  Perform ACSIMSEP for the case study
  Record Data
6: end for

B. THE PROPOSED TRANSMISSION-BOOSTING APPROACH

Several approaches and strategies can be used to decrease the impact of increased RESs penetration levels on the transmission network and improve the system's vulnerability to cascading failures. The authors in [32] compared different technical processes to increase transmission capacity, considering transmission lines reconductoring as one of these strategies since it only requires changing specific line conductors with conductors that have higher current-carrying capability. This option is attractive in many cases since it does not require a new right of way and may decrease the project timeline. Similarly, the authors in [33] recommended transmission lines reconductoring as a cost-effective solution for electricity system decarbonization. The authors in [34] investigated reconductoring transmission lines to increase transmission capacity. In this paper, the power capacity is increased of selected transmission lines to mitigate the cascading failure risk considering RES and loads uncertainties. Power capacity of transmission line 3 between buses 2 and 3 and line 17 between buses 10 and 13 is increased, as shown in the simulations and results in Section IV. The power capacity is increased by 50% by reconducting these lines to decrease the resistance. Lines 3 and 17 were chosen based on their high failure probability and the line-booting contribution to mitigate the risk of failure cascade considering the desired PV penetration level. Algorithm 3 shows the methodology used in this paper to select and boost the power capacity for a set of lines.

Algorithm 3 Update Transmission Lines Power Capacity

Require: Power system case study (Scenario 1)
1: Rank lines based on P_l using Algorithm 1
2: Select the set of lines to boost power capacity based on step 2
3: Check system performance using algorithm 2
4: Did bosting lines reduce systems vulnerability?
  No: Repeat from step 2
  Yes: end

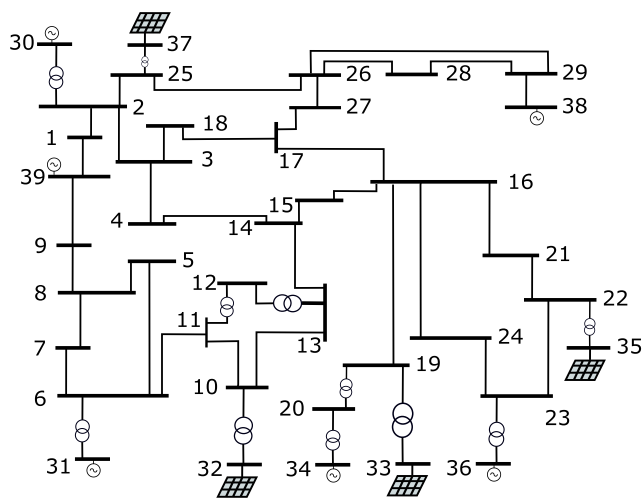

FIGURE 3. The modified IEEE 39-Bus system.

IV. SIMULATIONS AND RESULTS

In order to examine the impact of the integration of PV systems on the cascaded failure, the test system has been modified in such a way to consider several penetration scenarios that would be compared with each other and with the original system based on conventional synchronous generators (SGs). The simulations considered three scenarios: Scenario 1-A, where the power system is considered without PV systems which represents a base scenario. Scenario 2-A, where PV systems replace SGs at generation buses 32 and 33. Scenario 3-A: PV systems replacing more generation buses

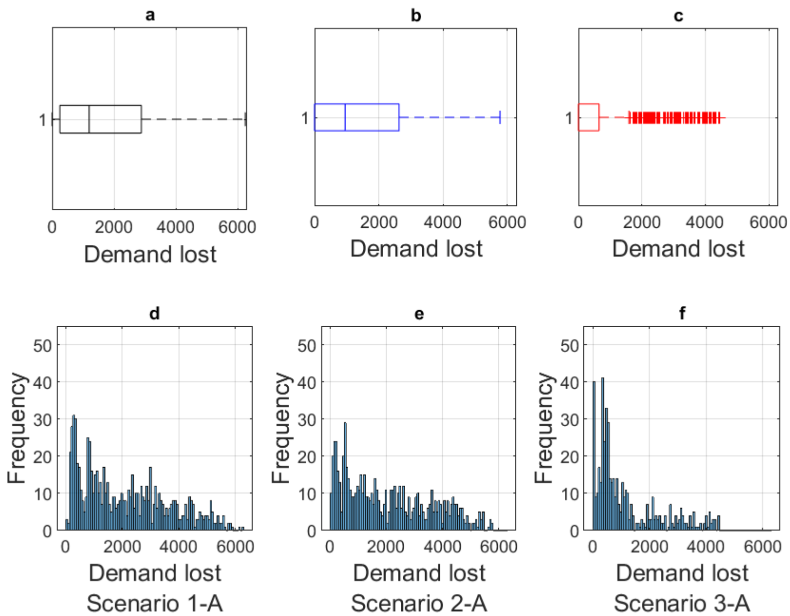

FIGURE 4. Demand lost in MW lost for the IEEE 39-bus system.

than scenario 2-A at buses 32, 33, 35, and 37. PV system is modeled in this paper as PQ buses with negative values. The real power values were randomly selected based on the Kernel distribution fit to reflect the uncertainty in solar radiation, as shown in Fig. 2 (a) and Equation 2. The analysis in Section III was tested and simulated in Matlab. Matpower [35] and the tool developed in [6] are used to obtain the case study information and perform the simulations of the cascading failure process. The IEEE 39-Bus system is used in the simulation. The single-line diagram of the IEEE 39-Bus system is shown in Fig. 3. Some of the generation units in the original case study are replaced with PV systems are replaced as the case in scenario 3-A. The case study consists of 10 generation units, including the slack at bus 1 and 46 transmission lines. The case study mainly represents a transmission network with typical generation units located at different buses: 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, with the generator at Bus 39 being the largest generation in the system.

The PV systems in scenarios 2 and 3 were modeled as PQ bus type with no ability to reduce the injected power to the grid during the failure cascade. The Monte Carlo simulations are performed in the three scenarios considering the following uncertainties: First, by applying the same N-2 contingencies to the three case studies. The N-2 contingencies followed a uniform distribution. Second, the amount of real and reactive loads on load buses was changed in each simulation for the three cases following a Gaussian distribution with mean (μ) equal to the nominal load and variance (σ), such that ($\sigma = 0.15 \times \mu$). Third, for case studies number 2 and 3, the generated real and reactive power from the PV systems is changed in every simulation following Kernel-based PDF that was fitted based on the solar radiation data and Equation 2. It is assumed that all the PV systems are subjected to the same solar radiation. Table 1 summarizes the probabilities used in each of the models used in this paper.

TABLE 1. Summary of probability distribution types used.

Quantity	Probability/PDF	Reference
$N-2$ for lines	Uniform	
Loads	Gaussian	[29]
PV output power	Kernel	[21] and solar irradiance data
Line outages probabilities	Calculated based on Algorithm 1	Algorithm 1

A. IMPACT OF INCREASED PV SYSTEMS ON CASCADED FAILURE

Comparing the results of the three case studies mentioned above, 1000 Monte Carlo (MC) simulations are performed for each case study, described by Algorithms 1 and 2 in Section III. The same uncertainties were implemented in the shared variables in the three case studies, such as the load variations and the N-2 contingencies, which we will discuss in the three scenarios:

1) SCENARIO 1-A: NO PV SYSTEMS ADDED TO THE IEEE 39-BUS SYSTEM

The results shown in Fig. 4 represent the simulations conducted by implementing the Quasi-Steady-State (QSS) model. The results in Fig. 4 (a) show that the MW lost as a box plot. The median is 1196 MW. A box plot describes a set of data, MW lost for each simulated sample in this case, the line inside the box represents the median, the left

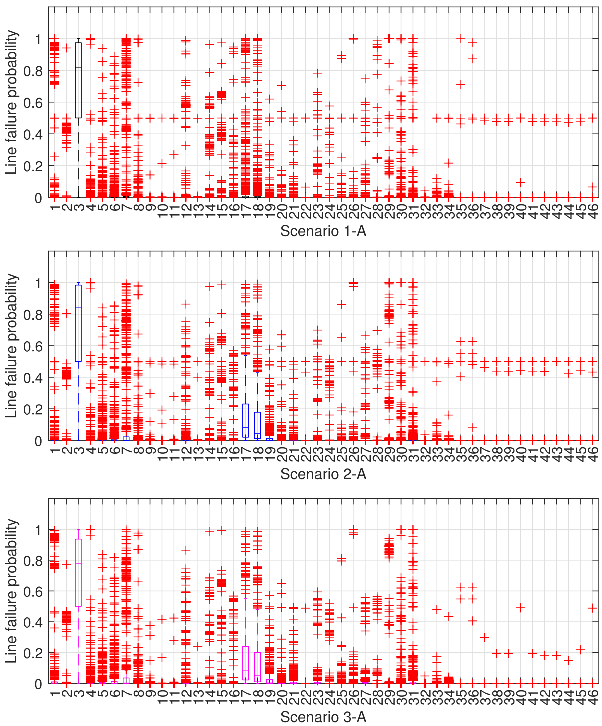

FIGURE 5. **Lines failures probabilities for the three studied scenarios, with transmission lines numbered from 1 to 46 in the x-axis.**

edge represents the lower quartile, the right edge represent the upper quartile, the horizontal line stops are the values of the lower and upper values of the data, the single points are the outliers. Fig. 4 (d) shows a histogram of the original IEEE 39-Bus system; the x-axis represents demand lost in MW, and the y-axis represents the frequency of each bin. The zero MW lost occurrences were omitted from this plot and the subsequent histogram plots in this paper. Most of the samples are below 4000 MW. The demand lost in MW is the summation of the load shedding resulting when the system tries to rebalance due to insufficient generation or after islanding. Added to the amount of load shedding to avoid voltage collapse.

2) SCENARIO 2-A: 21 % PV PENETRATION

Replacing the generation units at buses 32 and 33 with PV systems will result in 21% of the overall generation capacity being PV. Similar to the case without PV systems in Scenario 1-A, the results in Fig. 4(b) show that the demand lost as a box plot for scenario 2A. The median is 952 MW, which represents a difference from the case without PV system. Fig. 4(e) shows the histogram for scenario 2-A. A smaller number of samples have a higher range of MW lost than in the previous scenario.

3) SCENARIO 3-A: 41 % PV PENETRATION

Modifying scenario one above by replacing the generation units at buses 35, and 37 with PV systems will result in 41% of the overall generation capacity being PV. Similar to the two scenarios above, the results in Fig. 4(c) show that the demand lost as a box plot for scenario 3A. The demand lost is significantly less than the previous two scenarios with a 75th percentile of 650 MW. Fig. 4(f) shows the histogram for scenario 3A; fewer samples with a higher range of MW lost than in scenario 2-A, as the sample frequency between

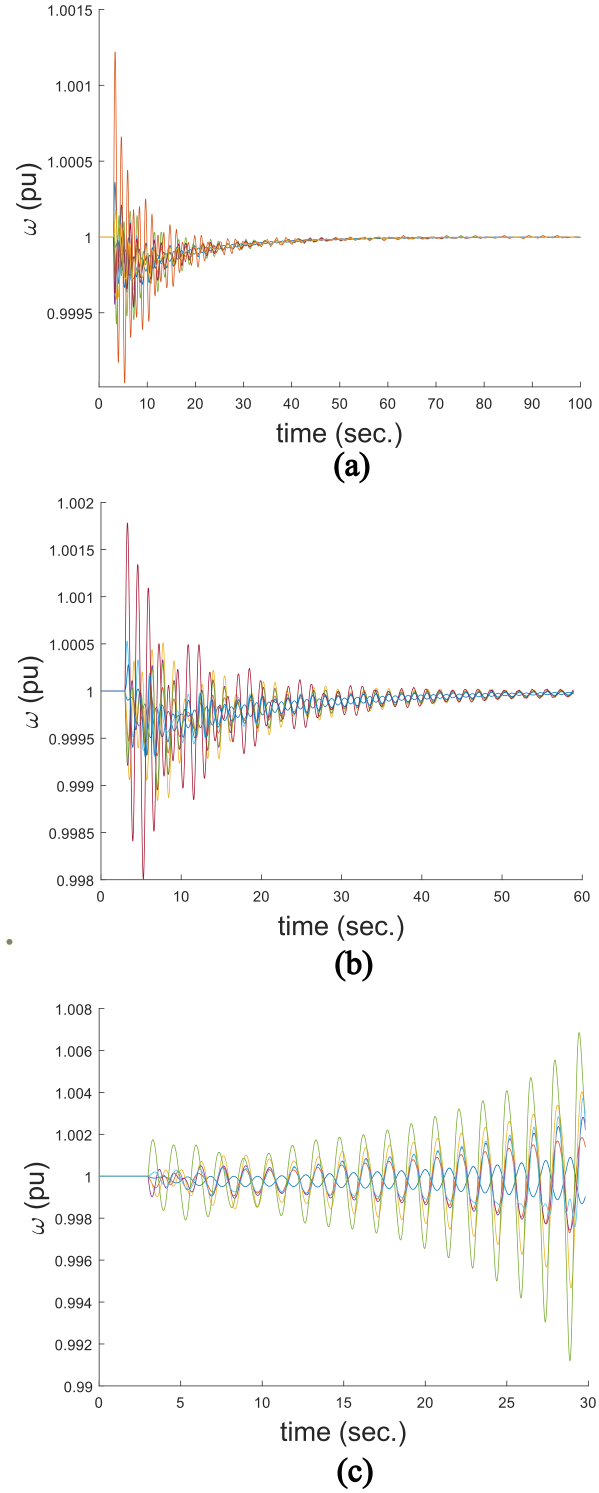

FIGURE 6. **Generators angular speed for the IEEE 39-Bus system: a-Scenario 1-A. b-Scenario 2-A. c-Scenario 3-A.**

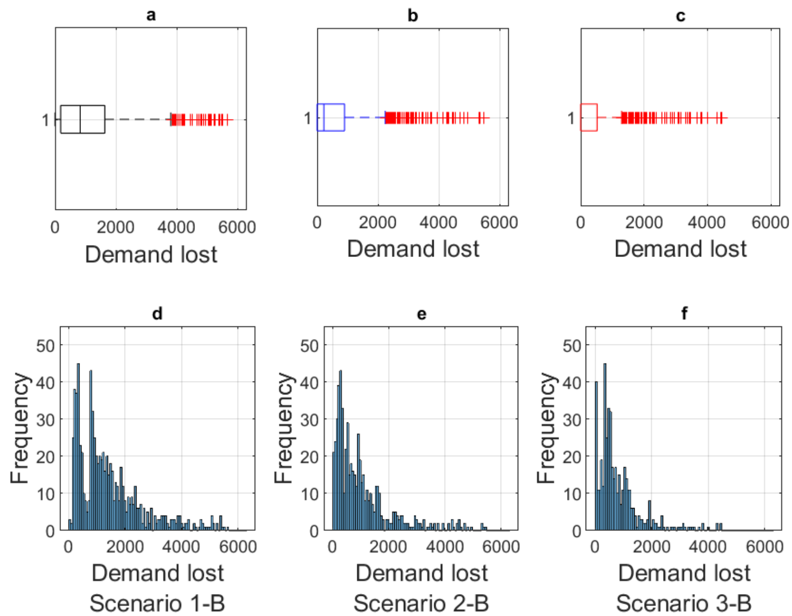

FIGURE 7. Demand lost in MW lost for the IEEE 39-Bus system after reconductoring.

2000 and 4000 MW lost is considerably fewer than scenario 2-A in the same range. The fewer values in demand lost due to load shedding results from the fact that the system had less chance to take corrective actions using load shedding. The system results in consecutive relay trips in a shorter period than in the previous two scenarios, resulting in a higher blackout risk. Indicating that the impact and size of outages in the system represented by scenario 3-A is higher than in scenario 2-A. This result can also be verified with the box plots in Figures: 4-a, 4-b and 4-c, where the median for 41% PV penetration in Fig. 4-c is considerably lower than in the previous two scenarios.

Comparing the three scenarios using the first model explained in Algorithm 1 in Section III, the same conditions of uncertainties employed in the above analysis were also used here, with the same number of Monte Carlo (MC) simulations. The results are shown in Fig.5, representing the transmission line failure probability after applying the N-2 contingency, line failure probability for each MC simulation was obtained from equation (5). The lines are enumerated from line number 1 to line number 46, with the probability presented as a box plot for each line. Similar to Fig. 4, box plots for each line of the 46 lines in Fig. 5 represent line outage probability as a box plot, where each box plot summarizes the data points collected from the MC simulations, each data point represent the line outage probability for a given line at a single simulation. The figure shows that scenarios 2-A and 3-A generally resulted in more lines having a higher probability of failure than scenario 1A. Scenario 3-A performs worse than Scenario 2-A with some lines, such as lines7, 17 and 19, with an increase in failure probability. The results shown in Fig. 5 show similar behavior when compared to the results illustrated by the authors in [19], where the total load shedding and the line trip count increased when increasing penetration levels of wind generation. The authors in their paper used forecasting errors as a part of their analysis. Forecasting error is not included in analyzing the uncertainty of the PV generation in this paper. Similar results were concluded in [17] and [18].

To further validate the proposed approach in this paper. The simulation results are verified with dynamic simulations using the tool developed by the authors in [36], where one of the contingencies used in the MC simulations of the previous two models is applied in the dynamic simulation model. The two lines tripped for the N-2 contingencies were 31 and 8. The PV generation was at 50.7% of the rated output power for the solar generation in scenarios 1 and 2 for this specific case. Before the N-2 contingency occurred, a rebalance function was added to the dynamic model to ensure the system is steady. The steady-state region is shown in Fig. 6 from 0 to 3 seconds, where at second 3, the N-2 contingency was applied. In the QSS simulation, after the N-2 was applied, transmission line 3 tripped due to over-current. Similar behavior occurred in the dynamic simulation model, further validating our previous analysis. Fig. 6 shows the dynamic simulator results. The N-2 contingency was applied at sec III for each scenario. Generators angular speeds ω were analyzed using the dynamic simulator. Results show that oscillations in scenario 3A did not reach a steady state before line 3 trip due to overcurrent at the end of the interval shown in Fig. 6-c. Oscillations reached a steady state in scenarios 1A and 2A as shown in Fig. 6-a and 6-b respectively. Simulation results in the previous subsection show that the risk of failure cascade and blackouts increases with increasing PV penetration levels.

The insight of lines mostly loaded after the N-2 contingency, shown in Fig. 5, can be used as a mitigation strategy. By redistributing the flows of the lines via means such as generation units redispatch and load shedding. The authors in [37] and [38] used similar approaches.

B. IMPACT OF THE PROPOSED TRANSMISSION-BOOSTING APPROACH

The simulations that were carried out in the previous subsections are repeated with the updated lines information for the IEEE 39-Bus system using Algorithm 3. Fig. 7 illustrates the shift in demand lost for the three scenarios compared to the original IEEE 39-Bus system. The shift mainly represents a decrease in the frequency of the higher demand lost, indicating that the system shed less load to rebalance the system after the contingency. This conclusion can be verified with the box plots in Figures: 7-a, 7-b and 7-c, where the median for 41% PV penetration in Fig. 7-b is considerably lower than in the without reconductoring in Fig. 4-b. Fig. 8 shows the line failure probabilities of the three scenarios considered in subsections I-III, indicated with scenarios 1-B, 2-B, and 3-B after boosting line capacity compared to scenarios 1-A, 2-A, and 3-A. Results show a significant decrease in the line failure probability of lines 3 and 17. Showing that reconductoring may improve the overall transmission system robustness.

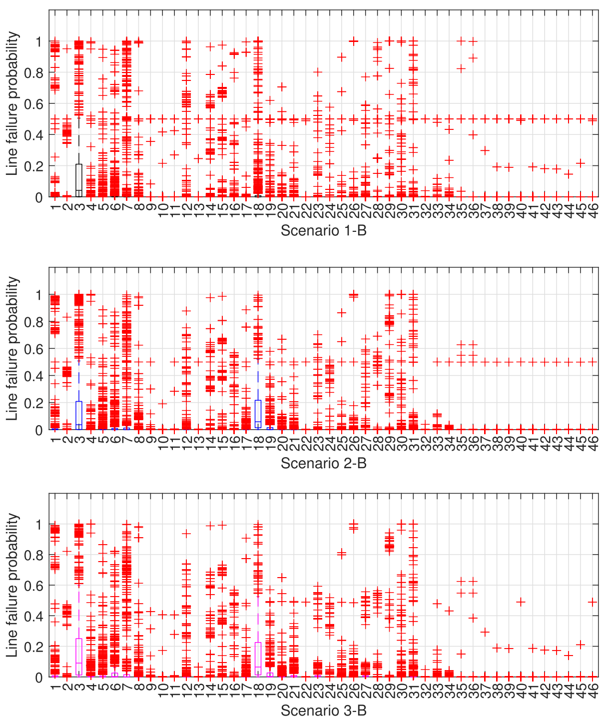

FIGURE 8. Lines failures probabilities for the three studied scenarios after reconductoring.

The overall system performance during the failure cascade process was improved in scenarios 1-B and 2-B. In scenario

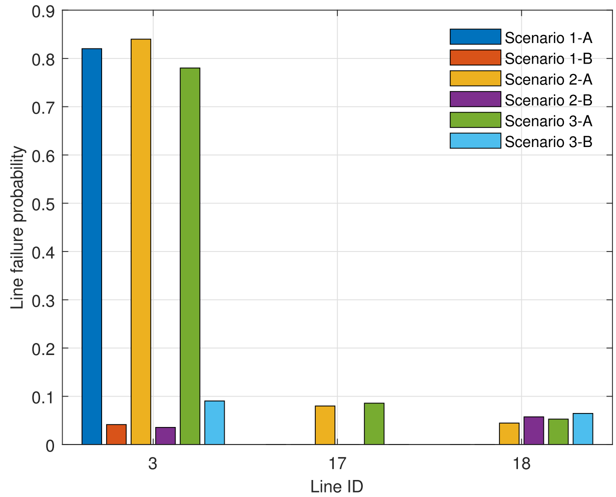

FIGURE 9. Lines failures probabilities for the three studied scenarios.

3-B, however, with a higher RES penetration level, the system didn't improve much than the case before increasing lines 3 and 17 power capacity. Indicating that further lines reconductoring may be needed to increase the transmission system robustness. Fig. 9 summarizes the lines probability of failure of the lines with the highest probability in all the cases discussed previously, considering PV penetration levels before and after reconductoring. The results are also summarized in Table 2.

TABLE 2. Lines failure probability (median).

PV levels	Case	Line 3	Line 17	Line 18
Scenario 1	Scenario 1-A	0.82	0	0
	Scenario 1-B	0.041	0	0
	Decrement in %	95%	-	-
Scenario 2	Scenario 2-A	0.84	0.08	0.044
	Scenario 2-B	0.0356	0	0.057
	Decrement in %	95.7%	-	−29.5%
Scenario 3	Scenario 3-A	0.7802	0.089	0.0027
	Scenario 3-A	0.09	0	0.065
	Decrement in %	88.46%	-	−23.07%

V. CONCLUSION

In this paper, we conducted a detailed analysis of the impact of high photovoltaic (PV) penetration on the susceptibility of transmission power systems to cascading failures. While PV systems offer numerous advantages, high penetration levels introduce challenges, particularly due to the inherent uncertainties in solar generation, which become even more complex when combined with load uncertainties. As a potential mitigation strategy, we proposed enhancing transmission line robustness by increasing their power capacity. Among the various available strategies, we adopted reconductoring the most vulnerable lines as a cost-effective and practical solution. This process involves replacing older conductors with newer, higher-capacity ones, providing immediate economic benefits and applicability in a short period of time in real-world scenarios. To account for the stochastic nature of solar irradiance, the uncertainty of PV generation was modeled using a Kernel distribution with tailored settings for mean and variance, reflecting typical solar characteristics. Both PV and load uncertainties were integrated into Monte Carlo simulations to assess their effects on cascading failures. To this end, we utilized two different approaches to quantify the severity of these uncertainties. Numerical simulations were conducted using the modified IEEE 39-Bus test system. Our findings were validated by incorporating random N-2 contingencies, which followed a uniform distribution. Moreover, dynamic simulations were executed for specific cases to further verify the robustness of the analysis. The results of the simulation show a direct relationship between the increased PV penetration and increased grid susceptibility to cascading failures. In particular, the probability of transmission line failures during N-2 contingencies increases with increased PV penetration. These findings were validated by multiple dynamic simulations, which ranked the probability of line outages. The implementation of the proposed transmission-boosting capacity of reconductoring involves replacing older conductors with newer, higher-capacity ones, providing immediate benefits without requiring extensive overhauls. Our methodology was validated by rerunning the Monte Carlo simulations, showing that reconductoring significantly reduces the risk of cascading failures, particularly at high PV penetration levels. As the proportion of PV in the grid increases, additional lines may require reconductoring to minimize the risk of cascading failure. These findings provide critical insights and tools for power grid operators and planners, enabling them to enhance the robustness of transmission networks while accommodating high levels of renewable energy. This research underscores the need for ongoing grid reinforcement as renewable energy adoption accelerates, ensuring a reliable and resilient power system for future energy demands.

REFERENCES

[1] P. Hines, J. Apt, and S. Talukdar, "Large blackouts in North America: Historical trends and policy implications," *Energy Policy* vol. 37, no. 12, pp. 5249–5259, 2009.

[2] B. C. Vaiman, D. Chowdhury, P. Hines, and Z. Miller, "Risk assessment of cascading outages: Methodologies and challenges," *IEEE Trans. Power Syst.*, vol. 27, no. 2, pp. 631–641, May 2012.

[3] H. Guo, C. Zheng, H. H. C. Iu, and T. Fernando, "A critical review of cascading failure analysis and modeling of power system," *Renew. Sustain. Energy Rev.*, vol. 80, pp. 9–22, Dec. 2017.

[4] M. Noebels, I. Dobson, and M. Panteli, "Observed acceleration of cascading outages," *IEEE Trans. Power Syst.*, vol. 36, no. 4, pp. 3821–3824, Jul. 2021.

[5] Z. Wang, A. Scaglione, and R. J. Thomas, "A Markov-transition model for cascading failures in power grids," in *Proc. 45th Hawaii Int. Conf. Syst. Sci.*, Maui, HI, USA, Jan. 2012, pp. 2115–2124.

[6] M. J. Eppstein and P. D. H. Hines, "A 'random chemistry' algorithm for identifying collections of multiple contingencies that initiate cascading failure," *IEEE Trans. Power Syst.* vol. 27, no. 3, pp. 1698–1705, Aug. 2012.

[7] P. Rezaei, P. D. H. Hines, and M. J. Eppstein, "Estimating cascading failure risk with random chemistry," *IEEE Trans. Power Syst.*, vol. 30, no. 5, pp. 2726–2735, Sep. 2015.

[8] S. Das and Z. Wang, "Cascading failure risk analysis of electrical power grid," in *Proc. Future Technol. Conf. (FTC)* (Lecture Notes in Networks and Systems), vol. 559, K. Arai, Eds., Cham, Switzerland: Springer, 2022, pp. 906–923.

[9] P. D. H. Hines, I. Dobson, and P. Rezaei, "Cascading power outages propagate locally in an influence graph that is not the actual grid topology," *IEEE Trans. Power Syst.*, vol. 32, no. 2, pp. 958–967, Mar. 2017.

[10] I. Dobson, B. Carreras, V. Lynch, and D. Newman, "Complex systems analysis of series of blackouts: Cascading failure, critical points, and self-organization," *Chaos: Interdiscipl. J. Nonlinear Sci.*, vol. 17, no. 2, 2007, Art. no. 026103.

[11] A. Azzolin, L. Dueñas-Osorio, F. Cadini, and E. Zio, "Electrical and topological drivers of the cascading failure dynamics in power transmission networks," *Rel. Eng. Syst. Saf.* vol. 175, pp. 196–206, Jul. 2018.

[12] F. Kaiser and D. Witthaut, "Topological theory of resilience and failure spreading in flow networks," *Phys. Rev. Res.* vol. 3, no. 2, 2021, Art. no. 023161.

[13] L. Guo, C. Liang, A. Zocca, S. H. Low, and A. Wierman, "Line failure localization of power networks Part I: Non-cut outages," *IEEE Trans. Power Syst.*, vol. 36, no. 5, pp. 4140–4151, Sep. 2021.

[14] L. Guo, C. Liang, A. Zocca, S. H. Low, and A. Wierman, "Line failure localization of power networks Part II: Cut set outages," *IEEE Trans. Power Syst.*, vol. 36, no. 5, pp. 4152–4160, Sep. 2021.

[15] S. Yang, W. Chen, X. Zhang, and W. Yang, "A graph-based method for vulnerability analysis of renewable energy integrated power systems to cascading failures," *Rel. Eng. Syst. Saf.*, vol. 207, Mar. 2021, Art. no. 107354.

[16] M. Z. Zakariya and J. Teh, "A systematic review on cascading failures models in renewable power systems with dynamics perspective and protections modeling," *Electr. Power Syst. Res.*, vol. 214, Jan. 2023, Art. no. 108928.

[17] D. Liu, X. Zhang, and C. K. Tse, "Effects of high level of penetration of renewable energy sources on cascading failure of modern power systems," *IEEE J. Emerg. Sel. Topics Circuits Syst.*, vol. 12, no. 1, pp. 98–106, Mar. 2022.

[18] Y. Dai, R. Preece, and M. Panteli, "Risk assessment of cascading failures in power systems with increasing wind penetration," *Electr. Power Syst. Res.*, vol. 211, Oct. 2022, Art. no. 108392.

[19] M. H. Athari and Z. Wang, "Impacts of wind power uncertainty on grid vulnerability to cascading overload failures," *IEEE Trans. Sustain. Energy*, vol. 9, no. 1, pp. 128–137, Jan. 2018.

[20] M. H. Athari and Z. Wang, "Stochastic cascading failure model with uncertain generation using unscented transform," *IEEE Trans. Sustain. Energy*, vol. 11, no. 2, pp. 1067–1077, Apr. 2020.

[21] A. Alamri, M. Alowaifeer, and A. P. S. Meliopoulos, "Probability characterization of solar farm power output and impact on system reliability," in *Proc. IEEE Int. Conf. Probabilistic Methods Appl. Power Syst. (PMAPS)*, Boise, ID, USA, Jun. 2018, pp. 1–6.

[22] B. Chen, D. Sun, Y. Zhu, D. Liu, and Y. Zhou, "Real-time risk assessment of cascading failure in power system with high proportion of renewable energy based on fault graph chains," *Eng. Rep.*, vol. 5, no. 10, 2023, Art. no. e12631.

[23] K. Kopsidas and S. M. Rowland, "Evaluation of potentially effective ways for increasing power capacity of existing overhead lines," in *Proc. Int. Conf. Sustain. Power Gener. Supply*, Nanjing, China, Apr. 2009, pp. 1–7.

[24] K. Kopsidas, S. M. Rowland, M. N. R. Baharom, and I. Cotton, "Power transfer capacity improvements of existing overhead line systems," in *Proc. IEEE Int. Symp. Electr. Insul.*, San Diego, CA, USA, Jun. 2010, pp. 1–5.

[25] A. Tokombayev and G. T. Heydt, "High temperature low sag (HTLS) technologies as upgrades for overhead transmission systems," in *Proc. North Amer. Power Symp. (NAPS)*, Manhattan, KS, USA, Sep. 2013, pp. 1–6.

[26] National Academies of Sciences, Engineering, and Medicine. (2017). *Enhancing the Resilience of the Nation's Electricity System*. [Online]. Available: https://nap.nationalacademies.org/catalog/24836/enhancing-the-resilience-of-the-nations-electricity-system

[27] Martin Heinrich. (2024). *How Renewable Energy Can Make the Power Grid More Reliable and Address Risks to Electricity Infrastructure*. Accessed: Oct. 18, 2024. [Online]. Available: https://www.jec.senate.gov/public/index.cfm/democrats/2024/1/how-renewable-energy-can-make-the-power-grid-more-reliable-and-address-risks-to-electricity-infrastructure

[28] A. Soroudi and T. Amraee, "Decision making under uncertainty in energy systems: State of the art," *Renew. Sustain. Energy Rev.*, vol. 28, pp. 376–384, Dec. 2013.
[29] A. R. Jordehi, "How to deal with uncertainties in electric power systems? A review," *Renew. Sustain. Energy Rev.*, vol. 96, pp. 145–155, Nov. 2018.
[30] M. Momani, W. Alrousan, and A. Alqudah, "Short-term load forecasting based on NARX and radial basis neural networks approaches for the Jordanian power grid," *Jordan J. Electr. Eng.* vol. 2, no. 1, pp. 81–93, 2016.
[31] I. Dobson, B. Carreras, V. Lynch, and D. Newman, "An initial model for complex dynamics in electric power system blackouts," in *Proc. 34th Annu. Hawaii Int. Conf. Syst. Sci.*, Maui, HI, USA, 2001, pp. 710–718.
[32] L. Reed, M. Dworkin, P. Vaishnav, and M. G. Morgan, "Expanding transmission capacity: Examples of regulatory paths for five alternative strategies," *Electr. J.*, vol. 33, no. 6, Jul. 2020, Art. no. 106770.
[33] P. R. Brown and A. Botterud, "The value of inter-regional coordination and transmission in decarbonizing the U.S. electricity system," *Joule*, vol. 5, no. 1, pp. 115–134, Jan. 2021.
[34] I. Pavičić and I. Pavić, "Investigation of influence of HTLS and compact design in transmission network considering transmission capacity and losses," *Tehnički Vjesnik* vol. 29, no. 3, pp. 818–826, 2022.
[35] R. D. Zimmerman, C. E. Murillo-Sánchez, and R. J. Thomas, "MATPOWER: Steady-state operations, planning, and analysis tools for power systems research and education," *IEEE Trans. Power Syst.*, vol. 26, no. 1, pp. 12–19, Feb. 2011.
[36] J. Song, E. Cotilla-Sanchez, G. Ghanavati, and P. D. H. Hines, "Dynamic modeling of cascading failure in power systems," *IEEE Trans. Power Syst.*, vol. 31, no. 3, pp. 2085–2095, May 2016.
[37] Y. Dai, M. Noebels, R. Preece, M. Panteli, and I. Dobson, "Risk assessment and mitigation of cascading failures using critical line sensitivities," *IEEE Trans. Power Syst.*, vol. 39, no. 2, pp. 3937–3948, Mar. 2024.
[38] W. Al-Rousan, C. Wang, and F. Lin, "A discrete-event system approach for modeling and mitigating power system cascading failures," *IEEE Trans. Control Syst. Technol.*, vol. 30, no. 6, pp. 2547–2560, Nov. 2022.

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