Identification of Worst Impact Zones for Power Grids During Extreme Weather Events Using Q-Learning

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Identification of Worst Impact Zones for Power Grids During Extreme Weather Events Using Q-learning

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***Abstract*—Both the frequency and intensity of extreme weather events have been trending higher in recent years, leading to significant infrastructure damage in the electric grid. The impact of these extreme weather events is desired to be analyzed and quantified to help transmission and distribution system operators prepare for and prevent significant damage and subsequent loss of power. In this paper, we develop an approach that models the impact of extreme weather on the grid and identifies the worst impact zone using Q-learning (a reinforcement learning approach). The identification results reveal grid vulnerability to weather events and provide insights for system operators to help achieve optimal resource allocation and crew dispatch to minimize the adverse impacts of extreme weather. Simulation studies are conducted on the IEEE 123-node system to demonstrate the performance of the proposed approach.**

***Index Terms*—Reinforcement learning, impact analysis, intensity, vulnerability, extreme weather, distribution system.**

I. Introduction

The traditional and aging electric power grid is integrated with intelligent controls, information, and communications technologies and has been turned into a cyber-physical electric grid. Even though the power grid is equipped with modern technology, power outage events cause significant damage. The U.S. Department of Energy defines a major outage as an event that impacted at least $50,000$ individuals or caused a load loss of at least 300 MW [1]. According to EATON Corporation's blackout tracker annual report for the United States, the total number of outage event was $3,526$ in 2017. Almost 36.7 million people were affected by these events. The total outage duration was $2,84,086$ seconds, which is almost equivalent to 197 days [2]. Different reasons for these major power outages on the grid include equipment failure, supply shortage, operator error, voltage reduction, fire, and weather (earthquake, tornado, hurricane, ice storm, lightning, wind/rain, etc.). Different extreme weather events are responsible for damaging the grid and interrupting the continuous supply of electrical power to residential and industrial customers. Hurricanes Harvey, Irma, Maria, and all of which occurred in 2017, caused electric power losses of more than \$200 billion, the most expensive loss in U.S. history [3].

Numerous research activities have been conducted using machine learning algorithms to analyze the vulnerability, reliability, and resilience of the grid (specifically the bulk power grid) to extreme weather conditions. In [4], the authors presented a framework to analyze the resilience of grid with an integrated microgrid under extreme conditions by representing the grid in a mesh view. The authors of [5] researched the resilience of power systems under extreme weather conditions, including forecasting the impacts of natural disasters, hardening the system, and exploring resilient optimization processes. The authors of [6] identified critical transmission lines of a skeleton network of the power system under extreme natural events using the VIKOR method. In addition, other research works [7]–[9] studied the resilience of the grid to extreme weather conditions. The authors in [10] performed a vulnerability assessment of the grid using the Q-learning algorithm and game theory considering malicious attacks on the grid. Few existing work has identified the vulnerable zones of the distribution system under extreme weather conditions. Learning-based methods to identify the vulnerable zones of the grid under extreme weather events will help utility operators plan restoration strategies or system hardening in advance to protect the power system components and provide uninterrupted power supply to consumers.

Motivated by these weaknesses or limitations in the existing literature, the contributions of this research paper are as follows: (a) we model a new metric to calculate the impact of extreme weather events on a power distribution system; (b) we model the MATPOWER test case for the IEEE 123-node test feeder, which is an approximate single-phase equivalent to a three-phase system; and (c) we model a Q-learning (a reinforcement learning algorithm) framework to identify the worst impact zones for grids caused by extreme weather events.

The rest of this paper is organized as follows. Section II discusses various definitions and the theoretical background of the Q-learning algorithm. Section III describes the calculation of generation loss and line failures from the outage model, grid representation of the distribution system, modeling the impact on the distribution system from extreme weather events, modeling the MATPOWER test case of the IEEE 123-node test feeder, and modeling the Q-learning algorithm to find the worst impact zone of extreme weather events in a distribution system. Section IV presents and analyzes the simulation results. Finally, Section V concludes.

II. Theoretical Background

A. Definitions

1) Impact: In a study of power system stability, reliability, and resilience, impact is considered the loss of grid functionality. Power system resilience is the ability of the network to minimize the negative impact caused by high-impact, low-frequency extreme events (such as hurricanes, storms, floods, and cyberattacks). The impact can be modeled in terms of loss of grid capacity in megawatts, number of customers affected, number of line outages, number of critical loads, and in terms of economic loss.

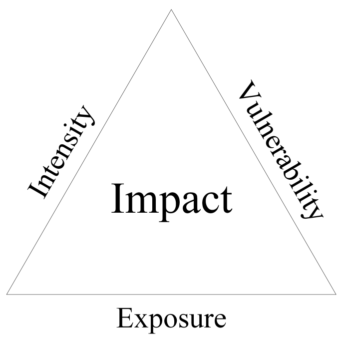

Figure 1: Impact triangle showing the determinants of a grid affected by extreme weather conditions.

Measuring the impact of extreme weather events on a grid is vital to evaluating and enhancing resilience. In [11], the authors presented an impact triangle where the determinants were in the form of multiplication presented as follows: $IM = I_{EW} \times E \times V$, where *IM* represents the impact of the extreme weather event on the grid, *E* represents the exposure of the grid to the event, and *V* represents the vulnerabilities of the grid to the extreme weather event. Inspired by this impact model, we consider the impact of extreme weather as a function of intensity, grid vulnerability, and exposure, described as Fig. 1.

2) Intensity: The intensity is represented as I_{EW} for the extreme weather condition. The intensity usually expresses the severity of the extreme weather events. For example, in a hurricane the intensity can be expressed in terms of wind speed (m/s), temperature $(°C)$, translation velocity, radius of maximum wind, etc. For simplicity, the intensity can be expressed as a single value that can be a weighted sum of multiple factors.

3) Exposure: The exposure (E) of the grid to an extreme weather event usually represents what percentage of the grid is exposed to the event. The exposure can be in terms of percentage of customers affected or percentage of lines or loads affected in the event area.

4) Vulnerability: Vulnerability of the grid during an extreme weather event can be expressed as V. Grid vulnerability represents the likelihood and severity of grid damage caused by an extreme weather event.

B. Q-learning

Q-learning is a reinforcement learning algorithm. The target of this learning algorithm is to learn a policy that tells the learning agent what action should be taken under certain circumstances. Typically, a Q-learning agent interacts with the environment to learn from it by trial and error.

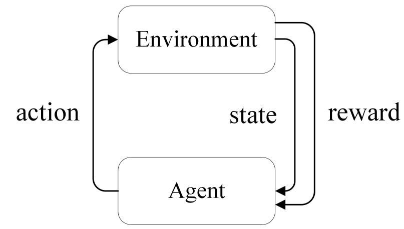

Figure 2: Typical agent-environment interaction in Q-learning algorithm.

Fig. 2 represents a typical agent-environment interaction in a Q-learning environment, where the agent takes action, a, executes it on the environment, and gets a reward, Re, as feedback at state s. Once an action is taken, the environment sends an evaluative feedback to the agent, which is termed as $reward$, Re. Based on the feedback, the agent learns through trial and error process. For a finite Markov decision process, Q-learning converges to an optimal policy that maximizes the discounted sum of future rewards. The Q-function is represented as follows:

$$Q(s, a) = Re(s, a) + \gamma Q_{max}(s', a') \tag{1}$$

where Q is the quality of the state, s, and action, a, Re represents the reward at state s from action a; and s' and a' represent the next state and action at the next state, respectively. Training the Q-learning agent requires some hyperparameters, such as discount rate, γ, exploration, and exploitation probability, ϵ. The value of γ ranges from 0 to 1. The higher the value of γ, the more the agent focuses on the long-term reward. A value of γ close to 0 forces the agent to focus on short-term or more immediate rewards. The value of ϵ also ranges from 0 to 1. The higher the value of ϵ, the more the agent explores by taking random actions and the less the agent exploits by taking optimal actions. With the gradual reduction of the value of ϵ, the exploration probability reduces and the exploitation probability increases. A value of ϵ close to 0 means there are very few random actions (exploration).

III. Proposed Research

In this section, we discuss the proposed research methods.

1) Calculation of generation loss and line failures: To calculate the generation loss and line failures caused by extreme weather events, we adopt the cascading failure simulator from [12], [13] as the outage model. We consider line failure to calculate the total losses (includes generation loss and cascading failures).

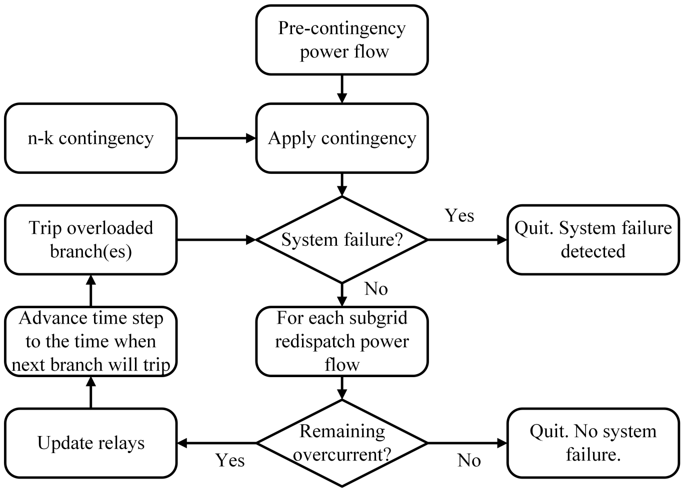

Figure 3: Workflow of outage model to calculate generation loss and total outages caused by extreme weather events.

As depicted in Fig. 3, the outage model initializes with the application of precontingency power flow. After that, the model executes the $n-k$ contingencies, where k is the order of the contingencies. The value of k is determined from the area/zone of the grid that the extreme weather event impacts. After the application of $n-k$ contingencies, k transmission lines are switched from the system, and the system may be separated into multiple islands. The generators or distributed energy resources are adjusted by ramping up or down to match the demand and supply. $P_{g,min}$ and $P_{g,max}$ are the ramping limits of the generators. After that, the generation and the demand are compared, which is defined by Z, $Z = (\sum_{g \in G} P_g - \sum_{d \in D} P_d)$, where Z represents the difference between the generation and the demand; and $\sum_{g \in G} P_g$ and $\sum_{d \in D} P_d$ represent the total generation and total demand, respectively. If $Z > 0$ (generation is higher than demand), then the generators are tripped one by one until $Z = 0$. If $Z < 0$ (generation is less than the demand), then the loads are shed in the island. After that, a DC power flow checks for overloads. If there are no overloads, the simulation is terminated. If there are overloads, then the overloaded branches are tripped according to the relay settings and the overloads.

2) Grid representation of distribution system: A geographic information system (GIS) can be integrated with the distribution system to create a mesh view of the grid with geographic locations mapped. Fig. 4 represents a mesh view of the IEEE 123-node system placed on a mesh grid based on GIS data. The whole mesh grid is a 10×10 box. The colored 3×3 box or marked region represents a sample event zone. The dark colored zone represents the event center, and the light colored zone/box represents the edge of the event zone. For ease of simulation, we consider the effect of the extreme event is uniform throughout the whole 3×3 zone. To place the GIS information of the nodes of a power system on top of a 10×10 mesh grid, the coordinates of the nodes are scaled down between the range of 0 to 10. In short, the coordinates of the nodes (GIS information) are normalized within the range from 0 to 10.

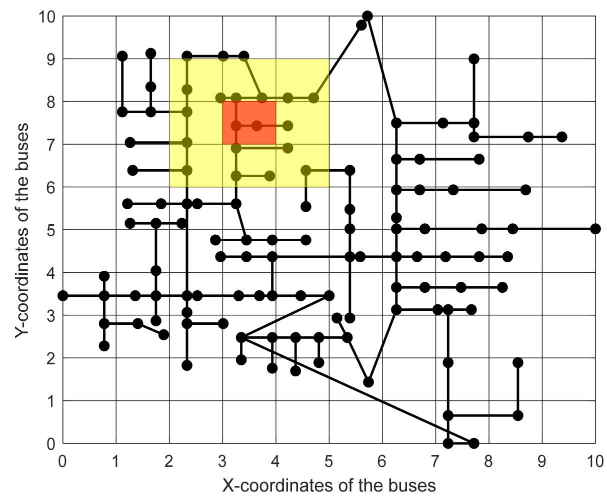

Figure 4: Mesh view of IEEE 123-node system. The black circles are the nodes of the IEEE 123-node test system.

3) Impact modeling: We calculate the impact of any extreme weather event on the grid based on the following equation:

$$IM = w_1 \times I_{EW} + w_2 \times E + w_3 \times V \tag{2}$$

where impact, IM, is a weighted sum of the three determinants, intensity of the extreme weather (I_{EW}), exposure (E), and vulnerability (V). w_1, w_2, and w_3 represent the weights of these three determinants of impact, IM. For ease of simulation, we consider that these three weights equal $w_1 = w_2 = w_3$ and $\sum(w_1 + w_2 + w_3) = 1$. This is a simple way to model the impact of extreme weather on an electric distribution system. Future work includes modeling the impact as a nonlinear function of grid vulnerability, intensity, and exposure. Fig. 4 demonstrates how we calculate the exposure of the grid. For example, the event region is a 3×3 box including 9 cells. Now, based on the GIS system, there might be multiple nodes placed on these regions. The exposure is expressed as follows:

$$Exposure, E = \frac{\textit{Number of buses exposed to the event}}{\textit{Total number of buses in the grid}} \tag{3}$$

To calculate vulnerability, we use the following equation:

$$Vulnerability, V = w_4 \times \frac{\textit{Total generation loss}}{\textit{Total generation capacity}} + w_5 \times \frac{\textit{Total line outages}}{\textit{Number of total lines in the system}} \tag{4}$$

where w_4 and w_5 represent weight factor for the generation loss and line outages. With these vulnerabilities, the intensity of the extreme weather and exposure of the grid to the extreme weather event, we calculate the impact, IM, following equation (2).

4) Modeling MATPOWER test case for IEEE 123-node system: To make the IEEE 123-node system compatible with the outage model, we model the MATPOWER test case. We convert the three-phase system of the IEEE 123-node test feeder to an approximately equivalent single-phase system for MATPOWER. All the line parameters (resistance, reactance, susceptance, etc.) are converted from three-phase to equivalent single-phase. The loads are also converted from three-phase to equivalent single-phase. Then we conduct standard DC and optimal power flow to validate the model. After preparing the test case for MATPOWER, we convert the MATPOWER test case compatible with the outage model described in Section III-1. The process of preparing the test case for the outage model is shown next:

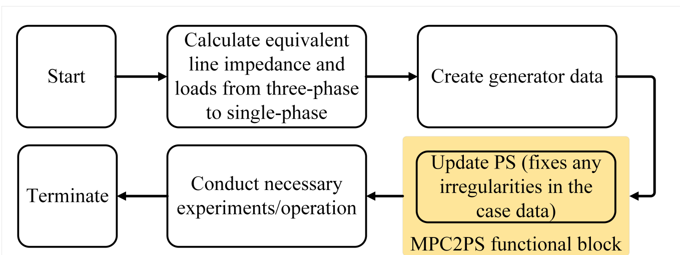

Figure 5: Test case preparation of IEEE 123-node test feeder for MATPOWER and outage model.

5) Modeling Q-learning algorithm: To design the Q-learning algorithm, we define the parameters correlating with the power system environments and the grid. We use the 10×10 grid as the environment, where the top layer is the node coordinates of the IEEE 123-node test feeder. We consider the extreme weather as the agent, and we aim to find the worst impact zone for the agent. The cells are considered as state s. The initial state is considered as 0. This means that the event has not yet landed on the grid. The actions, a, represent the agent to fall on any location of the 10×10 grid. The calculated impact of the extreme weather is considered as the immediate reward of the agent. We consider the temporal effect to find the worst impact zone for the landing of the extreme weather event. Keeping that in mind, the aim of the agent is to maximize the cumulative reward; thus, the agent will have the worst impact zone considering the next propagation zone.

IV. Simulation Studies

The simulation is conducted using MATLAB R2019a on a standard PC with an Intel(R) Core(TM) i7-3720QM CPU running at 2.60 GHz and with 16.0 GB RAM. We conduct the simulation for 100 rounds to find different optimal strategies (worst impact zones of the grid caused by extreme weather conditions). The initial value of epsilon (ϵ) is considered as 0.8 (ensures higher initial exploration probability), and the value of discount rate, γ, is considered as 0.9. The total number of episodes (trials to learn via exploration and exploitation) is considered as $1,000$.

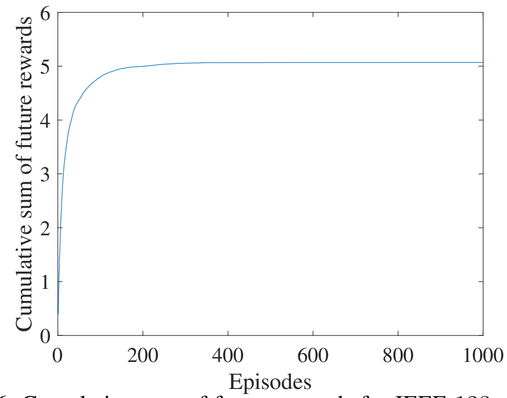

Figure 6: Cumulative sum of future rewards for IEEE 123-nodes test feeder during training to find the worst impact zone for n extreme weather event.

Fig. 6 represents the convergence of the cumulative sum of future rewards.

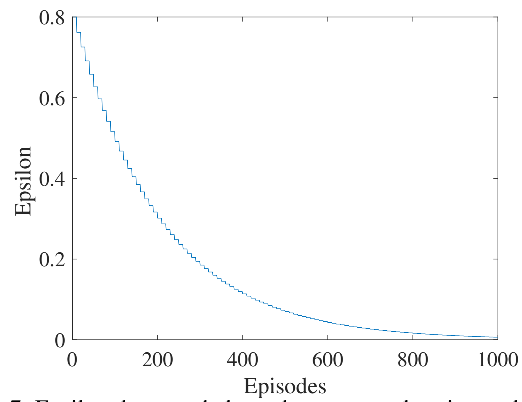

Figure 7: Epsilon decay to balance between exploration and exploitation.

Fig. 7 shows the decay of the exploration-exploitation parameter. The value of epsilon starts with a very high number (which represents a very high random action selection in the beginning). Then the value of epsilon decays gradually to a very small positive number. The small value of epsilon represents a very low exploration and very high exploitation action selection policy.

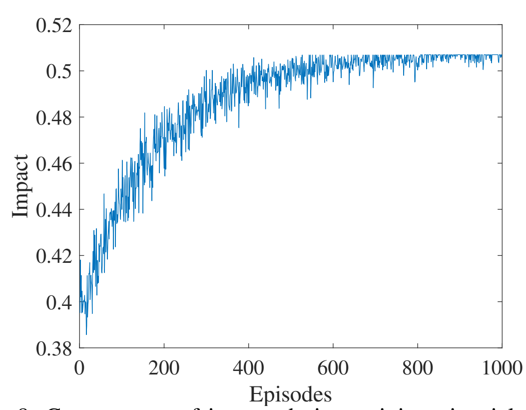

Figure 8: Convergence of impact during training via trial and error of a Q-learning agent.

Fig. 8 shows the convergence of the impact of the worst impact zones during the learning process via trial and error through exploration and exploitation. The impact converges to a value between 0.5 and 0.52 (maximum impact) .

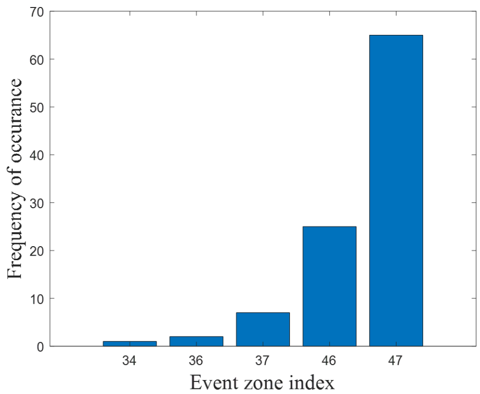

Figure 9: Frequency of occurrence of the worst impact zones.

Fig. 9 shows the frequency of the occurrence of the event zone as the worst impact zone for an extreme weather event. The event zone index 47 appears most frequently (approximately 65%) out of 100 rounds. Table I shows the associated impacts of the extreme weather events. As shown in Table I, the impact associated with event zone index 47 is the maximum, and the value is 0.5015.

Table I: Worst event zone index and their associated impact

Event zone index	Impact caused by extreme weather
47	0.5015
46	0.4832
37	0.4659
36	0.4622
34	0.4463

Similarly, event zone indices 46, 37, 36, and 34 and their associated frequencies of occurrence are shown in Fig. 9 and their associated impacts in Table I. We can conclude that the event zone index with higher impact appeared in the worst event zone index most frequently. Similarly, the event zone index with lower impact appeared less frequently than the others.

V. Conclusion

Extreme weather impact assessment is highly significant in the study of grid resilience. In this paper, we identified the worst impact zone of a distribution system under extreme weather conditions using the Q-learning algorithm as a one-shot process. The proposed work can be extended to include the propagation of the event to the next zone of the grid, which maximizes the total impact of the extreme event. Information about the identified worst impact zones will help utility operators prepare resource allocation, system hardening, and service restoration in advance, as well as enhance grid resilience.

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References

[1] S. Mukherjee, R. Nateghi, and M. Hastak, “Data on major power outage events in the continental u.s.,” *Data in Brief*, vol. 19, pp. 2079 – 2083, 2018.

[2] EATON, *Blackout Tracker*, 2017 (accessed November 2, 2018). Available at: http://electricalsector.eaton.com/forms/BlackoutTrackerAnnualReport.

[3] A. Fritz, *The Washington Post*, 2018 (accessed August 15, 2019). Available at: https://www.washingtonpost.com/news/capital-weather-gang/wp/2018/04/12/hurricanes-harvey-irma-maria-and-nate-were-so-destructive-their-names-have-been-retired.

[4] X. Liu, M. Shahidehpour, Z. Li, X. Liu, Y. Cao, and Z. Bie, “Microgrids for enhancing the power grid resilience in extreme conditions,” *IEEE Transactions on Smart Grid*, vol. 8, pp. 589–597, March 2017.

[5] Y. Wang, C. Chen, J. Wang, and R. Baldick, “Research on resilience of power systems under natural disasters—a review,” *IEEE Transactions on Power Systems*, vol. 31, pp. 1604–1613, March 2016.

[6] C. Han, Y. Zhao, Z. Lin, Y. Ding, L. Yang, G. Lin, T. Mo, and X. Ye, “Critical lines identification for skeleton-network of power systems under extreme weather conditions based on the modified vikor method,” *Energies*, vol. 11, no. 6, 2018.

[7] M. Panteli, D. N. Trakas, P. Mancarella, and N. D. Hatziargyriou, “Boosting the power grid resilience to extreme weather events using defensive islanding,” *IEEE Transactions on Smart Grid*, vol. 7, pp. 2913–2922, Nov 2016.

[8] Y. Li, K. Xie, L. Wang, and Y. Xiang, “Exploiting network topology optimization and demand side management to improve bulk power system resilience under windstorms,” *Electric Power Systems Research*, vol. 171, pp. 127 – 140, 2019.

[9] P. Dehghanian, B. Zhang, T. Dokic, and M. Kezunovic, “Predictive risk analytics for weather-resilient operation of electric power systems,” *IEEE Transactions on Sustainable Energy*, vol. 10, pp. 3–15, Jan 2019.

[10] Z. Ni and S. Paul, “A multistage game in smart grid security: A reinforcement learning solution,” *IEEE Transactions on Neural Networks and Learning Systems*, pp. 1–12, 2019.

[11] F. H. Jufri, J.-S. Kim, and J. Jung, “Analysis of determinants of the impact and the grid capability to evaluate and improve grid resilience from extreme weather event,” 2017.

[12] M. J. Eppstein and P. D. H. Hines, “A “random chemistry” algorithm for identifying collections of multiple contingencies that initiate cascading failure,” *IEEE Transactions on Power Systems*, vol. 27, pp. 1698–1705, Aug 2012.

[13] S. Paul and Z. Ni, “Vulnerability analysis for simultaneous attack in smart grid security,” in *2017 IEEE Power Energy Society Innovative Smart Grid Technologies Conference (ISGT)*, pp. 1–5, April 2017.