Q-Learning Based Impact Assessment of Propagating Extreme Weather on Distribution Grids

Preprint

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Q-Learning Based Impact Assessment of Propagating Extreme Weather on Distribution Grids

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***Abstract*—Increasing number of power outage events due to extreme weather condition is hampering us socioeconomically. Preparing in advance for the extreme weather event is critical and can help utility operators to reduce grid damages, restore grid service quickly, allocate energy resources and repair crews strategically, and hence dramatically increase grid resilience. In this paper, we propose a method to identify the sequence of worst impact zones in the power grid caused by extreme weather events based on Q-learning (a reinforcement learning algorithm). To quantify weather severity and it's effect on the grid, we model the impact of extreme weather on the grid as a function of intensity, vulnerability and exposure. A modified IEEE 123-node distribution feeder is presented in a mesh grid and experimented for sequences of zones identification. Finally, simulation results present the identified sequences and their associated impacts on the grid caused by the extreme weather events.**

***Index Terms*—Q-learning, impact analysis, grid vulnerability, grid resilience, extreme weather, distribution system.**

I. Introduction

In recent years, the necessity of research in the area of grid vulnerability and resilience has increased due to the high frequency and intensity of power outage. A majority of power outage incidents are caused by the extreme weather, leading to significant infrastructure losses and service failures. According to *EATON*, the United States is unprepared for catastrophic power outage. Two back-to-back winter storms caused severe harm to the residents of east cost of the United States in early March of 2018. In New Jersey, almost 600 poles were broken, $1,700$ spans of wire needed replacement. The number of residents affected in New Jersey, New York, Massachusetts, and Connecticut was more than a million. Hurricane Florence made around 1.4 million customers suffer without power across the Carolinas [1]. To prevent from such significant damages for future extreme weather, it is indispensable for grid operators to possess certain knowledge of grid vulnerability, and identify the critical but vulnerable zones which are liable to suffer the worst impact caused by the event.

Some research activities have been attempted to assess the vulnerability of power grid utilizing machine learning approaches. The authors of [2] analyzed the resiliency of a microgrid during extreme weather event representing it in a mesh grid approach. The authors of [3] analyzed the resilience of the grid under natural disaster including the impact forecast of the event leading to system hardening. The impact of extreme weather events on the power grid was studied in [4], where impact is modeled as a multiplication of exposure, vulnerability, and intensity. In [5], the authors conducted vulnerability assessment of a power grid considering malicious attacks on the grid adopting Q-learning and game theory. Although the impact of extreme natural events on the power grid has been widely studied, most of the existing literature overlooked the sequential propagation of the event and its corresponding dynamic impact on the grid. Moreover, a scalable modeling of the event impact is necessary to consider multiple/several weather parameters which affects the quantification of impact caused by extreme weather events.

To overcome the identified limitations, this paper proposes a Q-learning based impact assessment approach, which is able to identify the geographic zones that suffer from the worst impact caused by extreme weather with the consideration of weather severity and propagation. The contributions of the paper include the following:

- We propose a novel approach to identify the sequences of vulnerable zones of a power grid adopting Q-learning algorithm. The outcome of this research provides insightful knowledge of the system's critical component, which in turn will help utility operators to conduct pre-event resource allocation, and/or quick system restoration.
- While identifying the sequences of vulnerable zones, we propose a novel method of impact modeling for the grid due to extreme natural events considering different weather parameters. The proposed model is a generic one, and can be extended and scaled for including other relevant weather parameters.

Rest of the paper is organized as follows. Section II provides theoretical background of Q-learning algorithm, the proposed impact model, and the calculation of generation loss and line outage. The overall block diagram of the proposed research, our proposed algorithm using Q-learning, and the design parameters are explained in Section III. Section IV analyzes the simulation results and Section V concludes the paper summarizing the outcome of this research.

II. Theoretical Background

In this section, we will provide a brief discussion on reinforcement learning, modeling of impact, and calculation of generation loss and line outage.

A. Reinforcement Learning

We utilize Q-learning algorithm to conduct the proposed research. Q-learning is a model free reinforcement learning algorithm. The goal of Q-learning agent is to learn a policy/strategy, which informs the agent what action to execute under certain circumstances. Q-learning is capable of handling problems with stochastic transitions and rewards. In Q-learning, a learning agent interacts with the environment to learn the optimal policy/strategy. To interact, an agent executes actions in the environment and in return receives a feedback for the executed action. Q can be formulated as follows:

$$Q(s,a) \ = R(s,a) + \gamma \sum_{s' \in S} V(s') \tag{1}$$

where R is the reward. The reward is used to find the optimal strategy/policy at the end of learning by maximizing the cumulative sum of future rewards. The value of the state S, $V(s)$ can be formulated as follows:

$$V(s) = \max_{a \in A} \sum_{a \in A} Q(s,a) \tag{2}$$

where V is the value of the state S due to action a. γ is the discount rate which helps the learning agent to focus on long term/short term reward. γ ranges from zero to one. The value of γ close to zero helps the learning agent to focus on short term reward, whereas the value of γ close to one helps the learning agent to emphasis on long term reward. Another hyper-parameter that helps the learning agent learn faster is ϵ. ϵ is the exploration probability. A reinforcement learning agent learns from trial and error process which is known as exploration and exploitation, respectively. The value of ϵ helps to trade between exploration and exploitation, and ranges from 0 to 1. Initially, the value of ϵ starts with a very high value close to 1 which reflects higher probability of exploration (random action) and gradually reduces to a value close to 0 ensuring maximum probability of executing greedy action selection. A reinforcement learning agent optimize the cumulative sum of future rewards to find the optimal policy/strategy.

B. Impact Modeling

To model the impact, IM of the extreme weather (EW) events on the grid, we formulate the following:

$$IM_{EW} = w_1 \times V_{EW} + w_2 \times In_{EW} + w_3 \times E_{EW} \tag{3}$$

where IM_{EW} represents impact on the grid caused by extreme weather events, V_{EW}, In_{EW}, and E_{EW} represent the vulnerability of the grid due to extreme weather, intensity of the extreme weather event, and exposure of the grid to the extreme weather event, respectively. w represents the weights. Hence, w_1, w_2, and w_3 are the weight factor of these three components of the impact.

The definition of vulnerability is dependent on domains. For critical infrastructures like cyber-physical power system (CPPS), the understanding of vulnerability is more focused and specified. Vulnerability of a cyber-physical power grid can be defined as the measure of the system's weakness to failures, threats, disasters, or attacks. The weakness is with respect to a sequence of cascading events that may include line outage (LO) or generation loss (GL), malfunctions or undesirable operations of protection relays, information or communication failures, etc [6], [7]. In this paper, vulnerability of the grid caused by extreme weather events is defined as follows:

$$V_{EW} = w_4 \times \frac{GL_{EW}}{GC_T} + w_5 \times \frac{LO_{EW}}{L_T} \tag{4}$$

where, V_{EW}, GL_{EW}, GC_T, LO_{EW}, and L_T represent vulnerability of the grid due to extreme weather event, generation loss caused by the extreme weather event, total generation capacity of the grid, line outage caused by the extreme weather event, and total number of lines in the grid.

Intensity of the extreme weather can be defined in several ways. Mostly, intensity of the extreme weather is a function of different weather parameters. To quantify the intensity of the extreme weather, we are considering five different weather parameters. The generic equation to quantify the intensity of the extreme weather is proposed as follows:

$$In_{EW} = \sum_{n=1}^{N} w_n \times Wp_{EW}^n \tag{5}$$

where In_{EW} stands for the intensity of the extreme weather event, Wp_{EW}^n stands for the weather parameter associated with that extreme weather, n is index of the weather parameter, and $n = 1, 2, 3, \ldots, N$. In this paper, intensity of the extreme weather event is defined as follows:

$$\begin{aligned} In_{EW} = w_6 \times \frac{Ws_{EW}}{Ws_{worst}} + w_7 \frac{T_{EW}}{T_{worst}} + w_8 \times \frac{P_{EW}}{P_{worst}} \\ + w_9 \times \frac{Pr_{EW}}{Pr_{worst}} + w_{10} \times \frac{H_{EW}}{H_{worst}} \end{aligned} \tag{6}$$

where w_6, w_7, w_8, w_9, and w_{10} are the weight factors and considered equal for all the parameters. Ws_{EW}, T_{EW}, P_{EW}, Pr_{EW}, and H_{EW} stand for the wind speed, temperature, pressure, precipitation, and humidity of the specific location/zone during the extreme weather event, respectively. Ws_{worst}, T_{worst}, P_{worst}, Pr_{worst}, and H_{worst} stand for the worst wind speed, temperature, pressure, precipitation, and humidity out of all the weather impacted zones.

The exposure of the grid to the extreme weather event can be defined as a percentage of the grid exposed to the event. The exposure, E_{EW} caused by the extreme weather event can be formulated as:

$$E_{EW} = \frac{N_H}{N_T} \tag{7}$$

where N_H stands for number of buses affected in the event horizon, and N_T stands for the total number of buses in the grid.

C. Calculation of generation loss and line outage

In order to calculate the vulnerability, we calculate the generation loss and line outage during an extreme weather event. During calculation of line outage and generation loss, we consider the consequence of the cascading outages. To calculate generation loss and line outage, we use the following algorithm which is adopted from [5], [8]. Time-delayed overcurrent relay is used to measure the overloads in the branches. The threshold for the overload is considered as 150% of the regular line limit. Based on these generation loss and line outage, the vulnerability and the impact is calculated.

Algorithm 1: Generation loss and line outage calculation

```
Input  : Test case, bus coordinates
Output: Cascaded outages, total generation loss
Initialize and load the test case;
Represent the grid in a mesh view and place the buses
  based on their coordinates;
for A specific zone do
    Determine the buses and branches involved;
    Run the pre-contingency power Flow ;
    Remove the buses connected to the impact zone;
    Divide into sub-grids according to the overloads;
    Re-dispatch the power flow;
    Update the relay settings;
    if There is overloads then
        Trip the branches according to updated settings;
        Check for the overloads again;
    else
        Calculate total generation loss;
        Calculate total number of line outages;
    end
    Store and display the loss and line outages ;
end
```

III. Proposed Research

In this section, we explain the overall block diagram that we propose in this research. Then, we discuss the mesh representation of the revised IEEE 123-node test feeder, proposed algorithm, and the design parameters.

A. Overall Block Diagram

The identification of the sequence of the worst impact zones during a propagating extreme weather involves learning process, action execution process, and evaluation process. Figure 1 represents the overall block diagram for process flow of this research. The process starts with initializing the power system parameters. We provide weather data and coordinates of the test system as input. Based on the coordinates, the power system is represented as a mesh grid. Initially, we assume the weather hasn't landed/stroked yet. We divide the whole event propagation into five time steps. We consider the weathers for those five time steps of a day and assume the weather event is going to propagate to different zones during these time steps. For every time step, we select a zone from the mesh grid and following the generation loss and line outages calculated using Algorithm-1. After calculating the generation loss and line outages, we calculate the impact of that event using equation (3). After that, we assign reward/feedback. In the next time step, the event propagate to the next time step and we select next impact zone. Similar to the previous process, we calculate the impact of the event to that selected zone. If the event is done with propagation, we check if the learning is complete or not. After enough trial and error, evaluating the rewards/feedback the learning agent converges to the optimal policy. After the learning is complete, we terminate the process.

B. Test system and mesh representation

In order to validate the proposed approach, the IEEE 123-node system is selected to conduct simulation analysis. The IEEE 123-node distribution feeder is modified and converted to equivalent single phase test case. Then we represent the revised IEEE 123-node system as a mesh grid by using geographic information system (GIS) information of the buses.

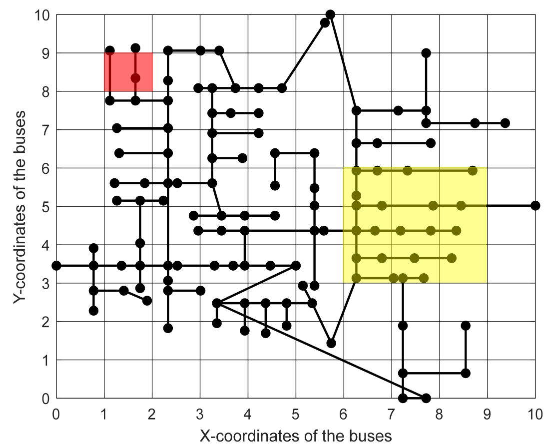

Figure 2: Mesh representation of the revised IEEE 123-node test system.

The GIS information or the coordinates of the grids are normalized and presented in the mesh grid as a 10×10 grid. The lower left box is representing zone number 1, the lower right box represents zone 10, the upper left box represents zone 91, and the upper right box represents zone 100. Based on the normalized coordinates, the nodes are placed. The connection between the nodes represents the lines between them. The red colored zone in Figure 2 represents the zone having the worst weather parameter of all time steps. The yellow colored zone represents the zones where the event is currently happening.

C. Proposed Algorithm

In this sub-section, we will discuss our proposed research algorithm based on Q-learning to identify the sequences of worst impact zones caused by extreme weather event. Algorithm 2 represents the pseudo code for the Q-learning based sequence identification of worst possible impact zones caused by extreme weather event. The algorithm starts

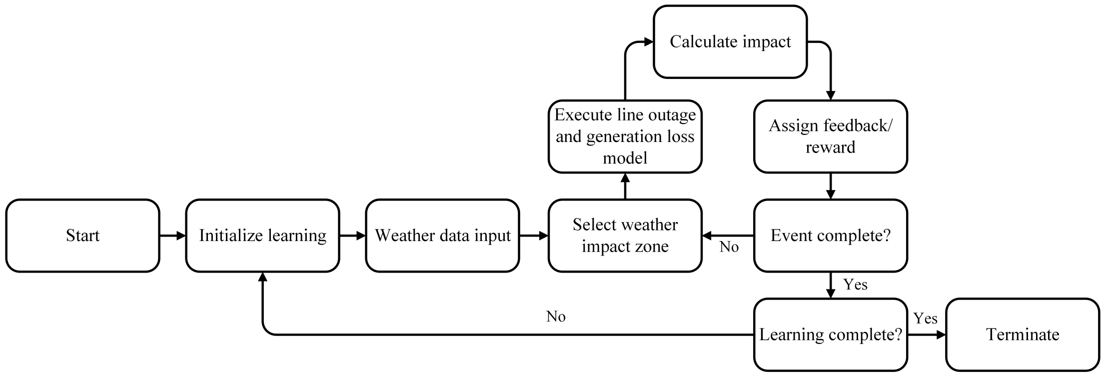

Figure 1: Overall block diagram of the proposed research to identify the worst impact zones for extreme weather event.

with initializing the learning and power system parameters. Given the test case information, number of total episodes, maximum iterations in each episode, discount factor, and weather data as input. This algorithm terminates with providing the information of the sequences of impact zones.

Algorithm 2: Proposed Q-Learning for Sequence Identification of Weather Impact Zones

Input : Power system case information, Number of total episodes, maximum iteration for each episode, learning parameters, weather parameters.
Output: Sequence of weather impact zones.

Initialization;
for *Maximum number of rounds* **do**
  Reset the learning and power system parameters;
  for *Maximum number of run* **do**
    Initialize the current state;
    for *Maximum number of iterations* **do**
      if *Prob* $> \epsilon$ **then**
        Select a random zone from the grid;
      else
        Select an impact zone from Q-table following greedy policy ;
      end
      Calculate intensity, vulnerability, and exposure following eqs. (6), (4), and (7);
      Calculate impact of the extreme weather using (3) ;
      Assign the impact as the reward ;
      Update the Q-value using eqn. (1);
    end
  end
end

D. Design Parameters

The design parameters of this research includes states (S), actions (a), rewards (R), etc. The states are the conditions of the power grid during different time steps. When a state transits to another state in the next time step, it carries the information from the previous time step. This information includes the topological information of the power system. The system states can be represented as, $S = \{s_1, s_2, \ldots, s_n\}$ where n represents the total number of zones visited in the time steps. The actions are the execution of line outage calculation of impact caused by the extreme weather event. The possible action set is represented as follows: $A = \{a_1, a_2, \ldots, a_p\}$ where a_1, a_2 represents the possible actions at a given state, and p represents the number of total possible actions at that state. In the grid, the span of the event for a specific time step is distributed within 3×3 zones. The center of this 3×3 zone is the event center, and the rest 8 zones are the event edge. In reality, the intensity of the weather and the impact caused by it will vary from the center to the edge. But for the ease of simulation, we are assuming the event will have distributed and separate impacts based on the weather input. The reward is the feedback for the executed actions performed by a learning agent. In this research, we are assuming the impact as the reward for executing an action at a time step. The main target is to find the propagation sequence of the zones where the cumulative sum of rewards (impacts) are maximum. The value of ϵ is considered as 0.8 as the initial exploration rate which ensures initially there will be 80% exploration (random action selection) and gradually the value of ϵ will be reduced to a value close to 0. At this stage, the learning agent will follow the greedy policy to select actions which maximizes the cumulative sum of future rewards. The value of γ is considered as 0.9, which ensures that the agent will focus more on the future rewards instead of short term rewards.

IV. Simulation and Results Analysis

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. To conduct the simulation we used weather data (four types of weather parameters) of 20 different locations and distributed randomly among the 100 zones. We collected wind speed, temperature, pressure, relative humidity, and precipitation to conduct this study. We collected the weather data of Hurricane Katrina of August 26^{th}, 2005. Using the weather parameters shown in those above tables, we identify the sequences of the worst impact zones for the grid caused by extreme weather events.

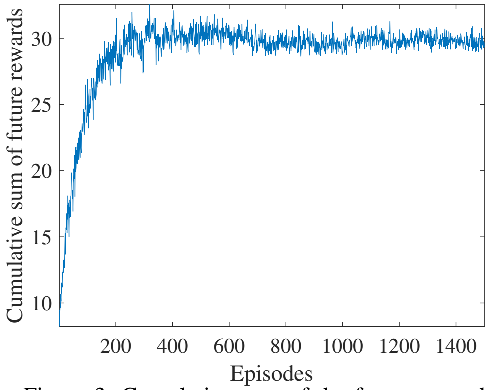

Figure 3: Cumulative sum of the future rewards.

Figure 3 shows the convergence curve for the learning agent to the optimal strategies (average of 150 rounds). Table I shows the identified sequences of zones.

Table I: Sequences of the weather impact zones

#	Sequences	Impact	#	Sequences	Impact
01.	[90, 60, 30, 27, 57]	0.4953	06.	[53, 83, 86, 89, 59]	0.5110
02.	[98, 95, 92, 62, 32]	0.4931	07.	[83, 53, 23, 26, 29]	0.5522
03.	[18, 45, 45, 42, 72]	0.5327	08.	[73, 76, 46, 16, 13]	0.5365
04.	[32, 2, 5, 35, 65]	0.5112	09.	[25, 22, 52, 55, 58]	0.5430
05.	[83, 86, 89, 59, 56]	0.5154	10.	[73, 43, 13, 16, 19]	0.5262

Table I shows the sequences of worst impact zones caused by extreme weather event in IEEE 123-node distribution system. The numbers in the sequences represent different zones in the grid representation of IEEE-123 nodes distribution system. For example, the first sequence from Table I consists of zone 90, 60, 30, 27, and 57. These numbers represent different area of the IEEE - 123 nodes distribution system based on the zone numbering from section III-B. The sequences depicts that, the impact of the extreme weather event is going to cause severe damage to the grid if the weather propagates in the grid following the sequence. The impact values are normalized and range from 0 to 1. There are multiple sequences, which represent different propagation path of the events that can impact the grid severely.

Table II: Intensity, exposure, and vulnerability calculated from associated zones in the sequences from Table I

Zone Index	Intensity	Exposure	Vulnerability
90	0.7737	0.0163	0.0154
60	0.8075	0.0325	0.0309
30	0.7224	0.0163	0.0179
27	0.6856	0.1057	0.1781
57	0.7421	0.1545	0.2044

Table II represents different intensity value of the zones from the first sequence of Table I. These intensities are then used to calculate the impact of the sequences.

Table III: Nodes in the associated zones

Zone Index	Nodes in the Zones
90	[113, 114]
60	[71, 100, 104, 123]
30	[75, 85]
27	[56, 61, 72, 73, 74, 76, 77, 78, 79, 80, 86, 87, 88]
57	[60, 62, 63, 64, 67, 68, 69, 70, 97, 98, 99, 101, 102, 103, 105, 106, 107, 119, 120]

The nodes/lines involved in the first sequence from Table I are given in Table III. The impacts from the sequences in Table I are calculated based on the nodes mentioned above.

V. Conclusion

Power grid is vulnerable to extreme weather events. Identification of worst impact zones during an extreme weather event in a grid can reveal the critical areas/components which are most vulnerable to the extreme weather causing most significant damages. In this paper, first we propose a novel approach to quantify the impact caused by the extreme weather events. Second, we introduce a novel approach of identifying the worst impact zones of a grid using Q-learning algorithm. The sequence of power grid zones is identified due to the consideration of weather propagation. The sequence of worst impact zones will provide guidance for utilities to harden system ahead and prevent from catastrophic grid failures, and it can also provide valuable information for system operators to dispatch repair crews by prioritizing the critical zones after the disastrous event hits the grid.

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