A temporal-spatial natural disaster model for power system resilience improvement using DG and lines hardening

Bei Li, Robin Roche and Abdellatif Miraoui
FEMTO-ST, CNRS, Univ. Bourgogne Franche-Comte, UTBM
rue Thierry Mieg, F-90010 Belfort Cedex, France bei.li@utbm.fr

***Abstract*—As natural disasters seem to become more and more frequent in some parts of the world, power system resilience is a growing concern, especially due to the economic consequences of the induced blackouts. In this paper, we use a temporal-spatial model to describe natural disasters. Based on fragility curves, we use a Monte Carlo method to estimate the destructive dynamic of such disasters, and simulate a hurricane occuring in the IEEE 37-bus network. We then propose an optimization method to find the most suitable nodes to integrate distributed generators (DG). With the resulting DG additions, we select the lines to be hardened to further improve system resilience.**

***Index Terms*—distributed generation, natural disaster, power system, resilience, temporal-spatial model**

I. Introduction

The recent years have seen an increase in the frequency of natural disasters, in the form of hurricanes, storms, floods or earthquakes. Most of these events lead to significant damages on electric power systems, and sometimes even blackouts [1]. Avoiding such difficulties is thus an increasingly important topic [2], [3], especially due to their large economic consequences, e.g., for industry. A general approach to such problems is that systems should ideally have the ability to "bend" rather than break, i.e., become more resilient. In this paper we adopt the following definition of power system resilience: "the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions" [4].

Conventional distribution networks have a radial structure, where power is generated in large centralized power plant [5]. Consequently, if a node of the radial tree is damaged, all child nodes will typically also be out of service. This might however not be the case anymore when we consider distributed generation (DG) and storage, which are becoming increasingly popular. By integrating such units (e.g., photovoltaic panels, fuel cells or microturbines) at the edge of the grid, additional options for resilience emerge. Another (classical) solution is to harden power lines [6] to reduce their failure probability, e.g., by changing the overhead power lines to underground cables.

Due to the nature of a natural disaster (e.g., a hurricane), the probability that grid components fail changes with time as well as location. This implies that natural disasters must be modeled with temporal-spatial models. Fig. 1 shows a ficticious example of such an input model. From this model, the problem is to determine where to install DG and which power lines to harden in the distribution network. In this paper, we therefore discuss (a) how to use a Monte Carlo method to calculate the influence of natural disasters; and (b) how to determine the best DG and line hardening options.

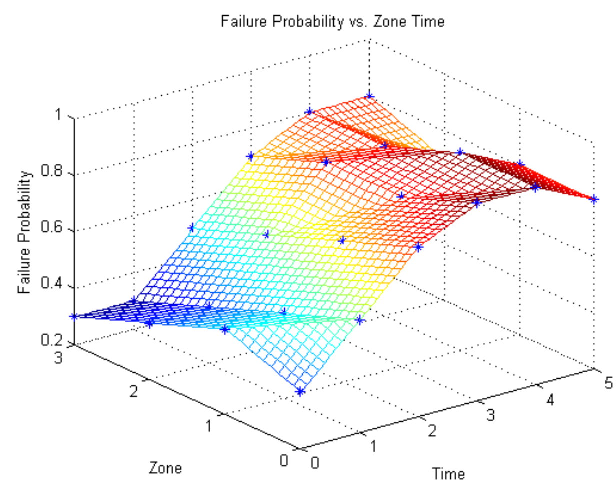

Fig. 1. Failure probability vs. zone and time.

The remainder of this paper is organized as follows. Section II discusses related work. Section III introduces the studied temporal-spatial natural disaster model. Section IV describes the method used to evaluate where to install DG and which power lines to harden in distribution network, and Section V concludes the paper.

II. Related work

In this section, we review related work under two perspectives: (a) methods used to quantify disasters influence; and (b) solutions to improve power system resilience.

A. Methods used to quantify disasters influence

First, [1] reviews the resilience of power systems under natural disasters: it discusses forecasting models with statistical simulation-based models; then discusses corrective actions, hardening and resilience activities; and thirdly, proposes two restoration strategies including DG, microgrids and distribution automation with decentralized restoration.

[7] presents a methodology for resilience analysis. Firstly, it analyses the structure of the system, using interaction and

coupling metrics; then it builds a dynamic model considering failure time and recovery time, and analyses the dynamic model using state transitions with an event-driven method. It then provides a resilience metric, by summing the nodes' states; and at last, it analyses the sensitivity to the variability of disturbances.

[8] uses fragility curves to express the relation between the failure probability of a system component, the loss of load frequency (LOLF) and the loss of load expectation (LOLE). These are used as reliability indices, and for dividing the system into different regions in order to precise the influence of weather, then evaluate the impact of weather in four cases: normal network, robust network, redundant network, and response network.

In [9], the authors propose a resilience model including four sub-models: firstly, using a Poisson process to build the hurricane model; then building the fragility model of power system components; thirdly, building the power system response model; and last, building a restoration model considering component repair priorities. With this model, the authors are able to assess resilience in four dimensions: technical, organizational, social and economic.

Paper [10] uses a spatial-temporal non-stationary random process approach to model large-scale disruptions in power distribution induced by severe weather. Firstly, it describes the dynamic failure and recovery processes, then it quantifies the disruption rate and recovery rate, and gives a definition of resilience. At last, it uses hurricane Ike data to calculate the non-stationary process of the hurricane.

[11] provides a grid-centric model for natural hazards, that considers the probability and severity of events, the geographical span of disaster events, the impact on component availability, and the impact on component capacity.

Finally, [12] proposes a cascading outage analysis model to evaluate the short term impacts of attacks or disasters. This model uses four outage checkers, namely a transient stability checker, a frequency outage checker, an overload outage checker, and a voltage outage checker to simulate the system behavior after an initial disturbance. Authors also propose a tool to analyze power system security under hurricane threats, by firstly building the hurricane model, then using the model to simulate transmission line failures based on the failure rate of the transmission line, thirdly applying these transmission line failures to the cascading outage analysis model, and finally obtaining the total system outage.

The above papers provide methods to quantify the influence of natural disasters. However, they do not address the method to withstand disasters. In summary, natural disasters are spatial-temporal non-stationary random processes, which means that when disasters occur on power systems, the failure probability of components is different in different geographical zones, and also as time goes, the destructive dynamic of components is different.

B. Power system resilience improvement

Once the mechanism of propagation of disasters is known, we can develop methods or strategies to improve power system resilience.

For example, [6] proposes several defense plans for boosting resilience, including short-term resilience measures and long-term resilience measures. [13] discusses improving resilience in three ways: utilizing microgrids to restore more loads, using remote-controlled switches to decrease restoration time, and providing redundant sources to critical loads. In [14], authors research about the topology of the system, and find that networks typically have a number of highly-connected hub buses. These networks appear to have a scale-free network structure, so these hub buses are key elements to improve the resilience of the overall system. In [15], authors propose an extended topological method by incorporating electrical distance, power transfer distribution factors, and line flow limits to research about the vulnerability of the system. In [16], authors use a simulation method to find which recovery strategy is the best. It adopts line flow violations and voltage violations as metrics to calculate the resilience of the system. Then authors compute power flow for the IEEE 9 nodes model to compare resilience results with different recovery strategies.

Methods using DG to improve system resilience are also proposed. In [5], authors present a microgrids forming method in distribution systems after a natural disaster, and the impacts of multiple faults are considered. In [17], authors restore the distribution system using spanning tree search method, in which microgrids are regarded as virtual feeders. In [18], the authors propose a three-stage restoration strategy using DG, with: (a) network cell formation, (b) network cell expansion, and (c) reconnection with upper level networks. [19] researches on the sectionalization of a distribution system into multiple networked self-supplied microgrid, after an outage. [20] proposes a self-healing planning strategy for all possible future faults by optimally dividing the distribution system into microgrids.

In summary, the main methods discussed in the literature to resist disasters include: 1) using multiple power sources, i.e., integrating DG sources; 2) hardening highly-connected lines. Another aspect is that the above papers research on using DG to improve resilience after disasters are over, but do not consider using DG to resist disasters while they are happening.

In our previous research [21], we presented a Monte Carlo method to calculate the influence of natural disasters, but the natural disaster was built on a simple model. We also did not consider the optimal connection of DG. The main contribution of this paper are as follows: 1) we build a spatial-temporal dynamic model to describe natural disasters; 2) we use a time series Monte Carlo method to simulate this dynamic model; 3) we study the optimal siting of DGs to improve system resilience; 4) with the resulting DG additions, we select the lines to be hardened to further improve system resilience.

III. MONTE CARLO MODEL

Due to the fact that the destructive dynamic of a disaster is random [10], the Monte Carlo approach [22] is used to simulate a large number of disaster scenarios using a probabilistic approach. Because a natural disaster is a spatial-temporal random process, we first divide the area of the distribution network into several zones, and then divide time (the disaster duration) into several time steps. We assume that the failure probability is constant during a time-step, but that in different zones, the failure probability is different.

Then, for each time step and each zone, we use the Monte Carlo method to calculate the damage. Results at the next time step depend on damage determined at the previous step.

With the Monte Carlo method, we need to decide the number of simulations. Based on our previous research [21], we compute this number as $N_{MC} = 10,000$, and the error between the calculated average value of survival loads and expectated value of survival loads is less than 10^{-3}. In this paper, the term surviving loads is defined as follows. At each node, the load is 1 unit. If there is no power source to serve a node, then the load of this node will be 0. For each time step, there are a total of 37 unit loads (one for each node), and there are 19 time steps, so if the system is fully operational over the entire duration, the surviving loads value is equal to $37 \cdot 19 = 703$. As a consequence, we try to maximize this value.

A. Simulation process

Based on the forecast data of the natural disaster (for example, a time series of wind speed for a hurricane, a time series of rainfall for a flood), and the fragility curve of components [8], we can get the failure probability of these components.

We note the time step $t \in \mathbf{N}$. Based on geographical criteria, we divide the area into several zones, $Z_i, i = \{1, 2, 3, ...\}$, and the number of power lines in each zone is noted N_{Z_i}.

The number of nodes in the network is N_n, where $S_{pl}^i \in \mathbb{R}^{1\times m}, i = \{1, 2, ..., m\}$ represents the state of power lines (there are m power lines). $S_{pl}^i = 0$ represents a line that is destroyed, while $S_{pl}^i = 1$ represents an operational line. From this, we can form matrix LM that represents the route between the loads $L_i \in \mathbf{Load}, i = \{1, 2, ..., N_n\}$ and the different power sources $PS_i \in \mathbf{PS}, i = \{1, 2, ..., N_n\}$:

$$LM = \begin{bmatrix} & PS_1 & PS_2 & PS_i \\ L_1: & S_{11} & S_{12} & S_{1i} \\ L_2: & S_{21} & S_{22} & S_{2i} \\ \cdots & \cdots & \cdots & \cdots \\ L_i: & S_{i1} & S_{i2} & S_{ii} \end{bmatrix} \tag{1}$$

where $S_{11} = S_{22} = ... = S_{ii} = 1; S_{ij} = S_{pl}^k \cdot S_{pl}^l \cdot ...$, etc., $k, l = \{1, 2, ..., m\}$.

We use vector $y_i \in \mathbf{Y}, i = \{1, 2, ..., N_n\}$ to represent whether there is a power source connected at the node or not. $y_i = 1$ means that there is a power source connected at node i, and $y_i = 0$ that there is none. This can be represented as matrix PN:

$$PN = \begin{bmatrix} PS_1: & y_1 \\ PS_2: & y_2 \\ \cdots & \cdots \\ PS_i: & y_i \end{bmatrix} \tag{2}$$

The overall simulation process is shown in Algorithm 1. The only input variable of this algorithm is $P_{pl}^{Z_i \times t}$, that represents the power line failure probability.

Here, Pl_{Z_i} corresponds to random values (uniformly distributed random numbers in the interval (0,1)) used to simulate the severity of the natural disaster. $Pline_{Z_i}$ is the state of each power line (0 or 1), used to describe whether the power line is destroyed or not. function $prod$ is a Matlab function, that, for example, for 'prod(A)' returns the product the elements of vector A. And $R(t)$ is surviving loads, we calculate $R(t)$ as follows:

$$R(t) = \frac{\sum_{ct=1}^{N_{MC}} \frac{LM_1^{ct} + LM_2^{ct} + ... + LM_i^{ct}}{N_n}}{N_{MC}} \tag{3}$$

where:

$$LM_1^{ct} = (S_{11}^{ct} \cdot y_1 + S_{12}^{ct} \cdot y_2 + ... + S_{1i}^{ct} \cdot y_i) \tag{4}$$
$$LM_2^{ct} = (S_{21}^{ct} \cdot y_1 + S_{22}^{ct} \cdot y_2 + ... + S_{2i}^{ct} \cdot y_i) \tag{5}$$
$$LM_i^{ct} = (S_{i1}^{ct} \cdot y_1 + S_{i2}^{ct} \cdot y_2 + ... + S_{ii}^{ct} \cdot y_i) \tag{6}$$

Algorithm 1 Monte Carlo simulation algorithm

```
for t = 1 : N do
    for ct = 1 : N_MC do
        Pl_Zi = rand(t, N_Zi)
        for i = 1 : t do
            for j = 1 : N_Zi do
                if Pl_Zi(i, j) < P_pl^Zi(1, i) then
                    Pline_Zi(i, j) = 0
                else
                    Pline_Zi(i, j) = 1
                end
            end
        end
        for j = 1 : N_Zi do
            S_pl(1, j) = prod(Pline_Zi(:, j))
        end
        Calculate LM · PN
    end
    Calculate R(t)
end
```

B. Model results

We select the IEEE 37-bus distribution network (Fig. 2) [5] as the model to simulate the influence of natural disasters occuring on power system. We divide the area into 3 zones, namely, zones 1, 2 and 3. We then assume that a hurricane occurs in this area, and lasts for about 95 minutes. The time duration is divided into time steps of 5 minutes. In each time step, we assume that the wind speed is constant, but changes for each time step, as shown in Fig. 3.

Based on fragility curves [8], we can obtain the failure probability of power lines, $P_{pl}^{Z_i \times t}$. In order to compare the difference between before and after connecting DG sources into the distribution system, we arbitrarily define 6 scenarios:

1) Without any DG;
2) Case1: with DG at nodes {3, 21, 30, 35};
3) Case2: with DG at nodes {11, 17, 23, 29};
4) Case3: with DG at nodes {3, 17, 23, 29};
5) Case4: with DG at nodes {11, 17, 29, 35};
6) Case5: with DG at nodes {17, 21, 29, 35}.

Fig. 4 shows the loss of loads in different zones over time, and Fig. 6 shows the average loss of load in the whole system. From these two figures, we can see that after connecting DG sources into the distribution network, the loss of load in the system is reduced. However, determining where to connect these sources has not yet been investigated. This is covered in the next section.

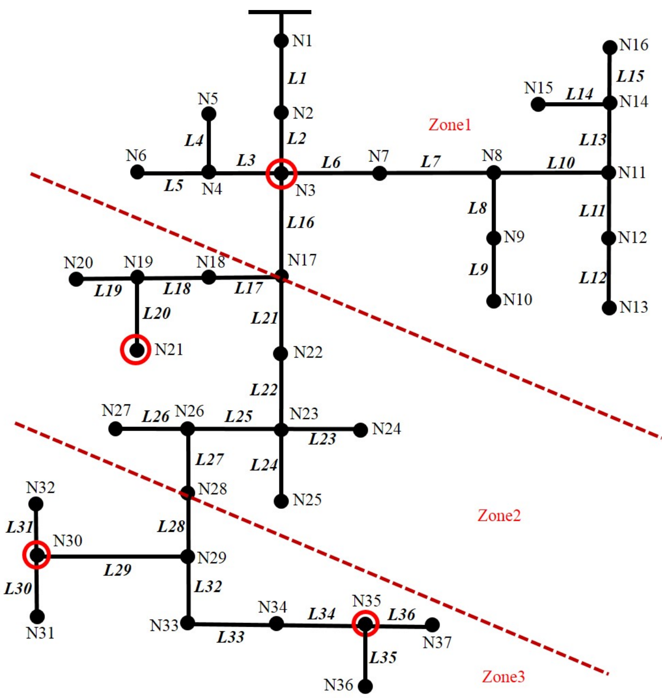

Fig. 2. 37-node distribution network used in the simulations.

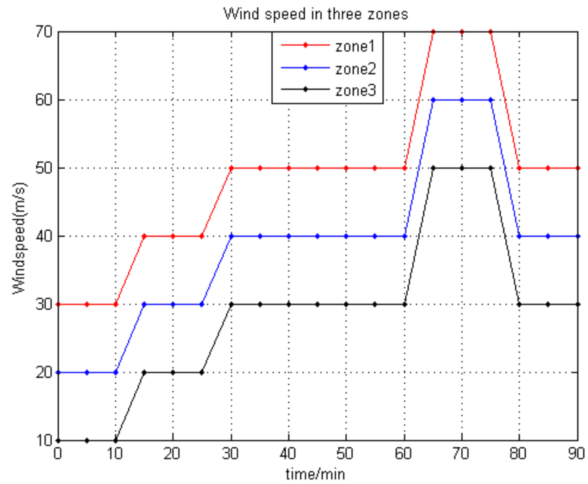

Fig. 3. Wind speed profiles.

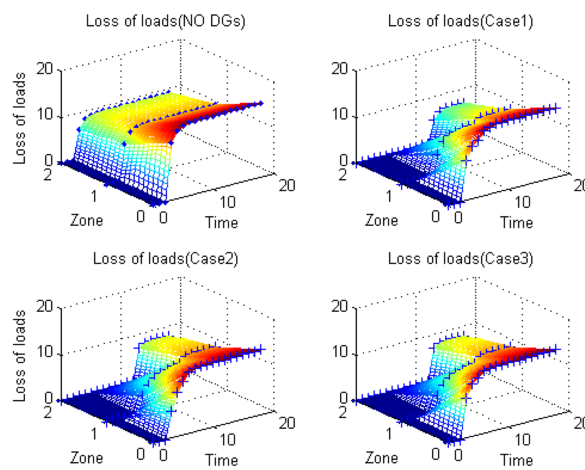

Fig. 4. Loss of load vs. zone and time.

IV. Resilience improvement method

Ideally, we could connect DG at all nodes of the system, which would maximize the resilience. However, the cost would also be high. We thus need to find an optimum between the number of DG sources, costs, and resilience improvement.

Firstly, we need to find an index to describe the influence of connecting DG sources at some nodes. Because we want the surviving loads to be maximal, the sum of surviving loads is adopted, namely $\sum_{t=1}^{N} R(t)$.

A. Problem description

The variables correspond to vector $Y = y_1, y_2, \ldots, y_{N_n}$, which represents whether there is a power source connected at the node or not, namely, PN. We run Algorithm 1, and compute values for the objective function $\sum_{t=1}^{N} R(t)$. Here, contrary to section III.A, vector $Y = y_1, y_2, \ldots, y_{N_n}$ are decision variables, and not inputs. This linear optimization problem is implemented in Matlab. Gurobi is used as a solver to obtain solutions.

For any time t, we calculate $R(t)$ as equation 3.

Then with the time series, we can compute the objective function defined as follows:

$$\max_{Y} \sum_{t=1}^{N} R(t) = \max_{Y} \sum_{t=1}^{N} \frac{\sum_{ct=1}^{N_{MC}} \frac{LM_1^{ct} + LM_2^{ct} + \ldots + LM_i^{ct}}{N_n}}{N_{MC}} \quad (7)$$

B. Results

Algorithm 2 describes the methodology used to determine the best locations for connecting DG sources at system nodes. For example, when we interconnect 4 DG sources into the system, the optimal node results are {29, 30, 33, 35}, while

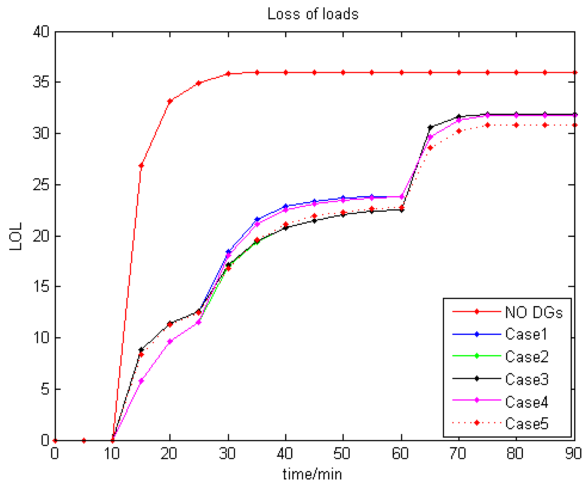

Fig. 5. Average loss of load vs. time

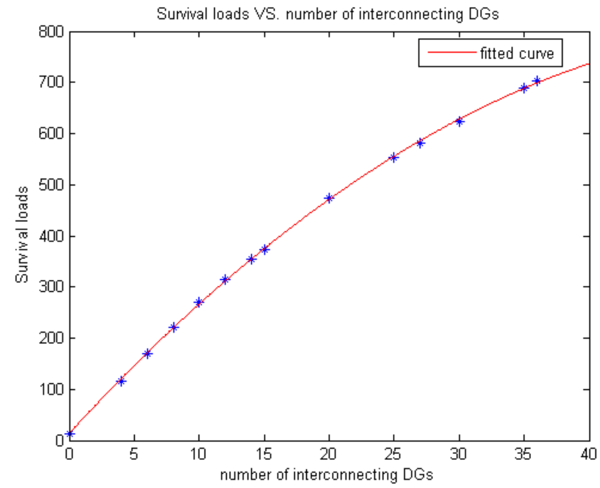

Fig. 6. Surviving loads vs. number of connected DG sources.

Algorithm 2 DG placement optimization method

Initialize variables $PN(Y = y_1, y_2, \ldots, y_{N_n})$
for $t = 1 : N$ **do**
  Run Algorithm 1
  Calculate $LM \cdot PN$
  Calculate resilience $R(t)$
end
Run optimization: $\max\limits_{Y} \sum_{t=1}^{N} \frac{\sum_{ct=1}^{N_{MC}} \frac{LM_1^{ct}+LM_2^{ct}+\ldots+LM_i^{ct}}{N_n}}{N_{MC}}$

when we connect 5, the nodes are {29, 30, 33, 34, 35}, as shown in Tab. I. We then compare the results in Fig. 6, and observe that when we increase the number of connected DG sources, the surviving loads also increase.

In zone 1, the probability that power lines get destroyed by the hurricane is the highest among these three zones. On the contrary, DGs installed in zone 3 can support the whole system during the whole hurricane duration.

TABLE I
RESULTS FROM THE OPTIMIZATION.

Case	Number of DGs	Optimal nodes for connecting DG sources
Case6	4	29, 30, 33, 35
Case7	5	29, 30, 33, 34, 35
Case8	6	28, 29, 30, 33, 34, 35
Case9	7	28, 29, 30, 31, 33, 34, 35
Case10	8	28, 29, 30, 31, 33, 34, 35, 36

C. Hardening lines

After the optimal nodes for connecting DG sources have been determined, we can choose which lines are to be hardened to further improve power system resilience. We assume that if a power line is hardened, then it will not be destroyed by disasters (in reality, the probability it is destroyed is decreased). In the previous sections, we used the route matrix to represent the route between power sources and loads. This is represented using the multiple results of state of each power line. Then, if we choose which power line is to harden, the final optimization problem will be a large nonlinear problem, difficult to solve.

To circumvent this problem, we rank the influence of hardening each line. We set 36 different hardening line cases, in which only one power line is hardened (horizontal axis in Fig. 7). Based on these cases, we can get Fig. 7, (where 'case 6'-'case 10' represent different DG integration configurations, as in Table I) that represent the relationship between surviving loads and the hardening line cases. For example, in case 6, hardening lines {29,32} returns the best results to further improve resilience; and in case 7, hardening lines {29, 32, 33, 34} returns the best results.

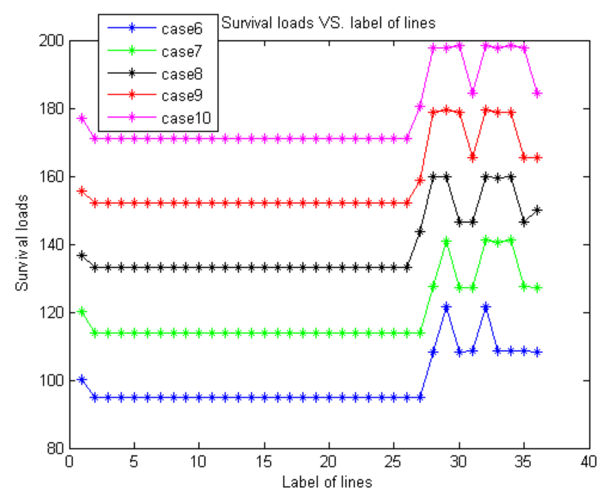

Fig. 7. Surviving loads vs. label of hardening line cases.

V. CONCLUSION

In this paper, we discussed how to improve power system resilience by integrating DG sources and hardening power lines. Firstly, we built a temporal-spatial natural disaster model based on fragility curves. Then, we presented a Monte Carlo method to calculate the surviving loads under natural disasters. Afterwards, we simulated the IEEE 37-node network with a hurricane. With the proposed method, the loss of load can be calculated in different areas and different times. We then proposed an optimization method to find the optimal nodes for integrating DG sources. At last, with a given multiple power source configurations, we find the lines to be hardened to further improve system resilience. Future work will include comparing these results with other approaches.

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