Identification of Cascading Failure Scenarios of Infrastructure Systems using Multi-Group Non-Dominant Sorting Algorithm

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ABSTRACT: Power transmission networks are critical infrastructure systems of urban communities, but are prone to cascading failures due to their high level of interconnectivity. Therefore, it is of great interest to identify critical components of the network that may trigger cascading failures. However, existing approaches to identify critical cascading failures focus on topological effect for a limited number of initial component failures. Meanwhile, identification based on load flow analysis without a limit on the number of triggering component failures has not been extensively studied. In this study, we simulate the overload-induced cascading failures to find the most critical scenarios of initial failure events in a power grid. The proposed approach uses the multi-group non-dominant sorting algorithm (Choi and Song, 2017) with two objective functions, i.e. network impact measure, and the number of initial component failures. Numerical experiments on a 30-bus network demonstrate that the identified critical cascading scenarios, triggered by single and multiple component failures, may not share common components necessarily. The proposed approach is expected to identify a group of critical components, which may be neglected by existing approaches.

1. INTRODUCTION

Electric power supply networks are considered one of the most critical infrastructure systems supporting urban communities which thus needs to be secured with a priority. Due to the ever-growing demand of electric energy and the high interdependency of infrastructure networks, however, the disaster risk of power networks also increases. Moreover, estimating the propagation of the damaging effect through the power system becomes challenging. For instance, the electric power blackouts in Italy (2003), the North-Eastern U.S and Canada (2003), and Eastern India (2012), which brought catastrophic losses, were triggered from unexpected damage scenarios with low likelihoods (Andersson et al., 2005). To secure the service continuity and to avoid such significant direct and indirect losses due to the blackout, therefore, identification of critical post-disaster scenarios of the power grid is an important task.

To date, to identify critical scenarios of the infrastructure network, which are defined as a small number of initial component failures resulting in disproportionate consequences, various optimizing methods and impact measures have been proposed. Consequence-based search using multi-objective algorithms were proposed to detect critical components in the fields of reliability engineering, computer science and operational research (Rocco et al., 2009; Zio et al., 2012; Ventresca et al., 2015 and 2018). Particularly, NSGA-II (Deb et al., 2002), a non-dominant sorting genetic algorithm has been popular as the main search algorithm. While NSGA-II approach successfully resolved many of critical component identification problems, it has been reported in a few papers that some of the final non-dominant solutions were neglected as the network size increases (Ventresca et al., 2018). This issue is partly related to the loss of the population diversity in early generations of NSGA-II. Therefore, to preserve the diversity of samples, the authors recently proposed a multi-group non-dominant sorting algorithm (MG-NSGA) in previous work (Choi and Song, 2017).

In such an optimization-based search, defining proper impact measures is a key to finding critical components of the networks. Even for the identical network, a different set of the critical components could be identified depending on the definitions. As for the power grid, it is important to assess the impact of the final stage of the cascading failure since the initial failure and the final consequence could differ greatly.

A number of recent studies addressed the cascading analysis mainly in terms of the topology of the power system (Zio et al., 2012; Li et al. 2013). This is mainly because the topological approach has an advantage in the simplicity of analysis and requires relatively less input data. However, a cascading failure in a power grid is sequential failures with strong interdependency due to the load re-distribution, which is affected by both network topology and electric properties of the individual components. Therefore, for improved simulations of cascading failure sequence, load flow analysis should be performed using additional information instead of relying on network topology only.

There have been limited studies that consider the cascading failures triggered by more than one initial failure. The previous research focused on the cascading failures triggered by a single component failure (Li et al., 2013) or up to four (Zio et al., 2012). This may due to the complexity and the computational cost required for simulating cascading failures in a power grid. However, in practical circumstances, natural and manmade disasters often induce multiple component failures simultaneously. Therefore, cascading failures caused by *multiple* component failures should be considered.

To identify critical cascading scenarios of a power system with consideration of power flow analysis but without imposing constraints on the number of trigger components, this study uses overload cascading model (OCM) and multi-group non-dominant sorting genetic algorithm (MG-NSGA). The main features are summarized as follows: (1) To identify the critical post-disaster scenarios, the damage impact at the final cascade stage is considered as one of the objective functions; (2) To evaluate the impact measure, over-load cascading failure analysis, which includes repeated DC load flow analysis, is performed; and (3) The cascading failures triggered by not only single component, but also multiple network components are investigated using the MG-NSGA approach.

Through applications to numerical examples, we investigate whether critical cascading scenarios, simulated by overload cascading model and induced by one or more initial component failure can be effectively identified using the MG-NSGA. Through further development, this methodology is expected to broaden the understanding of cascading failure risk inherent in power supply networks.

Sections 2 and 3 respectively provide the formulations and procedures of the cascading model, and MG-NSGA. In Section 4, the power grid example is presented as the case study. After providing the results and discussions in Section 5, Section 6 summarizes the paper along with concluding remarks.

2. SIMULATING CASCADING FAILURE OF POWER SYSTEM

In this paper, power supply networks are modeled such that power flow of transmission lines are estimated based on computational simulation of overload cascading failures. To this end, the sequence of interdependent failures is modeled using overload cascade model (OCM). Damage measures of this study, which are evaluated using the final cascading results, are also described.

2.1. Modeling power system

Using graph theory, network topology of the power system could be expressed by nodes and edges. Each bus of the power system, including the generator and/or load, becomes a node while the power transmission lines become edges.

2.2. Estimating line power flows: DC load flow

To estimate the load flow in each line component of a power system, the power flow equations (Grainger, J. J. and Stevenson Jr, W. D.,1994) are employed in this study. Depending on whether the reactive power is accounted or not, the power flow analysis could be conducted using two different equations, i.e. AC flow analysis and DC power flow analysis. The AC power flow considers both active and reactive powers while the DC power flow considers only active power. Since the AC load flow analysis considers both active and reactive power, the analysis may require iterative calculations, and also does not ensure the convergence. As the simplified and linearized version of the AC load flow, on the other hand, the DC load flow analysis provides the solution without iterations. Therefore, in the optimization problem of the power supply system problem, the DC load flow estimation is often used because of its simplicity and effectiveness (Koh et al., 2003). In this research, we adopt the DC load flow analysis to avoid time-consuming iterations of load flow analysis during the cascading analysis and the search by use of a genetic algorithm.

In the DC load flow analysis, the AC system is simplified through the following assumptions: (1) Line resistance is negligible; (2) Voltage angle difference is assumed to be small; and (3) Magnitudes of bus voltage are set to the flat voltage profile. By these assumptions, the DC flow equations can be expressed as

$$f_{ij} = b_{ij}\theta_{ij} \tag{1}$$

where f_{ij} and b_{ij} are respectively the active power flow and susceptance of the line l_{ij} connecting node i and j; and θ_{ij} is the voltage phase difference between the nodes. The power grid can be expressed in terms of the active power flow, i.e.

$$P_i = \sum_{j=1}^{d} f_{ij} = \sum_{j=1}^{d} b_{ij}\theta_{ij} \tag{2}$$

where P_i is the active power flow at node i and d is the degree of node i. As a result, the active power flows in a certain transmission line i, which connects the bus s and r can be calculated as

$$P_{Li} = \frac{\theta_{sr}}{X_{Li}} \tag{3}$$

where X_{Li} is the reactance of line i. The load flows through branches are expressed using a matrix form

$$\Theta = [\mathrm{B}]^{-1}\mathrm{P} \tag{4}$$

$$\mathrm{P}_{\mathbf{L}} = (\mathbf{b} \times \mathbf{A})\Theta \tag{5}$$

where P denotes the vector of bus active power injections, B is the admittance matrix, and Θ is the vector for bus voltage angles. $\mathrm{P}_{\mathbf{L}}$ is the vector for branch flows, $\mathbf{b}$ is the susceptance matrix, and $\mathbf{A}$ is bus-branch incidence matrix (Grainger, J. J. and Stevenson Jr, W. D.,1994).

Eventually, when the network topology and electric properties (i.e. generated power and/or power demand at each node, reactance of each line) of the network component is given, power flow of each line can be evaluated using DC load flow equation.

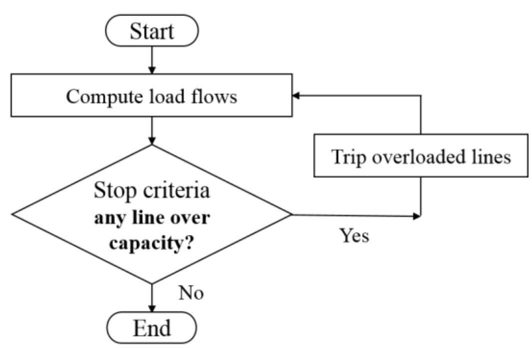

Figure 1: Flowchart of the Overload Cascade Model

2.3. Overload cascade model (OCM)

To simulate the cascading failure, the Overload Cascade Model (OCM) is adopted (Koc et al., 2013; Pahwa et al., 2014; See flow chart in Figure 1). The DC load flow analysis is first performed using the initial power grid topology. Afterwards, each flow of the lines in the power system is compared with its line capacity. The lines with loads beyond their capacity due to the load redistribution are removed from the network topology. For each iteration of cascading failure analysis, the topology of the power grid is re-constructed. With the updated network topology, the load flows are computed again until none of the line component trip due to the overload flow. The overload cascading process is completed when the load flow is finally stabilized.

2.4. Damage measures

After cascading failure simulation, the damage of the network is quantified in terms of selected damage measures based on the condition of the final cascading stage. In this paper, the post-disaster scenario which has more nodes disconnected from the power source is considered to be more critical. Therefore, the number of disconnected nodes from the generator nodes at the final stage of cascading failure is selected as a damage measure.

A subjunctive node, which connected to the generator node with imaginary non-breakable links, is introduced to assess the number of nodes isolated from a *group* of generator nodes (Lee et al., 2011). To identify such nodes, the connectivity analysis is performed using breadth-first search (BFS) algorithm (Moore, E. F., 1959).

3. IDENTIFICATION OF CRITICAL POST-DISASTER SCENARIOS USING MG-NSGA

In this study, we use the multi-group non-dominant sorting algorithm (MG-NSGA) to search the sample space and identify the most critical cascading scenarios. To apply MG-NSGA to the network cascading failure scenario problem, genetic representation of network failure scenario and proper objective functions need to be defined.

3.1. GA-based representation of network component failure scenarios

As shown in Figure 2, each scenario of component states can be expressed by a binary string. The values 1 and 0 indicate the survival and failure of the network component respectively. For the example power supply system consisting of 5 nodes and 4 links in Figure 2(b), the post-disaster scenarios can be represented by the binary string with length 4. It is important to note that the network scenario sampled in the optimization process are to simulate the *initial* failure of the network, not the final cascading failure condition of the network.

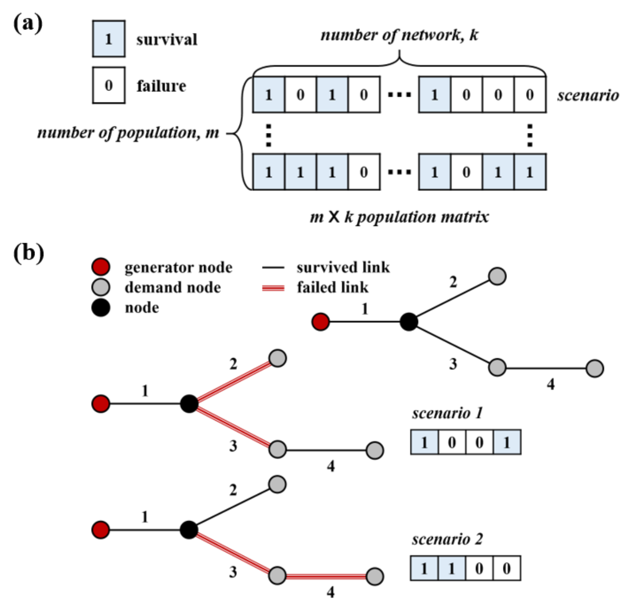

Figure 2: (a) General structure of genetic representation of network scenarios; and (b) example of link failure scenarios and corresponding genetic representations

3.2. Objective functions

To identify critical scenarios of interest, two objective functions are defined for MG-NSGA: (1) damage measure, i.e. the number of nodes still connected to power generator node at the final cascading stage, and (2) the number of links failed at the initial stage. In this paper, we consider scenarios in which a small number of the initially failed link induce a large number of disconnected nodes as most critical ones. Using the two objectives conflicting with each other, MG-NSGA can effectively identify the most critical scenarios.

In evaluating the first objective function, i.e. the number of nodes connected to the generator after potential cascading failures, cascading analysis is performed using the Overload Cascading Model (OCM) described in section 2.

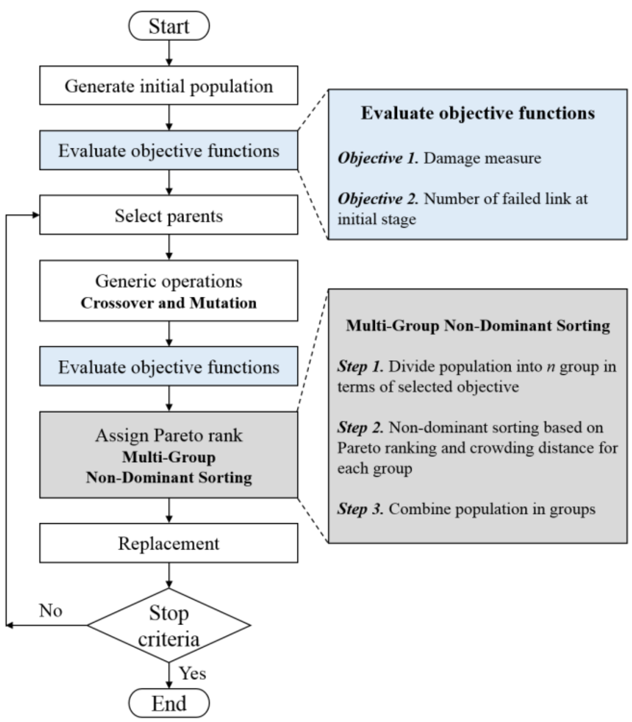

Figure 4: Flowchart of MG-NSGA

3.3. Multi-Group NSGA (MG-NSGA)

MG-NSGA framework (Choi and Song, 2017) is a heuristic optimization-based approach to find optimal non-dominant solutions using genetic operators, i.e. crossover and mutation, and selection process.

As illustrated in Figure 4, the main feature of MG-NSGA is in the procedure to assign Pareto rank procedure. To resolve the issue of losing population diversity in large-size problems, raised by various research (Ventresca et al., 2018), the authors recently proposed to divide the sample space into multiple groups. It is shown in Figure 5 that more diverse samples are given the first Pareto rank when compared to the original NSGA-II. By dividing the sample space into multiple groups at the rank assignment, samples with more diversity are expected to survive throughout the generations. Eventually, the final Pareto surface can be derived from the improved sample diversity.

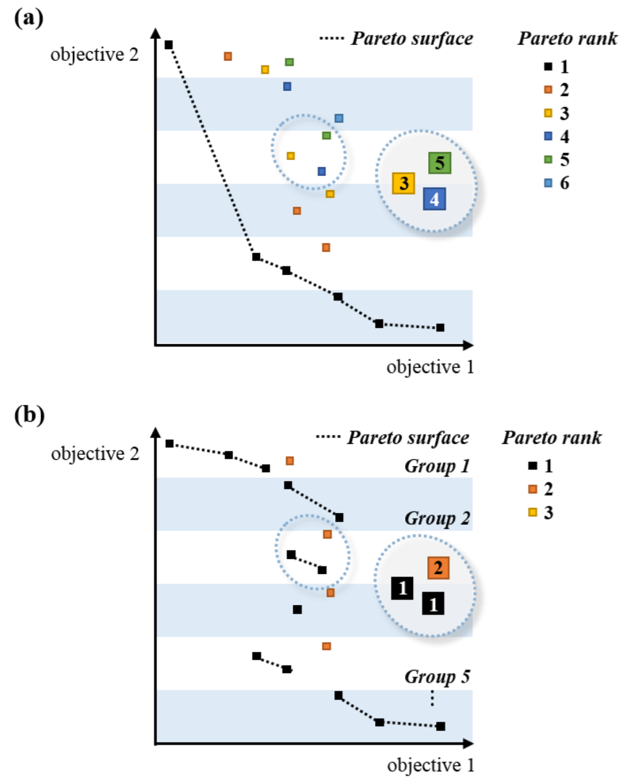

Figure 5: Comparison of (a) fast-non-dominated sorting (NSGA-II), and (b) proposed MG-NSGA

4. CASE STUDY

In this paper, a modified version of the IEEE 30 bus test case in Figure 6(a) is studied. Critical cascading scenarios of the power system are identified by incorporating OCM into MG-NSGA-based search. The topology and the electric properties of the power system are obtained from Alsac and Stott (1974). The power generated at each generator node is selected within the maximum power limit. The test power supply network is modeled as the graph of total 30 nodes (generator and substations), including 6 generators, and 41 edges (transmission lines) as shown in Figure 6(b).

Additionally, overload cascade analysis is performed using an open source Matlab code, MATCAS (Koc et al., 2013) after several modifications. First, the initial failure is defined by the sampled population generated by MG-NSGA instead of the removal strategies suggested in original MATCASC. Through this modification, the initial failure is not restricted to single component failure scenarios, and thus cascading failure scenarios induced by multi-component breakdown can be simulated. Second, the line capacity is modified to use the given data.

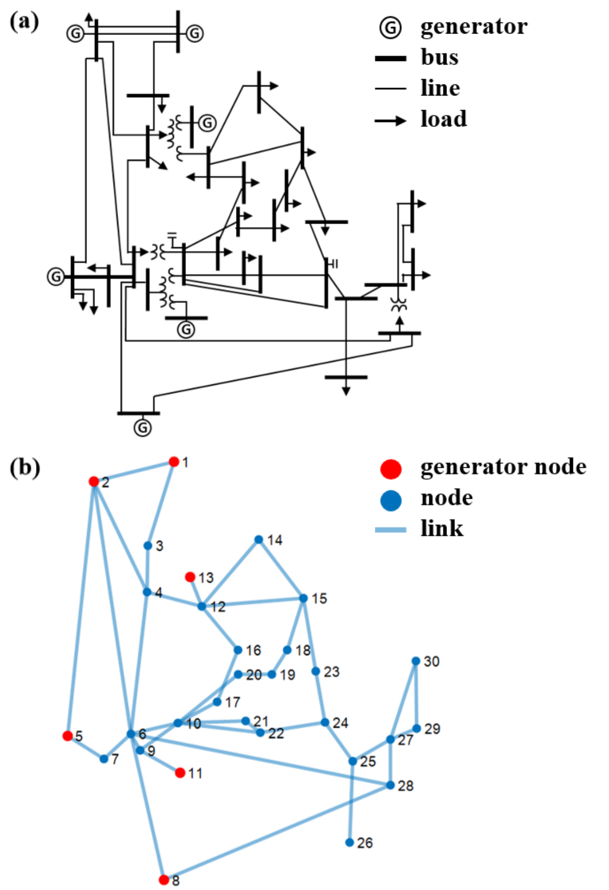

Figure 6: the IEEE 30-bus test system: (a) single line diagram; and (b) network graph

5. RESULTS AND DISCUSSIONS

Figure 7 shows the critical cascading scenarios of the test case, identified by the proposed method. Each point in the plot represents a cascading scenario which was archived through the evolution process of MG-NSGA. Especially, the final Pareto surface, the blue line in the figure, indicates the most critical cascading scenarios induced by the corresponding number of failed links at the initial stage.

5.1. Critical zone selection

"Critical zone" is a sub-area of the sample space, which is considered particularly important in the decision-making process (Choi and Song, 2017). For example, suppose the stakeholder of the test power network wishes to prevent critical scenarios leading to at most 15 network nodes still connected to the generator, and the probability that more than 10 links fail at the initial stage is negligible. In this case, the gray area in Figure 7 can be considered a critical zone. The samples located in the intersection between the critical zone and the feasible domain identified by the Pareto surface require further investigation. For example, the management strategy could be designed to minimize the intersection between the critical zone and the Pareto surface. In determining the boundary of a critical zone, both engineering and non-engineering aspects, e.g. financial condition of network management authority should be taken into account.

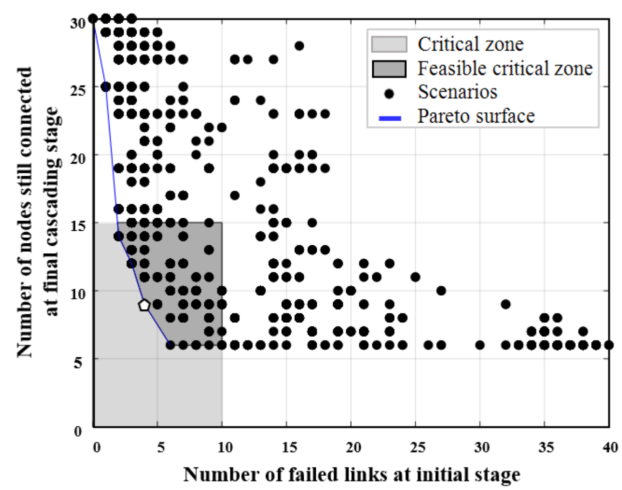

Figure 7: Cascading scenario archive and final Pareto solutions for IEEE30 bus network in the sample space defined in terms of the number of nodes connected to generators after final cascading stage and the number of failed links at the initial stage

5.2. Verification of results

Since the proposed search algorithm is heuristic, the results from the MG-NSGA should be taken with caution. To validate the result of the numerical example, we compare the final Pareto surface with the solutions obtained by thorough enumerations. As shown in Figure 8, Pareto surface derived from the MG-NSGA and that identified by checking all possible scenarios induced by six cases of the number of initial component failures match each other.

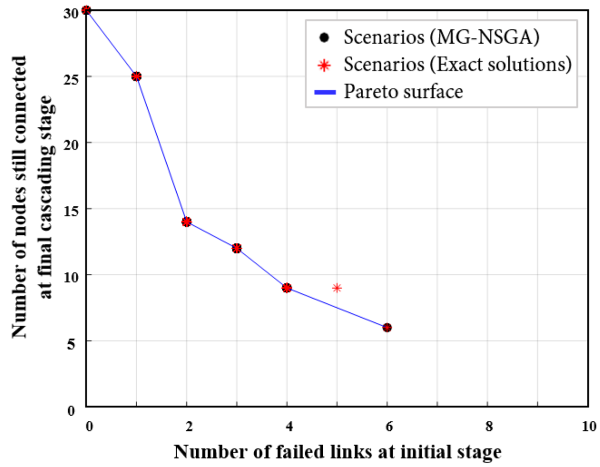

Figure 8: Comparison between Pareto surfaces achieved from MG-NSGA and all possible solutions.

5.3. Findings from results

As indicated in Figure 7, the cascading failure impact triggered by the initial failure increase disproportionately as the number of initially failed links increases. The disproportionate impact is mainly due to the non-linearity of the power grid cascading failure. As an example, one of the critical scenarios is presented in Figure 9 (represented by "⬠" markers in Figure 7). The sequence of cascading failures is the most critical case that can be induced from four component disruptions. Initial failure itself does not impact on the connectivity directly because of network redundancy. However, due to the sequential loss of the links caused by the overload line trip, 21 nodes among the 30 nodes in the power network eventually lose the connection to the power source at the final stage.

It is also noteworthy that the set of most critical components, which triggers the most critical cascading failure induced from single to three initial component failures, is not a subset nor has intersection with the set of components identified from scenarios induced by four component failure scenario. Unless cascading scenarios induced by more than four component failure are examined, the components identified in the first stage of Figure 9 attract less attention than many other links of the network. However, included in the combination of four, these links are identified as the most critical failure combination. Therefore, the cascading scenario triggered by the multiple failures of the link should not be neglected during critical cascading failure identification.

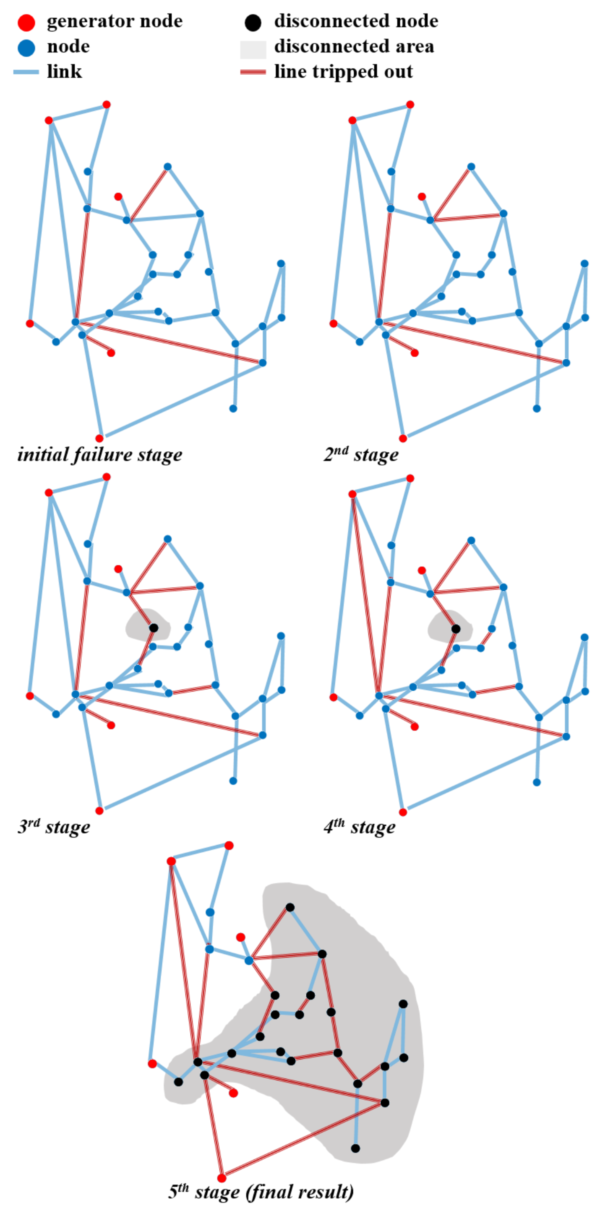

Figure 9: Most critical cascading scenarios induced by the 4-component failure ("⬠" marker in Figure 7)

6. SUMMARY AND CONCLUSIONS

In this study, we proposed a method to identify critical cascading scenarios of power supply systems using MG-NSGA. The critical cascading scenarios, which bring serious consequences such as large scale blackout but triggered by a relative small number of initial component failures were effectively identified. In this approach, cascading failures are simulated with consideration of the redistribution of the power flow caused by the overload line trips, using OCM. As a result, several critical combinations, which otherwise would attract less attention as a single component, were indicated as critical component of the system.

The presented work is expected to support decision makers to mitigate the cascading failure risk within the power supply networks through a comprehensive decision making process. Through a broad demonstration of cascading scenario cases, the decision maker would be able to identify feasible cascading risk inherent in the power grid.

With additional development of protection and recovery model, the post-disaster condition of the power supply network can be further explored. Future work will focus on constructing an effective decision-making framework to prevent the identified worst-case scenarios. It will be also meaningful to upgrade the current infrastructure network management process by systematic treatment of critical post-disaster scenarios.

ACKNOWLEDGMENT

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