# Maintenance Planning of Complex Power Grids based on Critical Cascading Failure Scenarios

Eujeong Choi[a], Junho Song[b*]
[a]*Korea Atomic Energy Research Institute, 111, Daedeik-daero 989 gil, Yuseong-gu, Daejeon, 34057, Rep. of Korea*
[b]*Seoul National University, 599 Gwanak-ro, Gwanak-gu, 08826, Seoul, Rep. of Korea*
[*]*Corresponding author: ejchoi@kaeri.re.kr*

## 1. Introduction

Power supply networks are exposed to the risk of cascading failures, which may entail a significant amount of social and economic losses. Therefore, it is imperative for urban communities to identify critical cascading failure scenarios to find effective countermeasures. Such efforts for disaster risk reduction of power girds, however, often encounter various technical difficulties due to large network size, interdependency between network components, and complex mechanism of cascading failures. Recently, for effective identification of critical post-disaster scenarios, researchers utilized multi-objective optimization algorithms, including the multi-group non-dominate sorting genetic algorithm (MG-NSGA) [1]. In this paper, by combining a flow-based simulation model of power grids and MG-NSGA, critical cascading failure scenarios are first identified. Besides, to find the most cost-effective retrofit combinations against the identified critical failure scenarios, the 'elite set updating' method is proposed.

## 2. Identification of Critical Cascading Failure Scenarios using MG-NSGA

### *2.1 Overload Cascading Model*

In this paper, to simulate the cascading failure phenomenon a flow-based cascading model, termed overload cascading model (OCM) [2, 3], is adopted. The algorithm of OCM illustrated in Fig. 1 can simulate the sequential overload line trip mechanism. First, the load flow demands are estimated for the initial post-disaster topology of the power grid. Next, the load flow demand at each power transmission line is compared with its capacity, and the overloaded lines are removed from the initial network topology. These processes are repeated until the load flows are completely stabilized, i.e. no further cascading failures occur.

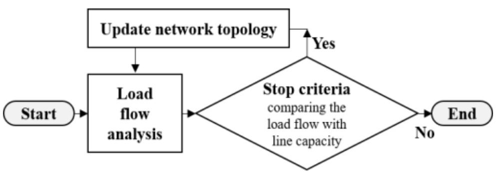


Fig. 1. The overload cascading model (Pahwa *et al*., 2013)

### *2.2 Multi-Group Non-dominate Sorting Genetic Algorithm (MG-NSGA) and Critical Zone*

Multi-objective optimization can be used to obtain a set of critical failure scenarios. In particular, MG-NSGA and the concept of the critical zone were adopted to identify the network cascading failures [1]. As illustrated in Fig. 2, By dividing the objective space into multiple groups, MG-NSGA delivers the results with better optimality and less variability than NSGA-II. To apply the MG-NSGA to critical scenarios identification, genetic representation of the initial post-disaster scenarios and the objective functions should be defined.

For the genetic representation of the initial post-disaster failure scenarios, binary string with the length of components is adopted. The values 0 and 1 in those binary string indicates the survival and the failure of the components respectively. Besides, to identify scenarios entailing devastating consequence even with a relatively small number of component failures, i.e. scenarios leading to out-of-proportion consequence, the ‘number of components that failed at initial stage’ and ‘total active link capacity’ are introduced as objective functions. The 'active link' is defined as the link that withstands the power flow demand at the final cascading failure stage, which are results of OCM (section 2.1), while connected with at least one single generator node [3].

By combining OCM and MG-NSGA, cascading failure scenarios could be collected. However, not all samples are necessarily critical. Therefore, to select the critical scenarios among the sample set, the critical zone is defined in objective space (shaded area in Fig. 2). For example, ‘scenarios which are induced by the less than $x$ link failure and total active link capacity at the final stage is less than $y$’ could be defined as critical scenarios.

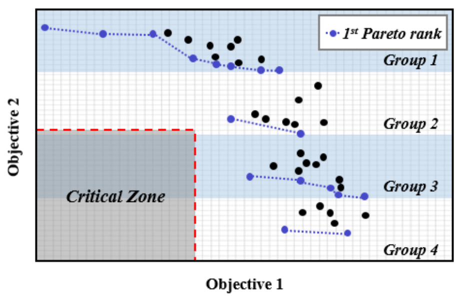


Fig. 2. The example of MG-NSGA and critical zone

## 3. Optimization of Retrofit Combinations using Elite-set Updating Method

Using the identified critical scenarios, optimal retrofit combinations which effectively reduce the cascading failure risk could be searched. However, evaluating all possible retrofit combination is computationally intractable. Therefore, in the section, the 'elite-set updating' method is proposed.

### *3.1 Selecting Candidates and Elite Components*

Since generating all possible combinations is requiring expensive computational cost, candidates and elite components are selected among the components. The first candidate component is selected regards on 'impact.' The impacts of retrofitting the single component are measures by the improved final cascading failure consequence of selected scenarios. Those retrofit impact measure could be expressed as follow:

$$impact_{i,j} = \sum_{i=1}^{N_{cs}} (f_{i2} - f_{i2,j})/N_{cs} \quad (1)$$

where $f_{i2}$ is the 'total active link capacity at the final cascading stage' of the initially identified *i*th critical cascading scenario, and $f_{i2,j}$ denotes the 'total active link capacity at the final cascading stage' of the *i*th critical cascading scenario with *j*th component withstanding at the initial cascading stage. In addition, *Ncs* is the number of total critical cascading failure scenarios identified by the method presented in section 2. The components which exceed the threshold value of impact measure is selected as impact candidates for the retrofit (Fig. 3). In addition, elite set components are selected by those impact and the cost of the retrofit, which are proportional to the length of the transmission line. By selecting the elite component, some the not impactful yet cost-effective components are also included in the candidate set as the elite component (e.g. component #11 in Fig. 4).

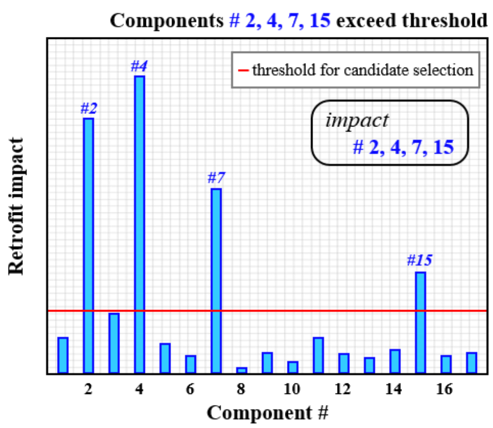


Fig. 3. Conceptual demonstration of selecting 'impact' components with high retrofit impact

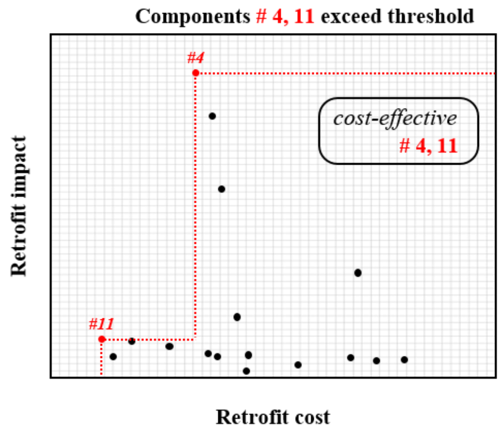


Fig. 4. Conceptual demonstration of selecting 'cost-effective' components

### *3.2 Generating Retrofit Combination*

Next, retrofit combinations are generated by using the candidate and elite components. The 'elite set updating' method proposed in this section gradually updates the elite set as generating and exploring more retrofit combinations in the candidate set. In this step, elite components are assumed to have higher chance to be part of optimal retrofit combinations. Under those assumption, the following two groups of combinations with size *n* are generated. For the first group, *n* components are selected from the elite set only while the second group chooses $(n-1)$ components from the elite set and one from non-elite component in the candidate set. This second group is proposed by the rule of thumb. While evaluating the optimal retrofit combinations, the non-dominated solutions, which include more than one non-elite candidate, are not identified. Fig. 5 shows an example with $n = 2$. As illustrate in the figure, exploring retrofit combinations focus on the elite components would reduce both the number of combinations and computational time cost when compared to those by the complete enumeration using candidates (termed "all-candidates" method henceforth).

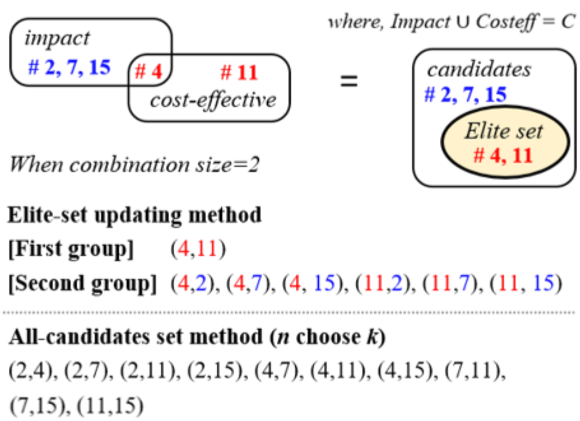


Fig. 5. Example of generating retrofit combinations using elite set updating method and all-candidates method

### *3.3 Evaluating the Cost and Benefit of Generated Retrofit Combinations and Updating Elite Set*

Once retrofit combinations are generated, the cost of each retrofit combination is estimated, and the improvement of the post-disaster network functionality by protecting the retrofit combinations are evaluated. In particular, the increase in the mean 'total active link capacity' in Equation (1) is measured for each combination. After, the non-dominated cost-effective solutions are checked to identify the new component(s) appearing in the Pareto solution set. If new components are identified as elite component, the elite set is updated. It is important to note that only updating the elite-set through the process while the size of the candidate set remains the same, i.e. searching within the candidate set. These procedures are repeated until the algorithm meets one of the prescribed stopping criteria such as retrofit budget, size of the combinations.

## 4. Case Study

The proposed method is applied to the IEEE 30-bus system. The topology of the power grid, which is consists of 30 bus and 41 transmission links, is illustrated in Fig. 6. By combining the OCM and MG-NSGA, cascading failure scenario samples are successfully collected. Especially, scenarios which have 'less than 800 MW total active capacity by less than 8 components failure at the initial post-disaster stage' are selected as the critical cascading failure scenarios. Later, using those scenarios, optimal retrofit combinations are identified using the elite-set updating method. To validate the proposed elite-set updating method, the results and the number of simulations used in the evaluation are compared with the 'all-candidates method.' The cost and benefit curve by those two methods are plotted in Fig. 7. It could be indicated in the figure that both methods deliver identical results for the test case. In terms of computational cost, however, proposed method only require 11% of the computation of the all-candidates method.

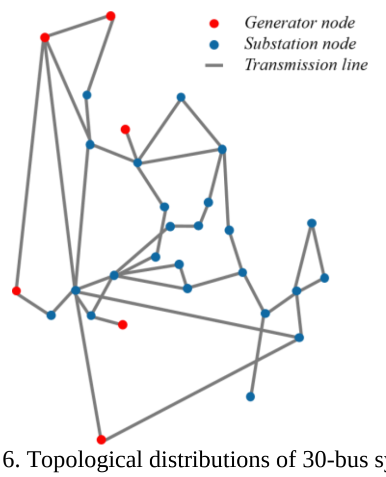


Fig. 6. Topological distributions of 30-bus system

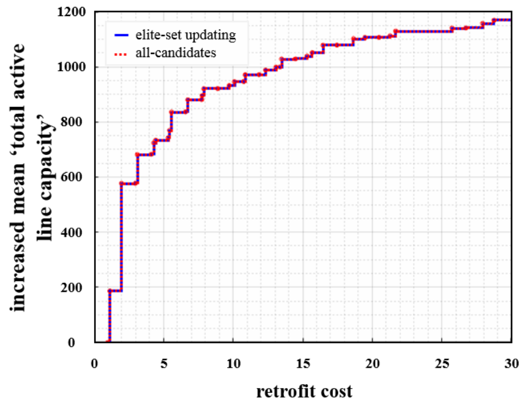


Fig. 7. The cost-benefit curve of retrofit 30-bus system

## 5. Conclusions

To identify the optimal cost-effective retrofit combinations, the elite-set updating method is proposed and illustrated for a 30-bus power supply system. While delivering identical results using all possible combinations of the candidate components, the proposed method requires the significantly reduced computational cost for evaluation. Hence, the authors believe that the proposed method is supporting the disaster risk mitigation plans by delivering the optimal retrofit combinations within the budget.

## ACKNOWLEDGEMENT

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