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Time Series Analysis of Preventive Islanding as a Measure to Boost Power Grid Resilience

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***Abstract*—The increasing number of large-scale power outages caused by extreme weather events or other natural hazards raises the need for higher power system resilience. The impacts of cascading faults, one of the main mechanisms leading to disruptive events affecting hundreds of thousands of people, can be mitigated by intentionally sectionalizing the network into stable and self-adequate islands. However, there is only little research on the benefit of such preventive actions on power grid resilience. This paper presents a model for investigating the performance of a power network exposed to extreme weather events, and compares preventive islanding with different numbers of islands to a business-as-usual scenario. A suitable set of metrics is used in order to quantify resilience while taking into account preventive actions undertaken ahead of the event. The implementation of the model is tested and demonstrated in detail on a modified IEEE 30-bus network. The results clearly show that preventive islanding greatly improves the performance of a network both during a disastrous event, and can reduce the energy not supplied by up to 24%.**

***Index Terms*—Cascading faults, extreme weather, islanding, resilience**

I. Introduction

The number of weather-related power outages has increased significantly over the last decades [1], while at the same time power outages caused by extreme weather often affect vast areas and large numbers of people [2]. The impact of these outages on economy and society has drawn attention to a rising need for power system resilience. Although definitions of the term resilience vary [3]–[5], it is commonly understood as the ability of the network to "rapidly recover from such disruptive events, and adapt its operation and structure to prevent or mitigate the impact of similar events in the future" [5].

One of the main mechanisms causing widespread blackouts of the power network are cascading faults [6]. The loss of a transmission line, for example, can subsequently result in overloading of other lines or reactive power problems, and leads to an increased system instability. Cascading faults also become more likely if the overall system loading is increased, as the network is then operated closer to the maximum ratings and redundancy is decreased.

Strategies to improve power system resilience can usually be split into hardening and operational measures [7]. Hardening measures include fortifying overhead lines [8], usage of underground cables [9], and increased redundancy [10], while operational measures include demand-side management [11], advanced control and protection schemes [12], [13], and islanded operation [5].

Islanding aims at forming isolated sections in the network, which are stable and self-adequate [5], [14], and are thus not affected from faults happening outside of the island boundaries. While islands can be created unintentionally as a result of the protection system trying to isolate a fault [15], they can also be created intentionally in order to increase resilience [16]. Many publications focus on the contribution of microgrids [17], [18], which can either support the network under extreme conditions, or operate isolated from the main grid in case of a fault. The authors of [19] aim at decreasing the vulnerability of a microgrid by optimizing the dispatch of distributed energy resources based on weather forecasts. Islanding on transmission level is investigated in [5], where a defensive islanding scheme is proposed which isolates vulnerable parts of the U.K. transmission network during a windstorm.

Assessing the impact of these strategies on resilience requires a suitable metric. A widely used concept is the resilience triangle or trapezoid [20], which visualizes a resilience indicator, such as the load supplied or number of lines operating, over time. A comprehensive way of analyzing the resilience trapezoid is provided by [21]. This paper presents a generic, time-resolved model for assessing the benefits of preventive actions on mitigating the impacts of cascading faults, which are initiated by weather events. The preventive action investigated in this paper is islanding, which sectionalizes the network ahead of the event, and maintains the island boundaries throughout the entire event. The results are compared to a business-as-usual scenario. It is clearly demonstrated that the energy not supplied due to the event reduces significantly through this preventive action.

The rest of this paper is structured as follows: Section II describes the methodology used for time series simulation of an event and its impact on the network, as well as the preventive strategies used to improve network resilience. Section III defines the test network and event, and presents the results for the different preventive strategies. The key findings and possible future work are discussed in Section IV.

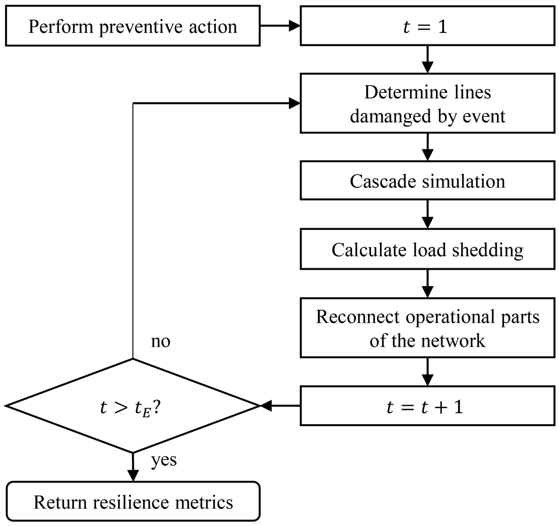

Fig. 1. Flow chart illustrating the simulation procedure.

II. Methodology

The flow chart shown in Figure 1 illustrates the procedure for simulating an extreme weather event, starting at $t = 1$, with duration t_E, its impacts on the power network, and possible preventive actions. At the beginning of the simulation, the network is assumed to be fully operational. First, a preventive action, such as islanding is performed. Then, an iteration over discrete time steps t is started. During each time step, the lines which are damaged by the event are determined, and a fault cascade may be triggered. As soon as the cascade comes to an end, the load shedding for this time step is calculated. Afterwards, lines that have been opened due to overload are closed again and some loads may be reconnected. Lines that have been damaged by the event and nodes that have been blacked out due to insufficient generation will remain out of service. The iteration is repeated with the next event step, until the end of the event is reached.

A. Network Description

A network is described by a graph-like pair of N nodes and L lines. Loads and generators can be present at every node n, and are fully dispatchable, as it would be possible with the implementation of demand-side management. This means that the actual amount of demand and supply at each node can be set arbitrarily, as long as it does not exceed their maximum load or generation capacity, respectively. The geographic position of each node is described by its coordinates $\boldsymbol{r}_n = (x_n, y_n)$. These coordinates are later used to identify which areas are exposed to an event, as the event can obviously affect different areas in the network differently. For each line $L_{n,m}$, which connects the corresponding nodes n and m, the power flow $P_{n,m} = -P_{m,n}$ and a failure probability $p^e_{n,m}$ for an event e are given. These failure probabilities obviously depend on the type of event, as, for instance, a storm affects a line in a different way than flooding. All failure probabilities are normalized to the highest failure probability in the network. The maximum power rating of each line is set to 150% of its initial power flow, simulating that the lines are designed by the network operator in a way that matches the expected loads.

The model only considers active power flows and neglects network losses, power system dynamics and transient behavior during switching as well as synchronization between nodes and islands before connecting. The protection system in the network is assumed to be capable of changing network topology, loops, and reverse power flows.

B. Preventive Actions

In this paper, preventive islanding with different numbers of islands is compared to a business-as-usual (BAU) scenario. Preventive islanding sectionalizes the network into a fixed number of islands ahead of an event. This leads to an initial, controllable load reduction, which can be achieved, for example, using existing smart-grid capabilities, such as demand-side management. These capabilities require no additional investments in bulk electrical power infrastructure. The island boundaries are kept for the whole duration of the event. The island boundaries are calculated using spectral clustering as described in [22] using the un-normalized Laplacian matrix, which, for two graphs $A, B, A \cap B = \emptyset$ optimizes the objective function

$$\frac{\mathrm{cut}(A,B)}{\min\left(|A|,|B|\right)}, \tag{1}$$

where $\mathrm{cut}(A,B) = \sum_{n\in A, m\in B} |P_{n,m}|$. In terms of power networks, this aims at identifying areas in the network of similar total load which exhibit a minimum power exchange with each other. Consequently, the required load shedding due to the islanding process is minimized.

C. Fault Simulation

In each time step t, a set of faulty lines, $\mathrm{faulty}(t)$, is determined, which contains the lines that are damaged by an event e and are therefore not operating. The event severity at time t and for a geographic point $\boldsymbol{r}$ is given by the event function $w^e(t, \boldsymbol{r}) \in [0, 1]$. Any weather event, intensity, and trajectory can be considered and simulated by specifying this event function appropriately. The event- and time-dependent failure probability $p^{w_e}_{n,m}(t)$ of a line from n to m for this event, normalized to the line length, can thus be calculated using a line integral

$$p^{w_e}_{n,m}(t) = \frac{\int_{\gamma_{n,m}} p^e_{n,m} \cdot w^e(t, \gamma_{n,m}) \mathrm{d}s}{\int_{\gamma_{n,m}} \mathrm{d}s}, \tag{2}$$

where $\gamma_{n,m} : [0, 1] \to \mathbb{R}^2$ describes the path of the line. The path function can be a straight line from n to m or any other non-closed path. The set of faulty lines is then determined by comparing $p^{w_e}_{n,m}(t)$ of each line with a random number $r_{n,m}(t) \in [0, 1]$, which is generated for each line and time step individually. In case that faulty lines are not repaired during the event, and thus in each time step new lines are added to the existing set, this gives

$$\text{faulty}(t) = \text{faulty}(t-1) \cup \left\{ L_{n,m} \mid p^{w_e}_{n,m}(t) > r_{n,m}(t) \right\}. \quad (3)$$

The loss of lines due to the event can trigger a fault cascade, as it may lead to overloading of parallel routes, which then causes the protection system to trip those lines as well. In the worst case, this can lead to unintentional disintegration of the network into islands. In order to simulate this fault cascade, the power flow (PF) after deactivating the initial set of faulty lines is calculated, whilst retaining the load and generation at all nodes. This is done for each island in the network individually. If the PF algorithm does not converge, a dispatch tolerance is introduced, which enables loads and generators to reduce their input and output power, respectively, by a certain percentage, until an equilibrium between demand and supply is reached and the PF algorithm converges. If the power through a line exceeds its rating, the line is tripped and a new power flow is calculated. This process is repeated until no more lines exceed their earlier defined line rating. The load supplied after the fault cascade is stored, and the next event time step is executed.

III. Results

A. Test Network

The test network used for simulations in this paper is based on the topology of the IEEE 30-bus test network and shown in Figure 2. Nodes shown with a square indicate nodes with generators attached, while nodes shown with a circle only have loads connected. The lines are assumed to form a straight connection between two nodes, hence the path function for a line from n_1 to n_2 is

$$\gamma_{n,m}(s) = \begin{pmatrix} x_n + s \cdot (x_m - x_n) \\ y_n + s \cdot (y_m - y_n) \end{pmatrix}. \quad (4)$$

The coordinates $\boldsymbol{r}_n$ of the nodes have been taken from the Matlab graph plot, however, any other assignment of coordinates would also be valid.

B. Event Modeling

The event modeled in this paper is a wind storm, which is moving within three time steps $t = 1, 2, 3$ from west to east over the test network. The value of the event severity $w^e(t, \boldsymbol{r})$ is either 0 or 1, as shown in Figure 2, simulating a simplified case in which the wind speed is either severe or low. The failure probabilities of the lines can be chosen arbitrarily. In this study, the line impedances, normalized to the highest impedance in the network, are used in order to model that longer lines, i.e. lines with a higher impedance while assuming the same impedance per unit length for all lines, have a higher failure probability than shorter lines.

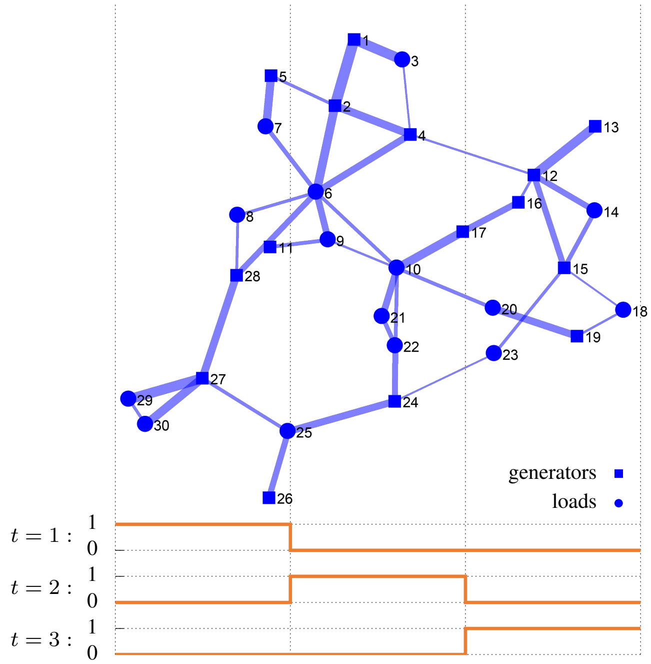

Fig. 2. Graphic representation of the test network and value of the event severity $w^e(t, \boldsymbol{r})$ for different parts of the network at three time steps t.

C. Time Series Simulation Results

For the BAU case and the preventive islanding strategy, the impact of the given event on the network is averaged over 200 scenarios, i.e. sets of lines damaged by the event, which we consider an adequate number of scenarios to limit statistical variation. Figure 3 shows the load supplied over time for the BAU case. Initially, for $t = 0$, all loads in the network are supplied. At time steps $t = 1, 2, 3$, the load supplied by the network decreases (white bars), as lines are damaged by the event and others are tripped due to subsequent fault cascade. After each time step, lines that have been tripped due to overload are reconnected and the load supplied by the network increases again (gray bars). Lines which have been damaged by the event cannot be reconnected. As the event passes, the ratio of supplied load has decreased by 44%.

Figure 4 shows the load supplied over time when preventive islanding is applied. Before the first fault occurs at $t = 1$, the network is for demonstration purposes split into four islands, which causes initial controllable load reduction. Other numbers of islands are investigated in the next section. This intentional load shedding is highlighted with a solid black bar in the pre-event phase. The initial island boundaries are kept for the whole duration of the event and are only removed for the final redispatch, when the event has passed. Figure 4 shows that the impact of the event for the first two time steps is significantly less compared to the BAU case, and that the final load supplied is higher. The ratio of loads supplied has dropped by only 30%, which is considered to be a notable improvement compared to the 44% in the BAU case. The slightly increased unintentional load shedding for the last time

Fig. 3. Average load supplied during an event in the business-as-usual case, related to the total network load. The white bars indicate loads shed unintentionally due to faults, while the gray bars indicate loads that were reconnected by reclosing lines that tripped earlier due to overload.

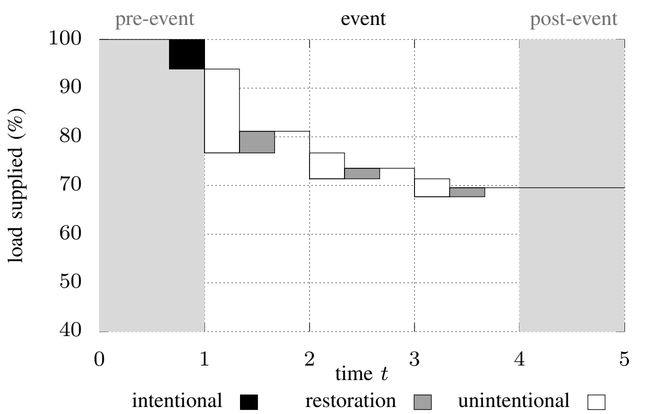

Fig. 4. Average load supplied during the event with preventive islanding (4 islands). In addition to Figure 3, the solid black bar indicates initial load shedding due to the islanding.

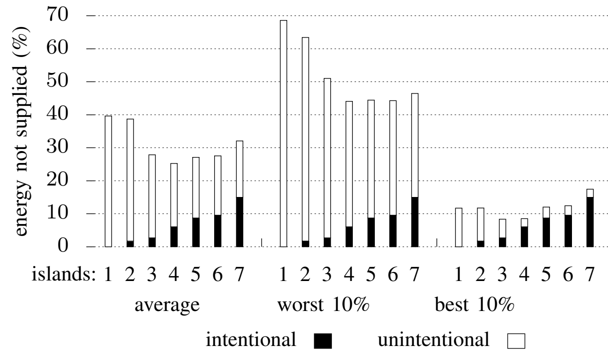

Fig. 5. Average energy not supplied during the event, related to the energy that would have been supplied without an event, for 1 to 7 islands, where 1 island relates to the BAU case. The solid black bars indicate the energy not supplied due to pre-event load shedding, while the white bars indicate energy not supplied due to faults.

step in case of preventive islanding can be related to a high degree of disintegration of the network at this point, which limits the functionality of the operating part of the network.

D. Energy Not Supplied

Next, the performance of preventive islanding for different numbers of islands is analyzed by calculating the energy not supplied during the event. Energy not supplied can be intentional or unintentional. Intentional energy not supplied is caused by an intentional, pre-event load reduction. Unintentional energy not supplied is caused by a damage to the network and a subsequent fault cascade. Figure 5 shows in the left part the energy not supplied on average for 1 to 7 islands, where 1 island relates to a fully connected network, i.e. the BAU case. For the calculation of the values it is assumed that the reconnection happens immediately after the fault as the system operator aims to react to faults as quickly as possible. It can be seen that while the intentional energy not supplied increases with higher number of islands, the unintentional energy not supplied decreases. On average, it is observed that the optimum number of islands is 4 islands, where the total energy not supplied, i.e. the sum of intentional and unintentional energy not supplied, is minimal. For higher number of islands, the benefit of reduced unintentional energy not supplied is outweighed by a larger intentional energy not supplied.

Figure 5 also shows the energy not supplied when only looking at the 10% scenarios with the worst and best impact, i.e. the scenarios that show the highest and lowest energy not supplied, respectively. In case of the worst 10% scenarios, the optimum number of islands is 4, 5 or 6, which decreases the total energy not supplied by 24% compared to the BAU case. For the best 10% scenarios, the benefit of preventive islanding is marginal, but the total energy not supplied does not exceed the impact in the BAU case when the number of islands is less than 5. This is because for large numbers of islands, there is not enough generation capacity available in every island, so the intentional load shedding increases significantly.

The identification of the optimum number of islands is further analyzed in Figure 6. For this graph, all scenarios have been sorted according to their total impact, i.e. the total energy not supplied, and grouped into 10 bins with a size of 20 scenarios each. For each bin, the average total energy not supplied in the BAU case has been subtracted from the average total energy not supplied for different numbers of islands, which is shown in Figure 6. The figure shows that for the best scenarios, the greatest reduction in energy not supplied can be achieved by sectionalizing the network into 3 islands. As soon as bin 5 is reached, benefit for 3 and 4 islands is similar. For worse scenarios, the ideal number of islands is 4. The figure also shows that the benefit for the worst scenarios in bins 9 and 10 is very similar for 4 and 5 islands.

IV. Conclusion

This paper presented a generic model for a time series analysis of preventive actions on the performance of a power network during cascading faults. Preventive islanding, as one

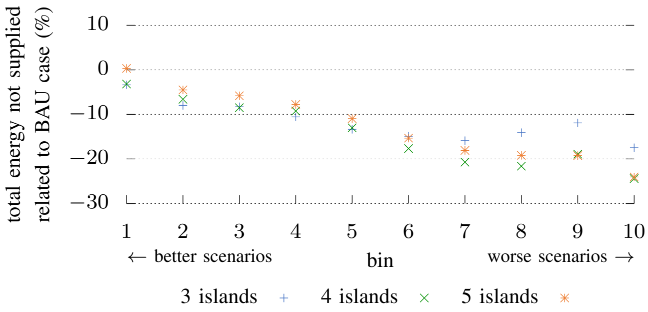

Fig. 6. Difference between the average total energy not supplied during the event for 3, 4, and 5 islands, and the BAU case, when grouping the sorted total energy not supplied into 10 bins.

possible preventive action, was assessed in detail for different numbers of islands, and the results were compared to a business-as-usual case. The capability of the model has been tested and demonstrated on the IEEE 30-bus network.

The results show that preventive islanding reduces the load shedding caused by the external event and prevents spreading of fault cascades. When including intentional reductions in energy supplied due to preventive actions, an optimum number of islands can be defined, in which the total energy not supplied is minimal. The time series simulations reveal that when only looking at the 10% worst cases, islanding reduces the energy not supplied by up to 24%. This includes any intentional reductions in energy supplied due to preventive actions. As these worst cases affect the largest number of customers in a network and lead to the severest outages, mitigating their impact is most important. The number of islands has been chosen according to the expected severity of the event. It has been shown that depending on the severity of the scenarios, the number of islands that lead to the minimum total energy not supplied, changes. For the worst scenarios, generally a larger number of islands is favourable, whereas for less severe scenarios, the number of islands should be reduced.

For the network operator, islanding in general proves to be a viable strategy to improve the resilience of the network. In contrast to other measures, such as creating redundancy or hardening the infrastructure, islanding does not require any costly investments in the infrastructure, but exploit existing capabilities of a smart grid, such as demand-side management and flexible network topologies.

Future work in this area will include simulation of other event types as well as assessing further preventive strategies based on event predictions.

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