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Cascading dynamics and mitigation assessment in power system disturbances via a hidden failure model

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Abstract

A hidden failure embedded DC model of power transmission systems has been developed to study the power law distributions observed in North American blackout data. We investigate the impacts of several model parameters on the global dynamics and evaluate possible mitigation measures. The main parameters include system loading level, hidden failure probability, spinning reserve capacity and control strategy. The sensitivity of power-law behavior with respect to each of these four parameters and the corresponding blackout mitigation are discussed and illustrated via simulation results from the WSCC 179-bus equivalent system and the IEEE 118-bus test system. It is our intention that this study can provide guidance on when and how the suggested mitigation methods might be effective.

Keywords: Power system reliability; Protective relaying hidden failures; Blackout mitigation

1. Introduction

An overriding factor in power system operation is to maintain system reliability. As we have embarked on the deregulation of the power utilities, the role of the transmission system to provide reliable energy transportation is even more crucial. However, the US power transmission grid suffered from more than 400 major blackouts in the 16 years from 1984 to 1999 [1] in spite of technological progress and huge investments in system reliability and security. Although they are relatively rare events, their impact can be catastrophic. In the past, investigators tended to focus on individual causes of these disturbances and assume that the probability of blackout occurrence falls off exponentially with the event size. But recent analyses of 16 years of North American disturbance data showed a probability distribution of blackout size that has heavy tails and evidence of power law dependence in these tails [2–5]. These analyses indicate that large blackouts are much more likely than might be expected. These power tails merit attention not only because of the underestimation of the likelihood of large blackouts [6] but also due to the enormous cost to society of large blackouts.

Recent NERC (North American Electric Reliability Council) studies of major disturbances have shown that over a long interval, more than 70% of the major disturbances involved relaying systems, not necessarily as the initiating event, but contributing to the cascading nature of the event [1]. For example, the 1965 Northeast Blackout was initiated by a relay tripping on load current, a number of relays failed to trip in the 1977 New York City Blackout, and there were incorrect relay operations in the multiple WSCC (Western Systems Coordinating Council) disturbances in the summer of 1996. Among many of these incorrect relay operations, a common scenario exists: the relay has an undetected defect that remains dormant until abnormal operating conditions are reached, which is often referred to as a *hidden failure* [7]. Hidden failures in protective relays and their impact on power transmission system reliability have been examined in several recent

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studies [7–9]. Possible vulnerable links subject to hidden failures were located in various systems such as the WSCC 179-bus equivalent system and the NYPP (New York Power Pool) 3000-bus system. An optimal investment to enhance overall system reliability was also suggested [9].

Understanding and being able to analyze the risk and possible mitigation of large blackouts is no doubt a high priority. However, the 16 years of NERC data, although the best data available, is still far from enough for thorough investigation, which necessitates proper modeling and simulation of the observed cascading dynamics. In this paper, we present a hidden-failure embedded transmission network model to explore the characteristics of cascading events. The impacts of various model parameters on the system dynamics are examined, and the corresponding mitigation measures are also suggested. Readers are also referred to the OPA model in [10–12] for a different cascading blackout model at a similar level of model detail.

2. Hidden failure model

2.1. Hidden failures

A hidden failure is undetectable during normal operation but will be exposed as a direct consequence of other system disturbances, which might cause a relay system to incorrectly and inappropriately disconnect circuit elements. Ref. [7] shows that, if any line sharing a bus with a transmission line L trips, then hidden failures in line L are exposed. That is, if one line trips, then all the lines connected to its ends are exposed to the incorrect tripping. These cascading misoperations are what lead to major system disturbances. The probability of such occurrence is small but not negligible as shown in the NERC report [1].

Line protection hidden failures are incorporated here in the simulation to model the operation of protective relays. Each line has a different load dependent probability of incorrect trip that is modeled as an increasing function of the line load flow seen by the line protective relay. The probability is low below the line limit, and increases linearly to 1 when the line flow is 1.4 times the line limit, as shown in Fig. 1.

An improvement of the hidden failure model over the previous version [7–9] is applied here for the simulation scenario when a line is exposed multiple times during a cascading event. The previous version of the model allowed relay misoperation with equal probabilities on all the line exposures. However, it is more plausible that if relay misoperation occurs, it would be more likely to occur on the first exposure than the subsequent exposures. That is, the probability of misoperation should be decreased with the increasing exposure times during one cascading event. The improved model adopted here simply reduces the probability of misoperation to zero after the first exposure. This modification prefers the tripping of most recently

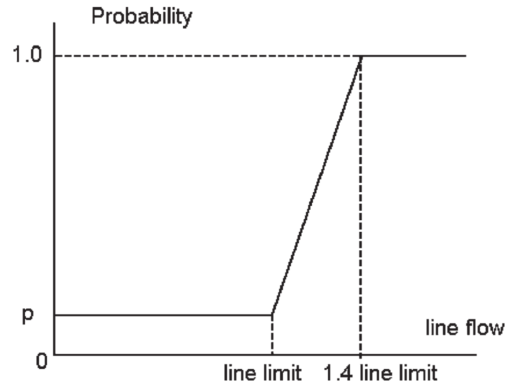

Fig. 1. Probability of an exposed line tripping incorrectly.

exposed lines, and enables the cascading event to spread in the network. This particular cascading pattern is consistent with the observed NERC events [1].

2.2. ‘DC’ load flow approximation

The hidden failure model uses the ‘DC’ load flow approximation, in which the linearized, lossless power system is equivalent to a resistive circuit with current sources. In particular, transmission lines may be regarded as resistors and generation and load may be regarded as current sources and sinks at the nodes of the network.

For a purely DC system, assuming the system has $(n+1)$ nodes (one of them is defined as the reference bus) and m branches, we can define following network vectors:

voltage vector

$$\bar{V} = [\,V_1 \quad V_2 \quad \cdots \quad V_n\,]^{\mathrm{T}}$$

current vector

$$\bar{I} = [\,I_1 \quad I_2 \quad \cdots \quad I_n\,]^{\mathrm{T}}$$

diagonal conductance matrix

$$g = \mathrm{diag}(g_1, g_2, \ldots, g_m)$$

network adjacency matrix $A_{m\times n}$ with entry

$$a_{ij} = \begin{cases} 1 & \text{line } i \text{ exits bus } j \\ -1 & \text{line } i \text{ enters bus } j \\ 0 & \text{otherwise} \end{cases}$$

line current vector

$$\bar{J} = [\,J_1 \quad J_2 \quad \cdots \quad J_m\,]^{\mathrm{T}}$$

network admittance matrix, $Y_{m\times n}$.

By Kirchoff’s current and voltage laws, the following equations hold

$$Y = A^{\mathrm{T}} \cdot g \cdot A \tag{1}$$

$$\bar{I} = Y \cdot \bar{V} \tag{2}$$

$$\bar{I} = A^{\mathrm{T}}\bar{J} \tag{3}$$

$$\bar{J} = g\cdot A\cdot \bar{V} \tag{4}$$

The hidden failure model uses the 'DC' load flow approximation of the AC system, assuming:

- All bus voltage magnitudes are 1.0 per unit.
- Transmission line resistance is negligible.
- Let θ_i be the voltage angle at bus i, then $\cos(\theta_i - \theta_j) \approx 1$, and $\sin(\theta_i - \theta_j) \approx \theta_i - \theta_j$.

Define, for the AC system, $\Theta = [\,\theta_1 \quad \theta_2 \quad \cdots \quad \theta_n\,]^{\mathrm{T}}$ as *bus voltage angle vector*, $\bar{P} = [\,P_1 \quad P_2 \quad \cdots \quad P_n\,]^{\mathrm{T}}$ as *real power injection vector,* and $n\times n$ matrix B as *system susceptance matrix*. The 'DC' power flow equations, usually derived from the standard AC circuit equations in a more formal way [13], however, can be relatively easily obtained by a one-to-one correspondence between DC and AC system variables: (1) the DC voltages $\bar{V}$ correspond to the AC angles Θ, (2) the DC currents $\bar{I}$ correspond to the real power $\bar{P}$, and (3) the DC admittance matrix Y can be substituted by the susceptance matrix B. Then the corresponding equations for the 'DC' load flow approximation can be written as

$$B = A^{\mathrm{T}}\cdot b\cdot A \tag{5}$$

$$\bar{P} = B\cdot\Theta \tag{6}$$

$$\bar{P} = A^{\mathrm{T}}\bar{F} \tag{7}$$

$$\bar{F} = b\cdot A\cdot\Theta \tag{8}$$

where $\bar{F} = [\,F_1 \quad F_2 \quad \cdots \quad F_m\,]^{\mathrm{T}}$ is the *line power flow vector,* and $b = \mathrm{diag}(1/x_1, 1/x_2, \ldots, 1/x_m)$ is the matrix with each diagonal entry representing the susceptance of each transmission line.

2.3. LP (linear programming) power redispatch

When a line is overloaded, or the system breaks into multiple islands, it is necessary to redispatch the injected powers to satisfy the system constraints. The redispatch is formulated in a traditional way as an optimization to minimize the amount of load shed subject to the system constraints. The optimization minimizes the objective function

$$\text{Loss of Load} = \min \sum_{\text{loads}} C_i \tag{9}$$

subject to overall power balance

$$\sum_{\text{generations}} P_i + \sum_{\text{loads}} C_i - \sum_{\text{loads}} D_i = 0 \tag{10}$$

and generation capacity limits for generator i

$$P_i^{\min} \le P_i \le P_i^{\max} \tag{11}$$

and the line flow limits

$$-F_j^{\max} \le F_j \le F_j^{\max}, \quad j = 1, 2, \ldots, m \tag{12}$$

and load shedding limits for load k

$$0 \le C_k \le D_k \tag{13}$$

where D_k is the initial load at bus k.

2.4. Simulation procedure

The simulation procedure begins from a base load flow and follows these steps:

1. Randomly select a transmission line as the initial triggering event.
2. Trip the selected line and compute the DC load flow using Eqs. (5)–(8).
3. Check for violations in line flow constraints and trip the line upon violation.
4. If there is no violation, determine currently exposed lines, which are all lines connected to the last tripped line, and find the probability of incorrect tripping for each exposed line according to Fig. 1 and the improved hidden failure mechanism. Note that the spread of hidden failures is one-dimensional in power systems [1], hence the case that more than one line trips at the same time rarely happens. In the simulation, we let one and only one line trip at one time. Specifically, if more than one line might trip, the one with higher tripping probability is selected to be the next tripping line.
5. Check the connectivity of the network.
6. Fork the simulation if the system breaks into multiple islands.
7. Shed load, if necessary, to keep the system 'stable', which requires all line flows less than their limits. LP redispatch defined as Eqs. (9)–(13) is used to determine the load shedding.
8. If no further lines will be tripped, record the total load loss, the sequence of line outages and its associated path probability, then STOP. Otherwise, go back to step 2.

The above simulation is repeated over an ensemble of randomly selected transmission lines as the initiating fault locations.

2.5. Importance sampling technique

NERC reports [1] show that there are only about 400 major system disturbances during the 16 years from 1984 to 1999 in the US power grid. A direct simulation of these rare events would require an unrealistically huge amount of computation. One way out of this quandary is to use the technique of *Importance Sampling* [14]. In importance sampling, rather than using the actual probabilities, the simulation uses altered probabilities so that the rare events occur more frequently. Associated with each distinct sample path, SP_i, a ratio of actual probability of the event p_i^{actual} divided by the altered probability p_i^{simulate} is computed. We then form the estimated probability of SP_i as

$$\hat{\rho}_i = \frac{N_{\text{occurring}}}{N_{\text{total}}} \frac{p_i^{\text{actual}}}{p_i^{\text{simulate}}} \tag{14}$$

where $N_{\text{occurring}}$ is the number of times that SP_i occurred and N_{total} is the total number of samples. The mean value of $\hat{\rho}_i$ is unbiased [14]. The power loss P_i associated with each sample path is also recorded.

3. Cascading dynamics and mitigation assessment

The hidden failure model yields power tails remarkably consistent with the NERC data and therefore allows us to further study the cascading dynamics in power system blackouts. We investigate here the impact of different model parameters on system dynamical behaviors and assess possible mitigation measures for large blackouts. In what follows, we discuss the impact of each of the four main model parameters: loading level, hidden failure probability, spinning reserve capacity and control strategy. The WSCC 179-bus network and IEEE 118-bus network have been used for the study and a few selected examples from both networks will be presented.

The power tails in the distribution of blackout size are more precisely a power law region that applies until the limiting of the blackout size by the system size. The power tails imply a greatly increased probability and risk of larger blackouts compared to the exponentially decaying tails of many common probability distributions [6].

For the base system settings, we assume that the base load is at the critical loading level (explained in what follows), all lines exhibit the identical hidden failure characteristics in Fig. 1 with $p=0.01$, the spinning reserves carried are 5% of the system load, and that LP redispatch is performed once every three line trips. The impact of these four parameters is examined individually; that is, when examining one parameter, the others are kept in their base settings.

3.1. Impact of loading level

Consider interactions between outages in a power system in the extreme cases of very low and very high loading. At very low loading, any outages that occur generally have minimal impact on other network components and these other components have large operating margins. Multiple outages are possible in this case, but they occur approximately independently so that the probability of multiple outages and the consequent large blackout is well approximated by multiplying the probabilities of each of the outages. Since cascading outages tend to produce blackouts of size proportional to the number of outages, we can expect the probability distribution of large blackouts to have an exponential tail.

The probability distribution of blackout size is different if the power system were to be operated recklessly at a very high loading in which every component was close to its emergency loading limit. Then any outage would necessarily cause a cascade of outages, and large or total blackouts are likely.

It is clear that the probability distribution of blackout size must somehow change from the exponential tail form to the certain total blackout form as the system loading increases from zero to a very high level. The nature of the transition between these two extremes is of great interest to us.

Fig. 2 shows the expected power loss

$$\text{EP} = \sum P_i \hat{\rho}_i \tag{15}$$

as a function of loading level L for the IEEE 118-bus network. The change in slope occurs near loading $L=0.79$, where L is the average ratio of line flows divided by line limits.

To estimate the Probability Distribution Function (PDF) of blackout size P, binning of the data is used. Assume there are K sample points in bin j, and that each of the K points has the associated data pair $(P_i, \hat{\rho}_i)$. The representative $(\bar{P}_j, \bar{\hat{\rho}}_j)$ for bin j is then defined as

$$\bar{P}_j = \frac{1}{K}\sum_{i=1}^{K} P_i \tag{16}$$

$$\bar{\hat{\rho}}_j = \frac{\sum_{i=1}^{K} P_i \hat{\rho}_i}{\bar{P}_j} \tag{17}$$

Variable binning is used here in such a way that each bin starts with the minimum scale and ends with at least a minimum number of samples.

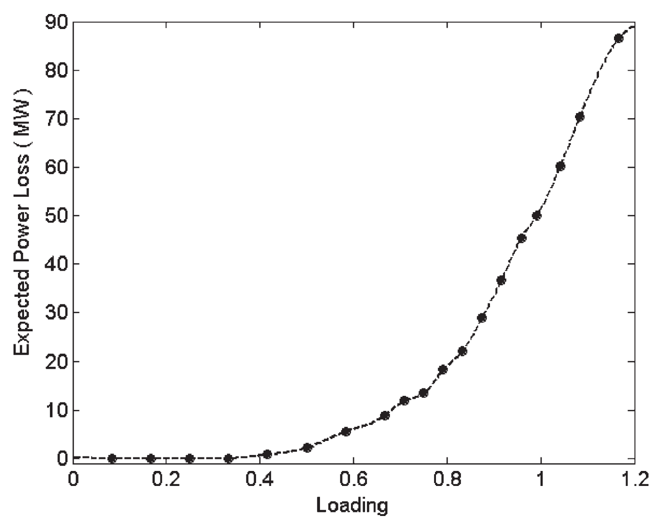

Fig. 2. Variation of expected blackout size EP with loading L.

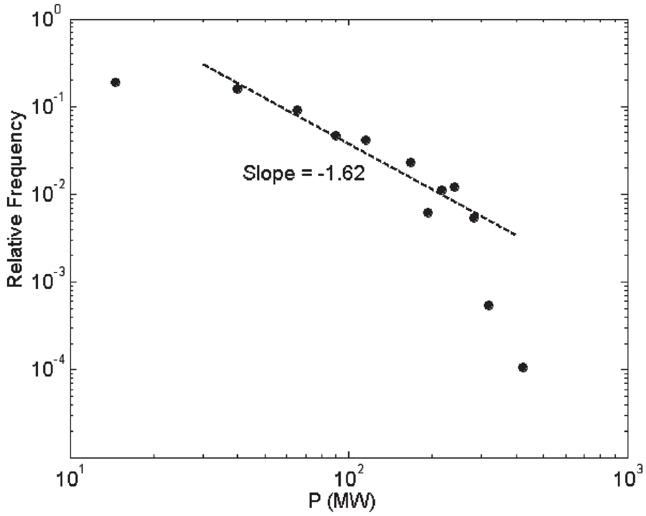

Fig. 3. Distribution of blackout size P at loading $L=0.79$.

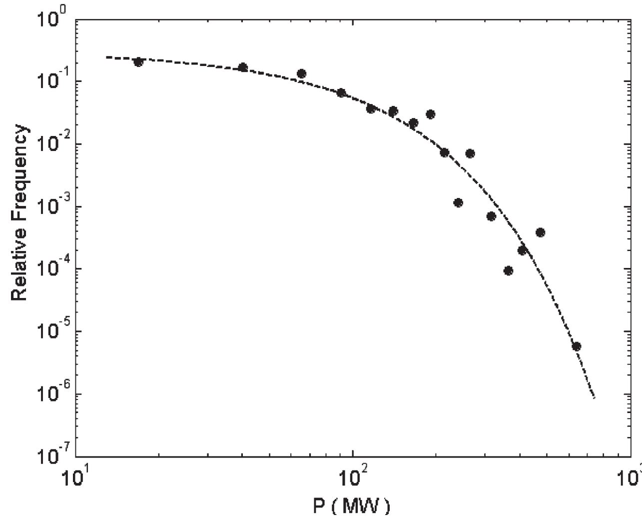

Fig. 5. Distribution of blackout size P at loading $L=0.93$.

Figs. 3–5 show the PDF of blackout size P at critical loading level 0.79, a lower level 0.65, and a higher level 0.93. The PDF of loading level 0.79 shows some indication of power tails (the relatively short interval of the power law region and the fall-off at the very end are due to the relatively small network size [15]). On the other hand, the PDFs of loading level 0.65 and 0.93 show some indication of a more exponential decay.

Qualitatively similar results have been obtained for the OPA model on artificial tree networks and the IEEE 118-bus network [12,16] and for the hidden failure model on the WSCC 179-bus system [16]. Qualitatively similar, but sharper results are obtained in the CASCADE analytic model of loading-dependent, probabilistic cascading failure [16,17]. This suggests that it is the loading-dependent, probabilistic cascading failure aspects common to the hidden failure and OPA simulation models that cause the critical loading and the power tails.

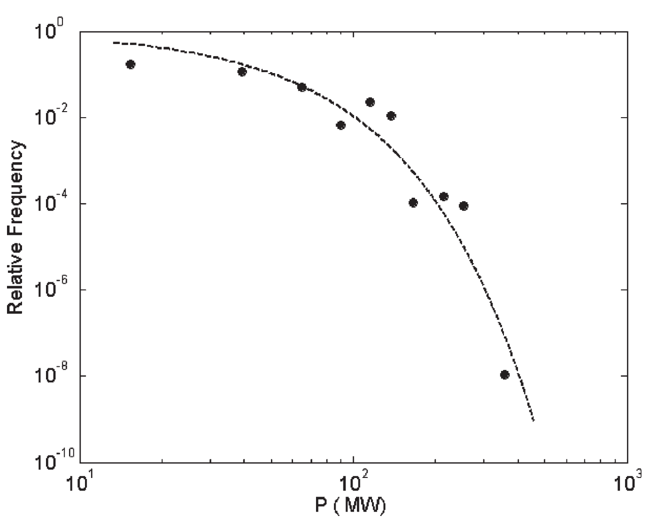

Fig. 4. Distribution of blackout size P at loading $L=0.65$.

The existence of the critical loading and the associated power tails would have significant consequences for power system operation. For then the NERC blackout data suggests that the North American power system has been operated near criticality. Moreover, it is then plausible that the power tails and the consequent risk of large blackouts could be substantially reduced by lowering power system loading to obtain an exponential tail for large blackouts. Indeed, one can envisage that simulation to find the loading margin to the critical loading could be used to determine the appropriate limits on loading in order to reduce the risks of large blackouts due to cascading outages. It would be better to analyze this tradeoff between catastrophic blackout risk and loading instead of just waiting for the effects to manifest themselves in the power system!

Why would power systems be operated near a critical loading? One possible answer is that overall forces, including the system engineering, economic and operational policies, organize the system towards criticality as proposed in [10,11,15].

3.2. Impact of spinning reserve capacity

Ample spinning reserve is a necessity to maintain system reliability in case of unit loss or other contingencies. In this section, we examine the impact of the capacity of available spinning reserves on the power tail of cascading outages.

Usually certain rules set by regional reliability councils specify how the required reserve is allocated. Typically, reserve is needed to be a given percentage of forecasted peak loads. Here, we assume that for each generator, the ratio of available spinning reserves, R, over its generation in base-load condition, P, is the same. For example, if the system reserve capacity is 10% of power demand, then for any generator i, its available reserve will be $R_i=0.1\times P_i$. This pro-rata method is simple; however, it ignores circumstances in which the location of the reserves is

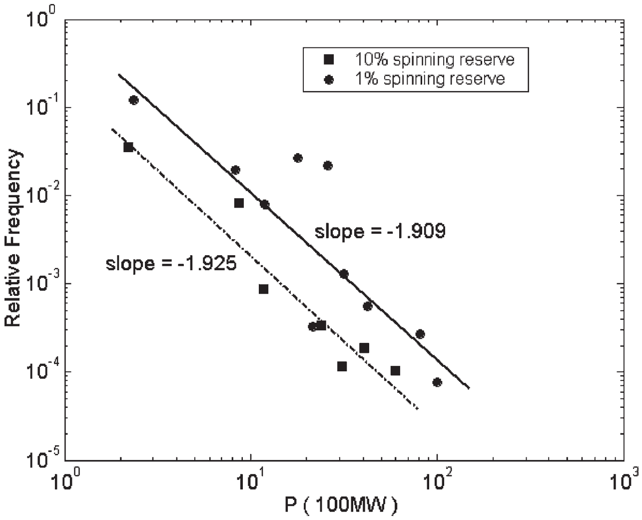

Fig. 6. Distribution of blackout size *P* with reserve capacity of 1 and 10%.

important. For example, consider a power network with a load pocket. The transmission capability between the inside and the outside of the load pocket is limited compared to other parts of the system and usually this transmission interface is congested, which means that if a contingency happens inside the load pocket, the outside reserves cannot help much. Then having sufficient reserves inside the load pocket is crucial to maintain system reliability at the desired level. For example, one could require a reserve capacity of 8% of local demand for the outside of the load pocket and 12% inside the load pocket. The optimal allocation methodology usually is tailored to specific network structures. We, however, will simply set the reserve capacity to be 12% at all locations. Figs. 6 and 7 show the PDF of blackout size *P* for the WSCC system with 1, 10, and 20% reserve capacities, respectively. The power tail is preserved with low reserve capacity, but changes to a more exponential tail when the reserve capacity increases to more than 20%. These results suggest to us that increasing the capacity of system spinning reserve would substantially reduce the risk of large blackouts.

Usually the generation and load are set such that the line flows are well below line limits. Therefore, the power tail at critical loading can possibly be 'fixed' (i.e. changed to an exponential tail) by supplying ample spinning reserves. It seems that the role of reserves is to eliminate the critical point. However, this is not the case when the load growth is also taken into account. If the load keeps growing but without transmission capability upgrade in the mean time (i.e. line limits remain the same), then finally the load level will approach the full system capacity. Meanwhile, the 'effective' reserve capacity will keep dropping even possibly to zero due to unchanged line limits. During this evolving process, the exponential tail will change back to the power tail at some point, which is another critical point, a 'shifted' critical point. Therefore, reserves are able to put off the critical region but cannot eliminate it due to the bottleneck of line limits. The combined effects of loading increase and system upgrade when attempting to mitigate the power tail are studied in [6].

3.3. Impact of hidden failure probability

The hidden failure probability, *p*, is another important parameter in this model. Its impact on the system behavior is of special interest to us. Fig. 8 shows the probability distribution of blackout size of WSCC system with different hidden failure probabilities. As we can see, the power tail persists but becomes steeper as *p* decreases, which means that reducing the hidden failures in the protection system makes the system more robust. For example, upgrading the protection system with adaptive digital relays or perhaps consistent maintenance will shift the observed power tail

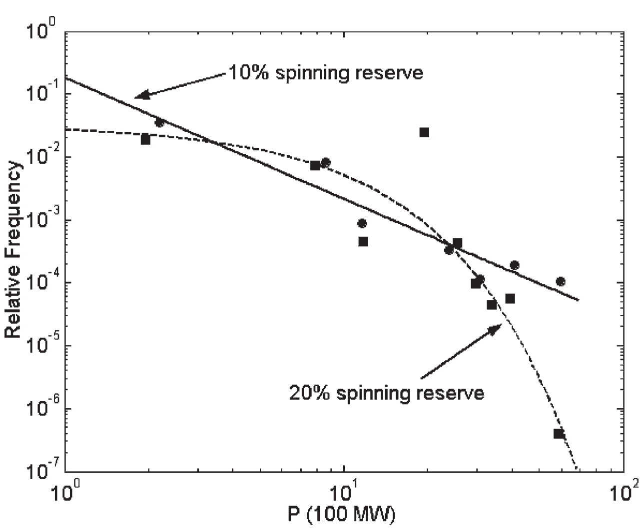

Fig. 7. Distribution of blackout size *P* with reserve capacity of 10 and 20%.

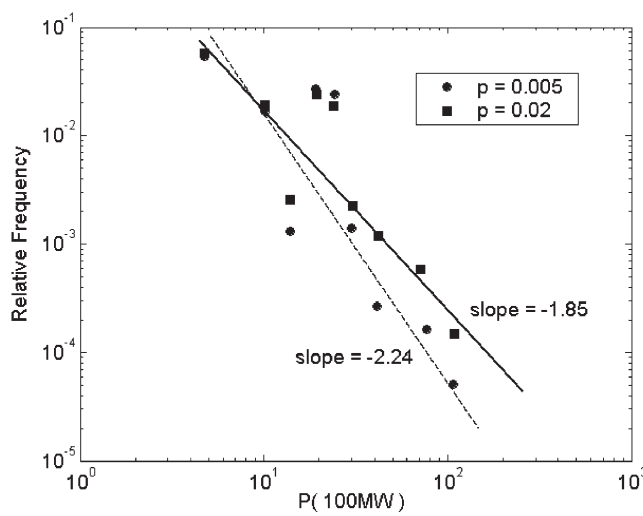

Fig. 8. Distribution of blackout size *P* with different hidden failure probabilities.

downwards. But, unfortunately, the system does not go through dramatic change by varying hidden failure probabilities (i.e. the power tail remains).

Thorp et al. [7–9] have also explored the hidden failures in protective relays and their impact on power transmission system reliability in recent studies. The previous work focused on detection of the weakest links in the bulk power system and corresponding economical system upgrading strategy under a 'limited budget' that assumes that only several weakest links can be improved. Here we examine the change of overall system cascading behavior assuming given an 'unlimited budget', with which we are able to improve all links at the same rate instead of just a subset. This is obviously not economically sound, because each link contributes quite differently to overall system reliability and security. An optimization of system upgrading should allocate more resources to more crucial links rather than equally distribute them to all links. However, we examine an idealized 'unlimited budget' here because it defines an upper bound for achievable improvement of system reliability. For instance, suppose that the hidden failure probabilities of all links in current protection system are 0.02, and we are able to reduce all probabilities to 0.005 with an 'unlimited budget'. Then with a 'limited budget', the hidden failure probability for each link after upgrade will range from 0.005 to 0.02 depending upon specific upgrading strategies applied. Apparently, any optimal system upgrading strategy with 'limited budget', such as aforementioned studies [7–9], will generate a new PDF located somewhere between the two power tails shown in Fig. 8. The power tail with $p=0.005$ is therefore the ideal 'upper bound'. Although it would be nice to develop an economic system upgrading scheme that can closely approach this 'upper bound', it is beyond the scope of this paper.

A byproduct that can be obtained from this analysis is the rough order of magnitude of p. The idea is to adjust p until roughly the same power tail exponent as obtained from NERC data appears. Refs. [2,5] show that the power exponent of the NERC data is around -1 to -2, which corresponds to a p with a rough order of 10^{-2} in our hidden failure model. The rough order of p can also be double checked by the following estimation. Since the major disturbances typically involve four to five unlikely hidden failures [1], the approximate probability of one typical sample path will be p^{-5}. According to NERC report [1], around 150 events happened in WSCC area during the 16 years from 1984 to 1999. Assume one cascading event could be initiated in every power circle, thus the probability of one event will be approximately$150/(16\times 365\times 24\times 60\times 60\times 60)=5.4\times 10^{-9}\approx p^{-5}$. Again, we have $p\approx 10^{-2}$.

3.4. Impact of control strategy

Typical major blackouts involve not only hidden failure trips but also overloading line outages. An improved robust protection system will reduce the risk incurred by hidden failures, while various prompt system controls will play the role of preventing cascading overloads.

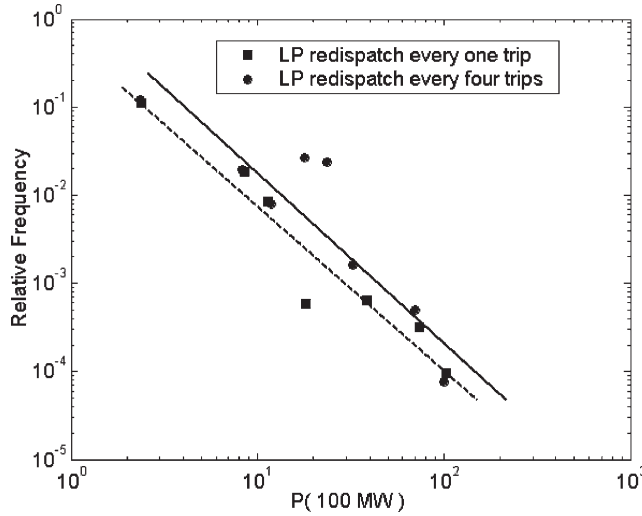

Fig. 9. Distribution of blackout size P with different LP redispatch intervals.

The only control used in the model is LP redispatch, which can be regarded as representative of various control strategies in real power systems. The only adjustable parameter here is the responding speed of LP redispatch to cascading overloads. To simplify the implementation, LP redispatch is applied in a certain fashion. For example, one LP redispatch is performed for every three line trips. Notice that LP redispatch is effective only when there exist overloads in the system, but would not change the system state if there is no line constraint violation. Besides the regular 'checkpoints', redispatch will be performed additionally whenever the system breaks into islands.

When a cascading event is triggered, the sooner the system reverts back to 'stable' with no overloads, the better. The PDF of blackout size in Fig. 9 shows that the power tail of the WSCC system is shifted downwards when the 'regular' interval is changed from once every four trips to once every trip. The measured expected power loss reduces almost 60%. Here, once every trip means every overload is 'captured', while once every four trips indicates possible cascading overloads. The gap between these does indicate the improvement we can achieve by adding prompt control. If we cannot take any precaution against possible cascading outages, 'once per trip' is the best we can do to prevent disturbances spreading in the network. The lower power tail then can be treated as an upper bound when evaluating the system reliability with respect to system control.

4. Discussions and conclusions

A DC model with an improved hidden failure mechanism has been developed to investigate the cascading behavior of power transmission systems. We examined the impacts of various parameters on system dynamics. In particular,

(1) The system shows indications of power law behavior near a critical loading, at which the expected power loss increases sharply.
(2) Maintaining ample spinning reserves can greatly reduce the risk of big blackouts. The system shows exponential tails with large reserve capacity in service but shows power tails as available reserve capacity diminishes.
(3) A more robust protection system (reduced hidden failure probabilities) will increase the system reliability. The system still exhibits power law behavior but with steeper slopes.
(4) Prompt control actions will prevent cascading overloads hence further reducing the risk of big disturbances. The power tail is shifted downwards with faster system control actions.

The tradeoff among these parameters with respect to system reliability and economic operation is essential to power system design or upgrade. Although it turns out to be complicated and beyond the scope of this paper, the full understanding of it would have significant consequences for power system operation and hence is worth further investigating.

Due to the lack of data, such as system load characteristics, actual hidden failure probability, and likelihood of initiating events, we have made some simplifying assumptions in the simulation. Therefore, the results qualitatively, but not necessarily quantitatively reflect actual system dynamics. It is also well known that the DC approximation of the actual AC system leaves out some outstanding aspects of power networks, such as voltage issues and frequency oscillations, that may make significant contributions to cascading outages. In addition, the hidden failure mechanism applied here is merely a conceptual representation of an indeed very complicated relaying operation, which generally not only involves the application of various different types of protective relays but also requires appropriate coordination between them. The hidden failure DC model presented here is no doubt an oversimplified model compared to the complexity of real power system operations. Nonetheless, since this basic model can remarkably produce similar results as seen in the NERC data, we believe it can serve as a good starting point for future research in order to fully understand what is behind the cascading outages. It is also our intention that this type of analysis can be pursued further and can be beneficial not only in areas such as major disturbance mitigation but also in system planning and upgrading.

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