

# 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 observed power tails of 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 parameters and the possible blackout mitigation are discussed and illustrated using simulation results from the WSCC 179-bus equivalent system and IEEE 118-bus test system. It is our intention that the 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

## 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 U.S power transmission grid suffered from more than 400 major blackouts in the past 16 years [1] in spite of technological progress and huge investments on the 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 occurrence of blackouts falls off exponentially with the event size. But recent analyses of 16 years of North American disturbance data show 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 but also due to the enormous cost to society of large blackouts [6].

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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 the 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 called a *hidden failure* [7]. Hidden failures in protective relays and their impact on power transmission system reliability have been examined in recent studies [7-9]. Possible vulnerable links subject to hidden failures were located in various systems such as WSCC 179-bus system and 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. For a different cascading failure blackout model at a similar level of model detail see the OPA model in [10-12].

## **Hidden Failure Model**

### ***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. By the assumption of [7], 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 seen by NERC reports [1].

Line protection hidden failures are incorporated here in the simulation to model protective relays. Each line has a different load dependent probability of incorrect trip, which 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 Figure 1.

We apply here an improvement of the hidden failure model. Suppose a line is exposed multiple times during a cascading event. The previous version [7-9] of the model allowed relay misoperation with equal probability 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 misoperation probability 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 tripping newly exposed lines, and letting the cascading event spread in the network, which is consistent with the observed NERC events [1].

#### **“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:

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

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

diagonal conductance matrix,

$$g = \text{diag}(g_1, g_2, \dots, g_m)$$

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

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

$$\text{line current vector, } \bar{J} = [J_1 \quad J_2 \quad \cdots \quad J_m]^T$$

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

By Kirchoff's current and voltage laws, the following hold

$$Y = A^T \cdot g \cdot A \quad (1)$$

$$\bar{I} = Y \cdot \bar{V} \quad (2)$$

$$\bar{I} = A^T \bar{J} \quad (3)$$

$$\bar{J} = g \cdot A \cdot \bar{V} \quad (4)$$

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  $q_i$  be the voltage angle at bus i, then  $\cos(q_i - q_j) \approx 1$ , and  $\sin(q_i - q_j) \approx q_i - q_j$ .

Define, for the AC system,  $\Theta = [q_1 \ q_2 \ \dots \ q_n]^T$  as *bus voltage angle vector*,  $\bar{P} = [P_1 \ P_2 \ \dots \ P_n]^T$  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 among these DC and AC system variables: 1) the DC voltages  $\bar{V}$  stand for the AC angles  $\Theta$ , 2) the DC currents  $\bar{I}$  stand for the real power  $\bar{P}$ , and 3) the DC admittance matrix Y is substituted by the susceptance matrix B. Then the isomorphic equations for the “DC” load flow approximation are

$$B = A^T \cdot b \cdot A \quad (5)$$

$$\bar{P} = B \cdot \Theta \quad (6)$$

$$\bar{P} = A^T \bar{F} \quad (7)$$

$$\bar{F} = b \cdot A \cdot \Theta \quad (8)$$

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

### ***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

$$\text{Loss of Load} = \min \sum_{\text{loads}} C_i \quad (9)$$

subject to overall power balance

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

and generation capacity limits for generator i

$$P_i^{\min} \leq P_i \leq P_i^{\max}, \quad (11)$$

and the line flow limits

$$-F_j^{\max} \leq F_j \leq F_j^{\max}, \quad j = 1, 2, \dots, m \quad (12)$$

and load shedding limits for load k

$$0 \leq C_k \leq D_k, \quad (13)$$

where  $D_k$  is the initial load at bus k.

### ***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 Equ. (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 Figure 1 and the improved hidden failure mechanism. Note that the spread of disturbances 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 Equ. (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.

### ***Importance Sampling Technique***

NERC reports [1] show that there are only about 400 events during the past 16 years in the U.S 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 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

$$\hat{r}_i = \frac{N_{occurring}}{N_{total}} \cdot \frac{p_i^{actual}}{p_i^{simulate}} \quad (14)$$

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

### **Cascading Dynamics And Mitigation Assessment**

The Hidden Failure model yields power tails remarkably consistent with the NERC data and 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.

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 Figure 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.

### ***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 have minimal impact on other components and these other components have large operating margins. Multiple outages are possible, 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 loading increases from zero to a very high loading. The nature of the transition between these two extremes is what is of great interest to us.

Figure 2 shows the expected power loss

$$EP = \sum P_i \hat{r}_i \quad (15)$$

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  $(P_i, \hat{r}_i)$ . The representative  $(\bar{P}_j, \bar{\hat{r}}_j)$  for bin j is defined as

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

$$\bar{\mathbf{r}}_j = \frac{\sum_{i=1}^K P_i \hat{\mathbf{r}}_i}{\bar{P}_j} \quad (17)$$

The 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.

Figure 3, 4 and 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.

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 to reduce the risks of large blackouts due to cascading failure. 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 [3-5,10-11,15].

### ***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 examined the impact of the capacity of available spinning reserves on the power tail of cascading events.



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 reserve,  $R$ , 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  $R_i = 0.1 * P_i$ .

Figure 6 and 7 show the PDF of blackout size  $P$  for the WSCC system with 1%, 10%, and 20% reserve capacity 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 exponential tail) by supplying ample spinning reserve. It seems that the role of reserve is to eliminate the critical point. However, this is not the case when the load growth is also considered. Suppose that the load keeps growing without line upgrading ( i.e., line limits remain the same), then finally the load level will approach the full system capacity, meanwhile the "usable" reserve capacity will keep dropping even to zero due to line limits. Associated with this scenario, the "fixed" exponential tail will be changed back to the power tail, thus a shifted critical point appears. Therefore, the reserve can put off the critical region but cannot eliminate it because of 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].

### ***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 great interest to us. Figure 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 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. have also explored the hidden failures in protective relays and their impact on power transmission system reliability in recent studies [7-9]. The previous work focused on detection of the weakest links in the bulk power system and corresponding economical system upgrading strategy under "limited budget" assuming only

several weak links can be improved. Our focus here is to investigate a similar problem but with an “unlimited budget”, in which case we assume all lines can be improved at the same rate. Although this is far from optimum, it does give a sort of "upper bound" for achievable improvement of system reliability. For example, suppose the  $p$  of current protection system is 0.02, and we can reduce  $p$  at most to 0.005. Then any optimal system upgrading strategy with limited budget, such as aforementioned studies, will generate a new PDF located somewhere between the two power tails shown in Figure 8. The power tail with  $p = 0.005$  is therefore the "upper bound". It would be nice to develop an economic system upgrading scheme that can closely approach this bound, but this 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  $p$  to generate the same power tail exponent as in NERC data. Recall from [1-2] that the power exponent is around -2, we found out the rough order of  $p$  is  $10^{-2}$ . Another way to estimate  $p$  is by the following calculation.

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 past 16 years. Assume one cascading event could be initiated in every power circle, thus the probability of one event will be approximately  $150 / (16 \times 365 \times 24 \times 60 \times 60 \times 60) = 5.4 \times 10^{-9} = p^5$ . Again,  $p \approx 10^{-2}$ .

### ***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.

The only control used in the model is LP redispatch, which is representative of various control strategies in real systems. The only adjustable parameter here is the responding speed of LP redispatch to cascading overloads. To simplify the implementation, regular LP redispatch is used, say, one redispatch every three trips. Notice that LP redispatch is effective only when there exist overloads in the system, but won't 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 "normal" with no overloads, the

better. The PDF of blackout size in Figure 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. And 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 further spreading. The lower power tail is then an upper bound when evaluating the system reliability with respect to system control.

## **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 reserve can greatly reduce the risk of big blackouts. The system shows exponential tails with high reserve capacity but power tails as reserve capacity goes down.

(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 down with faster 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 fully 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 event, we have made some simplifying assumptions in the simulation. Therefore, the results qualitatively, but not necessarily quantitatively reflect actual system dynamics. However, it is our intention that this type of analysis can be pursued further (assuming suitable data is available) and can be beneficial not only in areas such as

major disturbance mitigation but also in system planning and upgrading.

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## Biographies

**Jie Chen** was born in China in 1974. He received a BS degree and a MS degree in Electrical Engineering from Tsinghua University, China in 1997 and 1999. He is currently enrolled in the PhD program in Electrical Engineering at Cornell University in Ithaca, NY, USA. His research interests include computer simulation of power systems, electricity market and complex systems.

**James S. Thorp** is the Charles N. Mellowes Professor in Engineering at Cornell University. In 1976, he was a faculty intern at the AEP Service Corporation. He was an associate editor for IEEE Transactions on Circuits and Systems from 1985 to 1987. In 1988, he was an overseas fellow at Churchill College, Cambridge, England. From 1994 to 2000, he was Director of the School of Electrical Engineering at Cornell University. He is a member of the National Academy of Engineering, a Fellow of IEEE and a member of the IEEE Power System Relaying Committee, CIGRE, Eta Kappa Nu, Tau Beta Pi and Sigma Xi.

**Ian Dobson** received the BA degree in Mathematics from Cambridge, England in 1978 and the PhD degree in Electrical Engineering from Cornell University in 1989. He worked from 1978 to 1983 as a systems analyst for the British firm EASAMS Ltd. In 1989 he joined the University of Wisconsin-Madison, where he is now a professor in electrical and computer engineering. His current interests are applications of complex systems and nonlinear dynamics, cascading failure and self organized criticality in blackout risk, electric power system instabilities, and power electronics.

## Figure Caption List

Figure 1. Probability of an exposed line tripping incorrectly

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

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

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

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

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

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

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

Figure 1

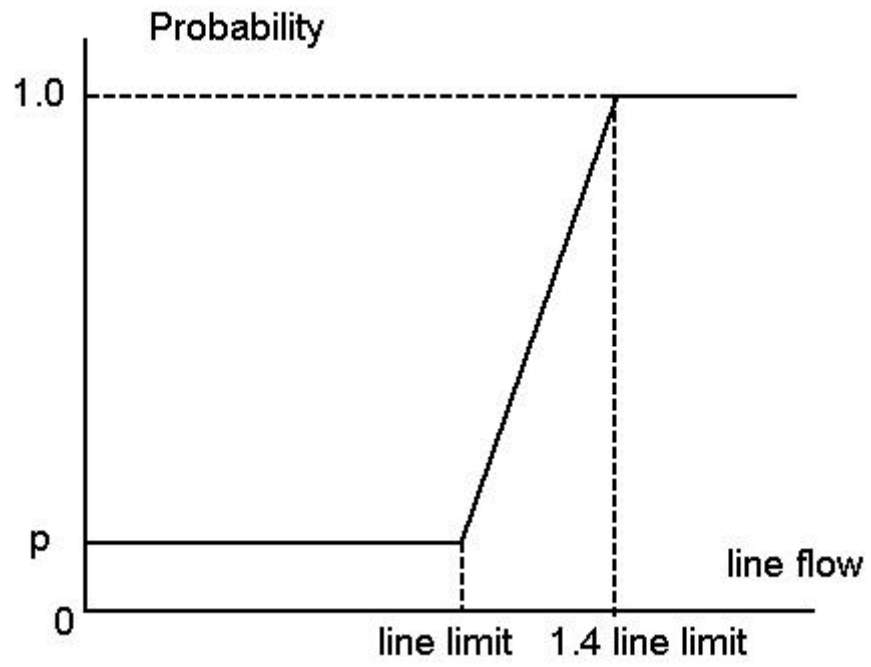


Figure 2

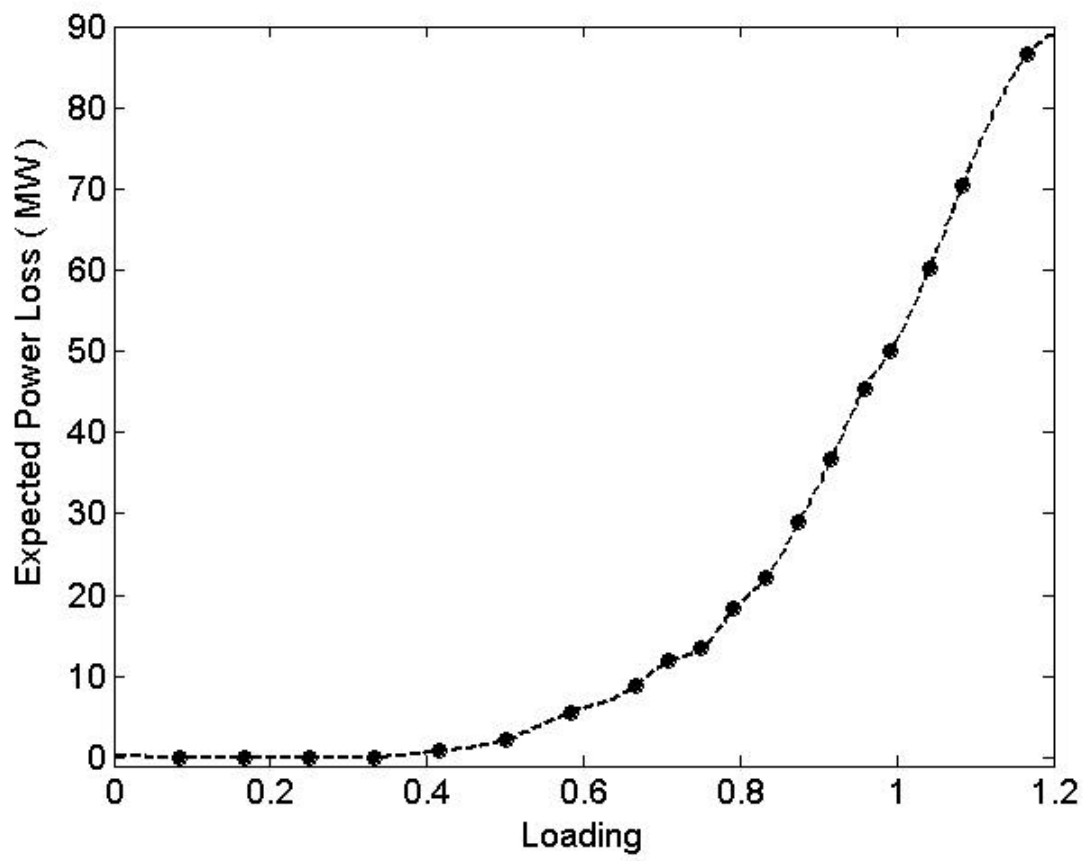




Figure 3

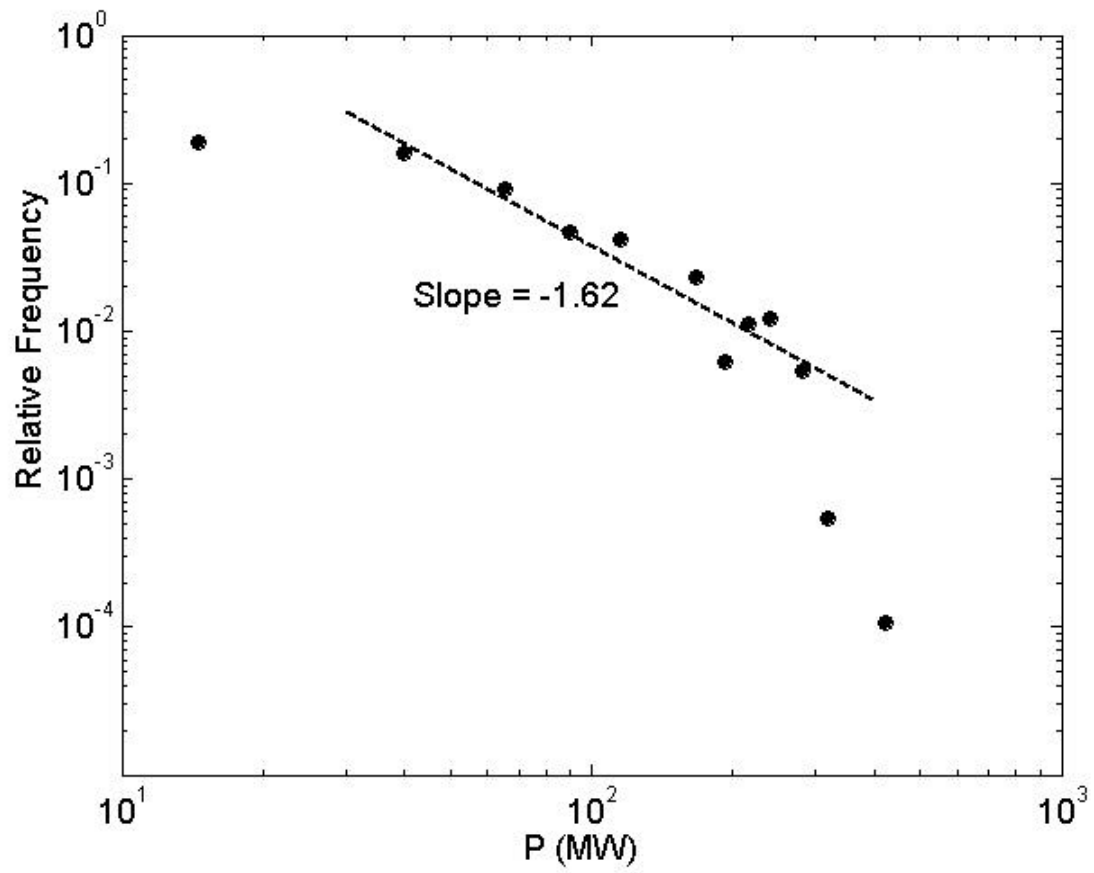


Figure 4

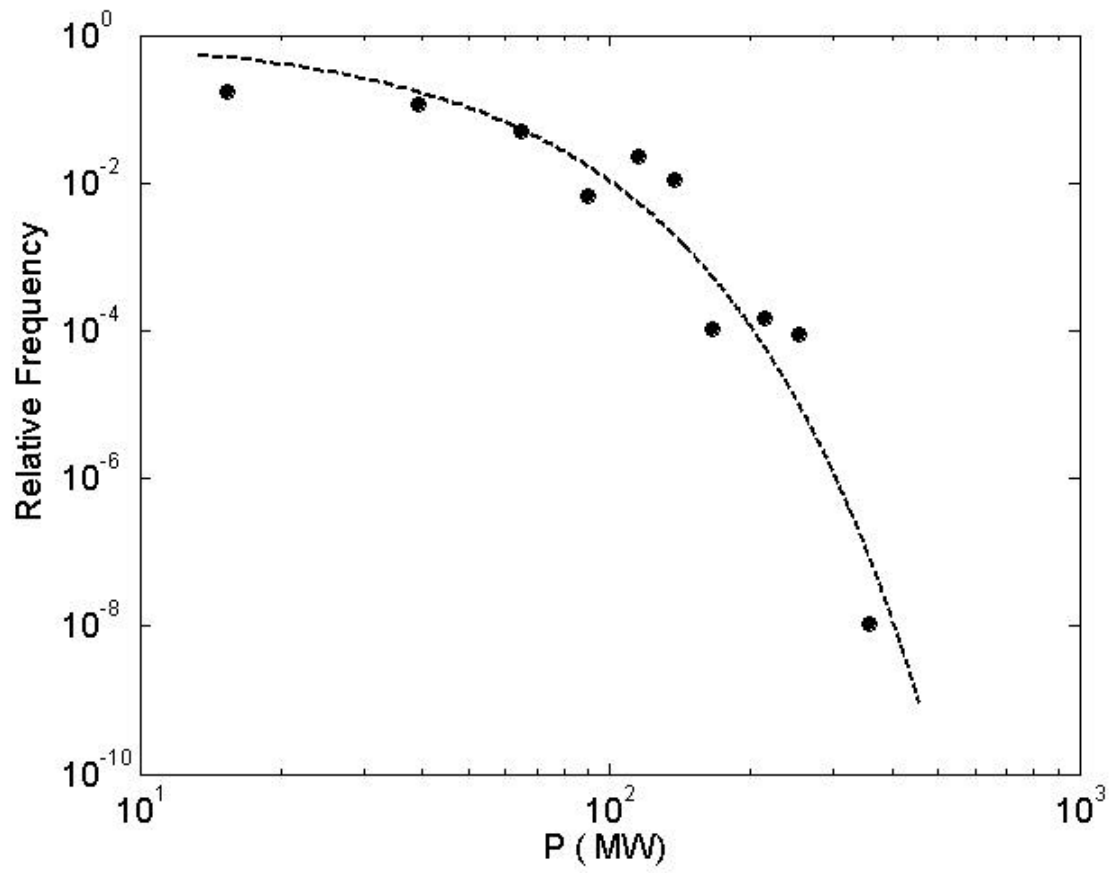


Figure 5

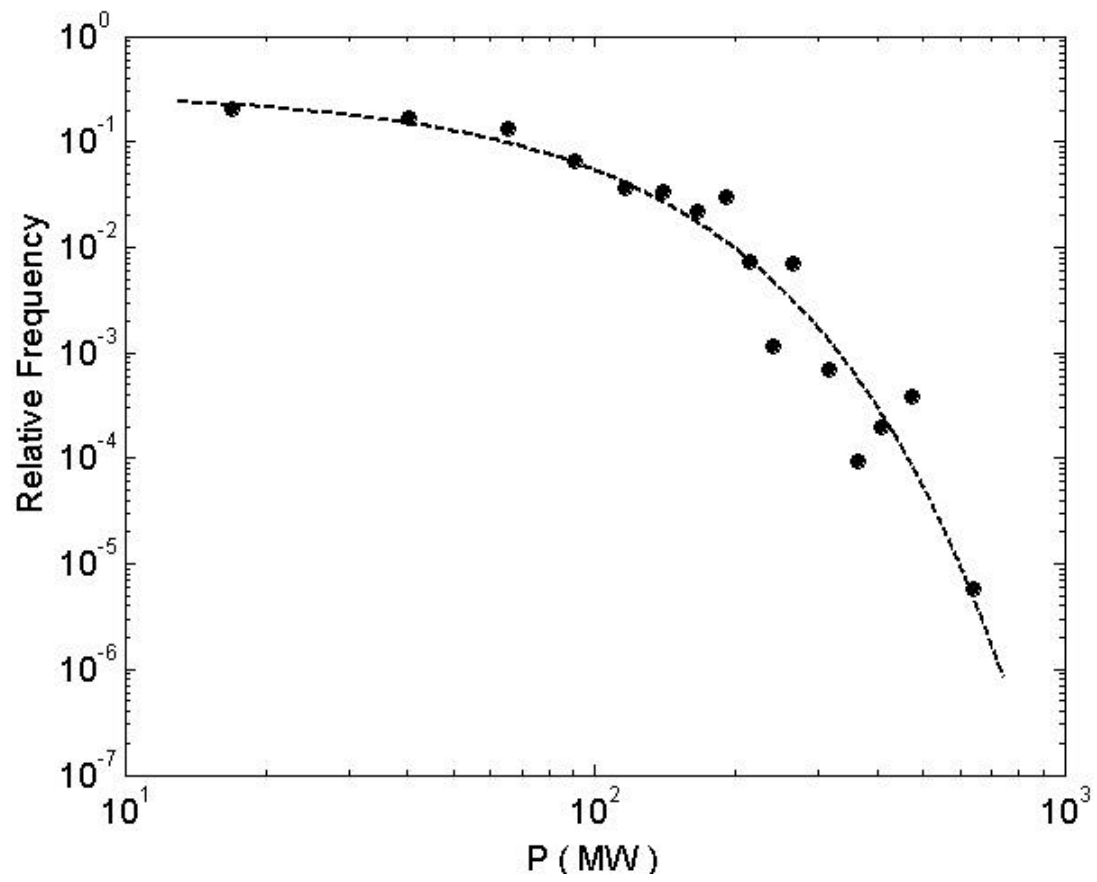


Figure 6

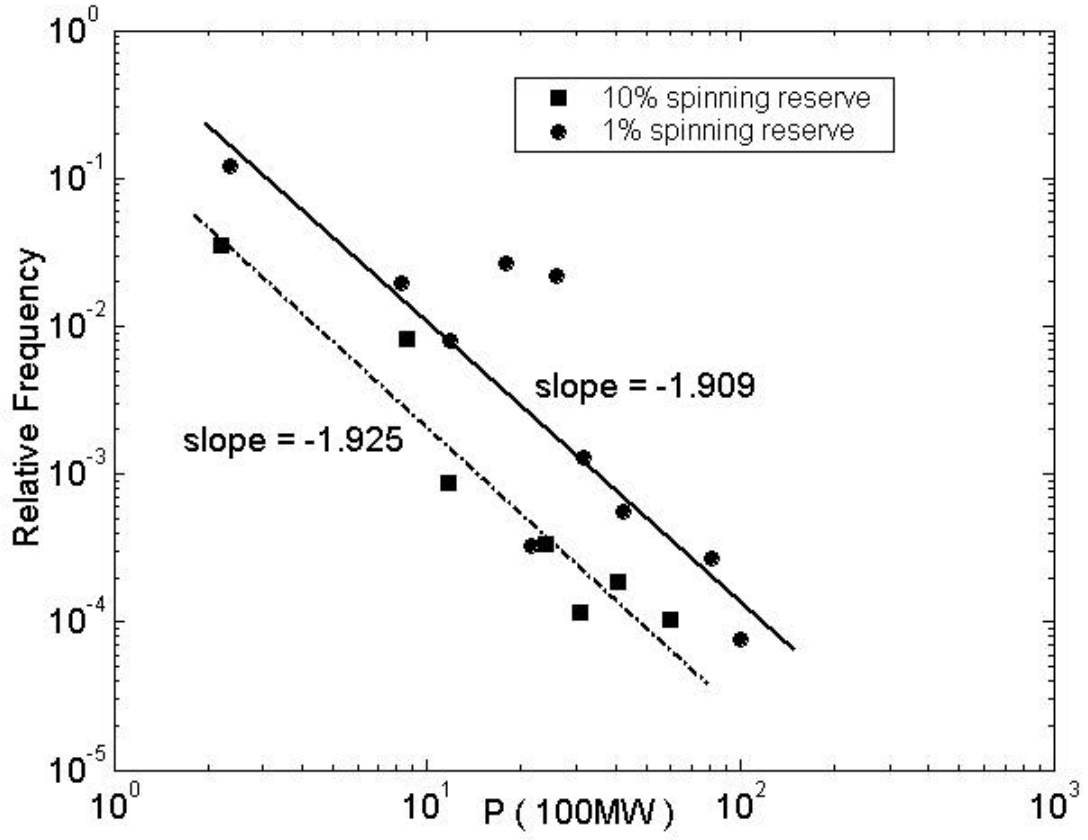


Figure 7

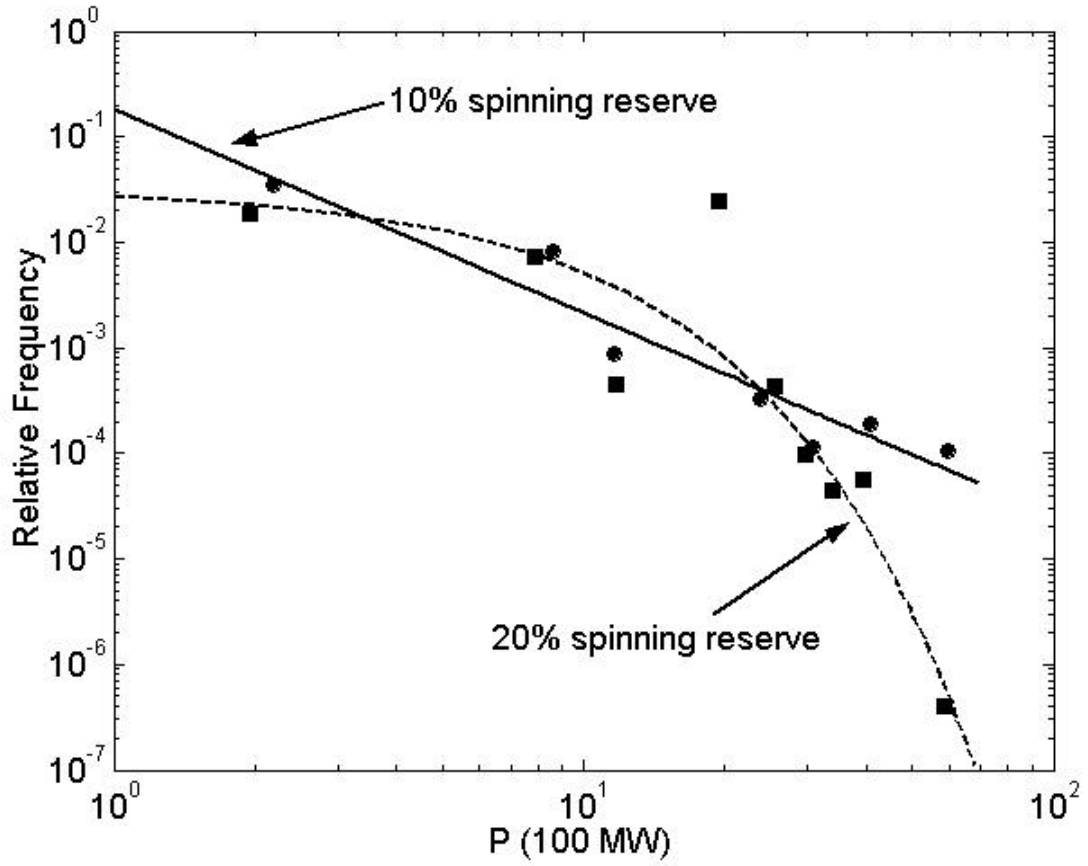


Figure 8

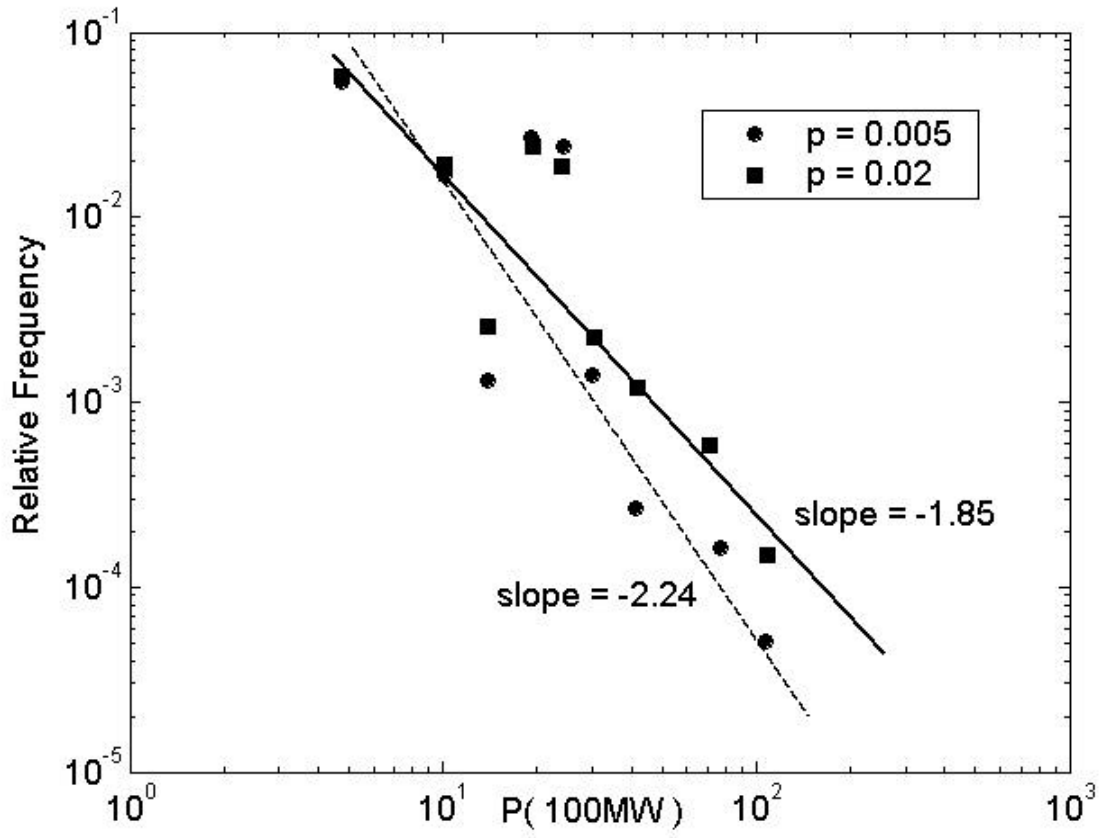


Figure 9

