The Impact of Distributed Generation on Power Transmission Grid Dynamics

D. E. Newman

Physics Dept.
University of Alaska
Fairbanks AK 99775
denewman@alaska.edu

B. A. Carreras

Depart. Fisica
Universidad Carlos III
Madrid, Spain
bacarreras@gmail.com

M. Kirchner

Physics Dept.
University of Alaska
Fairbanks AK 99775
mjkirschner@alaska.edu

I. Dobson

ECE Department
Univ. of Wisconsin
Madison WI 53706
dobson@engr.wisc.edu

Abstract

In this paper we investigate the impact of the introduction of distributed generation on the robustness of the power transmission grid using a dynamic model of the power transmission system (OPA). It is found that with different fractions and distributions of distributed generation, varied dynamics are possible. An important parameter is found to be the ratio of the variability of the distributed generation to the generation capacity margin. Somewhat counter-intuitively, in some of these cases the robustness of the transmission grid can be degraded with the potential for an increased risk of large failures with increased distributed generation if not done carefully.

1. Introduction

With the increased utilization of local, often renewable, power sources, coupled with a drive for decentralization, the fraction of electric power generation which is "distributed" is growing and set to grow even faster. It is often held that moving toward more distributed generation would have a generally positive impact on the robustness of the transmission grid. This intuitive improvement comes simply from the realization that less power would need to be moved long distances, and the local mismatch between power supply and demand would be reduced. We approached the issues of system dynamics and robustness with this intuitive understanding in mind and with the underlying question to be answered, is there an optimal balance of distributed verse central generation for network robustness. In the interest of understanding the impact of different factors we start by intentionally ignoring the differences in the economics of centralized vs distributed generation and try to approach the question in a hierarchical manner, starting from the simplest model of distributed generation and

adding more complexity. Since we are exploring the network robustness as characterized by the risk of large failures and temporal dynamics, we use the OPA model. The OPA model [1, 2, 3] was developed to study the failures of a power transmission system under the dynamics of an increasing power demand and the engineering responses to failure. In this model, the power demand is increased at a constant rate and is also modulated by random fluctuations. Transmission lines are upgraded when they are involved in blackouts. The generation power is automatically increased when the capacity margin is below a given critical level.

Using the OPA model we have been able to study and characterize the mechanisms behind the power tails in the distribution of the blackout size. These algebraic tails obtained in the numerical calculations are consistent with those observed in the study of blackouts for real power systems [4, 5]. Most importantly, this model permits us to separate the underlying causes for cascading blackouts from the triggers that generate them and therefore explore system characteristics that enhance or degrade robustness and reliability of the power transmission grid. One of these characteristics, the one investigated here, is the amount of distributed generation present.

To understand the impact of distributed and renewable generation, and thereby improve the realism of the model, we have added a new class of generation to OPA. This distributed generation class allows us to vary: 1) fraction of power from distributed generation 2) fraction of nodes with distributed generation 3) reliability of the distributed generation 4) economic upgrade models for the various types of generation and 5) dispatch models for the distributed generation.

In this paper, we describe the beginning of these investigations and the impact on the reliability of the system from the changes introduced in this model.

2. The OPA model

The OPA (ORNL-PSerc-Alaska) model for the dynamics of blackouts in power transmission systems

[1, 2, 3] showed how the slow opposing forces of load growth and network upgrades in response to blackouts could self organize the power system to dynamic equilibrium. Blackouts are modeled by overloads and outages of lines determined in the context of LP dispatch of a DC load flow model. This model has been found to show complex dynamical behavior [1, 2] consistent with that found in the NERC historical data for blackouts [4]. Some of this behavior has the characteristic properties of a complex system near a critical transition point. That is, when the system is close to a critical point, the probability distribution function (PDF) of the blackout size (load shed, customers unserved, etc) has an algebraic tail and large temporal correlation lengths are possible. One consequence of this behavior is that at these critical points, both the power served is maximum and the risk for blackouts increases sharply. Therefore, it may be natural for power transmission systems to operate close to this operating point.

The fact that, on one hand, there are critical points with maximum power served and, on the other hand, there is a self-organization process that tries to maximize efficiency and minimize risk may lead to a power transmission system that is naturally driven to this point.

In general, the operation of power transmission systems results from a complex dynamical process in which a variety of opposing forces regulate both the maximum capacity of the system components and the loadings at which they operate. These forces interact in a highly nonlinear manner and may cause a self-organization process to be ultimately responsible for the regulation of the system. This view of a power transmission system considers not only the engineering and physical aspects of the power system, but also the engineering, economic, regulatory and political responses to blackouts and increases in load power demand. A detailed, comprehensive inclusion of all these aspects of the dynamics into a single model would be extremely complicated if not intractable due to the human interactions that are intrinsically involved. However, it is useful to consider simplified models with some approximate overall representation of the opposing forces in order to gain some understanding of the complex dynamics in such a framework and the consequences for power system planning and operation. This is the basis for OPA.

In the OPA model the dynamics involves two intrinsic time scales. There is a slow time scale, of the order of days to years, over which load power demand slowly increases and the network is upgraded in engineering responses to blackouts. These slow opposing forces of load increase and network upgrade self organize the system to a dynamic equilibrium. There is also a fast time scale, of the order of minutes to hours, over which cascading overloads or outages may lead to blackout.
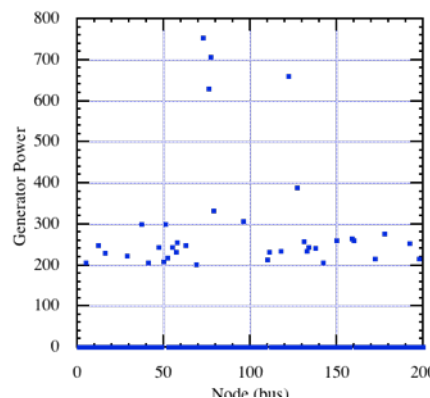
The main purpose of the OPA model is to study the complex behavior of the dynamics and statistics of series of blackouts in various scenarios. This allows us to extend the modeling of the system evolution to represent generator types, distributions and upgrades as well as network characteristics.

3. Distributed generation and its impact

There are a number of issues involved in the exploration of distributed generation. These include 1) simply defining a characteristic number to quantify the amount of distribution from some combination of the fraction of power from distributed generation and the fraction of nodes with distributed generation, 2) the effect of adding distributed generation in the grid, 3) the impact of the reliability of the distributed generation, 4) economic upgrade models for the various types of generation and 5) dispatch models for the distributed generation.
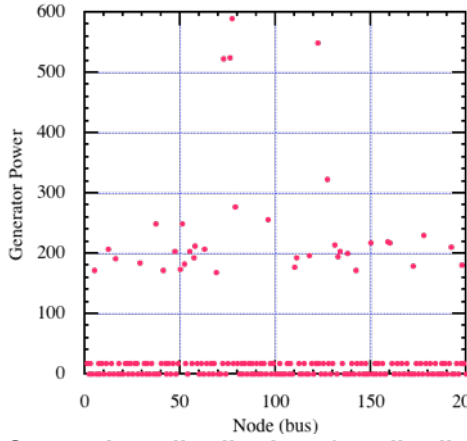
3.1 Measures of distribution

The first among these are a characterization of the distributed fraction. Figures 1 and 2 show the distribution of the generation over the nodes in a 200 bus system. In figure 1, a standard distribution is used with 35 generators in the 200 nodes. We call this the reference case and consider this to be centralized generation.

Fig.1 Generation distribution for reference case (centralized generation).

Figure 2 shows the distribution for a uniform distributed generation case we will discuss in this paper. In this case ~25% of the power generation is removed from the "central generation" and randomly distributed among ~ 50% of the nodes. The characterization of the distributed fraction will be some combination of those two numbers.

Fig.2 Generation distribution for distributed generation case (25% power to 50% of nodes).

Though the best combination is yet to be determined and there is probably not a unique measure of this, we will propose and use a simple characterization which we will call the degree of distribution based on the standard deviation of the distribution. Let us consider a very simple situation in which we have N_g generators with high power to provide central generation with total power P_g and N_d distributed generators providing P_d power to the system. Therefore, each central generator has power P_g/N_g and each distributed generator has power P_d/N_d. The total power in the system is then

$$P_T = P_g + P_d \qquad (1)$$

The reference case being a case with no distributed generation has $N_d = 0$ and $P_d = 0$. It is useful to introduce the following notation

$$f_d = \frac{P_d}{P_T}, \quad f_g = \frac{P_g}{P_T}, \quad n_d = \frac{N_d}{N_T}, \quad n_g = \frac{N_g}{N_T} \qquad (2)$$

Here, N_T is the total number of nodes. Since, $f_d + f_g = 1$, we have three independent parameters. However, we start from the standard case where n_g is fixed, so really we have only two independent parameters to characterize the different distributed generation configurations. We can therefore define a configuration of distributed generator by specifying f_d and n_d.

The first parameter used to characterize the distributed generation is the ratio of the power at the distributed generator to the power in the central generators

$$m_1 = \frac{n_g}{n_d} \frac{f_d}{f_g} \qquad (3)$$

The second parameter, the degree of distribution, is based on the standard deviation of the generator power distribution. It is defined as

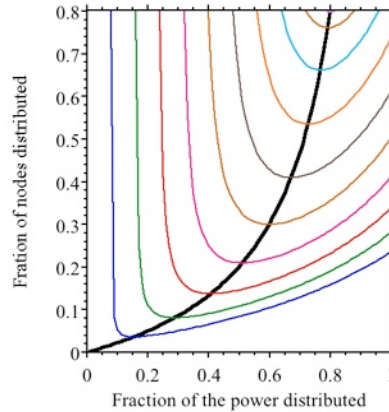$$m_2 = 1 - \frac{\sigma(f_d, n_d)}{\sigma(0,0)} \qquad (4)$$

where $\sigma(f_d, n_d)$ is the standard deviation for the power distribution corresponding to a given set of n_d and f_d values. For the case of both sets of generators having a uniform distribution, this parameter is given by

$$\bar{m}_2 = 1 - \sqrt{\frac{n_g}{1-n_g}} \sqrt{\frac{(1-f_d)^2}{n_g} + \frac{f_d^2}{n_d} - 1} \qquad (5)$$

For a given reference configuration, the phase space is then defined by

$$\begin{cases} 0 \le n_d \le 1 - n_g \\ 0 \le f_d \le 1 \end{cases} \qquad (6)$$

However, it does not make any sense to consider configurations with $m_1 > 1$. Therefore, this phase space will be bounded by curve $m_1 = 1$. For a reference case with $n_g = 0.2$, we have plotted the phase space in Fig. 3. In this figure, the thick black line is the curve $m_1 = 1$. The other color lines are $m_2 = $ constant lines corresponding to ten equal spaced values of degree between 0 and 1.
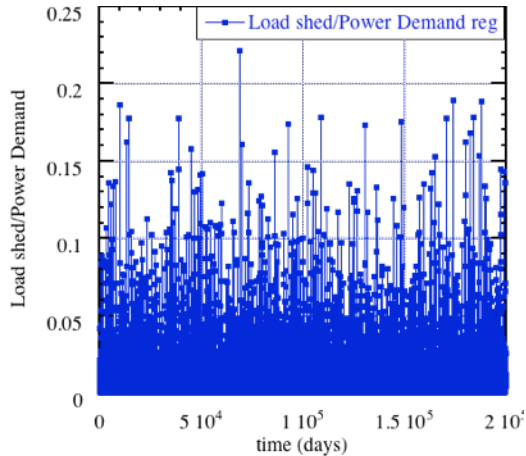

Fig.3 Distribution degree as function of distributed power fraction and distributed node fraction.

The analytical expressions are useful for an initial mapping of the phase space. For the particular cases that we consider in the numerical calculations, we can use Eq. (4).
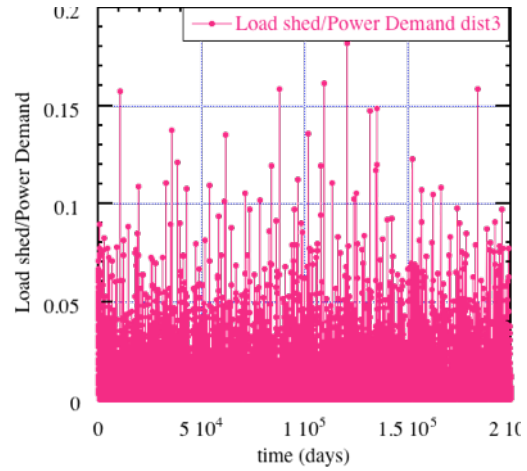
3.2 Impact of distribution without variability

Next we investigate the impact of adding reliable distributed generation to the system. Since distributed generation is not likely to be uniform in the real world we look at 2 distributions of the "distributed generation" for this initial study. These two cases are, uniform and proportional. The uniform case simply takes the distributed power P_d and uniformly divides it over N_d distributed generator nodes. The proportional case takes the distributed power P_d and divides it over N_d distributed generator nodes in proportion to the local demand. This is meant to simulate planning and while nice in practice in reality renewable generation is usually placed where the resources are (wind, sun etc) rather then where the demand is. For this study, we will treat distributed generation in much the same way as the central generation with two differences. The first difference is that we do dispatch of the distributed generation first (ie our effective cost function is lower so as to utilize all the distributed generation capacity when possible). Second, we build into the distributed generation the ability to vary the reliability of the distributed generation capacity. This mocks up the variability of the wind and solar generation capabilities. This second part will be discussed in the next section.

Figures 4 and 5 show the time evolution of the normalized load shed for two systems. Looking at them, there is little obvious difference.
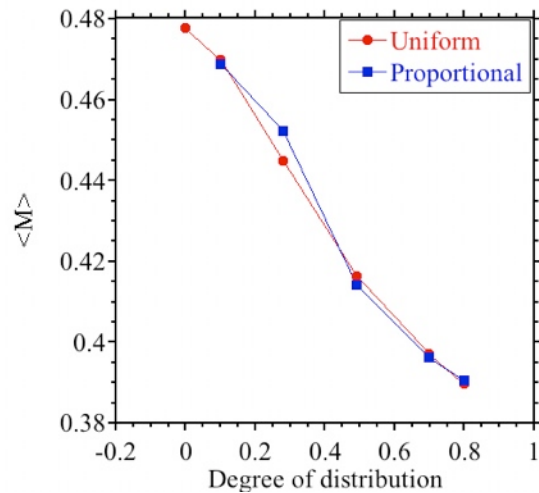

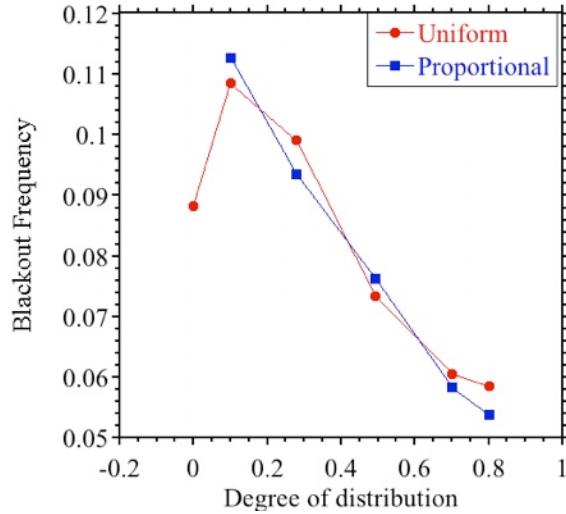**Fig.5 Normalized load shed vs time for distributed generation case (25% power to 50% of nodes).**

However, as the degree of distribution is changed characteristic measures of the system state do in fact change substantially. Figure 6 shows the average line loading <M> for the reference case and the distributed cases for both the uniform distribution and proportional distribution cases. The uniform and proportional cases are virtually indistinguishable so they will not be discussed separately. The average line loading falls consistently as the system gets more distributed. This suggests that the system is moving away from the critical point and is becoming more robust.

Fig.4 Normalized load shed vs time for reference case (centralized generation).
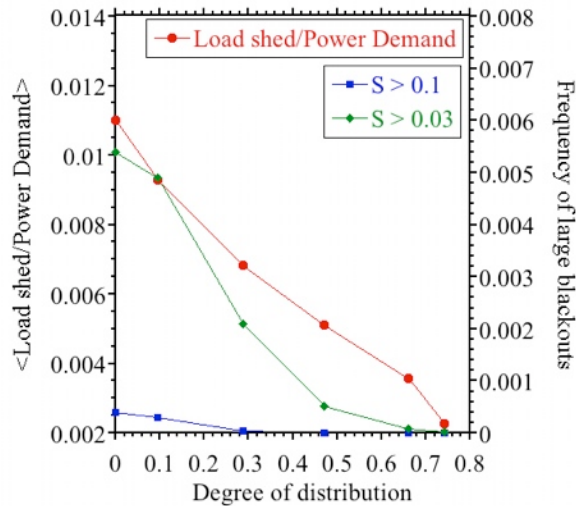

Fig.6 Average fractional line loading vs distribution degree.

Perhaps more importantly from a reliability point of view, figure 7 shows the blackout frequency as a function of the distribution degree and figure 8 shows 3 measures of the sizes of events also as a function of the distribution degree. The frequency of blackouts goes down as the system get more distributed and the size of the blackouts also decreases. In fact the frequency of the large events (shown in figure 8 for events larger then 10% of the system size as S>0.1 and for larger then 3% of the system size as S> 0.03) goes down to near zero for the most distributed systems.

Fig.7 Blackout frequency vs distribution degree.

Fig.8 Average normalized load shed vs distribution degree and frequency of events over 3% of the system size and over 10% of the system size also vs distribution degree.
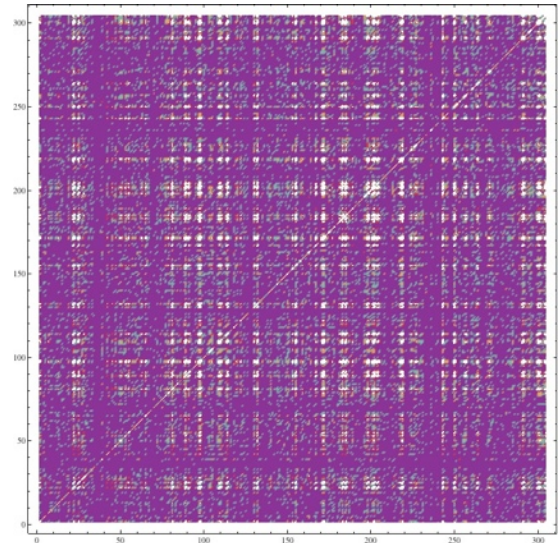
Figures 9 and 10 show synchronization matrices for 2 of the cases. These are defined as :

$$S(i,j) = \sum_{\text{large blackouts}} \text{Ov}(i)\text{Ov}(j)$$

Here, Ov(i) is a variable that takes only two values, 1 if the line i overloaded during the blackout and 0 if does not. In the definition above, and for each pair of lines, i and j, the sum is taken over all large blackouts. The definition of large blackout is flexible and depends on what we want to study. Here we define a large blackout as a blackout with load shed over power delivered is greater than 0.1.
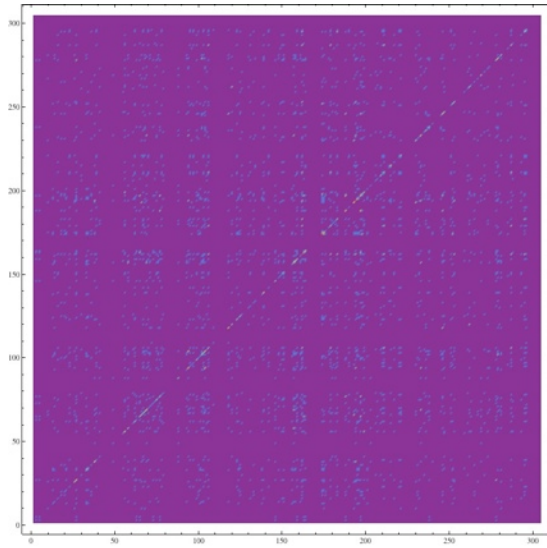
Note that S(i, i) is equal at the total number of large blackouts in which line i has overloaded. The S(i, j) is equal to the total number of large blackouts in which lines i and j have both overloaded. Therefore, this matrix has the combined information on the frequency of overloading of the two lines and their synchronization.

These matrices characterize the likelihood of 2 lines going out together in large blackouts. The reference case shows much more structure (clumping) then the distributed case which suggests that these are more correlated cascading failures in the reference system then there are in the distributed system.

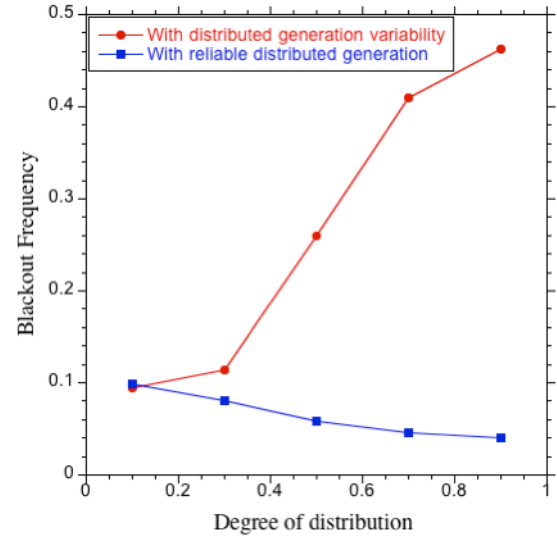**Fig.9 Line synchronization matrix for reference case.**

If one were able to build a power transmission system with highly reliable distributed generation, these results suggest that system would be very robust and reliable. This makes sense from the point of view of the dynamic reorganization that can occur. When an element of the system fails, there are many other routes and generators that can take up the slack. The problem of course is that distributed generation, particularly from renewables like wind and solar, are much less reliable then central generation facilities.

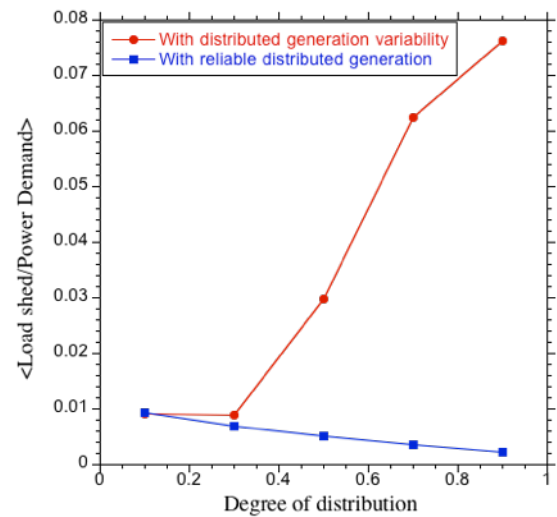**Fig.10 Line synchronization matrix for distributed generation case (m1=0.1).**

3.3 Impact of distribution with variability

As mentioned in the last section, distributed generation is not in general as reliable as the central generation. Wind, and therefore wind energy, in a given location can vary greatly as to a lesser degree can solar power. When added to the generation mix, this less reliable generation source can impact the transmission grid. To investigate this, we use the same distributed generation model as before, but now allow the distributed generators to have a daily random fluctuation in their capacity. For this study, we have set a fraction (P_g) of the distributed generation nodes to probabilistically be reduced to a fixed fraction (f_g) of their nominal generation limits. In the cases shown here we have used $P_g = 0.5$ and $f_g = 0.3$. This means that half of the distributed generators can have their capacity reduced to 0.3 of their nominal capacity. While these added fluctuations in the system increase the probability of failure, the most pronounced effect comes when the total amplitude of these distributed generation variations start to become close to the total system generation margin. At that point a huge change in the dynamics occurs and increasing the distributed generation seriously degrades the system behaviour. Figure 11 shows the blackout frequency as a function of the degree of distribution for 2 uniform distribution cases, one without any variability of the distributed generators and one with variability. At 0.1 degree of distribution the frequencies are the same but after 0.3 they diverge sharply with the improvement seen in the reliable distribution cases reversed in the variable distribution case and becoming much worse.

Fig.11 Blackout frequency for a reliable distributed generation case and variable distributed generation cases showing much higher frequency of blackout with the variable generation.
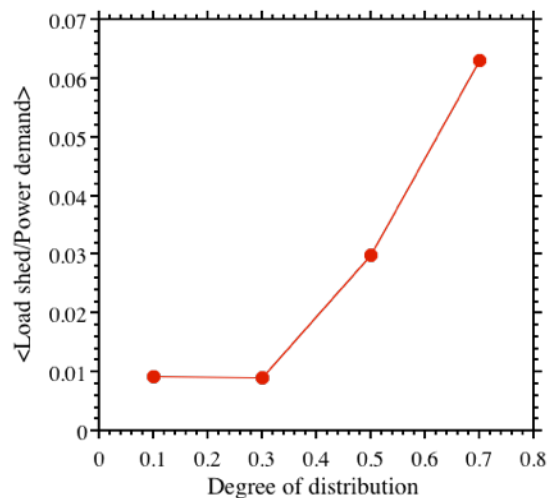
Figure 12 shows a similar result for the average normalized load shed with a large increase in the average when there is variability in the distributed generation.

Fig.12 Normalized average load shed for a reliable distributed generation case and variable distributed generation cases showing much higher frequency of blackout with the variable generation.
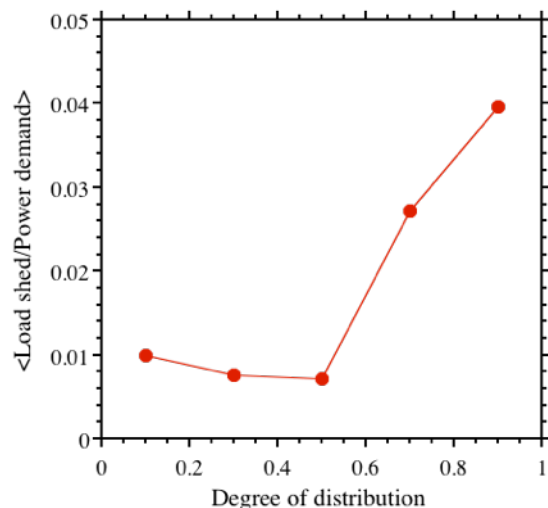
If the critical generation margin is increased the degree of distribution at which the system starts to

degrade is increased. Figures 13 and 14 show the normalized load shed as a function of degree of distribution for 2 values of the generation margin. In figure 13 the critical margin is 0.25, namely there is a 25% spare capacity that is maintained. In this case the system starts to degrade at a distribution degree of 0.3

Fig.13 Normalized average load shed for a variable distributed generation case with a generation margin of 25%.
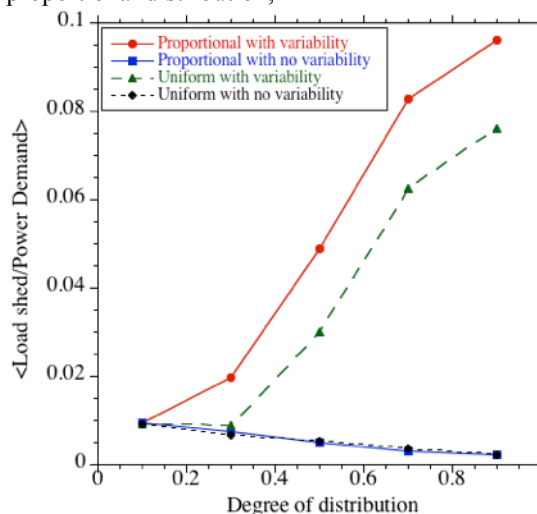
In figure 13 however the critical margin is 0.35, or a 35% spare capacity margin. In this case the system starts to degrade at a distribution degree of 0.5

Fig.14 Normalized average load shed for a variable distributed generation case with a generation margin of 35%.

Similar changes are seen in the frequency of blackouts, the frequency of large events and the tail of the PDF.

All of these results have been for the uniform distribution case and it is worth noting that for the proportional distribution cases while the results are qualitatively the same there are some differences. Figure 15 shows the normalized load shed as a function of the degree of distribution. It can be seen that both with and without variability the results are similar, however they are somewhat intensified by the proportional distribution,

Fig.15 Normalized average load shed for reliable distributed generation cases (proportional and uniform) and variable distributed generation cases (also proportional and uniform).

4. Conclusions

A dynamic power transmission grid model (OPA) is found to be very useful in investigating the impact of increased distributed generation on the power transmission grid robustness and reliability. The results of this work suggest that distributed generation in general improves the system characteristics if the distributed generation is reliable. However, in the more common case in which the distributed generation has more variability, the system can become significantly less robust with the risk of a large blackouts becoming larger. It is found that for different overall nominal capacity margins, it is possible to find an optimal value of the degree of distribution which maximizes the system robustness. Further investigations of different models of the reduced reliability of the distributed generation power and different distributions of the distributed generation must be performed to determine if there are further impacts on the overall system reliability to be found.

It is clear that distributed generation can have a number of impacts, positive and negative, on the

system robustness coming from both the reliability of the generation (wind/solar etc) which both stresses the system and changes the actual generation capacity and from the fraction which is distributed which make the system less stressed. These results suggest that when planning for the incorporation of variable distributed generation into the transmission grid, careful analysis of the impact of the variable component on the nominal generation margin is essential.

Acknowledgements

5. References

[1] B. A. Carreras, V.E. Lynch, I. Dobson, D.E. Newman, Complex dynamics of blackouts in power transmission systems, Chaos, vol. 14, no. 3, pp. 643-652, September 2004

[2] I. Dobson, B.A. Carreras, V.E. Lynch, D.E. Newman, Complex systems analysis of series of blackouts: cascading failure, critical points, and self-organization, Chaos, vol. 17, no. 2, 026103, June 2007.

[3] H. Ren, I. Dobson, B.A. Carreras, Long-term effect of the n-1 criterion on cascading line outages in an evolving power transmission grid, IEEE Transactions on Power Systems, vol. 23, no. 3, August 2008, pp. 1217-1225.

[4] B. A. Carreras, D. E. Newman, I. Dobson, and A. B. Poole, Evidence for self organized criticality in a time series of electric power system blackouts, IEEE Transactions on Circuits and Systems Part I, vol. 51, no. 9, pp. 1733-1740, September 2004

[5] Xingyong Zhao, Xiubin Zhang, and Bin He, Study on self organized criticality of China power grid blackouts, Energy Conversion and Management, vol. 50, no. 3, pp. 658-661, March 2009.