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Effect of Short Term Risk Aversive Dispatch on a Complex System Model for Power Systems

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***Abstract*—In the analysis of time series of blackouts a power law dependency of blackout size with respect to frequency has been observed. It has been hypothesized that this behaviour is the result of the power system operating near critical points. Models have been created in order to analyze this type of behaviour in power systems. In this paper the effect of conservative versus non-conservative generation dispatch is studied using one such model. Conservative dispatches are ones that are performed in order to minimize stress on the system and therefore attempt to minimize possible outages and blackouts. This dispatch is compared with a non-conservative dispatch that attempts to maximize the stress and therefore increase the immediate risk of outages and blackouts. It is found that the non-conservative dispatch although attempting to maximize the immediate risk reduces the frequency of blackouts of all sizes over the conservative dispatch in the long term.**

***Index Terms*—power system modeling, power system reliability, risk analysis.**

I. Nomenclature

α - critical exponent of system
A - susceptance weighted adjacency matrix of the transmission system, (Siemens)
c - slope of the power law distribution
C - total relative generation capacity of the system
C_t - threshold for the addition of new generation
∂_i - line upgrade factor
f_i - power flow on a line *i*, (MW)
F - diagonal matrix of line capacity limits, (MW)
F_i - power flow capacity limits of a line, (MW)
g_i - generation capacity at a node, (MW)
h - generation allocation constant
i - line index number
j - node index number
k - time index number
K - large constant
l_i - load demand at a node, (MW)
l_i^{base} - base load demand at a node, (MW)
M_i - relative loading stress on line *i*
n - number of generation nodes
O - matrix of quadratic coefficients for quadratic programming
O_{max} - matrix of coefficients for global system stress maximization
O_{min} - matrix of coefficients for global system stress minimization
$\vec{p}$ - vector of power injections/consumptions into the system, (MW)
p_j - power injection/consumption at a node, (MW)
p_G - power injection at a generation node, (MW)
p_L - power consumed at a load node, (MW)
$P(S)$ - probability of an event of size S
q_0 - probability of random line failure
q_1 - probability of stress induced line failure
r_i - randomizing scalar factor
R - matrix of effective inductance between nodes in the transmission system, (Henry)
s - global system stress
S - blackout event size, (MW)
t_i - threshold of line stress for the onset of q_1
μ - load growth factor

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II. Introduction

Reliability assessment is of vital importance in the secure operation of an electrical power system. The goal of the system operator is to ensure that no blackouts occur during a given time period. Despite these efforts, load shedding events do occasionally occur. In fact, despite advances in technology and operational procedures, in the last decades, the frequency of blackouts does not appear to be decreasing [1].

Recently, several analyses of blackout time series for a range of different systems has shown that frequency distribution of blackouts follow a power law decay [2]. This is important as it suggests that the risk associated with large cascading failures may be comparable to that of smaller minor blackouts. The power law behaviour as well as long term correlations in the time series also suggests that the origin of the power law results from the system operating near criticality. In [3], the Manchester model was investigated and critical points in the power system were observed. In [2], a mechanism by which the power system may evolve towards a critical point was proposed. If these arguments are correct this suggests that the electrical power system belongs to a class of dynamical systems which exhibit Self-Organized Criticality (SOC) [4]. A SOC system is one that evolves dynamically with a critical point as an attractor. The system therefore exhibits properties that are similar to a thermodynamic system at a critical phase transition without the need for fine tuning of the system parameters. A critical point of a system is the region in its phase space where the correlation length tends to infinity, therefore the system exhibits scale invariance, i.e. perturbations to the system can propagate across the system for any lengths and are not necessarily localized. The scale invariance of the system manifests itself in the observation of power law distributions to the size of cascading events within the system. Another behavioural observation of SOC systems is long term time correlations in the time series of cascading events.

As a result of the system being in such a class, blackout mitigation efforts may produce unexpected results. An example of such behaviour is given in [5] where it was found that increasing the reliability of components in the system increased the risk of blackouts of all sizes in the OPA model for the possible SOC behaviour of the electrical transmission system [6]. OPA stands for **O**ak Ridge National Laboratory, **P**ower Engineering Research Centre at the University of Wisconsin and the University of **A**laska which are the institutions that collaborated in devising the model. In light of these findings it may be prudent to investigate the behaviour of other traditional mitigation methods to see what effect they have on the long term dynamics of the system.

In this paper, the effect of different generation dispatch policies in terms of short term risk to system security is investigated. The short term risk being defined as the probability of a blackout at the time of peak load demand for that day. The method in which the generators are dispatched affects the development of blackouts when they occur and as they evolve. This in turn affects the engineering response to the blackout. In the case of cascading line overloads and failure, the dispatch of the generators affects which lines are overloaded and thus deemed to be at risk of failure and to some extent those that fail. The engineering response to the security threat that is observed from these components would be to upgrade them so that such overloads do not occur in the future, increasing the reliability of the system. The result of this is that not only does the immediate generation dispatch affect the immediate risk of blackout in the system; it also affects the future state and therefore the future reliability of the system. In short, the basic premise is that online security procedures influence the long term dynamics of the power system.

In Section III a brief introduction of SOC in power systems is given. Section IV gives a description of the OPA model for the complex behaviour of power systems. Section V gives the results and a discussion for running various dispatch policies within the model and in Section VI conclusions are given.

III. Self-Organized Criticality in the Power System

The electrical power transmission system is an extremely complicated system with even relatively small systems being comprised of millions of components. The system also evolves dynamically as the impedances and ratings of various components are changed due to maintenance, repair and upgrades. The main objective of these changes to the system is the secure and economical supply of electrical power from the source generators to the final consumer. This evolution occurs in the presence of an increasing demand for electrical power over large time scales. It has been proposed that this evolution of the power system drives the system towards a critical state [2]. Near this critical state the time series of blackouts for the system show power law probability distributions and long term time correlations. These characteristics have been observed in numerous electrical power systems [7].

An important feature of the power system being at criticality is the observation of long-term memory in the time series of blackouts. This suggests that a load shedding event affects the system not just in the short term but also in the long term. Blackouts cannot be considered as a one off event and must be looked at as contributing to future blackouts and therefore the future reliability of the system. While it has been hypothesized that long term correlations may be the result of weather effects [8], in [2] it is shown that these effects continue to be observed even after weather related events are excluded from the analysis. This suggests that the correlations are the result of internal dynamics of the power system themselves. These internal dynamics include the operation of the system by the system operator and the extension and updating of system components by the system planner. The power system being defined in a holistic manner.

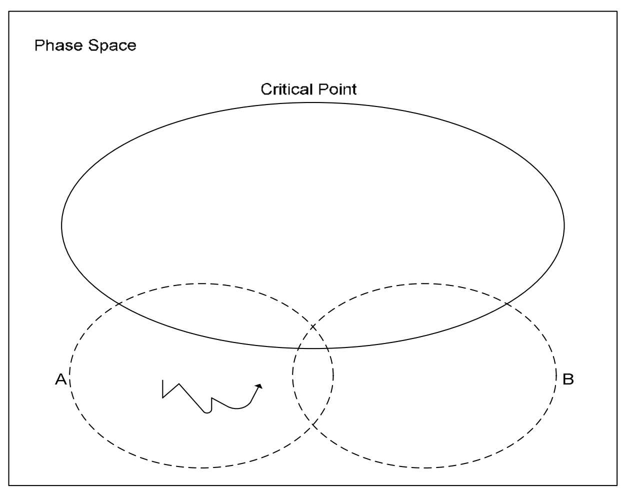

Fig. 1. Representation of a power system phase space.

In Fig. 1 a representation of a power system's phase space is given. The critical point of the system is represented by the solid line ellipse. Within this ellipse the power system behaves chaotically with large cascading failures occurring frequently. Outside of the critical point the system behaves in a more ordered fashion with little to no interruptions in the supply of electricity. The trajectory of the power system is represented by the arrowed curve which is the operating states of the system over the time scale of years. The system self-organizes into operations within a certain definable region. Such a region is represented by the ellipse A in the diagram. The region within which the power system operates is determined by network topology, the reliability of system components and the internal dynamics of the system described above.

Under the theory of SOC for power system operation this region, A, of the phase space that the system operates within is close to the critical point of the system. The probability density function (PDF) of blackout events of the system operating in a region of the phase space near the critical point is then defined by a power law function such as,

$$P(S) = cS^{-\alpha} \qquad (1)$$

where S is the size of the event, c is a constant, α is the critical exponent and $P(S)$ is the probability of the event. The constant c and exponent α are uniquely defined for the region of the phase space that the system is operating within. They are also the primary measures of the reliability of the power system.

Changes in the internal dynamics of the system can change the region within which the system operates and therefore change the reliability of the system. For example, a change in dispatch policy may result in the operation of the system in the region represented by the area enclosed by the ellipse B in Fig. 1. The long term efficacy of the change in increasing reliability can only be determined from analysis of this new region of operation. It cannot be determined by short term analytical procedures.

In this paper an example of a policy that produces short term benefit in risk reduction over another risk taking policy is given and their regions of long term operation are compared.

IV. The OPA Model

The OPA model was developed in order to replicate the long term dynamics of the electrical power system subject to cascading failures and responses to those events [6]. The model is based on the DC load flow approximations of electrical power systems. It does not lend itself to detailed examination of blackouts or in depth modeling of the system components. The intent of the model to replicate the long term dynamics, in terms of years and decades of the system, as it evolves in response to load shedding events and load growth and therefore such detail may not be essential to these dynamics. The DC load flow assumptions and component simplifications are justified under the principle in SOC modeling, expressed in [4], that the model accuracy should be based on the minimum needed to replicate the long term dynamics of the real world system. Long term being defined in terms of years. The high performance of the model in replicating empirically derived reliability statistics is shown in [9]. A more detailed model using AC load flow was developed in [10] however the statistics of the blackout time series were observed to be the similar to the DC model, this suggests that the accuracy of the AC model, in terms of component interactions, is extraneous to the SOC dynamics of the system. Therefore while the use of DC Load Flow analysis may not be adequate for some types of studies of power system [11] it is a valid approximation for use in complex system modeling. Despite the model's simplicity it produces very complex behaviour which replicates that of real world electrical power systems. The model also lends itself to analysis of various blackout mitigation strategies in the complex systems paradigm as has been done in previous work [5, 12-14]. The distinction between this work and that of [14] is to explicitly show the short term risk of the two dispatch polices. It also shows a divergence of the Linear Programming (LP) and the risk aversive dispatch for differing conditions. An initial investigation of the effect of generation site allocation and sensitivity to the factors are also explored.

A. *Modeling of Cascading Failures*

The model replicates cascading events by a loading dependent failure probability of the lines in the system. The lines here are not just modeling the transmission lines that connect buses but all other components in series with those lines such as transformers. The stress, M_i, of a line is given by,

$$M_i = \frac{f_i}{F_i} \qquad (2)$$

where f_i is the flow in the line and F_i is the capacity limits of the line. The capacity limits of the lines are modeled as absolute with no line being allowed above its limit. If a line is at its limit and more power is required to flow through it in order to meet demand then that extra load demand is shed. For each line there is a probability of failure that is a monotonically increasing function of the line stress. In this work, as with most other work on the OPA model, this function is taken to be zero below a threshold value, t_i, and assigned a probability q_1 for lines when,

$$\frac{f_i}{F_i} > t_i \qquad (3)$$

for all lines t_i being equivalent. The threshold value may be defined as the onset of the emergency operating conditions of the transmission line components. Cascading events occur when a tripped line redistributes its flow to other lines, including any changes in the flows due to the redispatch of generators, increasing their flows to that above the threshold. The method by which a line is taken out of the system is described in [14]. The lines now above their thresholds have a probability of failure which may continue the cascading event. The cascade stops after the last line is tripped.

The result of such cascading events is a weakening of the transmission system's ability to transmit power from the generators to the loads. If the system is weakened sufficiently load shedding occurs. The model does not replicate blackouts that occur due to failures or forced outage of generators or equipment failures due to hidden failures as in the model developed in [15]. Similarly the model does not include contingencies association with generation failures however these types of contingencies can easily be incorporated into the model.

B. Modeling of Generation Dispatch

In most studies involving the OPA model the generation is dispatched using a linear programming (LP) algorithm. The objective of the algorithm is to minimize the objective function,

$$\sum p_G + K\sum p_L \qquad (4)$$

where p_G and p_L are power injections into the system from the generator and load nodes respectively with the sum being over all the nodes of that type. In this model the load and generator nodes are considered to be distinct and therefore no bus is both a producer and a consumer of power simultaneously. The load consumed at a node is modeled as a negative injection at that node and therefore always has a negative value. The constant K is an arbitrarily large number that ensures that it is very costly to shed load and therefore load shedding only occurs when necessary. Here this type of dispatch is called the LP dispatch.

The objective function can be extended and the problem changed to one of quadratic programming such that the objective function is given as,

$$\vec{p}^{\,T} O \vec{p} + \sum p_G + K\sum p_L \qquad (5)$$

where $\vec{p}$ is the vector of power injections into the system. This gives more control over how the generation is dispatched in the system. It was used in [16] in order to include optimal power flow when the costs of the generators are given by non-homogenous quadratic cost curves and the matrix O is a diagonal matrix of the cost curve coefficients.

In this work the quadratic programming method is used to dispatch the system in terms of security rather than at minimum economic cost. The matrix O is derived from the DC load flow equations. Two opposing security based dispatches are considered. First we define the global stress of the system, s, as the sum of the squares of the individual line stress,

$$s = \sum M_i^2 \qquad (6)$$

Under this model a system with a higher s value is more likely to have lines above their threshold value and there is an increased likelihood of a line failure. Such a system is therefore less secure than a system with a lower s value.

In the case of immediate risk of cascading blackouts, at the time of dispatch, it would seem to be prudent to attempt to minimize global stress in order to minimize immediate global risk. In this paper, this type of dispatch is considered to be of a conservative risk aversive type. A second possible dispatch in terms of the global system stress, that may be performed, is the case of maximizing global stress in the system. This is considered to be a non-conservative risky dispatch. The non-conservative dispatch has the benefit of maximizing the use of the capital investment into the transmission system.

The values of s are determined as a quadratic expression of the power injections into the nodes of the system. In [13], the equations for the matrix, O, for (4) were derived as,

$$O_{\min} = \frac{1}{2} R A^T F^{-2} A R \qquad (7)$$

for the minimization case and as,

$$O_{\max} = -\frac{1}{2} R A^T F^{-2} A R \qquad (8)$$

for the maximization case. R is the matrix of effective inductances between the nodes of the transmission system and the matrix A is the susceptance weighted incident matrix of the lines on the nodes. The resistances in the lines are considered negligible as per the DC load flow assumptions [17].

When maximizing stress, the problem becomes concave and therefore occasionally no solution may be found in a reasonable amount of time. If this occurs, the LP dispatch as in (4) is used. It was also noted that in cases involving high congestion in the system that the three distinct objectives give approximately the same result. Therefore for large cascades the quadratic program will tend towards producing a solution that matches the LP dispatch.

The constraints to the objective function are the usual system constraints of a power system. They are given as,

$$\sum p_G + \sum p_L = 0 \qquad (9)$$

$$l_j \le p_j \le 0 \qquad \forall j \in L \qquad (10)$$

$$g_j \ge p_j \ge 0 \qquad \forall j \in G \qquad (11)$$

$$|f_i| <= F_i \qquad (12)$$

Equation (9) is the power balance constraint which represents the requirement that the sum of injections into the system is equal to those out of the system; there are no transmission losses due to the use of the DC load flow approximation. Equation (10) stipulates that any load shedding must be positive and that the load served is not greater than the load demanded, where l_j is the load demanded at node j. Equation (11) ensures that generation is positive and that it is not greater than the capacity at that node which is given as g_j. Finally (12) constrains the magnitude of the flow in a line to a value less than the capacity limits. The flows in the lines, f_i, are calculated using the formula,

$$\vec{f} = -\frac{1}{2} A R \vec{p} \qquad (13)$$

The chosen dispatch policy is run in all iterations that are required during the simulation. This includes redispatching after a contingency. The purpose of the dispatch policies investigated here are not to represent real world operations exactly but to show how a potential policy of a dispatcher may cause the opposite outcome than intended when the influence of the behaviour of the dispatcher on the planner is taken into consideration.

C. Fast Dynamics of the Model

The model can be divided into two time scales, the first described here is the fast dynamics. The fast dynamics represent the time scales of one day around the time of peak demand of a power system. This is the time that the system is closer to its critical points and therefore more prone to cascading failures [1]. At the start of each day the peak load, at each node, is determined. This is done by multiplying a base demand by a random number r_j such that,

$$l_j = r_j l_j^{base} \qquad (14)$$

This randomization of the peak load produces, at each node, small changes in the flows in the lines, which may instigate a cascading failure while keeping the total load demand relatively constant. The changes themselves also reflect uncertainties inherent in the daily peak load demand, due to weather changes and other effects, of power systems and also give a variation in the type of cascading events that may occur. The generators are then dispatched as described in Section IV.B.

A second triggering event is also incorporated in the model. In this case lines are given a small probability of failure, q_0, due to some random event such as fire or lightning strikes. Any of these failures may result in a cascading process as described earlier. It is not necessary that a cascading event occurs during an iteration.

After any cascade is completed and a load shedding event occurs the system is upgraded in response to this event. The upgrades occur to lines that were overloaded or forced out during the cascading event. An overloaded line is defined as one that was above its threshold at any time during the cascade. This type of response is considered to be a responsive rather that a preventative approach [5]. The upgrades are implemented by increasing the capacity limit of the line by a constant,

$$F_i^{k+1} = \partial_i F_i^k \qquad (15)$$

where F_i^k is defined as the capacity limit of line i at time k and ∂_i is the line upgrade factor which is greater than 1.

Occasionally the generator capacities are also increased. In response to increased load growth the relative capacity, C, of the system is decreased, it being defined as,

$$C = \frac{\sum g_j - \sum p_L}{\sum p_L} \qquad (16)$$

When the relative capacity is below a certain threshold, C_t, new generation is added to the system. In this paper, three distinct methods for generation allocation are used, however in all cases the amount added to a particular location is the same and is given by,

$$g_j^{k+1} = g_j^k + \left(\frac{h}{n}\right)\sum p_L \qquad (17)$$

where g_j^k is the generation capacity at node j at time k. h is a constant and n is the number of generation sites. New generation is continually added to different sites until the relative capacity is once again above the threshold. While it may seem strange that the build time for new generation may appear to be one day it has been observed, in [6], that including a build time is equivalent to a change in the magnitude of the constant h. Therefore the constant h may be interpreted as the build time.

Unless otherwise stated the method for choosing the generation sites to add the new capacity as stated in [6] was used. This is performed by choosing a generation site at random. If the generation at this site plus the generation to be added is less than the sum of the line capacity constraints attached to the node than the new generation is added. If on the other hand the sum of the line capacities is lower than the total proposed capacity for the site no generation is added and another site is selected randomly. In a recent paper [18] a new economic based approach for the selection of generation sites was proposed, this type of selection was not considered in this work.

As well as their physical interpretation as consumption and generation points the loads and generators may also be interpreted as connection to other balancing areas.

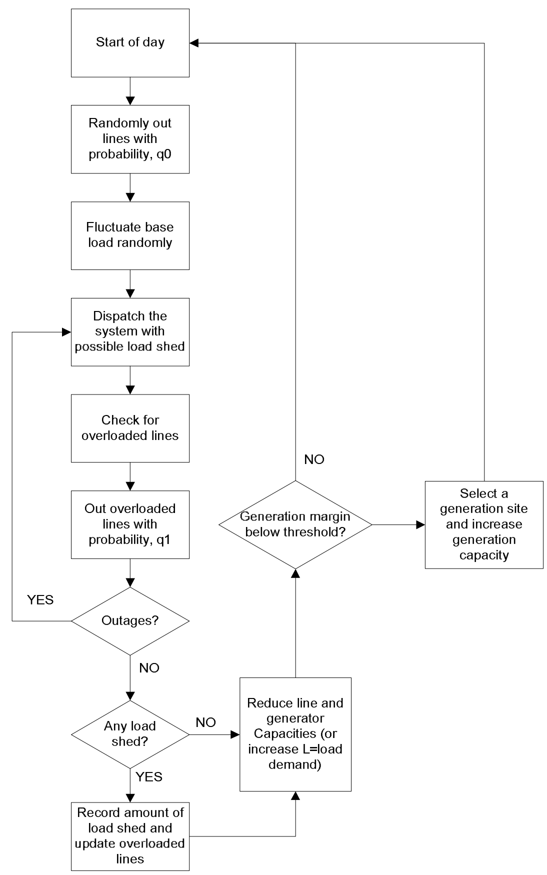

Fig. 2. Flowchart of the OPA model.

D. Slow Dynamics of the Model

The slow dynamics of the model involve the continual exponential increase in load demand. In the OPA model, as described in [6], this is implemented by multiplying the load at each node by a number greater than 1. This is given by,

$$l_j^{k+1} = \mu l_j^k \qquad i \in L \qquad (18)$$

where μ is a load growth factor. The exponential increase in the load demand causes the load to rise to very large numbers in the course of the simulation. In the implementation of the model using Matlab [19] this was found to cause difficulty in finding solutions in a reasonable time with the linear and quadratic programming algorithms when the magnitude of the numbers became excessive. To prevent their use the load increase was instead modeled, for the results shown in this paper, as a decrease in the line and generator capacities. This is given by the equations,

$$g_j^{k+1} = \frac{g_j^k}{\mu} \qquad (19)$$

and

$$F_i^{k+1} = \frac{F_i^k}{\mu} \qquad (20)$$

This implementation does not have much effect on the changes in the stress of the lines and on the relative generation capacity and therefore should not affect the dynamics of the model. This formulation of the OPA model is novel and may be useful in future studies. A flowchart for the model algorithm is given in Fig. 2.

V. Results & discussion

The IEEE 118 bus test system was employed to test the impact of the various dispatching methods. The system comprises of 179 individual lines with various impedances and contained 54 generator nodes [20].

In the case of dispatches which require load to be shed, the load shedding at each node was taken to be that produced by the LP dispatch. This was done to isolate changes in behaviour that result from generation dispatch and so as not to include reductions or increases in the global stress that would occur if the load shedding was optimized.

The values of the variables were set as follows unless otherwise stated. The line failure probabilities were set to 0.001 and 0.1 for q_0 and q_1 respectively. The threshold for the onset of q_1, t, was taken as 0.9. K was given a value of 10^6. r_j is evenly distributed between [1.2, 1/1.2] for all the load nodes and h was taken as 0.04. The line upgrade factor, ∂_i, for the results shown was set at 1.007 which for the maximizing stress dispatch gives an average period of 13 days between blackouts which is close to observed timings [2]. The load growth factor, μ, was set at 1.00005, this increase gives a yearly load demand increase of approximately 1.8% which mirrors the load growth in the North American power system [9]. The threshold for the addition of new generation, C_t, was taken as 1.3.

A. Short Term Blackout Risk Assessment

The comparative short term risk in terms of dispatch can be determined from running the OPA model with a non-evolving transmission grid and a fixed load. The capacity limits of the transmission system are fixed for the day in question and the simulation is run multiple times to determine the probability of blackouts of various sizes. This open loop form can therefore inform the dispatcher on which dispatch policy is the most prudent for use in that day.

The probabilities of blackout events for one day at peak load are shown in Fig. 3. It is clear that the dispatch which maximizes the system stress gives a much larger risk of cascading failures occurring in the system and that the preferred policy for that day would be to dispatch the system in terms of minimizing the global stress. However this analysis does not consider the effect of the policy on the behaviour of the system planner and the effect on the long term reliability of the power system.

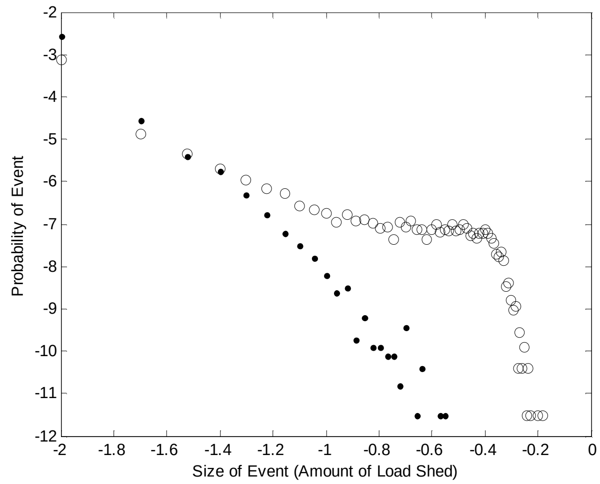

Fig. 3. Probability distribution of load shedding events. Circles are for the maximization case and the dots are for the minimizing case.

B. Blackout Statistics

To determine the long term reliability of the system for the differing policies the planner response is incorporated into the full OPA model. The system evolves initially through some transient phase towards the critical points of the system. Near the critical points the system reaches a dynamical equilibrium where the statistics, such as the frequency distributions of events, remain constant. The dynamical equilibrium is defined as the selection of a region within the phase space within which the continued evolution is confined as discussed in Section III. It is from this point onwards that the statistics of the system are examined. The dynamical steady state is observed when the average line stress over the system is seen to oscillate around a steady mean value as shown in Fig. 4.

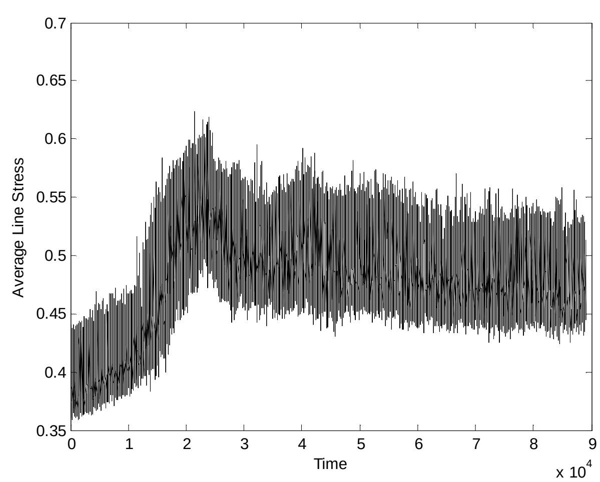

Fig. 4. Average line stress over the system as a function of time.

The expectation would be that the maximizing dispatch would increase the frequency of line outage events and thus make the power system more prone to load shedding events. The absolute frequency distributions of the maximizing case and the minimizing case are given in Fig. 5. They are plotted on a $\log_{10}$-$\log_{10}$ scale. As expected the frequency of line outage events increase for events with approximately 1 to 10 forced line outages. For larger line outage events the two methods are approximately the same. This increase may be considered a reduction in the reliability of the system due to component failure.

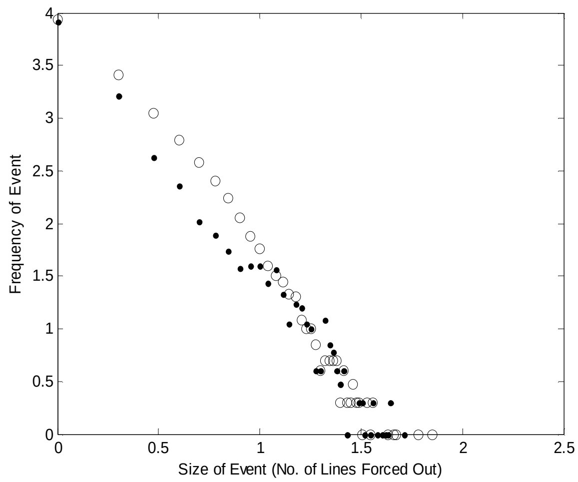

Fig. 5. Frequency distribution of line outage events. Circles are for the maximization case and the dots are for the minimizing case.

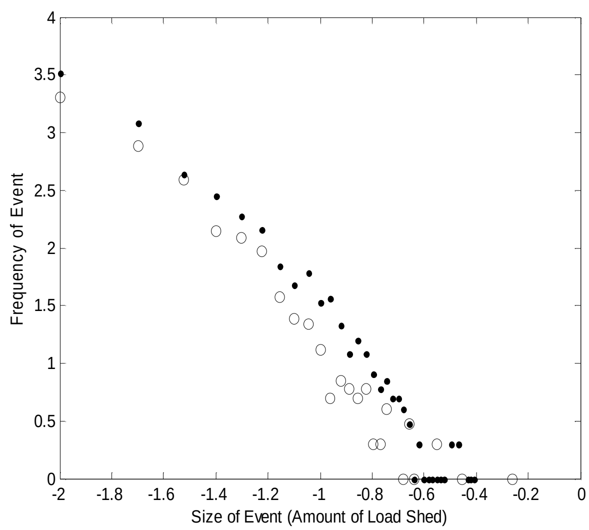

Fig. 6. Frequency distribution of load shedding events. The load shed is given as a percentage of load demand. Circles are for the maximization case and the dots are for the minimizing case.

However the reliability of a power transmission system cannot just be examined from the reliability of components. It also incorporates how robust the system is to failures. To understand how the system evolves to handle failures it is important to look at the absolute frequency of load shedding events. This is given in Fig. 6 as a $\log_{10}$-$\log_{10}$ plot. In this case the frequency of load shedding events is reduced in the maximization case. This shows that despite the increase in line failures there is an increase in the robustness of the system to those failures. As a consequence of the reduction in the frequency of all events the average number of days between blackouts increases dramatically in the maximization case to 13.37 days from 8.25 days in the minimization case.

In terms of the primary operating goal of a reduction of blackout risk, the strategy of maximizing immediate blackout risk causes the system to evolve into a more reliable and preferred state. This may seem counterintuitive as it states that continuous risky behaviour on the part of the dispatcher actually decreases the overall risk to the system. To understand how this can come about the changes to the upgrading response that occurs between the two dispatch methods must be considered.

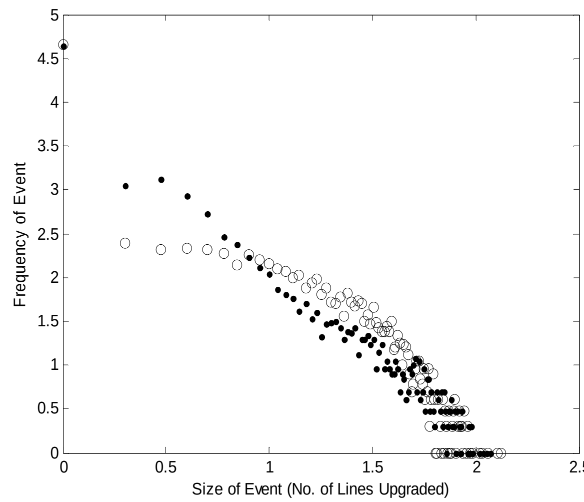

Fig. 7. Frequency distribution of upgrading events. Circles are for the maximization case and the dots are for the minimizing case.

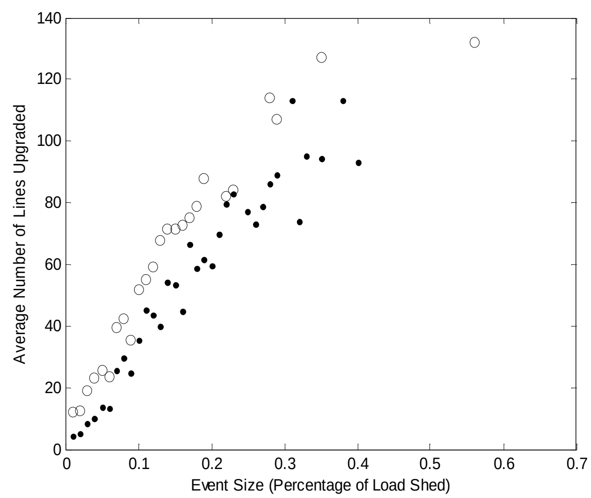

Fig. 8. Average number of line upgrades for blackouts of different sizes. Circles are for the maximization case and the dots are for the minimizing case.

In Fig. 7 the absolute frequency distribution of blackouts is given in terms of the number of upgrades that occur after a blackout. The number of upgrades represents the sum total of the lines that were forced out or the lines that were overloaded during a cascading load shedding event. These lines are the ones that may be considered to have taken part in the blackout from the planner's viewpoint. Again it can be observed from these distributions that the system is more reliable in terms of a small number of overloading events as there is a reduction in the number of blackouts involving cascades of approximately

9 or less components. However there is an increase in the number of events, in the maximization case, for events consisting of more than 9 lines. This increase in the number of components estimated to be involved in the blackout results in a greater increase in the number of capacity limits of lines that are upgraded. In the minimization case the average number of upgrades per blackout is 8.32 lines while in the maximization case this number is almost doubled to 16.48 lines. This results in greater robustness of the system to failure and therefore negates the influence of increased risk in the failure of a component for the immediately risky generator dispatch. The increase in the average number of line upgrades per blackout can be clearly seen in Fig. 8. Here blackouts have been binned by size and the average number of upgrades per bin is taken. As is seen in Fig. 8 the average number of line upgrades of any size of blackout is greater in the maximization case. These increases also show that the maximizing dispatch policy has an increase in cost of upgrades over that of the minimizing dispatch. Therefore, the increase in robustness seen in the maximizing case comes at a greater cost of investment into the system.

The above results were tested for sensitivity to the upgrade factor, ∂_i . It was found that there were no qualitative changes in the relative behaviour of the model under the different dispatch methods. These are given in Fig. 9.

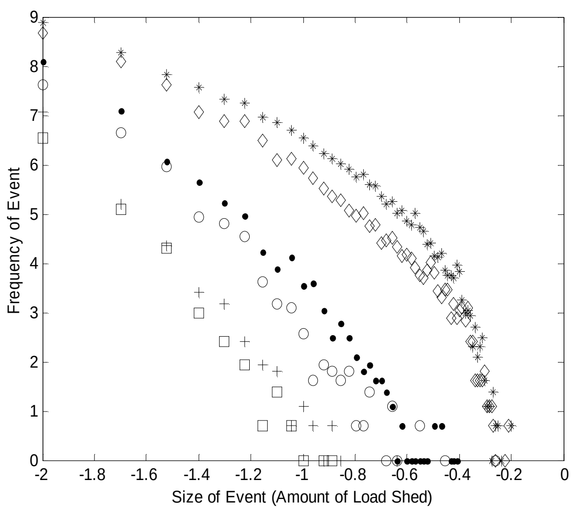

Fig. 9. Frequency distribution of load shedding events. The squares and plus signs are maximization and minimization case for upgrade factor of 1.05 respectively. The circles and dots are maximization and minimization case for upgrade factor of 1.007 respectively. The diamonds and asterisks are maximization and minimization case for upgrade factor of 1.0005 respectively.

C. Line Stress

While the generation dispatch in one case tries to maximizes the global stress of the system this attempt is opposed by the upgrade process. In Section VI.B. it was shown that the maximizing dispatch causes an increase in reliability of the system in terms of frequency of load shedding events and in terms of robustness to line failures. This result can be further understood by examining the steady state average line stress distributions over time. When the model enters its dynamical steady state the distribution of average line stresses become robust [21]. Therefore they can provide valuable information about the system. In [21] it was proposed that these distributions were the result of network topology and generation and load locations. These distributions can also be affected by the generation dispatch method.

The differences between the distributions of line stress can be clearly seen in Fig. 10. For line stress levels, M_i, of 0.4 and above the minimization case has a higher number of lines which are over that level than the maximization case. These heavier loaded lines are more likely to suffer an outage if a line is tripped and therefore the minimization case tends the system to a state that is more susceptible to cascading failure. This property of being more prone to cascading failure is also observed in the average stress over time. The average value of the global system stress, s, in the maximizing case is 47.41 compared to the minimizing case with a value of 54.45. In effect, the maximizing dispatch gives the paradoxical result of reducing the global stress of the system when the long term evolution and responsive upgrades of the system are taken into consideration.

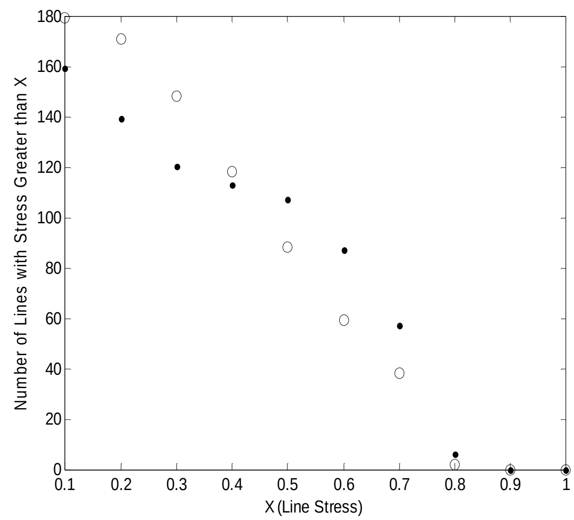

Fig. 10. Number of lines with stress greater than X. Circles are the maximization case and the dots are the minimizing case.

D. Comparison with LP Dispatch

Observations of the LP dispatch in comparison to the above dispatches showed no significant statistical difference between such a dispatch and the minimizing case. However the simulations were repeated for a failure probability, q_1, of 0.2 and some divergence in behaviour between the LP and minimizing dispatch was observed.

The frequency distributions for the two cases are given in Fig. 11. In it we observe that the LP dispatch gives a reduction in the frequency blackouts of most blackout sizes. This reduction shows that overall the LP dispatch is more reliable than the minimizing dispatch. However the maximizing dispatch is still an improvement on both methods in comparison to the LP dispatch, as seen in Fig. 12. Overall the average number of days between blackouts for the maximizing, LP, and minimizing dispatches were 13.89, 11.25 and 8.74 respectively and the total amount of the fractional load sheds during the period of observation were 123.47, 169.25 and 201.08 respectively.

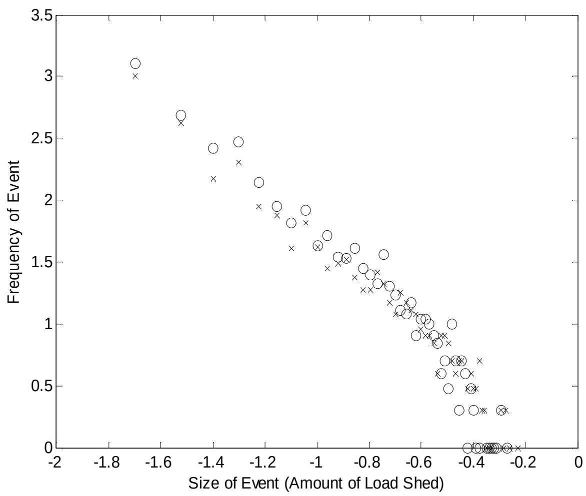

Fig. 11. Frequency distribution of load shedding events for q_1=0.2. The load shed is given as a percentage of load demand. Crosses are the linear programming case and the circles are the minimizing case.

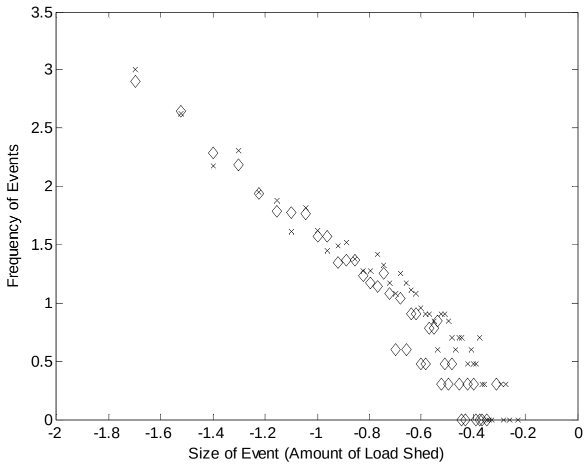

Fig. 12. Frequency distribution of load shedding events for q_1=0.2. The load shed is given as a percentage of load demand. Crosses are the linear programming case and the diamonds are the maximizing case.

It is worth noting that for the three dispatching methods the critical exponent, α, in the power law region of the frequency distribution as measured by load shedding remains approximately the same. This observation shows that the differences in dispatching policy do not affect the comparative risk of small blackouts to large blackouts as has been observed in the use of other mitigation policies in this model. The exponent changes occur for differences in the q_1 values so that the distribution is rotated. Smaller blackouts become less likely for smaller values of q_1 while there is a concurrent increase in large blackouts as observed in [12]. However no measurable difference in the exponent exists for the different dispatches when q_1 is held constant. In the case of q_1=0.1 the exponent was measured as approximately 2.0 and for q_1=0.2 the exponent was measured as approximately 1.8.

E. Effect of Methods of Site Choice

In the above results the method for choosing sites for generation allocation was performed as described in Section III.C. However this type of allocation does not take into consideration the effect on the stress of the system that the new generation will produce. To attempt to optimize the generation profile in the system in terms of stress, a profile was generated by finding the dispatch that minimized or maximized the stress when each site had a generation capacity equal to the total load demanded. This would give an optimal solution in terms of the current line capacities. This optimal generation profile was then compared to the current profile and generation was added to the site where the difference between the current profile and the proposed profile was minimized. It was found for both the maximization and minimization cases that this had no significant effect on the frequency distribution of the load shedding events. This suggests that the method of site choice for new generation may have little or no effect on the qualitative nature of the results described above.

F. Further Discussion

The model can be divided into two distinct processes controlled by two distinct actors; the planning process and the dispatch process. In [13] it was proposed that the upgrade process be considered as a feedback mechanism that increases the reliability of the power system. The planner is proposed to determine the capacity of the network from information about the last blackout of the system. The capacity of the network being defined as the ability of the system to transmit power from the generators to the load in normal and in contingency operating conditions. If a small blackout or no blackout occurs in the system then it is deemed reliable by the planner and little to no improvements in the line capacities are implemented. Conversely, large cascading failures are the result of a highly stressed system and one that is considered to have little spare capacity. In [13] it is also suggested that the feedback control operation of the power system supports the use of a simplified incorporation of the increase in reliability in the OPA model.

In this work the notion of the upgrading process as a feedback mechanism is kept and the effect of different redispatch policies on this mechanism have been explored. The feedback mechanism acts not only in response to the capacity of system but to the stress observed on transmission components in the system. While capacity is an important feature of the system and does play a major part in the security, grid utilization fills an important role as well. If we consider a power system with some arbitrary load demand, in most cases, the choice of generation to meet this demand has a number of possible solutions that lead to differences in the load flows in the lines that are needed to serve the load. Dispatching the generation in one manner may lead to higher stress on the components of the system while dispatching in another manner may lead to a lower stress globally on the components. While in both cases the capacity of the power system is the same, the stress of the components and thus the input into the feedback process is different. The planner does not receive any direct input from the dispatcher, i.e. it does not know if a risk taking dispatch was implemented and therefore that some upgrades are not necessary if viewed from the position of a low stressing risk aversive dispatch.

The relative simplicity of the OPA model may cause difficulty in a translation to more secure procedural operations in real world power systems. However, they do suggest that caution should be taken in the implementation of any procedural changes suggested as a result of a blackout. Blackout mitigation assessment should not just consist of determining how the previous event could have been prevented but also how the new measures will affect the evolution of the system in the future. As an example, in the case of the maximization policy, if the planner responded to information about the risk associated with the method of dispatch, they would on review of a cascading blackout correctly attribute most of the failure to that of a risky dispatch policy. The planner then may suggest that as an extra security measure that the minimizing policy be initiated. This would have reduced the risk associated with the last blackout and the risk of some further blackouts in the short term. However the system will then evolve dynamically in response to this new measure, after some transient, to a new attractor which is associated with the minimizing dispatch. This dynamical point, as seen above is, less robust to cascading failure than the previous point.

The inclusion of constraints on the number of updates allowed after a given event may be included in the model. If such an economic criterion was imposed, the system would organize itself into a different dynamical equilibrium with differing frequency distributions of blackouts. The new distributions could then be compared to the ideal cases which are represented in this work to determine if they are in fact economically viable or beneficial. Such type of analysis is beyond the scope of this paper.

VI. Conclusion

It has been shown that the process involved in attempting to minimize short term risk of blackouts in the OPA model and possibly power systems themselves is counteractive to the process that increases the system's robustness to failure. In minimizing risk of component failure the system does not produce as many signals to the planner about potential threats to security of supply. These result in underinvestment into the transmission system compared to an approach that maximizes the risk of component failure. This continual underinvestment in the system leads to an increase in blackouts in the long term.

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VIII. Biographies

Ronan Fitzmaurice (S'09) received B.E. degree from University College Dublin in 2005. He is currently conducting research in complexity theory as applied to power systems at the Electricity Research Centre in University College Dublin. He is a student member of the IEEE.

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