Validating OPA with WECC data

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Abstract

We validate the OPA cascading blackout simulation on a 1553 bus WECC network model by establishing OPA parameters from WECC data and comparing the blackout statistics obtained with OPA to historical WECC data.

1. Introduction

Over the last fifteen years, a range of models for simulating cascading failure blackouts have emerged [1], [2], and now it would advance the general state of the art to validate these models. This paper uses data for the Western Electricity Coordinating Council (WECC) electrical transmission system to validate the OPA model on a 1553 bus grid model of the WECC. The 1553 bus grid model was developed in a California Energy Commission project [3] for analysis of extreme blackout events and is shown in Fig. 1.

The OPA model [4], [5] is a simulation that calculates the patterns of cascading blackouts of a power transmission system under the slow, complex dynamics of an increasing power demand and the engineering responses to failure. The individual cascades are modeled by probabilistic line overloads and outages in a DC load flow model with LP generation redispatch. (O–P–A stands for Oak ridge–Pserc at wisconsin–Alaska, indicating the institutions of the authors when OPA was first conceived.) Section 3 gives a more detailed summary of OPA and its main parameters.

Validation of cascading failure models is necessary to find out which aspects of real blackouts are reproduced by the various models, and is crucial in determining what sort of conclusions can reasonably be drawn from model results, and what are the model limitations. In the case of cascading failure models, validation is particularly important, because it is currently infeasible, and perhaps inherently infeasible, to model and simulate all the mechanisms of cascading failure in great detail.

We pursue the validation of OPA in the following steps:

1) Review available data to extract some global parameters for WECC that can determine OPA input parameters (Section 2).
2) Examine available historical blackout and outage data of the WECC [6], [7]. This is the key statistical data to compare with the OPA results (Section 4).
3) Present the OPA results with parameters from WECC on the WECC 1553 bus network and compare them with the historical data (Section 5).
4) Discuss the strengths and limitations of OPA in the validation and indicate future work (Section 6).

2. Global WECC parameters

One of the first pieces of data used in trying to determine the parameters for modeling the Western interconnect is simply the average rate of increase of the electricity demand in recent years. For California the peak demand from 1980 to 2005 increases at a constant rate of 1.93% a year. Fig. 2 shows this constant rate of increase in data from the California Energy Commission [8].

Also, the U.S. Energy Information Administration has on its website [9] data for the net internal energy demand for the last ten years. A plot of these data in Fig. 3 shows that net internal demand has increased at a rate of 2.37% per year. The conclusion from these data is that an annual rate of growth of 2% is a reasonable value to model the rate of electrical usage growth in WECC.

Other information available from the Energy Information Administration [7] is the capacity margin for the last 10 years in WECC. Fig. 4 shows a plot of the capacity margin. The summer capacity margin oscillates around 20% with some large deviations. This value, 20%, is also the one estimated by NERC [10] for the year 2011. Therefore, in what follows, 20% is a reference value for the summer capacity margin in the modeling of WECC.

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DOI 10.1109/HICSS.2013.594

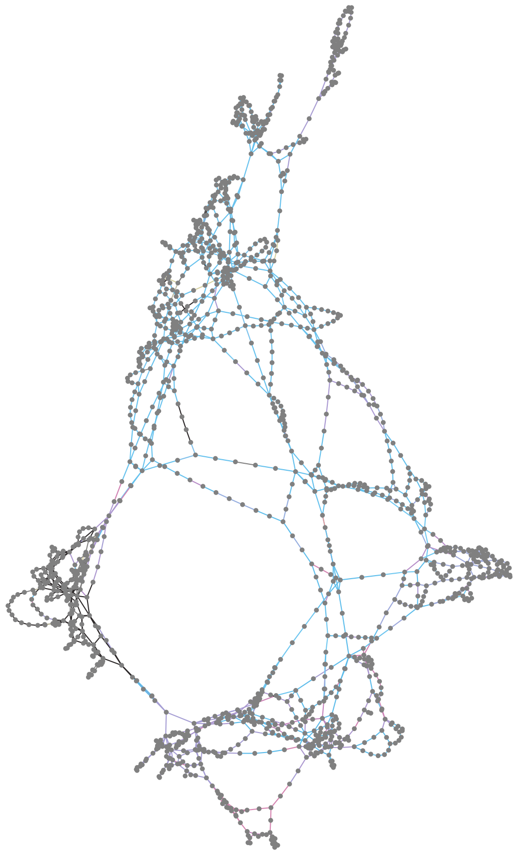

Fig. 1. I553 bus model of WECC grid (bus placement not geographic).

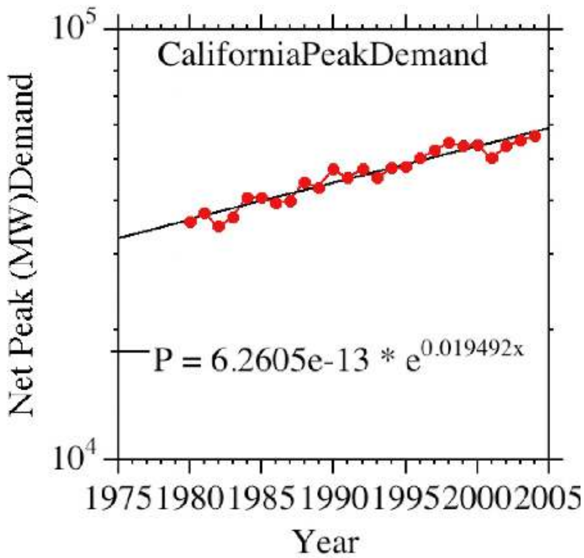

Fig. 2. California peak electricity demand from 1980 to 2005.

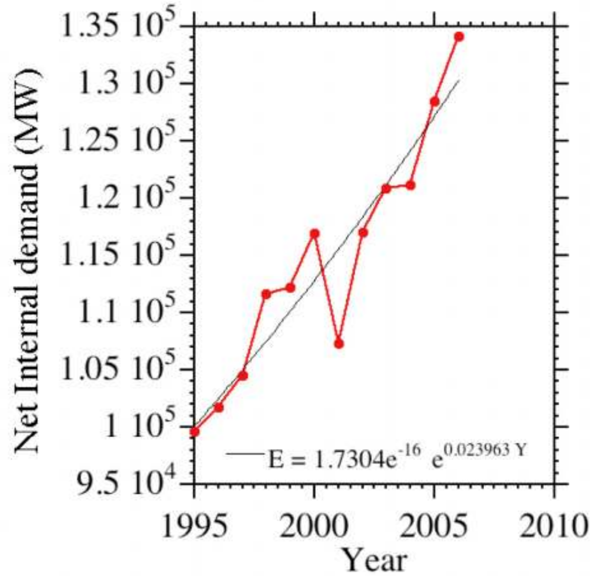

Fig. 3. Net internal energy demand for the last ten years.

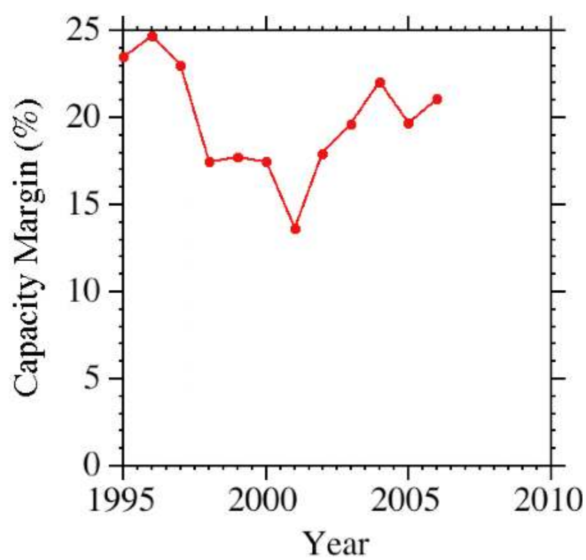

Fig. 4. California capacity margin from 1980 to 2006.

It is important to know the day-to-day variation of the demand. By looking at the hourly variation of the demand, it is possible to select the peak daily demand and to construct a time series of the daily peak demand. There is an yearly modulation of the demand that can be eliminated and from the remaining data it is possible to get a measure of the random daily variation. From data from different parts of the USA, a value between 10% and 15% seems a reasonable estimate with California in general being near 15%.

The next piece of information is the frequency of blackouts in WECC. The NERC data on (reportable) blackouts from 1984 to 2006 gives this information. The triggers of the blackouts can be classified in three groups: 1) Equipment failure, 2) Limits in generation and 3) Weather. Table I gives the annual frequencies for these three types of blackouts.

TABLE 1. Annual frequency of blackouts in the western interconnect from 1984 to 2006

Equipment failure	0.0075
Limit in generation	0.0029
Weather	0.0252
Total	0.0368

Using the rate of real increase of the demand, the real critical margin, and real daily load fluctuation level, the other OPA parameters can then be adjusted so that the OPA model gives the correct blackout frequency.

3. OPA model summary & key parameters

The OPA model [4], [5], [11] has two timescales: a fast timescale of cascading blackouts and a slow evolution of the grid. In the fast timescale, OPA represents transmission lines, loads and generators with the usual dc load flow approximation. Starting from a solved base case, blackouts are initiated by independent random line outages with probability p_0. Whenever a line is outaged, the generation and load are redispatched using standard linear programming methods. The cost function is weighted to ensure that load shedding is avoided where possible. If any lines were overloaded during the optimization, then these lines are outaged with a fixed probability p_1. The process of redispatch and testing for outages is iterated until there are no more outages. The total load shed is, then, the power lost in the blackout. The modeling of the cascade neglects many of the cascading processes in blackouts and the timing of events, but it does represent in a simplified way a dynamical process of cascading overloads and outages that is consistent with some basic network and operational constraints. It is necessary to provide some variation or noise in the input conditions to represent the varying conditions of the power grid so that a realistic variety of cascades can occur. This is done by making the pattern of loads vary up and down randomly about the average load, and the magnitude of this load variation is controlled by the parameter γ.

In the slow timescale, OPA models the complex dynamics of the transmission grid evolving in response to a slowly increasing power demand and the increases in system capacity caused by the engineering responses to blackouts. The slow dynamics is carried out by the following small changes applied each time a potential cascading failure is simulated: All loads are multiplied by a fixed parameter λ that represents the rate of increase in electricity demand. If a blackout occurs, then the lines involved in the blackout have their line flow limits increased slightly by multiplying by a parameter μ. That is, the parts of the system involved in the last blackout are upgraded. The grid topology remains fixed in the upgrade of the lines to ensure a realistic grid topology of the upgraded system in a simple way, and avoid the formidable complexities of realistic automation of the addition of new lines in transmission system expansion. To maintain coordination between generation capacity and transmission capacity, the generation maximum power increases automatically when the capacity margin is below a given critical level $\Delta P/P$. The slow timescale evolving power grid modeled in OPA enable the study of the grid as a complex system. This distinctive feature of OPA is discussed in much more detail in [4], [5], [11].

We now summarize the main parameters of OPA. This discussion refers to the basic OPA model, without n-1 constraints [11] or other possible modifications of the system modeling or operation [12]. A main input to OPA is a model network, in this case, the 1553 bus WECC network model [3]. In addition, Table 2 gives the four basic parameters that control the slow time evolution of the system in OPA.

TABLE 2. Input parameters for OPA slow time evolution

λ	Daily rate of increase of load demand
μ	Rate of upgrade of overloaded lines after blackout
$\Delta P/P$	Capacity margin
γ	Controls the daily variation of the loads

The WECC data presented in section 2 have already determined the rate of increase of the demand λ, the generation margin $\Delta P/P$, and the daily variance of the loads γ. The rate of upgrade μ is then determined in

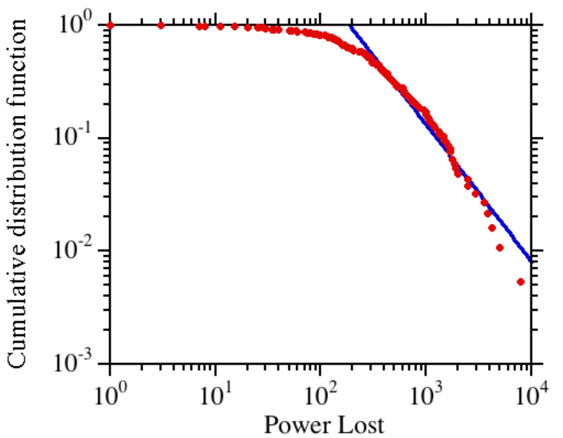

Fig. 5. Western interconnect cumulative distribution of observed blackout size in MW from NERC data.

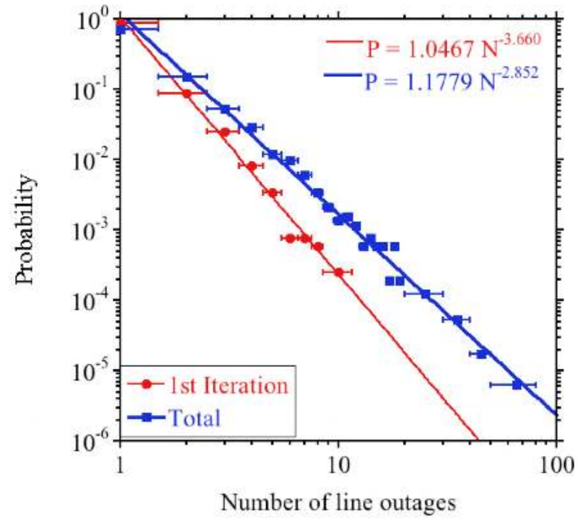

Fig. 6. Probability distribution of outages in the first generation, and the probability distribution of the total outages after cascading.

order to give a reasonable mean value for the frequency of the blackouts. There are two other parameters p_0 and p_1 shown in Table 3 that also affect the frequency and the detailed properties of the blackout dynamics. We must determine p_0 and p_1 in order to match the historical data for the Western interconnect.

TABLE 3. Key parameters of OPA cascading dynamics

p_0	probability of random initial line outage
p_1	probability of an overloaded line outaging

4. Historical data for WECC outages

There are a number of different types of data available (or potentially available) on blackouts and outages of the WECC transmission grid. They are all important for validation of all types of modeling of the blackout dynamics. The main source of data on blackouts in the North American grid is the North American Electrical Reliability Council (NERC). This data, which is inherently filtered by reportability criteria, is available on the web [6]. Analysis of this data [13], [14], [3] shows the existence of power law regions in the probability distribution function and in the rank function of the blackout size. There are a number of different ways of characterizing the blackout size, but here, the amount of load shed associated with the blackout is the main measure used. Fig. 5 shows a plot of the cumulative distribution function of the observed blackout size for the western interconnect together with a fit to the power law region of the distribution.

Another valuable source of information on failures is the TADS transmission line outage data for 8864 outages recorded by a WECC utility over a period of ten years [7]. The value of this TADS data for validation is noted and the authors are very grateful that this data has been made available. Because this is the only data currently available to us, we have to assume that this data for one WECC utility is representative of data across the entire WECC. The data for the WECC utility has been processed [15] to extract information on cascading events. For this analysis it is necessary to group the line outages first into different cascades, and then into different generations or stages within each cascade. One result of the grouping of the outages into cascades and generations is that there are 5227 cascades and the longest cascade has 110 generations. From this analysis, come a series of important characteristics that can be used to compare with the OPA model results. Some of these characteristics extracted from the analysis of the cascades are: the probability distribution of outages in the first generation, the probability distribution of the total number of outages after cascading, and the probability distribution of the number of generations in the cascades. These results are plotted in Figs. 6 and 7.

A third type of data used to validate the models is the λ parameter estimated from the TADS data that determines the propagation of the cascades. (This propagation parameter should be distinguished from the same symbol λ used to denote the load increase rate in the OPA input.) The way this analysis is carried out is

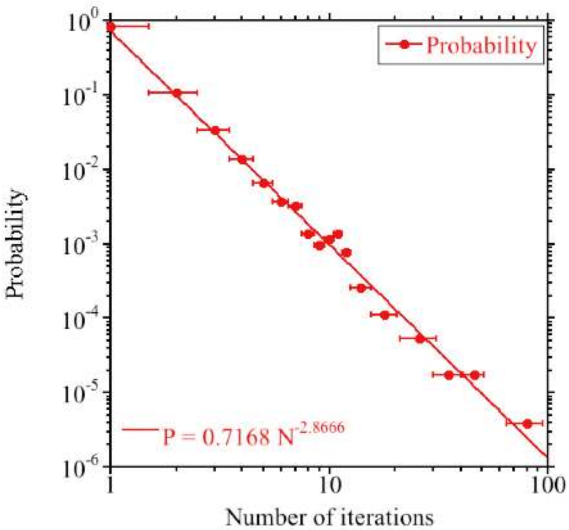

Fig. 7. Probability distribution of the number of iterations in the cascades.

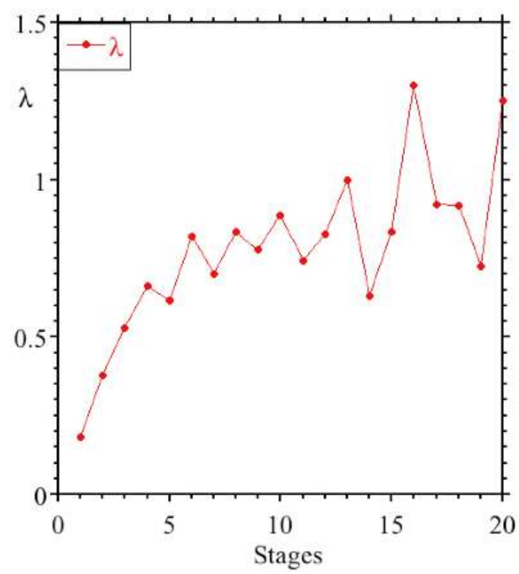

Fig. 8. The cascade propagation amount λ as a function of generation number in a WECC utility.

to divide the cascades into generations and count all the outages in the cascade that are "children" and divide this by all the outages that are their "parents" [15]. This gives the propagation λ averaged over the number of generations. Fig. 8 shows a plot of the result of this analysis; that is, the propagation λ as a function of the generation number.

These characteristics shown in Figs. 5-8 provide results characteristic of the Western interconnect that can be be compared to OPA results for validation. If successful, the OPA model should be able to describe these data.

5. OPA results on WECC 1553 bus model

Having essentially determined the parameters of Table 2 directly from the data, the next step is an exploration of parameters p_0 and p_1 to get the best description of the data plotted in Figs. 6-8. The full list of parameter values is given in Table 4.

TABLE 4. OPA parameters for WECC 1553 bus model

μ	1.07	Upgrade rate
p_0	0.0001	Probability of a random line failure
p_1	0.10–0.05	Probability that an overloaded line outages
γ	1.15	Controls variance of loads
$\Delta P/P$	0.2	Critical generation margin
λ	1.00005	Daily multiplier increasing load demand

Let us examine the different results from this choice of parameters. First is the frequency of blackouts. In OPA and for previous statistical studies, a blackout was defined to be an load shedding event which has size $S =$ Load shed/Power demand greater than 0.00001. However, this definition of blackout size is not the same as the definition of a reportable blackout from the NERC point of view, and here we need a blackout size definition consistent with that used in the NERC data. The NERC data arise from government incident reporting requirements. The thresholds for the report of an incident include uncontrolled loss of 300 MW or more of system load for more than 15 min from a single incident, load shedding of 100 MW or more implemented under emergency operational policy, loss of electric service to more than 50000 customers for 1 h or more, and other criteria detailed in U.S. Department of Energy form EIA-417. The definition for a real system is complex, but in the present calculations, an effective criterion is the loss of 300 MW or more. Therefore, a blackout is an event with $S > 0.003$. With this choice of criterion and for the parameters of Table 4, the frequency of the blackouts is between 0.03 and 0.04, depending on the value of p_1. This is consistent with the value of the blackout frequency for the western interconnect given in Table 1. Fig. 9 shows a comparison of the cumulative distributions of blackouts obtained in the OPA results with the NERC data. The agreement between the data and the OPA results shown in Fig. 9 is reasonably good.

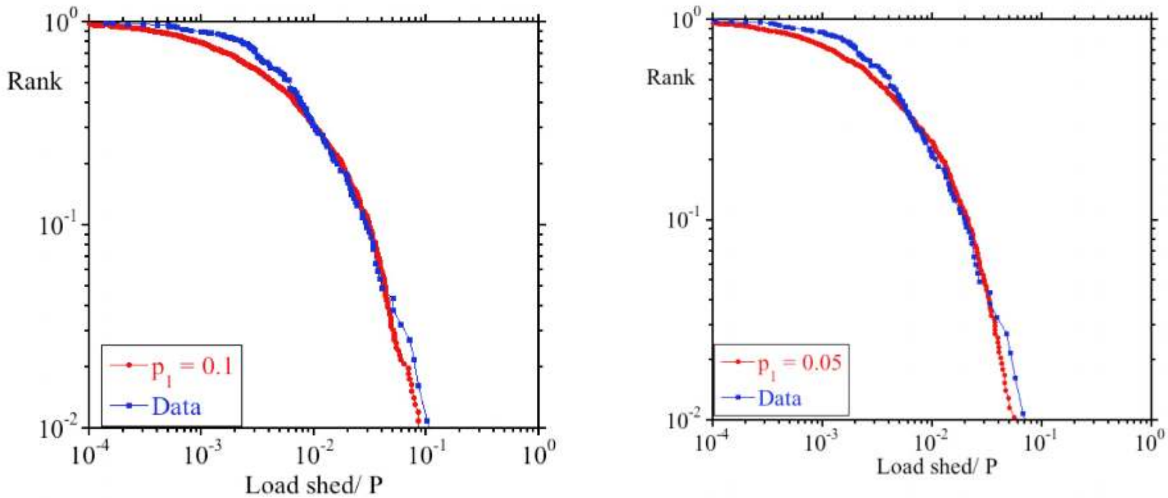

Fig. 9. Rank function for the normalized load shed from OPA for the WECC 1553 bus network and parameters of Table 4 compared with the data for the western interconnect.

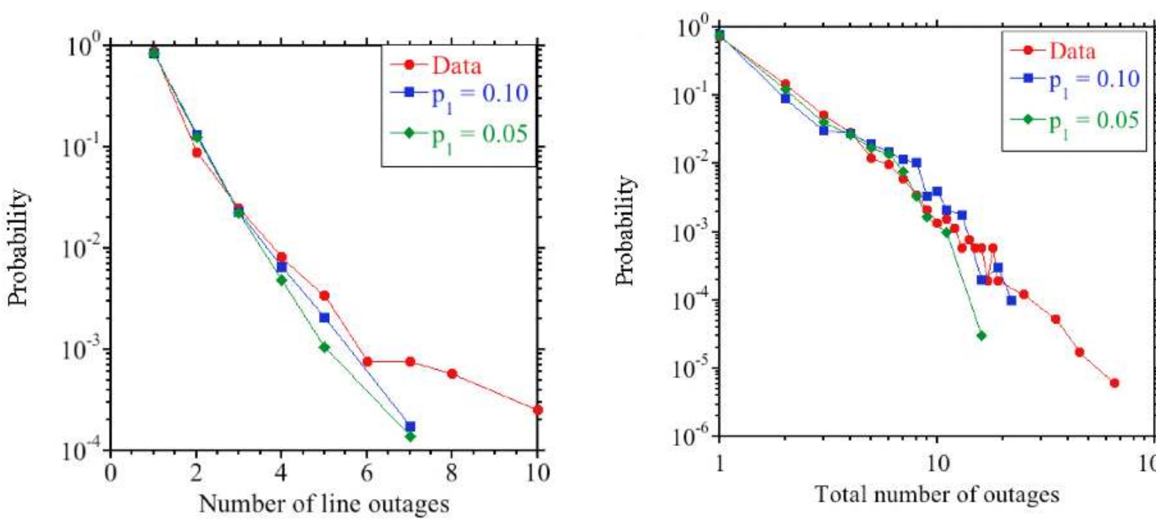

Fig. 10. The distribution of outages in the first generation and total outages from OPA for the WECC 1553 bus network and parameters of Table 4 compared with the data.

The next step is the comparison of the distribution of outages in the first iteration and total outages. Fig. 10 shows this comparison. Again the agreement is very good and the OPA model seems to give a remarkable description of these data. It is important to notice the difference of the initial distribution and the total one. This difference was clear in the data shown in Fig. 6, and it is an indication of the nonlinear hybrid system dynamics involved in cascading. Finally, Fig. 11 shows a comparison of the distribution in the number of generations of the cascade and the propagation parameter λ with data.

The comparisons in Fig. 11 are the least satisfactory of all the ones presented in this paper. The likely reason is that the system grid model of 1553 buses is still too small and cascades die out too soon. Therefore there is a need to look at larger network models in order to get a more satisfactory comparison for these quantities. This is being done by testing how the results scale with network size, particularly with a 2510 bus WECC model [3].

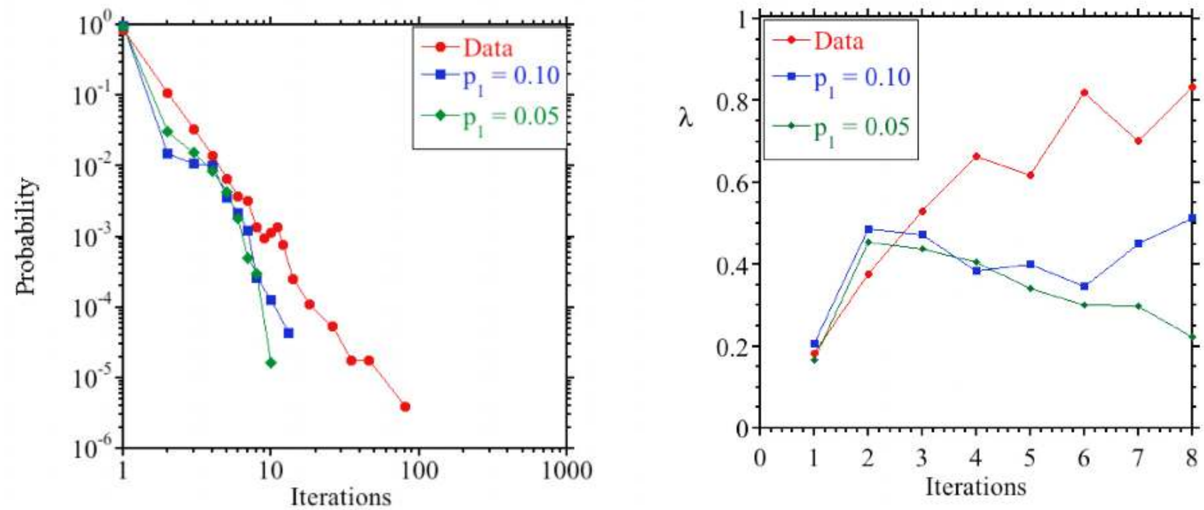

Fig. 11. The distribution in the number of iterations of the cascade and the parameter λ from OPA for the WECC 1553 bus network and parameters of Table 4 compared with the data.

6. Discussion of OPA validation

Using WECC parameters and the WECC 1553 bus network, a very reasonable agreement is obtained between the statistical data on blackouts from the Western interconnect and the OPA results. This serves to substantially validate the OPA model for estimating the statistical distributions of blackout size in terms of lines outaged and load shed on this 1553 bus network.

A set of parameters has been found giving sufficient agreement with WECC data to allow the use of the 1553 bus network case as a reference case to study the long-term WECC blackout statistics. Using this model and these parameters, it is now possible to determine and explore critical clusters of lines that are more vulnerable lines during cascading events [16] and metrics associated with large blackout risk [17].

Not so well predicted is the cascade propagation for later generations of the cascade. We strongly suspect that this discrepancy can be resolved by using larger network models of WECC, and we are continuing to investigate how the match of OPA with the WECC data scales with the size of the system model.

OPA simply represents only one cascading failure mechanism, namely cascading line overloads and outages, using standard and basic power system modeling assumptions such as DC load flow and LP generator redispatch. However, OPA is distinguished from other cascading simulations by also representing the complex feedback by which the power system slowly evolves and self-organizes over time, responding with system upgrades to both load growth and the blackouts. It is well known in the context of control theory that feedback loops strongly determine system performance and that feedback makes the system performance relatively insensitive to the modeling of the plant being controlled. The analogy between complex systems and control systems makes it plausible to suggest that the modeling of the complex system feedback loop that regulates the long-term system reliability may well be crucial for the promising results in validating OPA on the WECC, and that modeling the complex systems feedback in OPA makes the results less sensitive to modeling of the cascading outage mechanisms.

Acknowledgments

We gratefully acknowledge funding in part by California Energy Commission, Public Interest Energy Research Program, Power Systems Engineering Research Center (PSERC), DOE grant DE-SC0002283, and DOE project “The Future Grid to Enable Sustainable Energy Systems,” an initiative of PSERC. This paper does not necessarily represent the views of the Energy Commission, its employees or the State of California. It has not been approved or disapproved by the Energy Commission nor has the Energy Commission passed upon the accuracy or adequacy of the information. We gratefully thank Ms. Irena Green of the California Independent System Operator (CAISO) for expertly producing the 1553 bus WECC grid model. We gratefully thank Bonneville Power Administration for making publicly available the outage data used to benchmark the outage propagation in Figs. 8 and 10. The analysis and any

conclusions are strictly those of the authors and not of Bonneville Power Administration.

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