Utilizing Regulation to Improve Risk and Equity in Heterogeneous Transmission Grids

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Abstract

As electric power grid critical infrastructure grows increasingly heterogeneous, a key question is how to encourage and ensure relatively equitable access to the energy it supplies. With diverse socio-economic regions linked to the grid and various generation types, achieving equitable access to clean energy, as outlined in initiatives like DOE's Justice40, remains an important aspirational goal. Building on previous work, this paper describes our investigation of a heterogenous grid modeled on the Alaska Railbelt, allowing us to explore the intrinsic inequities and possible mechanisms to enhance the equity across regions. We apply risk and equity metrics to different regions to examine how penalties which change the cost can impact the equity as well as the overall grid's risk and dynamics.

Keywords: Risk, equity, socio-technical modeling, uncertainty, energy regulation.

1. Introduction

As our power transmission system evolves to include a more heterogeneous mix of generation (including more higher variability renewable generation, and a more heterogeneous mix of loads) equitable access to the energy becomes more of a challenge. Among the questions that must be asked are: how do we define equity, how do we achieve it and what are the goals for penetration of sustainable and low carbon generation? In this paper we build on previous work on defining a metric for regional equity and proposing a regulatory mechanism that can help achieve equity by improving underserved regions without degrading the rest of the grid. As our model grid we use a very heterogeneous grid based loosely on the Alaska Railbelt grid. This grid is so named because the main transmission lines largely follow the railway between the main population centers from Delta Junction and Fairbanks in central Alaska through Anchorage to Homer on the Kenai peninsula. Because it has very inhomogeneous loads from large energy intensive mining operations and a large city (Anchorage) to scattered small rural communities all with different levels of access to the power transmission grid the risk can vary greatly in different locations making it a good test case. It is also of interest because a new Electric Reliability Organization (ERO) for the Railbelt is just being established, making its operation more amenable to change. Additionally, because it makes a good test bed, the results of can likely be extended to many other critical infrastructure systems with their intrinsic heterogeneities including in equity.

In this paper, we describe early investigations of techniques to improve long-term reliability of the system while also improving equity. Section 2 will briefly review the OPA model, describe the grid and some of the metrics used for analysis. In section 3 we will use OPA to analyze our ability to modify the risk in the various regions using outage costing. Section 4 looks at the impact on equity and makes a preliminary stab at unraveling the underlying mechanisms for the differing dynamics in the different regions. Finally, section 5 is a brief discussion and conclusion.

2. Model and Grids

To explore how a complex systems model of a coupled socio-technological system can incorporate heterogeneous preferences along with heterogenous generation, load and transmission, this work uses the ORNL-PSerc-Alaska (OPA) model (Carreras et al., 2004; Ian Dobson et al., 2007, Mei et al., 2011). This is a multi-attribute optimization model with time evolution and importantly for this work, combinations of weighted objective functions. This view of a power transmission system considers the engineering and physical aspects of the power system, and also the engineering,

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economic, regulatory, and political responses to blackouts and increases in power demand. Comprehensive inclusion of all these dynamics in a single model would be extremely complicated if not intractable. However, it is useful to consider simplified models 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 this paper, OPA is used to explore possible techniques for adjusting regional (local) reliability risks or other local needs using a local objective function.

The OPA model demonstrates how slow opposing forces of load growth and network upgrades can self-organize the power system to a dynamic equilibrium. Blackouts are modeled by overloads and outages of lines determined using a Linear Programming (LP) dispatch of a DC load flow model. This model, originally motivated by the concept of Self organized Criticality (SOC), displays complex dynamical behavior (Carreras et al., 2004; Dobson et al., 2007; Newman et al., 2011) consistent with that found in NERC data (Hines et al., 2009). The various opposing forces in power transmission systems interact in a highly nonlinear manner and may cause a self-organization process to be ultimately responsible for the regulation of the system. OPA computes long-term reliability taking into account these complex systems dynamics and feedbacks. OPA is typically run until it converges to a complex systems steady state with stationary statistics and longtime correlations. Because the temporal dynamics permits the creations of the time correlations intrinsic to such a system, these simulations are fundamentally different from more common Monte Carlo methods for generating statistics. In the case of OPA, we run the simulation for longer times to generate better statistics, thereby sampling more of the allowed system states with the probabilities of sampling a given state being generated by the system itself. The system state, available at each time step includes the generation at each generator node as a fraction of the node capacity, the power flow in each line (M) as a fraction of the line capacity, the power served at each node as a fraction of the node demand as well as line and node status. From these many other quantities can be calculated such as average line loading (<M>), total generation margin, etc. This allows us to easily investigate the impact of different levels of inhomogeneity on risk and dynamics as well as other network characteristics. OPA has been extensively validated against real data (Carreras et al., 2013) making it ideal for this type of study. OPA results are used for the computational analysis in the rest of this paper.

In this case, our analysis uses an artificial test grid built from a backbone and local subgrids. This are made by linking the subnetworks, referred to as zones or regions on the backbone (fig 1 and 2).

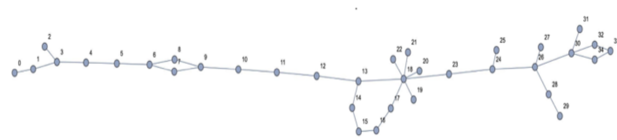

Figure 1. A model grid similar to the Railbelt transmission grid backbone in Alaska.

These are artificial power networks with realistic parameters constructed by following the algorithms of (Wang et al., 2010, 2008). The figures should not be taken as a real geographical representation and the length of the lines connecting the zones is really an approximated length of line. Six of the zones are a standard 86-node networks, with one being 211 nodes and one is 337 nodes. The total number of nodes is 1102.

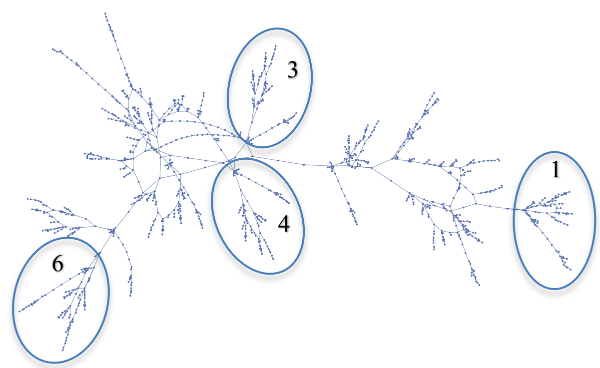

Figure 2. A hybrid "Frankenstein" model grid with additional detail added to the backbone, again similar to the Railbelt grid in Alaska.

The far right of the grid (fig 2) is roughly Delta Junction (zone 1) on the Railbelt and the far lower left is Homer (zone 6). In the grid, Zones 3 (Wasilla) and 4 (Palmer) both just to the left of the center, lower and upper grid structures, are disadvantaged zones for reasons described later.

Zone number	Zone Name	Population	Power generated
0	Railbelt	20920	1240
1	Delta	1000	27.000
2	Healy	900	0.0000
3	Wasila	10000	0.0000
4	Palmer	6500	0.0000
5	Girdwood	2500	0.0000
6	Homer	5700	0.0000
7	Fairbanks	32000	41.000
8	Anchorage	285000	200.00

Table 1. The 9 zones Railbelt grid in Alaska.

The basic approach we take is to examine a test grid that has inequity across zones. One approach to improve equity between the zones is to modify the objective function being minimized in the LP dispatch. For example, in a grid with differences in reliability across the zones, varying the penalty costs for unserved energy (e.g., in the model specifications the load shed) in the disadvantaged zones we can get better parity between the risk of the blackouts across the zones of the power grid. Next, we consider the objective function and the network used in the calculations.

As described before, the OPA model for a fixed network configuration represents transmission lines, loads, and generators with the usual DC load flow approximation using linearized real power flows with no losses and uniform voltage magnitudes. In the OPA code (Dobson et al., 2001), to do the power dispatch we minimize a cost function:

$$\text{Cost} = \sum \text{Cg}(i)\text{Pg}(i) + \sum \text{CLS}(i)\text{PLS}(i) \qquad (1)$$

In equation (1), Cg(i) is the cost of power generation by the generator i, Pg(i) is the power generated, CLS(i) is the cost given for the load shed in node i, and PLS(i) is the load shed in node i. In most of the OPA calculations, we use Cg(i) =1 and CLS(i) = 100. However, in investigating the impact of decarbonization or inequity or other objectives, the power generation cost function and the load loss cost functions can be made arbitrarily complicated allowing for multi-attribute optimization. For example, the "cost" of health impacts from local fossil fuel plants could be added to the generation costs of plants depending on their location, cost of inequity of reliability risk can be added to the load shed costs again depending on their location. In these first test-case calculations, we keep the generation cost the same for all generators but we vary the cost of the load shed CLS(i) depending on the zone in which the node is located. The normal cost of the load shed for the standard zones is kept at 100, but for the disadvantaged zone, we have considered various penalty costs for unserved energy including 100, 200, 400, and 600.

To quantify the system, we will use the risk metric first developed in (Carreras et al., 2014a) and an "Equity" metric. The risk metric is defined through two steps. First, a risk for a given size failure is calculated as the product of the probability of an n event of size i times the cost of an event of that size (Risk(i) = Probability(i) x Cost(i)). The cost of an event of size i is given by a cost factor A times the power lost times the duration (Cost(i)=A x Power lost x Duration of blackout). The second step is to integrate this over all sizes to construct a single metric R for the Risk to an electric system shown in equation 2 (Carreras et al., 2014a).

This can be done for the entire system or for parts of the system such as the zones

$$R \equiv \frac{1}{P}\int_0^P Risk\left(\frac{L}{P}\right)dL \qquad (2)$$

It is also worth noting that this Risk is normalized to the total load in the region being studied. This allows meaningful Risk comparisons between places or regions with very different loads and makes the value R dimensionless. With the equity metric (Lenhart et al., 2024) simply being the ratio of the "Risk" in the zone, i, to the average Risk in the other 8 zones shown in eq(3):

$$E = R(i)/(\sum R(j))/8 \qquad (3)$$

Here the summation is over all the other 8 zones different then zone i.

It is important to note that 1 is perfect equity and larger than one is inequity (smaller than one would also be inequity but with the inequitable region being better than average so perhaps advantaged).

Part of the utility of a model like OPA is that it captures the frequency and magnitude of the largest blackout events. This, combined with the duration which we infer from the magnitude and is an important part of the cost calculation, allows for this type of risk analysis. It also includes multi-attribute optimization and an ability to examine spatial heterogeneity locally. These capabilities are of particular interest in the decision-making process in which stakeholders have different preferences or disagree about how risk should be represented.

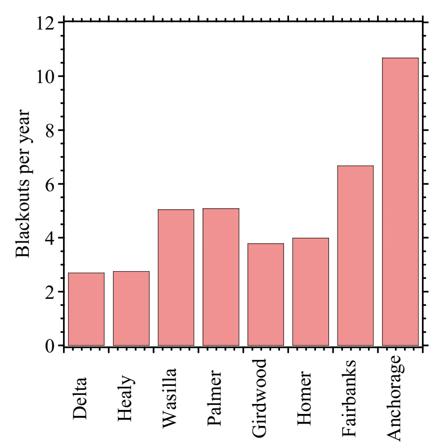

Figure 3. Blackouts per year in the 8 of the regions.

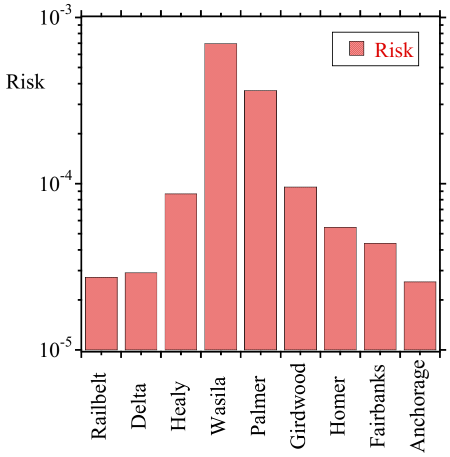

Figure 4. Normalized risk on a log scale in each zone with the load shed normalized to the zonal demand.

Figure 3 shows the number of blackouts in the 8 distinct regions (zones). This is not normalized to population or load which explains why the Anchorage region shows the largest number of blackouts, ie it is the largest followed by Fairbanks which is the second largest. In contrast, figure 4, which is the risk as defined above, normalized to the local demand, shows Wasilla and Palmer (regions 3 and 4) with by far the highest risk. Note the vertical axis (Risk) is on a log scale showing Wasilla and Palmer more than a factor of 10 higher risk than most of the other regions.

3. Risk and Regulation

We start by investigating the base case of the grid with all the standard parameters. As seen in figure 5 the normalized risk index, now on a linear scale, is much higher for zones 3 and 4 (Wasilla and Palmer). As mentioned above, figure 4 shows the same plot on a log scale showing those two zones have a risk index more than an order of magnitude higher than most of the other regions.

The Wasilla region has the highest risk value, significantly higher than all other locations with Anchorage and Delta being the lowest. Wasilla and Palmer are near the middle of the grid but are both just north (left on our grid) of the largest region, Anchorage. This proximity to Anchorage makes it susceptible to higher variability in the line loading due to fluctuations in the anchorage demand.

Building on our previous work we now investigate the impact of introducing a cost function penalty in the under served regions. Starting with Wasilla (zone 4 on this plot) since it had the highest risk. The standard value of the outage cost is 100. We leave it at 100 everywhere except in the Wasilla region where we use 100, 200, 400 and 600.

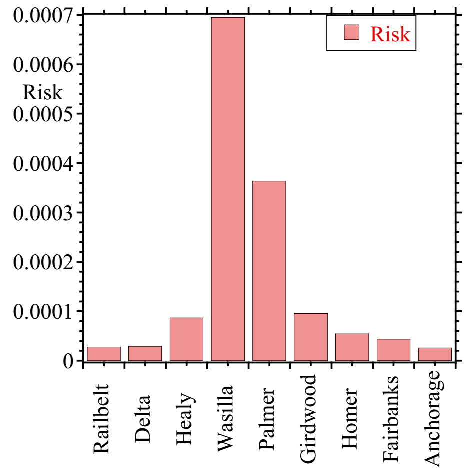

Figure 5. Normalized risk in each zone with the load shed normalized to the zonal demand.

In figure 6a, it is apparent that the frequency of the outages in Wasilla does not substantially change, however figure 6b shows a large change, almost an order of magnitude, in the risk for that region. The improvement occurs with increasing the cost to 200 and saturates with little further improvement. The impact on Palmer (zone 5 on this plot), physically neighboring Wasilla, is more complicated, the risk falls marginally and continues to fall slightly for increases in cost to 400 but then rises when the Wasilla outage cost is further raised to 600.

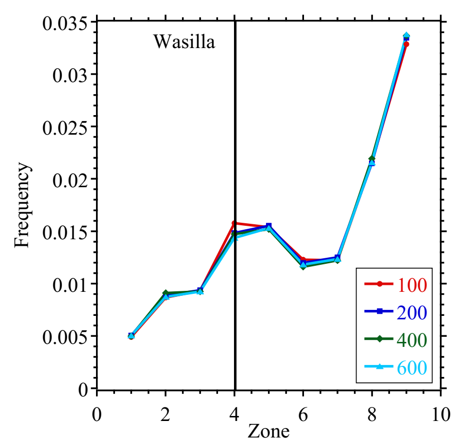

Figure 6a. Increasing the outage cost from 100 to 200, 400 and 600 shows practically no impact on the frequency of blackouts (top)

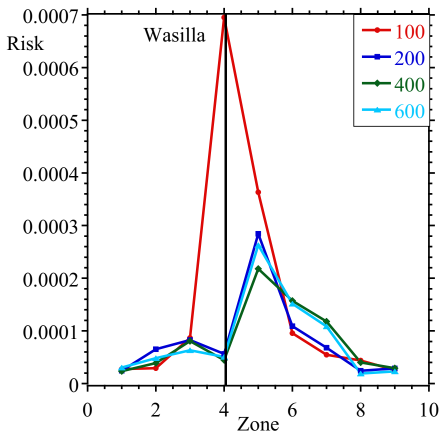

Figure 6b. Increasing the outage cost from 100 to 200, 400 and 600 shows practically no impact on the frequency of blackouts (top) but a large reduction of the risk (bottom).

This situation leaves Palmer with the highest risk in the grid, so we now try to change the outage cost in both the Wasilla and Palmer regions. The 4 panels in figure 7 shows the Risk in each of the regions as the outage cost in both Wasilla and Palmer is varied from 100 (top left panel) to 200 (top right) through 400 (bottom left) to 600 (bottom right). Note the vertical scale changes by a factor of four from the first panel to the three others in order to make the differences visible. In this case the improvement increases as the outage cost increases and does not saturate until the outage cost is 600 for both disadvantaged regions. At the same time there is little change in the other regions.

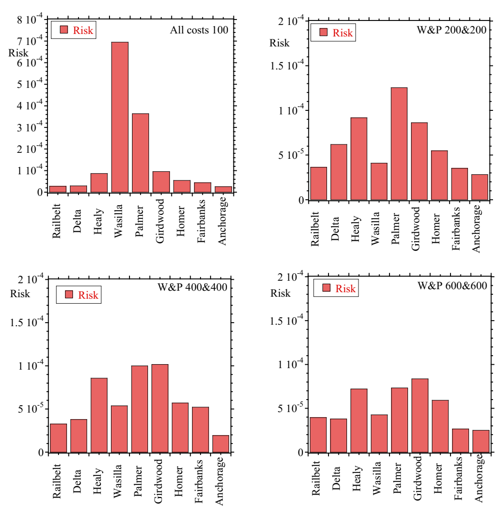

Figure 7. Changing cost of outage for both Wasilla and Palmer leads to a large reduction of the risk for both.

This can be seen more clearly in figure 8 which shows the overall risk for the entire grid as the outage cost in Wasilla and Palmer are increased. In these preliminary results no systematic change in the overall grid risk is found.

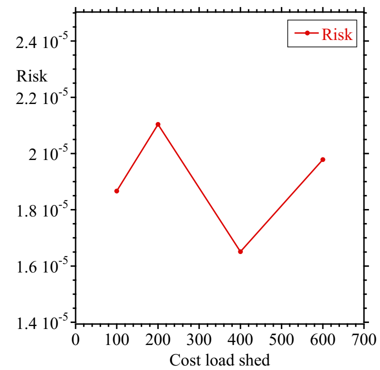

Figure 8. Changing cost of outage for both Wasilla and Palmer has little impact on the global risk.

The 3 panels in figure 9 shows three snapshots of the grid state including the generation (purple dots) demand (blue dots, or black when outaged) and line load fraction (line color from green-good to red-overloaded to black-out). Figure 9a shows a snapshot of the base case with the outage cost of 100 for all regions.

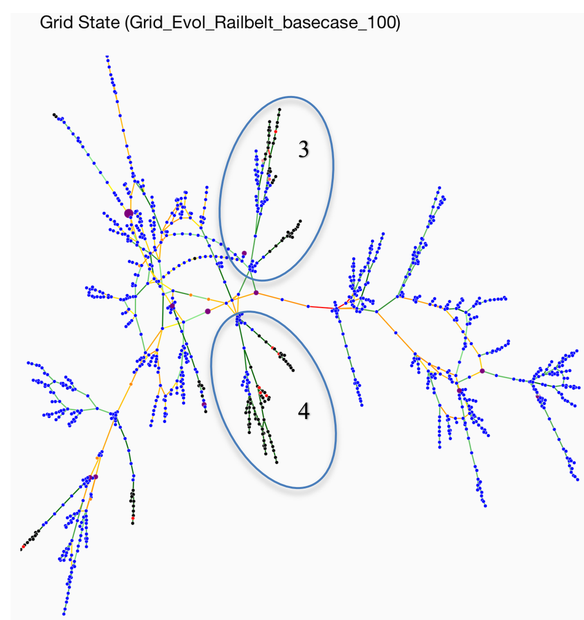

Figure 9a. A snapshot of the grid state with equal outage cost (no corrective intervention). This snapshot shows Wasilla and Palmer experiencing a large outage and stress along the railbelt backbone.

Large outages are seen in this snapshot in both the Wasilla (region 3) and Palmer (region 4) regions and the backbone is orange or red signifying a highly stress situation. It is important to note this is a system state snapshot and while the risk is overall higher in these two regions it is not always in this state at a given instant. The system state shown in figure 9b has an outage cost of 400 for Wasilla (region 3) and a cost of 100 for all other regions. In this case, as shown earlier, the risk is greatly reduced for Wasilla but largely unchanged for Palmer and the rest of the system. In this snapshot, Palmer is experiencing an outage with the rest of the system in fairly good shape though with some stress on the backbone.

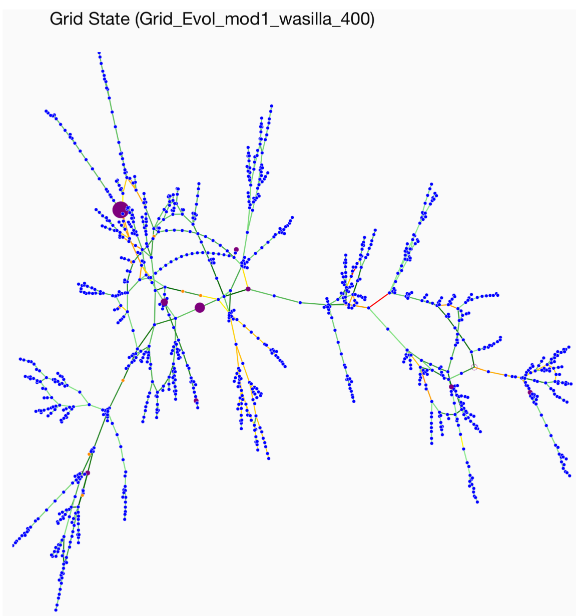

Figure 9b. A snapshot of the grid state with Wasilla having an outage cost of 400 (every one else still at 100). This snapshot shows Wasilla in a good operational condition and Palmer experiencing an outage again with some stress along the railbelt backbone.

Finally, the system state shown in figure 9c has an outage cost of 400 for both Wasilla and Palmer with a cost of 100 for all other regions. In this case, again as shown earlier, the risk is greatly reduced for both Wasilla and Palmer with the rest of the system largely unchanged. In this snapshot, other than some stress in the southern (left) end of the system backbone, the rest of the grid is in fairly good shape.

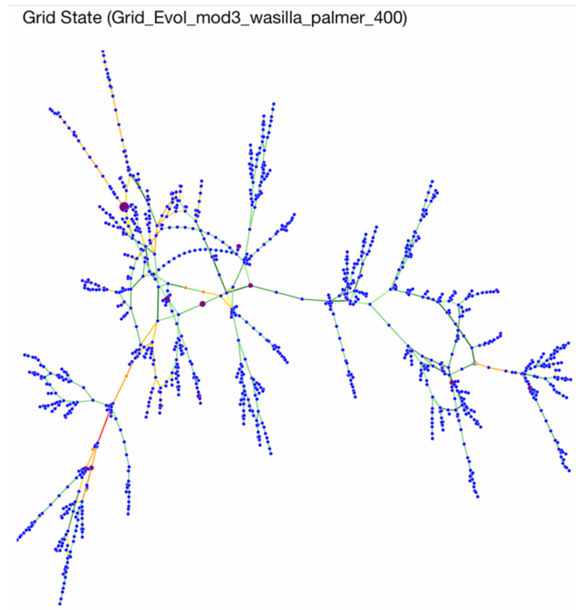

Figure 9c. A snapshot of the grid state with Wasilla and Palmer having an outage cost of 400 (all other regions still at 100). This snapshot shows Wasilla and Palmer in a good operational condition with stress on parts of the railbelt backbone.

4. Equity and Cause

Another way of looking at this is through the equity measure we defined in section 2. The equity measure for each of the zones is shown in figure 10. While it does come down to a nearly saturated value when the outage cost for Wasilla and Palmer are raise to 200, small improvements are still seen all the way to 600.

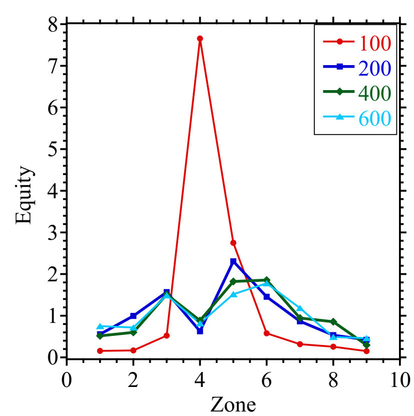

Figure 10. Changing cost of outage for both Wasilla and Palmer has a large impact on the equity for the individual regions.

This can be seen more clearly in figure 11 which shows the average equity over all the regions as the outage cost increases from 100 to 600.

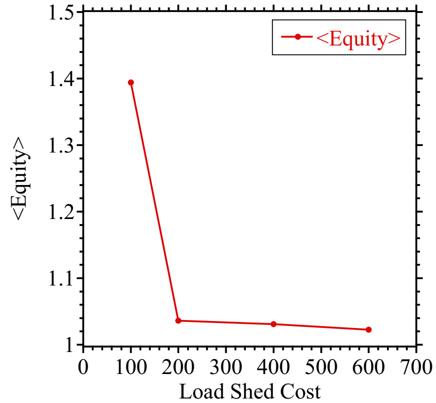

Figure 11. Changing cost of outage for both Wasilla and Palmer has large impact on the overall average equity.

An important question to address is, what in the dispatch is changing to make these improvements. The three likely changes are in the average line loading, the generators used and the variance in the line loading. To investigate the mechanism for the changes that lead to the decreased risk and improved equity we start with the best case shown in figure 12.

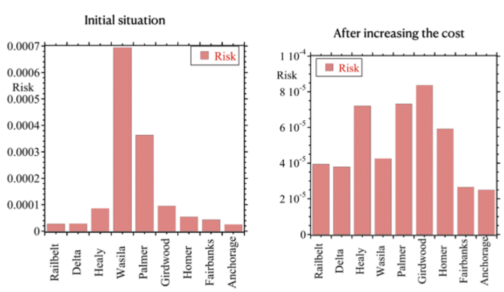

Figure 12. Risk in the base case, outage cost 100, and best case, outage cost 600. Again, note the vertical scale change.

Average line loading above a certain value has been shown in previous work to be related to increased risk of large blackouts. This is because as the line load approaches 1 the system is getting closer to the critical point. However as shown in figure 13 the average line loading in each zone across grid shows little of no change. This is particularly true for Wasilla and Palmer which if anything show a very small increase. However the average line load for those two regions is the highest in the grid meaning they are sitting near the critical point waiting for a fluctuation to push them over to failure.

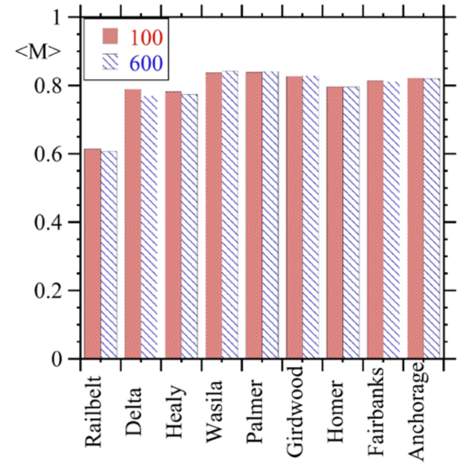

Figure 13. The average line loading <M> in each of the regions for the base case (100) and the outage cost of 600 case.

Next we look at the generation in the grid. Figure 14 shows the generation for each of the major generators in the grid once again showing little or no change between the base case and the very improved outage cost 600 case. Figure 15 shows the same thing for the average generation in each region.

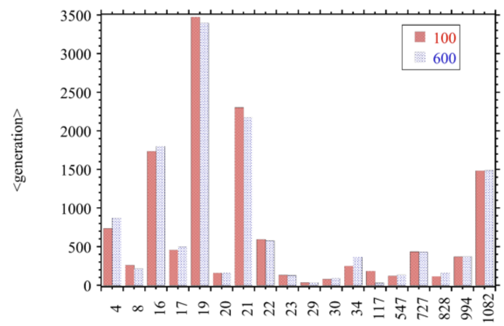

Figure 14. Average generation for each major generator in the grid for the two cases.

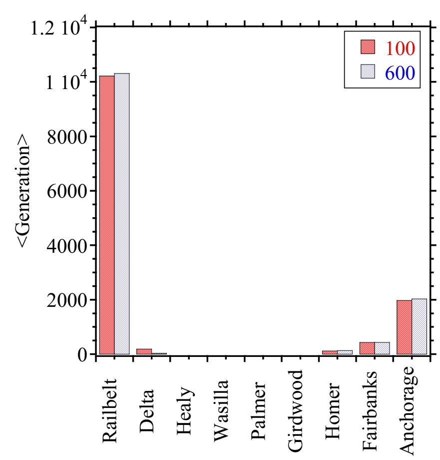

Figure 15. Average generation for each region in the grid for the two cases.

As an outage is not caused by the average value of the line loading but rather a fluctuation in the line load while the value is high enough, we now look at the next moment of the line loading statistics, namely the variance of the line loading. Figure 16 shows the variance of the line loading in each region. This plot does show a significant decrease in the variance in the Wasilla and Palmer regions. This decreases fluctuation in line load combined with the high average line load in those regions is a likely explanation for the decrease in large failures leading to a decrease in risk for those regions leading to an increase in equity (really a decrease in our equity values toward 1).

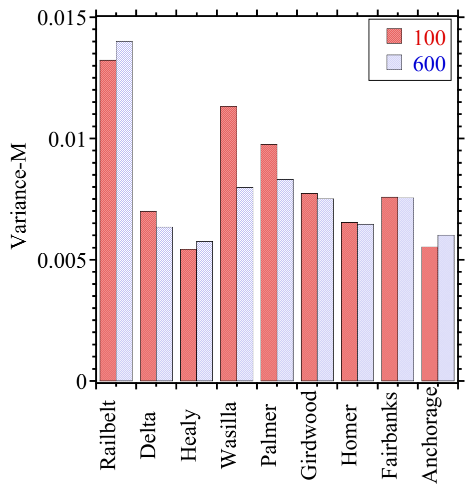

Figure 16. The variance in line loading M in each of the regions for the base case (100) and the outage cost of 600 case.

We finish this preliminary analysis by looking at the same two quantities for the lines connecting the regions. These are largely the lines we have been referring to as the backbone lines. Figure 17 shows the variance in M between the regions and shows a large decrease at the north end, Delta, and a large increase at the south end, Homer. This combined with figure 18 which shows a small decrease in the average M for Delta and a small increase in the average M into Homer could explain the small but significant increase in risk for Homer and a very small decrease for Delta. It also suggests that on average more energy might be flowing from the south to the two disadvantaged regions to make their regions more reliable.

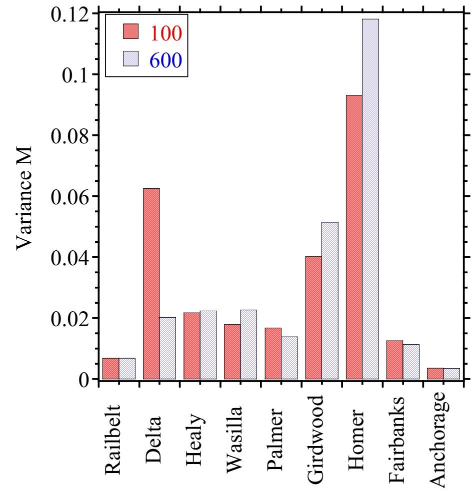

Figure 17. The variance in line loading M between the regions for the base case (100) and the outage cost of 600 case.

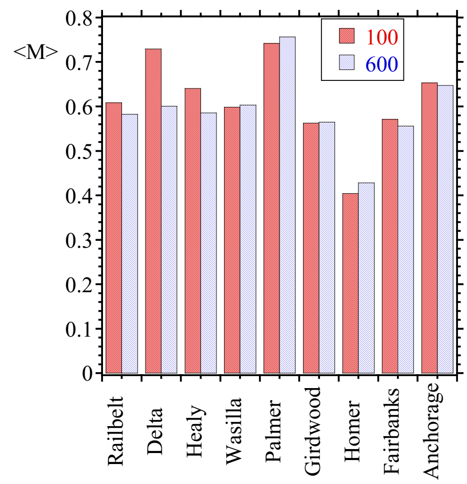

Figure 18. The average Line loading <M> between the regions for the base case (100) and the outage cost of 600 case.

5. Conclusions

Critical infrastructure systems like power transmission grids are often highly heterogeneous. Differences in load size (small rural communities vs. large cities) and load characteristics (residential vs. industrial/mining vs. high-tech needs), grid structure and quality, socio-economic characteristics, and power availability and reliability often lead to inequities in energy access and environmental impacts. Additionally, there are significant regional differences in generation type, variability, cost, and size, as well as variations in standards, rules, and regulations.

Given these factors, modeling the impact on risk and reliability is crucial for planning both technical aspects (new or upgraded generation, transmission lines, storage, load control) and regulatory measures. In this paper, we used a simplified representation of the Alaska Railbelt grid to examine equity and the role of regulation in addressing inequities. Our findings show substantial regional differences in risk, leading to significant inequities, particularly between regions 3 and 4 and the rest of the grid. We found that instituting a higher outage cost in underserved regions substantially ameliorated these inequities with minimal impact on overall grid risk and reliability. The improvement in equity resulted from reduced variability in line loading in underserved regions and a shift in some power generation to the south.

This suggests that similar regulatory policies could be used to enhance equity more generally in underserved regions, considering that economic dispatch is integral to real-world ERO operation. This would likely be true both if generalized to larger more interconnected regions like the WECC or even to other complex critical infrastructure systems like the internet or gas pipeline systems. The three next steps in this work are to apply this to larger systems like the WECC and to incorporate the siting of highly variable renewable power sources based on the same metrics to optimize the system for overall risk and equity and importantly working to quantify the connection between the modeling and policy to develop workable regulatory frameworks to implement this type of scheme.

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