# Unraveling Geographic Interdependencies in Electric Power Infrastructure

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## Abstract

*Interdependencies among infrastructure systems are now becoming commonplace, and present both opportunities and vulnerabilities. Initial attention was paid to functional interdependencies among infrastructure systems regardless of locational characteristics. Using electric power as a focal point, geographic interdependencies are evaluated, that is, outages that spread across several states rather than being confined to single states. The analysis evaluates the extent to which the two different groups have distinct characteristics. The characteristics examined include incident counts, number of customers lost, duration and energy unserved. Data are drawn from the Disturbance Analysis Working Group (DAWG) database, which is maintained by the North American Electric Reliability Council (NERC), and from the U.S. Energy Information Administration (EIA).*

## 1. Introduction

Interdependencies among infrastructure systems are now commonly recognized as both a key economic advantage to providing public services for energy, transportation, water and waste management and a point of vulnerability, since an outage in one system can produce outages in others thus magnifying the overall impact [3, 13]. The increasing reliance on information technologies to control and operate infrastructure systems has increased the amount and complexity of these interdependencies [14].

Interdependencies take many forms, which have been discussed extensively elsewhere. Some are functional in that one infrastructure system relies upon another to operate. Others are spatial in that one type of infrastructure system is co-located with another, and may or may not also be functionally interconnected.

Although specific trend data for interdependencies is difficult to obtain, it is believed that the extent of interdependencies has been growing over time as the production of infrastructure services has become more spatially concentrated necessitating increasing distances over which transmission and distribution lines have to travel to meet population demand. The spatial dispersion of population in many parts of the country has also exacerbated this problem.

## 2. Functional Interdependencies

Although complexity and variety of functional interdependencies often defy characterization, in a general way, functional interdependencies in the context of infrastructure systems, refer to two or more systems relying upon one another operationally, i.e., attributes of one system are required for another to function [3,13]. The consequences of functional interdependence are beginning to be quantified in a number of different ways. Zimmerman, for example, used a ratio based on the relative extent to which various infrastructure distribution lines disrupted one another for an illustrative sample of about 100 infrastructure failures [12]. The results showed differences in the extent to which a particular type of infrastructure, when disrupted, was first to initiate disruptions in other infrastructure. Zimmerman and Restrepo characterized the consequences of failures initiated by electric power failures, using the relative duration of electricity outages vs. outages for other infrastructure affected by the electricity outage, termed a cascade [15]. Using "T(e) = the duration of the electric power outage and T(i) = the duration of the infrastructure outage that is a consequence of the electric power outage, then: T(i) / T(e) is a measure of the direction of the cascade." [15, p. 7] That study found that for the August 2003 blackout, the duration of outages to infrastructure dependent on electric power (such as transportation and water) often far exceeded the duration of the outage of electric power. One of the more spectacular examples of how the interdependencies between electricity and other infrastructures can play out was the outage of two of the largest petroleum product pipelines in the United States due to electric power outages to pumps caused by Hurricane Katrina on the Gulf Coast in 2005. The Colonial and Plantation pipelines traverse and serve numerous states in the Southeast, Mid-Atlantic and Northeast regions. The Colonial pipeline is 5,500 miles long, delivering 100 million gallons of product daily, and the Plantation pipeline is 3,100 miles long, delivering 20 million gallons of product [2]. Both the Colonial and Plantation pipelines were shut down due to power outages at pump stations on August 30, 2005 [11].

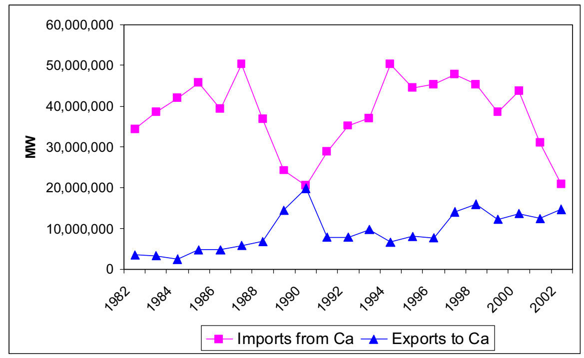
## 3. Geographic Interdependencies

Relatively less attention has been paid to geographic or spatial interdependencies that pertain not to co-location but rather to functional interdependencies across different geographic jurisdictions. In the electric power area, this type of interdependency has been growing, and is believed to be primarily a consequence of reorganizations of the electric power system enhanced by deregulation.

These geographic interdependencies can be domestic or international. Some international examples are noteworthy though this paper primarily addresses domestic cases. For example, the United States currently trades electric power with both Canada and Mexico. According to the U.S. Department of Energy (DOE), in 1998 the U.S. imported 45,408,101 MW from Canada and 11,249 MW from Mexico. Similarly, the U.S. exported 15,946,424 MW to Canada and 1,973,203 MW to Mexico [8]. Figure 1 shows electricity trade between the U.S. and Canada and indicates that U.S. electricity exports to Canada are increasing over time, whereas imports from Canada appear to vary significantly over time. Figure 2 shows the equivalent figures for electricity trade with Mexico. As the data show the U.S. trades more electricity with Canada than with Mexico but trade with Mexico started more recently and may grow in the near future. As with Canada, U.S. exports of electricity to Mexico are increasing over time but the data on imports show significant variability. The variability in the electricity trade data in recent years is due in part to an increase in power marketers and to inconsistent reporting in the data [9].

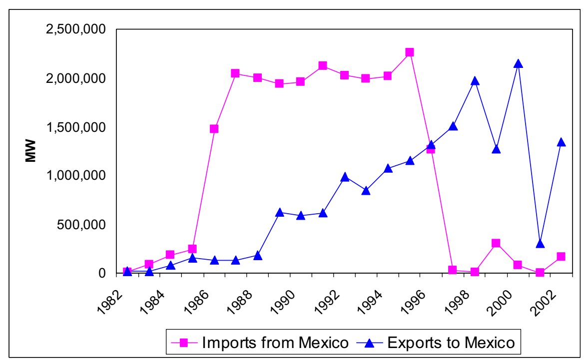
Electricity imports from Canada come from both hydropower and a nuclear plant.

**Figure 1. U.S. electricity trade with Canada**




Source: U.S. Department of Energy [10].

**Figure 2. U.S. electricity trade with Mexico**




Source: U.S. Department of Energy [10].

A statistical analysis of power outages by Simonoff that models characteristics of outages such as customers lost, duration and megawatts lost indicates that the dynamic underlying the U.S. outage data [6] is very different from that underlying the Canada data [5]. Regression modeling also indicated that although there are more incidents in the U.S. than in Canada, the numbers are increasing at roughly the same rate, with outages having zero customer loss becoming more common in Canada and less common in the U.S. The analysis used data from both countries from the Disturbance Analysis Working Group (DAWG) database, which is maintained by the North American Electric Reliability Council (NERC). As geographic interdependencies of infrastructure systems increase, understanding differences of these types has important implications for risk management policies that aim to reduce power disruptions.

Geographic interdependencies in the electricity sector are also commonly found domestically among states. Our analysis investigates the implications of this, and was conducted using data drawn from the Disturbance Analysis Working Group (DAWG) and U.S. Energy Information Administration (EIA) databases, for the period 1990-2004.

What is noteworthy from this small set of cases is that to the extent that the exact number of states was able to be identified for each event, up until the 2003 blackout, the number of states involved in these multi-state events was two or three. Broad regional impacts, however, without specific states identified prior to the 2003 blackout occurred in 1991 and 1999, i.e., they were relatively less frequent. The 2003 blackout involved over a half dozen states [7], and in 2004, three blackouts between February and July affected four states. Given these very qualitative observations, it seems important to identify whether or not more states are gradually being drawn into these outages.

In order to gain a better understanding of the differences between electric power outages that occur primarily in one geographic entity, which in this case is a state, relative to outages that occur over multiple geographic entities, we compare two datasets obtained from the Disturbance Analysis Working Group (DAWG) database, which is maintained by the North American Electric Reliability Council (NERC) and from the U.S. Energy Information Administration (EIA). The single state dataset includes 365 cases of electric power outages in the United States that occurred primarily in a single state during the period 1990-2004. The multiple states dataset includes 44 outages that involved multiple states over this period. Given the information in the DAWG database it is difficult to separate events involving multiple states caused by cascading interdependencies in the electric grid from events that resulted from a common cause such an extreme weather event that moved across several states and damaged several independent electricity grids. Hence, the multiple state events refer to those outages that crossed political boundaries, which in this case is state borders, without distinguishing the underlying cascading or common cause structure of the outage.

The datasets include information about variables of interest and availability such as number of customers lost during the outage, duration (measured in hours), and megawatts (MW) lost. Energy unserved was also estimated by multiplying duration times MW lost.

In addition, the primary cause of these outages were also coded from the DAWG database as follows: capacity shortage (C), demand reduction (D), equipment failure (E), fire (F), human error (H), operational error (O), natural disaster (N), system protection (S), third party (T), unknown (U), crime or vandalism (V) and weather (W). Table 1 summarizes these causes for both the single state and multiple state datasets.

### Table 1. Causes of outages that occurred in a single state

| | Single state events | | Multiple state events | |
|---|---|---|---|---|
| **Cause** | **Frequency** | **Percent** | **Frequency** | **Percent** |
| C | 15 | 4.1 | 1 | 2.3 |
| D | 3 | .8 | 1 | 2.3 |
| E | 106 | 29.0 | 10 | 22.7 |
| F | 12 | 3.3 | | |
| H | 21 | 5.8 | 2 | 4.5 |
| N | 5 | 1.4 | | |
| O | 6 | 1.6 | | |
| S | 6 | 1.6 | | |
| T | 6 | 1.6 | | |
| U | 3 | .8 | 4 | 9.1 |
| V | 9 | 2.5 | | |
| W | 170 | 46.6 | 26 | 59.1 |
| N/A | 3 | .8 | | |
| Total | 365 | 100.0 | 44 | 100.0 |

Compared to outages in single states, the outages that occurred over multiple states had a higher mean number of customers lost during an outage (639,040 versus 158,942), higher mean duration in hours (165 versus 39) and higher mean MW lost (2,139 versus 653). The medians show a slightly different pattern. The median number of customers lost was higher for single state outages (63,500 versus 36,006). However the median duration was higher for multiple state outages (13.3 hours versus 7 hours). Multiple state outages also had a higher median MW lost (300 versus 250). The mean for these variables are much larger than the medians, which is consistent with long right tails in the data. For this reason logged variables were used in the statistical analyses.

Overall, the data indicate that weather was responsible for a larger share of the outages that occurred over multiple states (59.1% versus 46.6%). But in both datasets weather and equipment failure were the most common causes attributed to the outages.

Simonoff et al. [6], when examining power outage data for outages confined to or separately affecting primarily a single state, showed that the duration, customer loss, and power loss (measured in MW lost) of an outage is related to many different factors, including the cause of the outage, the season, and the year in which it occurred. They also showed that outages where there is zero customer loss constitute a distinct group from those with nonzero customer loss.

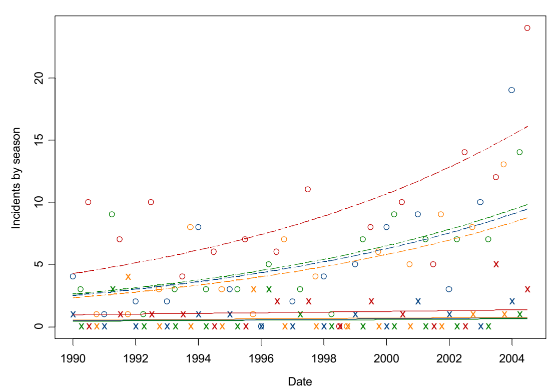
The comparison between the single state and multiple state datasets described above is divided in four parts. The first compares incident counts over time for outages. The second compares number of customers lost during the outages. The third looks at duration in hours. Finally, the fourth part examines energy lost which multiplies duration times megawatts lost.

## 3.1 Incident counts

The analysis of incident counts over time shows two key patterns. First, as mentioned above, for the total number of multiple state incidents annually is much smaller than the number of single state incidents. Second, whereas single state events appear to be increasing over time, there is no evidence of a time trend for multiple state events. Loglinear count (negative binomial) regression was used to model the number of incidents over time [4]. The estimated increase over time for single state events is 7.1% per year using annual data, 8.4% using semi-annual data, and 9.6% using seasonal data.

The differences in the two data sets are illustrated in Figure 3 which shows two sets of lines. The dotted lines on the top which curve upwards describe single state events and are divided by season. The line with the highest incidents refers to summer events, and these are significantly different from incidents in the other seasons, which are lower. The solid lines in the graph refer to multiple state events. As the lines show there is no apparent time trend in multiple states incident counts. There are also more events in the summer for the multiple state data but the season effect is not statistically significant.

**Figure 3. Incidents over time for single state (dotted lines) and multiple state (solid lines) events (spring points and lines are green, summer red, autumn orange, and winter blue).**




There is more overdispersion in the multiple state data (relative to the variability implied by a Poisson-based count model) than in the single state data. This suggests that there are differences in the process of outages occurring over multiple states from year to year that are not accounted for by just a time trend. Thus, we could speculate that interdependencies are changing over time in a complex way that is not accounted for merely by a time trend.

## 3.2 Customers lost during an outage

Customer loss was modeled in two parts. The data include a number of disturbances that did not affect customers. The first part of the analysis is aimed at understanding what characteristics are related to whether an incident has zero or nonzero customers lost. Then, given that the number lost is nonzero, we attempt to determine what characteristics help to predict the actual number of customers lost.

For single state events, incidents occurring in the earlier part of the period studied are more likely to have zero customer loss. As mentioned earlier the primary cause of the outage was coded into 12 categories. However, most causes have only one or two incidents, so it is impossible to say anything about them. Hence, when comparing the single state and multiple state event data, the causes were collapsed to three: equipment failure, weather, and other. Virtually no weather-related single state outages had zero customer loss, while almost one-third of the outages related to equipment failure had zero customer loss. Of the other causes, vandalism (crime) is more associated with zero customer loss than nonzero loss.

The patterns for customer loss are similar for multiple state events. Zero customer loss outages are also less likely in later years and less likely when the duration of the outage is longer. Zero loss outages are a bit more likely in multiple state outages for equipment failure and weather causes, and a bit less likely for other causes.

The second part of the analysis of customer loss during an outage used weighted least squares regression, which is used to correct for non-constant variance, to model the (logged) number of customers lost, given that that number is nonzero. In terms of duration of outage there is little difference between single state and multiple state events. Given the predictors in the model, and given that there was nonzero customer loss, longer outages are associated with more customers lost. A 1% increase in duration is associated with a 0.28% (single state) or 0.29% (multiple states) increase in customers lost. This is not a statistically significant difference; rather, it speaks to a broad pattern, since it applies in both cases.

For single state outages, there is an increasing trend over time, with an estimated 5.5% annual increase in customer loss. For multiple state outages, there is a decreasing trend over time, with an estimated 9.6% annual decrease in customer loss. This difference is highly statistically significant ($z$=2.91). As a result of this, the difference in customers lost for single versus multiple state outages is getting smaller. At the beginning of 1990, the estimated number of customers lost for an autumn outage caused by something other than equipment failure or weather that lasted one hour was 13,407 for a single state outage, and 7,514,273 for a multiple state outage, a factor of more than 500. By the middle of 2004, the numbers were 29,121 for a single state outage, and 1,731,180 for a multiple state outage, a factor of less than 60.

The differences mentioned above are overstated, in that for multiple state outages autumn has by far the highest average customers lost given all else in the model; while there is no evidence of seasonal effect in the single state data, there is a strong effect in the multiple state data, with winter, summer, and especially spring outages having much lower estimated customers lost than autumn ones. For early 1990, the model estimates 8,553 customers lost in the spring for a single state event and 247,857 for a multiple state event (a factor of less than 30); 16,020 for single state events in the summer and 2,877,546 for multiple state events (a factor of about 180); and 15,483 for single state events in the winter and 2,063,888 for multiple state (a factor of about 130). In mid-2004, the numbers are 18,579 for single state events in the spring and 57,103 for multiple state events (a factor of roughly 3); 34,797 for single state events in the summer and 662,945 for multiple state events (a factor of less than 20); and 33,631 for single state events in the winter and 475,490 for multiple state events (a factor of roughly 15).

A similar argument holds for the (simple) cause effect, since both equipment failure and weather are associated with much lower expected customers lost than the "other" category for multiple state outages.

Thus, the overall result is that the consequences of multiple state events are getting better in the sense that while single state incidents are increasing in number over time, multiple state incidents are not. The chances of an outage having zero customer loss are reasonably similar for the two types of outages. While single state outage expected customer loss is increasing (given that it is nonzero), multiple state outage expected customer loss is decreasing. If we view recent times as more relevant, we see the remarkable pattern that expected customer losses are generally *smaller* for multiple state outages for the two most common causes (equipment failure and weather), *except* in the autumn. This result is remarkable and suggests there may be differences in the efficiencies of interstate dependencies. It may be that autumn is different due to extreme weather events (such as hurricanes) that cause multiple state outages.

## 3.3 Outage duration

The next step in the analysis was to model outage duration using weighted least squares (WLS). The results for single state outages showed weak evidence of a time trend in logged duration. There is some evidence of a season effect, with winter and spring events being longer and autumn and summer events shorter (the expected duration in winter is roughly two times the expected duration of summer events). There is a clear relationship with primary cause, with equipment failure being associated with shorter outages and weather with longer outages for the two most common causes.

In multiple state outages there is marginal evidence of a time trend, unknown and weather incidents are longer (note that the August 2003 blackout is labeled to be of unknown cause), and winter and spring are associated with longer outages than in autumn and summer (and note that the August 2003 blackout was in the summer). Omitting the time trend from the model changes little.

For single state outages, there is an increasing trend over time, with an estimated 5.3% annual increase in duration. For multiple state outages, there is also an increasing trend over time, with an estimated 14.0% annual increase in. This difference is not statistically significant ($z$=1.00), but that could be because of sample size.

The season effects are similar for single state and multiple state events, but they are more pronounced in the multiple state data. While there is little difference in estimated durations during the summer, they are estimated to be much longer in the winter for multiple state outages.

Other than the general pattern of multiple state outages being longer, the only real difference in terms of the primary cause variable is in the "other" category, with high duration in the unknown category. This comes from the incidents listed on August 14, 2003 which were coded as having an "unknown" cause.

In summary, for duration the big effects are that multiple state winter outages are much longer, multiple state outages caused by "other" are much longer (this is really the "unknown" cause, and is attributed to the way the August 14, 2003 blackout was coded), and multiple state outages are getting longer at a faster rate than are single state outages. The August 2003 blackout was coded as "unknown" because it was a complex combination of factors such as human error, equipment, and weather (heat related) [7].

### 3.4 Energy unserved

The next part of the analysis looks at *energy unserved,* which is the duration of an outage multiplied by the megawatts (MW) lost. As with the analyses for customers lost and duration, energy unserved was modeled using WLS. The results of the model suggest there is a little evidence of a time trend in logged energy unserved. There is some evidence of a season effect, with winter and spring events higher and autumn and summer events lower. There is a clear relationship with primary cause, with equipment failure having less energy unserved and weather having more for the two most common causes. These are the same patterns as for logged duration, which suggests that duration may dominate patterns for this measure.

There is little evidence of a season effect. We do see higher values in winter and spring (as we see for durations), but multiplying duration by MW weakens the seasonal difference, presumably because there is not a seasonal difference in MW loss. Weather-related outages are at the high end of energy unserved in terms of the primary cause variable.

The effects for multiple state outages are similar to those noted earlier for logged duration: “unknown” cause has the highest energy unserved (and this is due to the August 2003 blackout being coded as having an unknown cause), and winter and spring having higher energy unserved than autumn and summer (even though the August 2003 blackout was in the summer). However, the estimated time trend is notably larger than that for single state outages, so the estimated difference in energy unserved between single and multiple state outages is higher in recent years.

In summary, for energy unserved the big effects are that multiple state winter outages have higher energy loss (they are much longer), multiple state outages caused by “other” have higher energy unserved (which is really unknown, and August 14, 2003), and multiple state outages are having increasing energy unserved at a faster rate than are single state outages.

Since the August 2003 outage is driving much of the unknown/other effect an analysis of multiple state outages with that outage classified to equipment failure was also carried out as a sensitivity analysis. This change makes the effects less statistically significant and equipment failure then has the highest energy unserved.

## 4. Conclusions

Understanding interdependencies among infrastructure systems is an important input to risk management policies that aim to improve the reliability of these crucial systems and reduce the economic costs associated with system breakdowns or failures. Infrastructure systems such as electricity, telecommunications, water supply, wastewater treatment, and oil and gas are highly interdependent either because they use each other as inputs or because they are physically located in close proximity to each other and can therefore affect each others’ performance. As mentioned in section 2 recent efforts at quantifying some of these interdependencies are beginning to shed some light on the magnitude of these effects.

Infrastructure systems can also be thought of as interdependent from a geographic perspective. There is reason to believe that over the next few decades some infrastructure systems may change from a number of isolated systems divided by geographic or jurisdictional boundaries to more integrated and interdependent systems. This paper examines geographic interdependencies for electricity, a sector that has been changing rapidly as a result of deregulation. Distributed energy generation could also contribute to a more decentralized system where smaller production units in remote locations become connected to more traditional sources of production in the grid. These changes could occur at the domestic level with electricity systems increasingly crossing state boundaries. In addition, these systems could become more interdependent with systems across country borders. The United States already trades a substantial amount of electricity with Canada. Similarly, electricity trade with Mexico has been growing over the last few years.

What can we expect in terms of potential impacts from more interdependent systems across geographic regions? This is a challenging question to address. Can we expect greater resiliency in these systems and hence improved performance? Or will multiple political jurisdictions sharing interdependent systems make it more difficult to address failures such as outages? This paper analyzes and compares available data for two distinct types of outages: those occurring in individual states and those occurring over multiple states. The results are limited by the data in the sense that the source of the data contains limited information about whether the multiple state events are the result of cascading failures among interconnected systems across states or simply multiple outages of independent systems resulting from a common cause such as an extreme weather event. Research in this area could be helped substantially if organizations such as NERC and EIA began to include more detailed information about outages in their databases. Despite these limitations the results of the comparison provide some interesting results that could help policymakers better understand what can be expected from policies leading to greater geographic interdependencies.

The statistical analyses indicate that single state outages are becoming more common, while the rate of multiple state outages is reasonably steady. This could be a benefit of increasing interdependencies. In both cases, there are more outages in the summer than in the other seasons.

Outages with zero customer loss are becoming less likely over time in both categories and at similar rates. Zero loss outages are a little more likely in multiple state outages for equipment failure and weather causes, and a little less likely for other causes. Overall, these differences are not dramatic.

Given there is nonzero customer loss, the expected number of customers lost in single state outages has increased over the last 15 years, while the expected number in multiple state outages has decreased. In fact, for the most common causes (equipment failure and weather), the estimated customer loss for multiple state outages is now lower than that for single state outages in all seasons except autumn. Again, this could be a positive effect of increasing geographic interdependencies.

Outages of both types are getting longer, but the duration of those in multiple states is increasing at a faster rate; multiple state outages now have much higher expected duration in all categories. This could be a negative effect of increasing geographic interdependencies. Multiple state outages are much longer than single state outages especially when they occur during the winter.

The fact that multiple state events do not seem to change in frequency over time, but do increase in duration has negative implications for the national economy. Studies have shown that the cost of an outage increases with duration [1]. This often occurs because recovery of systems dependent on electric power can take longer than the original outage [15], and the longer the outage, the longer readjustments in other systems may take.

In this paper we have focused primarily on geographic interdependencies associated with a single infrastructure sector, electricity. However, since electricity is a key driver of other infrastructure systems these interdependencies would translate into impacts on other infrastructure sectors. In addition, independent of what is happening in the electricity sector, if other infrastructure sectors are also showing consolidation across states in the provision of new services and consolidation of new sources of electricity, then we would expect greater impacts from electric power outages.

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