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A FRAMEWORK TO ASSESS NATURAL HAZARD-INDUCED SERVICE INOPERABILITY IN THE ELECTRICITY SECTOR

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Abstract: Our built environment is threatened with ever-increasing risks of climate change and natural hazard- induced extreme events. Recent natural catastrophes especially extreme hydro-climatological hazards such as floods, forest fires, droughts, and heatwaves often times lead to cascading severe weather-induced power outages. These outages affect immense economic loss. In this research, we propose a strategic planning and decision-making framework to predict the inoperability of the utility in face of several types of natural disasters. Inoperability can indicate the level of system malfunction caused by the severe weathers. In this research, inoperability refers to the interruption in power supply, measured by the extents of peak demand due to power outage. The proposed framework consists of the three main phases: (1) natural hazard-induced major disaster selection, (2) relevant feature selection, and (3) identify the factors that influence the levels of inoperability in the utility sector due to power outage (i.e., lack of power supply). First, we propose to leverage Principal Component Analysis (PCA) for dimension reduction and feature selection; then, using the selected features we propose to develop advanced statistical learning models to identify the key factors that will increase the risk of inoperability in the electric power sector. In this paper, we establish our framework using generalized additive model (GAM), although the framework can be easily extended to include other models as well. The data on major power outage events in the continental U.S., ranging between 2000 and 2016, is available to validate our propose framework at the state level. Our proposed framework will allow the decision makers and stakeholders such as the utility companies and state regulatory commissions to understand the risks of inoperability of the regional electricity sectors, help minimize the risk of natural hazard-induced extreme outages in the electricity sector, and improve the security of the electricity sector as a whole.

1 INTRODUCTION

Cascading outages happened due to physical damage or deviated patterns and shifts in electricity demand (Elsner et al., 2008; Elsner and Jagger, 2004; Jagger and Elsner, 2006; Knutson et al., 2010, Mukherjee et al., 2018a, 2018b). Recent natural catastrophes especially extreme hydro-climatological hazards such as floods, forest fires, droughts, and heatwaves resulted in severe weather- induced power outages. These massive outages caused by the natural disasters affect billions of dollars of economic loss (Elsner and Jagger, 2004; Jagger and Elsner, 2006; Mukhopadhyay and Nateghi, 2017; Nateghi and Mukherjee, 2017). Since the electric grid is a large, complex, geographically expanded overhead infrastructure system, highly interdependent with other critical infrastructure systems, a significant damage to this system can render the system to be inoperable to such an extent that it might take several weeks, months, or even years, to restore the system back to normal condition (Commission, 2011; Rudnick, 2011). For example, Southwest blackout in 2011 was considered to be the largest power failure in California's history causing a widespread blackout for about 12 hours affecting southern Orange County and several valleys, which affected 2.7 million people who were left without power for days (Ditler, 2011; Romero, 2011; Smith and Katz, 2013). Derecho, a severe thunderstorm, hit the Midwestern United States and the Mid-Atlantic region in 2012 causing major power failures; the power restoration in this case was very slow and the outages persisted for a long time. In West Virginia, the outages lasted longer than two weeks in most of the affected regions (Smith and Katz, 2013; Todd et al., 2012). Inoperability of electricity sector, in this paper, is defined as a metric that evaluates the extent of failure in the electricity sector in terms of various levels of supply disruption. Various research studies focused on defining and measuring the inoperability of a system. Based on the construct of the Leontief's economic input output (I-O) model introduced by Nobel Laureate Wassily Leontief (Leontief, 1986, 1951a, 1951b), Haimes and Jiang developed a derived model named Inoperability Input-Output model (IIM) Model (Haimes and Jiang, 2001). The IIM models are used to analyze the potential cascading impacts of any type of inoperability in a system due to an external shock such as terrorism, natural disaster, or high-altitude electromagnetic pulse (HEMP) and help to identify the critical infrastructures that would be affected the most (in terms of their inoperability) due to such shocks. The IIM model can quantify the total economic loss due to reduction in system capacity caused by any type of external shock on the system (Haimes, 2008, 2008; Haimes et al., 2005). In other words, it can quantify changes in monetary value owing to specific levels of inoperability; for example it can answer the question: "how much of economic loss is occurred by 33.49% inoperability of transportation sector?" (Santos, 2006). Generally speaking, the term inoperability can be expressed as a percentage of the malfunction of system due to a disruption and as-planned functioning of the system. Inoperability is expressed as a fraction ranging between 0 and 1, where 0 corresponds to a fully operational system state and 1 corresponds to a completely inoperable system state. Table 1 depicts the previous studies that use the concept of inoperability; the table indicates the causes of inoperability for various cases and states the initial values for the inoperability that were used in the studies. Santos and Haines (2004) developed Input-Output Inoperability Model (IIM) due to terrorism. The study considered a nationwide terrorism-induced 10% demand perturbation. Santos (2006) also developed Inoperability Input-Output Modeling to quantify the disruptions within an interdependent economic systems under two scenarios: (a) due to a 33.2% reduction in air transportation; and, (b) a 19.2% reduction in hotel occupancy for the 9/11 case study. Haimes (2005) developed modeling impacts of intentional attacks on interdependent sectors. The case study applied high-altitude electromagnetic pulse (HEMP) attack scenarios by assuming 5% of inoperability of all computers. Crowther (2007) evaluated major impacts of hurricanes Katrina and Rita to demonstrate this use of the IIM. The inoperability of utility sectors including electricity, water, and natural gas, resulted from the disasters as estimated by Department of Energy (DOE) report. Crowther and Haimes (2005) also used supply-side perturbation of 10% to the electricity sector to develop systemic risk assessment and management of interdependent infrastructures on the supply-side. Leung (2007) developed IIM model for a bomb explosion at an airport.

Table 1: Current studies for Inoperability analysis

Authors	Model	Cause of Inoperability	Source of Inoperability (Initial values)
Santos and Haimes (2004)	IMM	nationwide terrorism	10% inoperability (Assumption)
Santos (2006)	IMM	nationwide terrorism	33.2% reduction in air transportation and a 19.2% reduction in hotel (Data given)
Haimes (2005)	IMM	high-altitude electromagnetic pulse	5% of inoperability of all computers (Assumption)
Crowther (2007)	IMM	Hurricanes Katrina and Rita	Summary Table is given for three utilities from Sep. to Nov. (Data given)
Crowther (2005)	IMM	combination of natural disasters and terrorists attack	10% for national power outage (Data given)
Leung (2007)	IMM	A bomb at an airport	20% of the total final output of the transport sector (Assumption)

In this research, we develop a strategic planning and decision-making framework to evaluate the inoperability of the utility sector in face of several disaster types. A specific data set (Mukherjee et al., 2018c) on major power outage events in the continental U.S. ranging between 2000 and 2016 is leveraged to establish the framework based on the nine regions in the U.S. as defined by North American Electric Reliability Corporation (NERC). As a final outcome, the proposed framework will be able to evaluate the total inoperability owing to power outage caused by different disaster types in a region in a particular year.

2 METHODOLOGY

2.1 Data mining

The proposed framework consists mainly of two phases: (1) Data mining and (2) Disaster-induced utility inoperability prediction model as shown in Figure 1. The research uses the specific dataset on major power outages as described in (Mukherjee et al., 2018c). The data includes all the major power outage events in the U.S. occurred between 2000 and 2016; the dataset contains 55 variables and 1500 observations. Variable types include– duration of power outage, the geographical location of power outages, date and time of outage, local climate information, land use characteristics, consumption patterns and economic characteristics, among others.

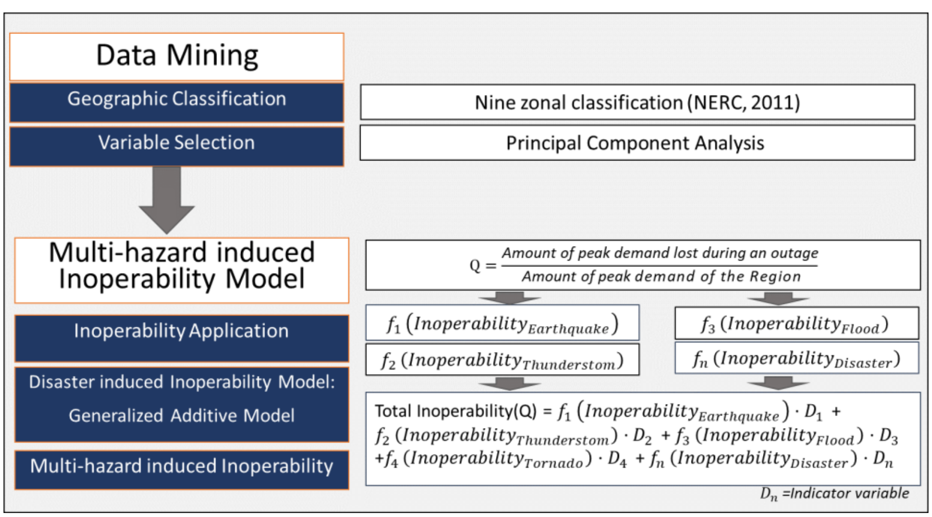


Figure 1: Research Framework

The first step of the proposed framework is for data mining including geographic classification and variable selection. The research categorized the disasters types from data set based on the NERC geographic classification (NERC, 2011). Natural disasters in the United States are affected by geographical characteristics. Federal Emergency Management Agency (FEMA) provides geographic classification with 11 regions (FEMA, 2011). The most common natural disasters to occur in FEMA region 5 including Minnesota, Indiana, Iowa, Ohio, Illinois, and Michigan were reported as severe storms (111), floods (76), and tornadoes (31), whereas floods (57), typhoons (46), and severe storms (29) were the most frequent natural disasters in FEMA region11 including California, Nevada, and Arizona. The comparison of natural disasters depending on the region classification is needed to define the inoperability and develop the inoperability predictive model. Therefore. this research applies the geographic classification provided by North American Electric Reliability Corporation (NERC) with nine regional entities. NERC provides a geographic region map to improve the reliability of the bulk power system (NERC, 2011). The map provides each reginal entity: Florida Reliability Coordinating Council (FRCC), Midwest Reliability Organization (MRO), Northeast Power Coordinating Council (NPCC), Reliability First Corporation (RFC), SERC Reliability Corporation (SERC), Southwest Power Pool, RE (SPP), Texas Reliability Entity (TRE), Western Electricity Coordinating Council (WECC) and Hawaiian Islands Coordinating Council (HICC) shown in Figure 2. In addition, NECR has published yearly based reliability assessment report with each region's total demand. This research will develop the prediction model of the utility failure for natural disasters that occurred in the designated region using the data set obtained from Imperial System of Measurement (Mukherjee et al., 2018c) and NERC reliability assessment reports (NERC, 2018a, 2018b).

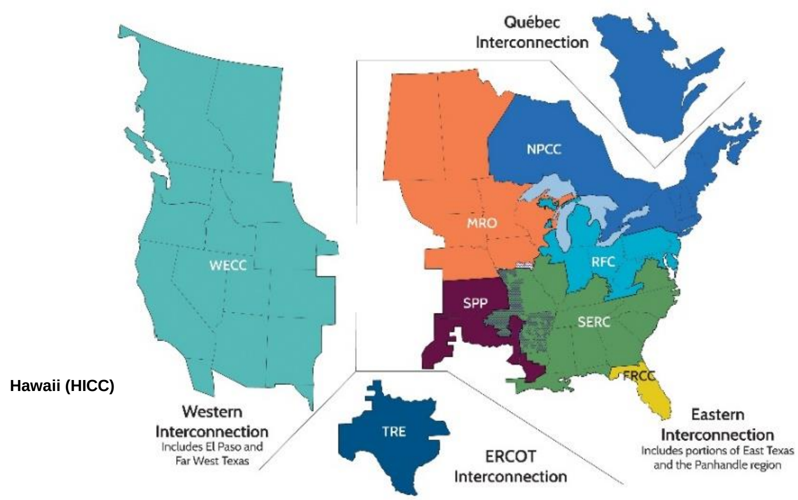


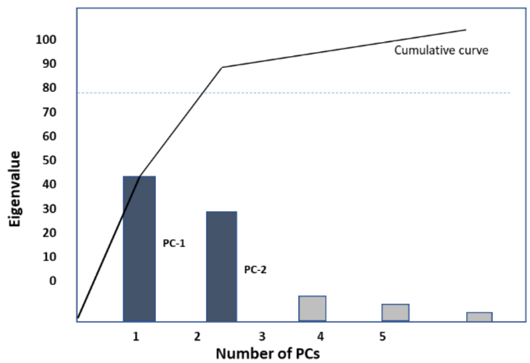
Figure 2: Geographic Map (NERC, 2011)

In order to develop the proposed inoperability model for the major power outages induced by severe weather events, variable selection was conducted using Principal component Analysis (PCA) to reduce the dimensionality of the data. PCA is performed based on the linear combination of the original variables using eigenvectors. The detailed fundamental concept of PCA as explained in detail in previous studies (Tabachnick et al. 2001, Noori et al. 2007, Nouri et al. 2008), transforms the input variables to principal components (PCs). For example, let the random vector X = $[X_1, X_2 \cdots X_p]^{\mathsf{T}}$ have the covariance matrix with eigenvalues $a_1, a_2 \cdots a_t \geq 0$. Consider the linear combinations, defined by Equation 1and 2 (Jolliffe et al. 2002, Shlens 2014).

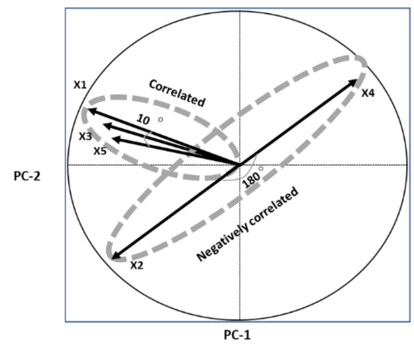
[1] $Y_i = a_1\, X_1 + a_2\, X_2 + \cdots + a_p\, X_p$

[2] $Y_i = {a_1}^T\, X$

where Y_i=principal components (PCs), a_p= eigenvector, X_p = input variables. The first principal component selects a vector value with the largest variance in the data set. This calculation continues until a total of p PCs have been calculated, which is equal to the original number of variables. One of the results of PCA is an eigenvalue chart and loading plot. The summation of the percentage of eigenvalues reaching at least 80% can help the determination of the numbers of PCs the eigenvalue chart (Lam et al. 2010) shown in (a) Eigenvalue Bar-chart in Figure 3. A loading plot is used to determine the correlations among the input variables. The angle between the two vectors in the loading plot is an approximation of the correlation between the two variables (Wold et al. 1987, Kamal-Eldin et al. 1997, Yoon et al. 2018). The two variables with 180 degrees indicate the strong negative correlation shown in (b) Loading plot shown in Figure 3.



(a) Eigenvalue Bar-chart



(b) Loading plot

Figure 3: PCA Interpretation

2.2 Multi-hazard induced Inoperability Model

Step 2 of our proposed framework is to develop a multi-hazard induced inoperability model. The original definition of inoperability (q) is the level of a system's disfunction expressed as a percentage of its 'as-planned' production capacity (Santos & Haimes, 2004). The equation of inoperability is given as:

$$[3]\ q = \frac{(as\_planned\ total\ output - reduced\ level\ of\ production)}{as\_planned\ total\ output}$$

Inoperability that is assessed using an Inoperability Input Output Model (IIM) reflects the risk of service disruption of the infrastructure that might result from various types of failures owing to complexity of the system, accidents, acts of terror, or natural disasters. This research focuses on the inoperability of the electricity sector caused by natural disaster impacts. Inoperability in our research is defined as:

$$[4]Q\ (\ Inoperability_{poweroutage}) = \frac{\textit{Amount of peak demand lost during an outage}}{\textit{Amount of peak demand of the Region}}$$

Where, $Reduced\ level\ of\ production$: Amount of peak demand lost during an outage (MW), and $As\ \_planned\ total\ output$: Amount of peak demand for the Region (NERC, 2018a, 2018b) (MW).

Generally speaking, inoperability can be explained as the ratio of the amount of peak demand during the period of reduced production (due to the disaster impact) to the total amount of peak demand of the region in a normal day. The estimated peak demand of a region in a blue-sky day refers to the "as-planned total output" of the region. NERC has estimated and evaluated the total amount of peak demand for the summer and winter for nine regions. The total amount of peak demand is estimated based on average weather conditions and assumed forecasted economic activity at the time of submittal (NERC, 2018a, 2018b). This research considers the given total amount of peak demand in 2017 or 2018 for each region as "as-planned total output". The numerator of the equation is a reduction in system capacity caused by natural disaster. The reduced level of production is expressed by the amount of peak demand lost during an outage which is one of variables obtained from the data set used in this research as described before. Therefore, the inoperability in the electricity sector resulting from a severe weather induced power outage is defined as a percentage of the amount of peak demand lost during an outage to the total peak demand of the region in a blue-sky day as shown in the Equation 4.

Next we propose to develop a Generalized additive model (GAM) to estimate and predict the hazard-induced inoperability in the electricity sector. GAM is semiparametric learning algorithm that generalizes linear models (Buja et al., 1989; Hastie and Tibshirani, 1990). The model can be applied to solve the regression problems and classification problems (James et al., 2013). The multilinear regression model is needed to explain as follows:

[5] $y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_m x_{ip} + \varepsilon_i$

Where y_i stands for the dependent variable, x_1 through x_m stand for the independent variables (predictive variables), and β_0 through β_m are the regression coefficients estimated by multiple regression. In the dependent variable y_i on the basis of several predictors, x_1 through x_m, the generalized additive model (GAM) extends traditional linear by allowing unspecified (non-parametric) functions to be considered as each predictor. The formulation of GAM is given as follows:

[6] $y_i = \beta_0 + \sum_{j=1} f_j\ (x_{ij}) + \varepsilon_i$

$= \beta_0 + f_1(x_{i1}) + f_1(x_{i1}) + \cdots + f_p(x_{ip}) + \varepsilon_i$

The smoothing function, f_i for each predictor variable x_{ij}, is estimated nonparametrically like regression splines and tensor product splines. Various functions including local regression, polynomial regression, or any combinations can be used, while implementing a GAM. In the case of this research, the GAM is applied to assess the hazard - induced inoperability for any disaster type depending on the NERC regions in the U.S. Equation 7 illustrates our proposed model:

[7] $Q(Inoperability_{Disaster}) =$

$\beta_0 + f_1\,(poweroutage\ duration) + f_2\,(number\ of\ customers\ affected) + f_3\,(demand\ loss) + \ldots\ldots +$

$f_3\,(selected\ variable) + \varepsilon_i$

Here, Q($Inoperability_{Disaster}$) is expressed as a summation of various smoothing functions of the predictor variables such as power outage duration, number of customers affected, demand loss, etc. based on the results of the variable selection process in Step 1. Individual inoperability models' response variables - $Q_1\left(Inoperability_{Earthquake}\right)$, $Q_2\,(Inoperability_{Thunderstom})$, $Q_3\,(Inoperability_{Flood})$, etc. indicate the levels of inoperability in the electricity sector that are caused by earthquakes, floods or thunderstorms, respectively. The last process of the framework is to estimate the total inoperability of the electricity sector in a NERC region caused by multiple disasters occurred in a year. After the individual inoperability models are developed for specific disaster types, they can be integrated into a single model using disaster-type indicator variables to estimate the total inoperability in a region (refer to in Equation 8).

[8] *Total Inoperability*

$= \sum Inoperability_{Disaster}$

$= Q_1\left(Inoperability_{Earthquake}\right) \cdot D_1 +$

$Q_2\,(Inoperability_{Thunderstom}) \cdot D_2 +$

$Q_3\,(Inoperability_{Flood}) \cdot D_3 +$

$Q_n\,(Inoperability_{Disaster}) \cdot D_n$

Where $D_n = 1\ if\ powere\ outage\ occures\ due\ to\ the\ n\ disaster$

$D_n = 0\ otherwise$

Q($Inoperability_{Disaster}$) is a smoothing function for each disaster obtained from the Equation 7 using GAM algorithm. Dn is an indicator variable described by 0 or 1 to indicate the absence or presence of the disaster affects on the outcome of total inoperability.

3 EXPECTED OUTCOME

Globally, with the growing frequency of disasters, risks of infrastructure failures are increasing that have threatened the communities and society, more than ever before. Especially failure of critical infrastructures leading to disruptions of essential services like power outages can impact the whole community and the economy resulting in huge cost burdens for our society and the economy. In this research, we proposed a strategic planning and decision-making framework to predict the inoperability of the utility due to several disaster types. The proposed framework mainly consists of two phases: (1) data mining and (2) inoperability model development using advanced statistical learning techniques. Step 1 is to identify the important variables that affect the inoperability model in Step2. In Step 1, feature selection is conducted leveraging principal component analysis (PCA) and regional categories as provided by NERC. The step 2 of the proposed framework is to develop an Inoperability-disaster based- prediction model based on (1) Inoperability function application, (2) Multi-hazard induced inoperability model: Generalized additive model (GAM), and (3) Total inoperability prediction. The disaster models are developed using generalized additive model (GAM) based on the regional disasters. The given data set was used to develop the inoperability prediction model for disasters. The proposed framework to predict the inoperability of the utility ultimately provides the total inoperability of utility due to several disaster types. Therefore, the proposed prediction model for inoperability can be used especially in Inoperability Input-Output Model (IIM) to identify the interdependency among industries. Furthermore, the proposed framework to predict the inoperability of the utility can help decision makers or stake holders establish natural disaster prevention and security policies in the electricity sector.

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