Modeling the economic impact of utility damage

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ABSTRACT: Infrastructure systems are vulnerable to natural hazards and typically account for a significant portion of the economic losses in a region following disruptive events. Also, disaster risk management for infrastructure requires large investments. However, probabilistic models for the economic impacts of utility damage and loss of service are not well developed, and there are no available models for predicting price increases after disasters. This paper describes the principal mechanisms by which utility damage may cause economic impacts. The paper also briefly introduces the utility rate cases used to set and regulate utility prices in the United States. The paper then develops a probabilistic formulation to predict post-disruption changes in utility prices and provides an academic illustration. The research outcomes expand the understanding of economic risk from damage to infrastructure assets, which can inform regulations for insurance requirements and price control policies in the utility sector.

Infrastructure systems are vulnerable to natural hazards (Bialek 2007; Ouyang 2014) and typically account for a significant portion of the economic losses in a region following disruptive events (Elnashai et al. 2009). Also, disaster risk management for infrastructure requires large investments, most of which are sourced locally from the region (Kane and Tomer 2019).

Most current research on the impact of natural disasters on regional economies primarily focuses on capital losses in buildings (Botzen et al. 2015; Markhvida et al. 2020). Literature has modeled the economic effects of building damage by reducing the corresponding amount of capital in the affected sectors. Buildings account for a portion of the capital in various economic sectors, and economic models capture damage to these buildings by reducing the corresponding amount from the capital of the affected sectors. Economic models (e.g., Brookshire et al. 1997; Hallegatte 2008, 2014) can then propagate the impact of building damage to various metrics of interest in the regional economy.

However, efforts to account for infrastructure damage and disruption in the regional economy have been rare, with studies excluding the damage to utilities, considering their rapid recovery (Butry et al. 2019; Cutler et al. 2016). This exclusion is unreasonable, as the limited existing research (Rose et al. 1997; Rose and Lia 2005) demonstrates that infrastructure damage can cause short- and long-term disruptions to essential resources and services, leading to significant economic impacts. Different infrastructure systems recover at different rates, with power and communications typically recovering within days, while water infrastructure recovery can take several weeks due to underground components (Sharma et al. 2020). The supply of essential resources and services, such as electricity, water, and transportation, is critical for the functioning of individuals and businesses in a region (Nocera and Gardoni 2019). Disruptions to these services can result in reduced productivity, higher operating costs, and loss of income for businesses. Infrastructure damage can also reduce a region's attractiveness for investment (Han et al. 2021), leading to long-term economic consequences. Probabilistic models for the economic impacts of utility damage and loss of service are not well developed, and there are no available models for predicting price increases after disasters. Therefore, there is a need to understand the mechanisms by which infrastructure damage and disruption may affect the regional economy.

This paper contributes to developing comprehensive and integrated approaches to modeling the economic impacts of natural disasters that consider the indirect effects of infrastructure damage and disruption. Specifically, this paper assesses the economic costs of damage and post-disaster recovery of utilities to support financial decision-making for risk mitigation. First, this paper describes the principal mechanisms by which utility damage may cause economic impacts. The paper also briefly introduces the utility rate cases used to set and regulate utility prices in the United States. The paper then develops a probabilistic formulation to predict post-disruption changes in utility prices. The formulation consists of predicting the damage to the utility assets, translating the damage to a probabilistic prediction of losses in terms of expenses and cost of replacement, and finally, predicting the rate increase based on the increased expenses and capital requirements. The paper then provides an academic illustration of the probabilistic formulation and concludes. The research outcomes can provide communities and utility companies with a clear understanding of the economic risk from damage to infrastructure assets.

1. MECHANISMS OF ECONOMIC IMPACTS FROM UTILITY DAMAGE

We identified four significant ways infrastructure damage and service disruption could impact the regional economy. We do not claim that these mechanisms are exhaustive. However, the purpose is to identify and describe significant ways which may have a significant economic impact and could also be considered using the current state of the art in modeling techniques.

1.1. Loss of building functionality

Infrastructure damage and service disruption can result in the loss of building functionality, leading to a decrease in the value of economic sectors. The impact of building damage is currently accounted for in economic models, but the loss of functionality due to infrastructure damage is often neglected. This loss of functionality due to the unavailability of infrastructure services can be short-lived. Still, it can cause a delay in the recovery of buildings, leading to a more significant and longer-lasting loss of value.

1.2. Increase in demand for materials and repair/recovery workforce

Another way in which infrastructure damage and service disruption can impact the regional economy is through the increase in demand for materials and repair and recovery workforce. This higher demand can affect the availability and price of the relevant trades, but this impact may not be significant compared to the demand for building repair and recovery. Infrastructure repairs typically require specialized materials and crews that are typically not local. Furthermore, the total scope of work in infrastructure may be small compared to the overall demand due to building damage.

1.3. Direct capital loss due to infrastructure damage

Similar to buildings, infrastructure also accounts for direct capital losses. Therefore, capital loss in infrastructure assets can significantly impact the regional economy. However, the data on financial losses of infrastructure assets is limited, and accounting for the capital loss in infrastructure damage will require the inclusion of infrastructure/utility sector(s) in economic modeling.

1.4. Rate hikes in infrastructure services

The fourth way in which infrastructure damage and service disruption can impact the regional economy is through rate hikes in infrastructure services. Infrastructure damage and service disruption can cause long-term rate hikes in infrastructure services as the infrastructure sectors spend significant funds on recovery. Both capital requirements and operation and maintenance expenses increase during the post-disaster recovery, leading to rate hikes in utilities. The rate increases can be due to legislation requiring infrastructure improvement or recovery of damages. Recent trends show that annual rate changes requested by utilities have been increasing (EIA 2018).

We identify the direct capital loss, and the utility rate hikes as the two most significant ways in which infrastructure damage and service disruption can impact the regional economy. The rest of the paper provides more details on these aspects.

2. UTILITY RATE CASES

A utility rate case is a process in which a utility company submits a request to a regulatory body, such as a state public utilities commission, to approve a rate increase. The utility must demonstrate that its current rates are no longer reasonable and that the proposed increase is necessary to cover the costs of providing its services, including capital expenditures, operation and maintenance expenses, and any other costs approved by the regulatory body. After reviewing the utility's proposal, the regulatory bodies decide whether to raise rates and to what extent. Regulatory commissions consider several aspects, such as the utility's costs, financial situation, and prospective impacts on the various classes of consumers. The rate case procedure is crucial for ensuring that utility rates are fair and reasonable and that utilities have the funds necessary to offer their customers safe, dependable, and economical services.

2.1. Typical structure of a rate case

A regulator-approved rate case means that the rates are not decided in a free market. Most utilities in the US operate on a cost-plus basis for electricity pricing. Hence the first step for a rate case is simply estimating the total cost of providing electricity, known as the *revenue requirement*. Mathematically, the revenue requirement (Davis 2017) is estimated as

$$\mathcal{R} = E + Ci \tag{1}$$

where $\mathcal{R}$ is the revenue needed to cover costs, including a fair return to investors, E is the total *expenses*, which may include operating and maintenance expenses, depreciation and amortization on assets, income, and general tax expenses, C is the *capital* supplied by the investors, which may include the net assets after depreciation, and working capital after excluding deferred income tax and other adjustments, i is the *cost of capital* that includes the cost of debt or the average interest rate paid on outstanding debt. It also includes the cost of equity, i.e., the return an investor expects to receive when they buy stock.

The price of electricity is then reached for different consumers based on the class of consumer and the portion of total energy usage by the class (Gonzalez 2019). There are primarily three classes, i.e., residential, commercial, and industrial. In theory, each class of consumer pays the utility's costs to serve their class. However, the distribution is debatable and ultimately decided after deliberations in a public process. There are many ways to distribute costs across consumers that may consider dynamic demand, total energy usage, peak usage, and economic status.

2.2. US electricity rate case trends

Figure 1 shows that the electricity rate cases submitted by the utilities have been increasing in recent years.

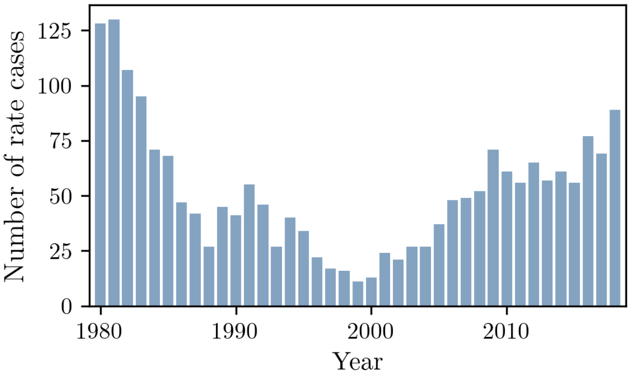

Figure 1: US electricity rate Cases filed with utility regulators (EIA 2018).

Figure 2 shows the value of the rate increases in billion dollars, both the amount requested by the utilities and finally approved by the regulators after the review process. We observe that the approved amounts typically follow the same trend as the requested amount, with regulators consistently approving a significant portion of the requested amount. The rate cases typically correlate with significant changes in the utility market. For example, utilities may request rate increases due to legislation requiring infrastructure improvement, such as risk mitigation actions. As a result, there were significant price increases after the Energy Policy Act of 2005, and the American Recovery and Investment Act of 2009 were enacted. The rate increases may also correspond to the recovery of losses from significant disruptions such as the Northeast blackout in 2003 and Hurricane Sandy in 2012. However, federal legislative actions show higher raises because disruptions do not affect the whole market but are typically limited to a small number of utility companies serving an affected region.

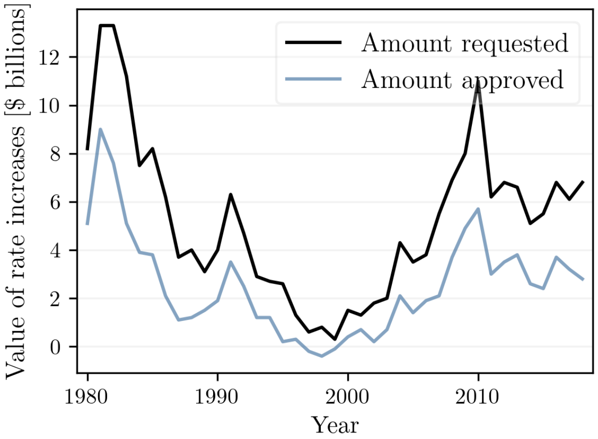

Figure 2: Total value of US electricity rate increases (EIA 2018).

2.3. Relevance to regional economic losses

Rate hikes are simply a distributed impact of infrastructure damage, which is directly experienced by the consumers. Furthermore, because most residential consumers pay the same price for utilities, rate hikes are a form of economic impact that is distributed inequitably. Also, the way rate cases are set up; utilities are often incentivized to spend more to earn more. Utility costs are passed down to consumers, so they may also have less incentive to perform proper risk mitigation.

Additionally, as price changes in utility services are regulated, they can be reasonably predicted based on damage estimates. The price predictions enable using economic models to understand better the indirect impacts that may occur on other sectors.

3. PROBABILISTIC FORMULATION FOR PREDICTING RATE INCREASES

This section provides a brief overview of the formulation for predicting rate increases. The formulation has three sub-models to predict 1) damage, 2) expenses and cost of replacement, and 3) regulatory approval.

3.1. Modeling damage

Modeling the damage to infrastructure components includes predicting their probability of being in a particular damage state(i.e., fragility), given the intensity vector of the hazard, $\mathbf{IM}$ and the state variables, $\mathbf{x}$, defining the components, such as material properties. Various predictive models in the literature provide such predictions for various types of infrastructure components and hazards. However, it is essential to consider various uncertainties in predicting the damage (Der Kiureghian and Ditlevsen 2009). We use probabilistic capacity models and demand models

$$C(\mathbf{x}) = C[\mathbf{x}, \mathbf{\Theta}_C] \tag{2}$$

$$D(\mathbf{x}) = D[\mathbf{x}, \mathbf{IM}, \mathbf{\Theta}_D] \tag{3}$$

to write the limit state function $g(\mathbf{x}) = C(\mathbf{x}) - D(\mathbf{x})$, where the event $\{[\mathbf{IM}, \mathbf{x}]: g(\mathbf{x}) \leq 0\}$ represents the failure to meet a specified performance level separating the two distinct damage states (Gardoni et al. 2002; Der Kiureghian 2008). Here $C(\mathbf{x})$ and $D(\mathbf{x})$ are the respective capacity and demand models, while $\mathbf{\Theta}_C$ and $\mathbf{\Theta}_D$ are the respective model parameters. We can then write the conditional failure probability (i.e. fragility) as $\mathcal{F}[\mathbf{IM};\mathbf{\Theta}] = \mathbb{P}[g(\mathbf{x}) \leq 0|\mathbf{IM}]$, where $\mathbf{\Theta} = \{\mathbf{\Theta}_\mathbf{x}, \mathbf{\Theta}_C, \mathbf{\Theta}_D\}$. Following Gardoni (2002), we can obtain the predictive estimate of the fragility as $\mathcal{F}[\mathbf{IM}] = \int \mathcal{F}[\mathbf{IM};\mathbf{\Theta}]f(\mathbf{\Theta})d\mathbf{\Theta}$, where $f(\mathbf{\Theta})$ is the probability density function (PDF) of $\mathbf{\Theta}$. Given the fragility function $\mathcal{F}[\mathbf{IM}]$, we can write the probability of failure for a specific limit state as $\mathcal{P}_f = \int \mathcal{F}[\mathbf{IM}]f(\mathbf{IM})d\mathbf{IM}$, where $f(\mathbf{IM})$ is the PDF of $\mathbf{IM}$.

3.2. Modeling replacement cost

The damage prediction models provide the probabilities of the components being in different damage states. The next set of models translates these probabilities into probabilistic loss based on the replacement cost. We can use two methodologies for this step based on the information on infrastructure inventory. First, following Bai et al. (2009) and HAZUS (FEMA 2014) we can estimate the damage factors, L_k for each damage state k. The damage factors are the ratio of the cost to restore a component in a specific damaged state to the cost of a complete replacement. We can then propagate the uncertainty in damage states to the uncertainty in the loss; for example, Bai et al. (2009) write the expected loss as

$$\mathbb{E}[L|\mathbf{IM}] = \textstyle\sum_k L_k|\mathcal{P}_{k|\mathbf{IM}} \tag{4}$$

where $\mathcal{P}_{k|\mathbf{IM}}$ is the proability of being in the damage state k given $\mathbf{IM}$. Alternatively, if we have more specific information on the recovery schedules and the recovery process for each component or the infrastructure as a whole, we can follow Sharma et al. (2020) to model the recovery process and estimate the cost of replacement using estimates for the material, labor, and contractual costs.

Using the financial loss estimates, we can then use Eq. (1) to arrive at a revenue requirement.

3.3. Modeling regulatory approval

The predictive model for regulatory approval is essentially a regression model based on various predictors such as the utility financial health variables, availability of federal and state support for disaster recovery, region demographics, and demand distribution in various classes.

In this paper, we use the data from EIA presented in Section 2 to develop a simple predictive model for estimating the proportion of approved rate increases versus the calculated rate increase.

4. APPLICATION

We apply the proposed formulation on the case of power infrastructure in Shelby County, TN, subject to a scenario earthquake. We use an M 7.6 earthquake scenario occurring more than 50 miles north of Shelby County, leading to moderate or strong ground shaking. Event details and hazard intensities are available online from USGS (2014). This scenario is from USGS Shakemap's Building Seismic Safety Council 2014 scenario catalog (Petersen et al 2014). The inventory of the power infrastructure is available in Sharma and Gardoni (2022). For the rate case prediction, we only consider the portion of electric infrastructure under the control of the local utility company. This example is a purely academic illustration and does not represent the financial reality of the utility companies in the region because we assume the financial variables and perform a simplistic accounting.

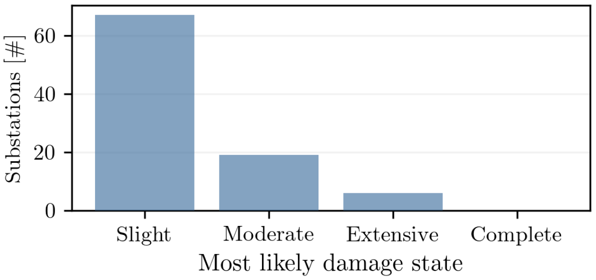

Figure 3: Most likely damage state of substations.

We perform the structural fragility analysis for 92 substations in 60 locations (different level voltage circuits at the same location have different fragilities) and corresponding distribution circuits. We use the structural fragilities available in FEMA (2014). Figure 3 shows the most likely damaged state of the substations. We observe that this scenario leads to minor to moderate damages, with only a few substations extensively damaged.

We then use the damage factors also available in FEMA (2014) to predict the loss percentage for each component in terms of the total replacement costs. The expected losses come out to be 14.3% of the replacement value of substations and 2.3% of the replacement value of all low-voltage distribution circuits.

According to the annual report of the local utility, their operating revenue for the electricity division is 1.3 billion dollars, with an asset value of 1.8 billion dollars (MLGW 2021). Considering the utility assets' overall diversity, we assume that the substation-like assets represent 70% of the total asset values, and distribution circuits represent 30%, which would require at least 190.2 million dollars in capital to recover the minor damages. Now, if the utility opts for recovering these damages directly as expenses, it would ask for a 14.6% increase in electricity prices (see Equation 1). We then model the approval rate using the marginal distribution of the approval ratio based on past data (EIA 2019). The expected approval proportion in value over past cases is 38.45% of the requested amount (see Figure 2). Hence, the expected increase in utility prices would be 5.6%.

This simple example shows that even if one considers a scenario earthquake with only moderate damage to the affected area, it still leads to significant damages and rate increases in utility prices over the region.

5. CONCLUSIONS

This paper presented a comprehensive approach to modeling the economic impacts of infrastructure damage. First, this paper described the various mechanisms by which utility damage may cause economic impacts. The paper then provided background and data on the utility rate cases in the United States. Finally. The paper then developed a probabilistic formulation to predict post-disruption increases in utility prices. The formulation was then illustrated using an example of an electric utility subject to a probabilistic earthquake hazard. The results indicate the capability of the proposed formulation in informing the communities and utilities of the economic risk of natural hazards on the financial health and, thus, utility cost for consumers. The results of the models can also be used as inputs to regional economic models for propagating the long-term indirect impacts on other sectors of the economy. Future work on the topic focuses on improving the predictive models for the regulatory approval process and generating the datasets for the financial information and past rate case records for various utilities, specifically for regions with frequent hazard exposure in the US.

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