Leader-follower equilibria to examine investment decisions in grid resilience-enhancing measures

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Abstract

Large-area, long-duration power outages are increasingly common in the United States, and cost the economy billions of dollars each year. Building a strategy to enhance grid resilience requires an understanding of the optimal mix of preventive and corrective actions, the inefficiencies that arise when self-interested parties make resilience investment decisions, and the conditions under which regulators may facilitate the realization of efficient market outcomes. We develop a bi-level model to examine the mix of preventive and corrective measures that enhances grid resilience to a severe storm. The model represents a Stackelberg game between a regulated utility (leader) that may harden distribution feeders before a long-duration outage and/or deploy restoration crews after the disruption, and utility customers with varying preferences for reliable power (followers) who may invest in backup generators. We show that the regulator's denial of cost recovery for the utility's preventive expenditures, coupled with the misalignment between private objectives and social welfare maximization, yields significant inefficiencies in the resilience investment mix. Allowing cost recovery for a higher share of the utility's capital expenditures in preventive measures, extending the time horizon associated with damage cost recovery, and adopting a storm restoration compensation mechanism shift the realized market outcome towards the efficient solution. If about one fifth of preventive resilience investments is approved by regulators, requiring utilities to pay a compensation of $365 per customer for a three-day outage (about 7 times the level of compensation currently offered by U.S. utilities) provides significant incentives towards more efficient preventive resilience investments.

Keywords: Grid resilience, preventive measures, corrective measures, bi-level optimization models, rate-of-return regulation.

1 INTRODUCTION

In the context of electricity supply, resilience describes the ability to "withstand and recover rapidly from disruptions" (United States, & Obama, B., 2013), including widespread, long-duration (WLD) power interruptions that often stem from extreme weather events (National Academy of Sciences, Engineering, and Medicine, 2017, 2021). The resilience of a system depends on its vulnerability (i.e., the fraction of electricity demand that is no longer served after the disturbance) and the speed at which it recovers its functionality. Translating vulnerability and recovery into metrics that can inform grid resilience planning and response after a major disturbance is not straightforward (Kwasinski, 2016; Vugrin et al., 2017). As a result, utilities do not currently have models to select measures that would enhance system resilience at the lowest cost. In particular, it is unclear how much utilities should allocate towards preventive measures that reduce vulnerability to long-duration outages (e.g., hardening distribution feeders), corrective actions that promote faster system recovery when major outages occur (e.g., deployment of restoration crews), and preventive measures that enhance flexibility to respond or lower the costs of corrective actions (e.g., installation of advanced metering infrastructure for faster power restoration).

State regulators in the U.S. currently allow recovery of restoration costs from the ratepayers after a major disruption, but resist funding preventive measures that may only yield occasional benefits, while raising costs for ratepayers (Keogh et al., 2013; Edison Electric Institute, 2014; National Academy of Sciences, Engineering, and Medicine, 2017; Plumer and Penn, 2021). According to a national survey by the North Carolina Clean Energy Technology Center, out of $15.7 billion in grid improvements under consideration last year, regulators approved only $3.4 billion, or about one fifth (MacMillan and Englund, 2021). As a result, utilities are reluctant to invest in preventive measures that may reduce costs and outage impacts from a major disruption, but spend heavily to fix components that failed during the event (Mukhopadhyay and Hastak, 2016). This approach may not yield the best mix of resilience-enhancing investments by the utilities. In addition, utility customers may take actions to mitigate losses associated with power interruptions, for example by investing in backup emergency generators. The misalignment between the objectives of private parties may contribute to an inefficient societal mix of resilience-enhancing investments. Going forward, these inefficiencies raise serious concerns due to the increasing frequency and intensity of severe weather events.

In this paper, we develop a game-theoretic model to examine the mix of preventive and corrective measures that enhances grid resilience to a severe storm event. The model represents a bi-level Stackelberg game between a regulated utility (leader) and utility customers with varying preferences for reliable power (followers). The utility makes investments in preventive and corrective resilience-enhancing measures, while the customers may invest in backup generators that reduce unserved energy during an outage. A bi-level approach is helpful in the analysis of resilience investment planning for several reasons. First, a non-cooperative framework is appropriate because private parties that are involved in making resilience investments have conflicting objectives (profit maximization for the utility, maximization of net benefit from power consumption for the consumers). Further, preventive resilience investments exhibit features of public goods in that their costs are certain, localized and borne by the utility, while the associated benefits are uncertain, diffused broadly across society, and may not accrue over the commercial lifetime of the project. As a result, inefficiencies may arise when self-interested parties make investment decisions, and utilities may tend to underinvest in resilience (Sanstad et al., 2020). Second, the sequential nature of the game is aligned with hierarchical decision-making in this setting. Specifically, utilities are often required to develop multi-year plans to mitigate the impact of major events on customers through infrastructure storm hardening. Their proposals for preventive investments are assessed in regulatory proceedings known as rate cases, and resulting decisions affect electric rates, outage probability, damage costs, and the electricity demand that could be served during the outage. Given the utility's decisions, consumers would invest in backup generation around the time of a major disruptive event. Finally, a bi-level approach allows us to account for potential distortions caused by the rate-making process. Under rate-of-return regulation, electric rates are set to generate enough revenue to cover utility costs approved by the regulator, and provide a fair rate of return. Rates based on average cost may not provide appropriate incentives to enable the type of investments that may be needed to enhance grid resilience.

The rest of the paper proceeds as follows. Section 2 discusses the paper contribution to three strands of the literature. In Section 3, we present a simple analytical model to develop intuition about why regulated utilities in a rate-of-return regime may not be inclined to overinvest in capital that enhances grid resilience, as posited by a well-known theory of regulation (Averch and Johnson, 1962). Next, we present our bi-level optimization model and discuss the solution approach in Section 4. Section 5 presents the data, Section 6 discusses the results, and Section 7 provides concluding remarks.

2 LITERATURE REVIEW

Thematically, our paper contributes to the literature that seeks to improve risk management for high-impact, low-frequency events, with a focus on utility spending on resilience-enhancing measures. Methodologically, our work builds on economic models that examine the effect of rate-of-return regulation on the decisions of regulated monopolies, as well as bi-level optimization models in the framework of non-cooperative game theory.

2.1 Risk management for high-impact, low-frequency events

As noted in Linkov et al. (2014), risk analysis quantifies the expected loss of critical functionality in a system, based on the characterization of threats, vulnerabilities and consequences of adverse events, while risk management helps the system prepare and plan for these events. Current risk management practices in the electric power sector are well-established for several types of threats (e.g., low-intensity hurricanes and wildlife), but nascent for high-impact, low-frequency events (e.g., severe storms) (Preston et al., 2016). Within the literature providing insights to policy makers for managing risks from these events, past work has focused on measuring resilience to identify critical components in the network (Henry and Ramirez-Marquez, 2012), analyze system performance (Zobel, 2014; Kwasinski, 2016) and quantify community resilience-enhancing interventions (Yu and Baroud, 2019; Logan and Guikema, 2020). In addition, some studies have developed methods for selecting resilience-enhancing projects (Barker et al., 2013; Baroud et al., 2014; Pant et al., 2014; Bostick et al., 2017), and conducted vulnerability assessments of interconnected infrastructures under natural hazards (Poljanšek et al., 2012; Hernandez-Fajardo and Dueñas-Osorio, 2013; Ouyang and Dueñas-Osorio, 2014; Baroud et al., 2015; Salman et al., 2015; Fang et al., 2019). Our study is most closely related to the literature that examines trade-offs between preventive and corrective measures to enhance resilience (MacKenzie and Zobel, 2016; Reilly et al., 2017; Eyer and Rose, 2019).

MacKenzie and Zobel (2016) present an optimization framework to help a decision-maker allocate resources to lessen the impacts of a disruption (preventive resilience measures) or improve recovery time (corrective resilience measures). An interesting feature of this analysis is the use of alternate functional forms to describe resource allocation, whose parameters are estimated based on utility data. The proposed model is applied to illustrate how an electric utility might spend $1 billion to improve grid resilience after a hurricane. The authors find that the utility should allocate between 50% and 65% of its budget to preventive measures, and the rest of the budget to corrective measures.

Reilly et al. (2017) explore how customer decisions to install backup generators affect system-level hardening and a community's likelihood of losing power after repeated hurricanes. A distinctive feature of the study is the combination of power outage forecasting and customer behavioral responses through an integrated outage prediction and agent-based model. Each agent's action depends on their experience during the storm, the experience of their neighbours, and their beliefs. If enough customers lose power or file a complaint, the utility is required to harden its system, and the number of customers who lose power in future events is reduced according to the extent of the hardening. From a policy perspective, sensitivity analysis of the integrated model is useful to show what parameters drive system-wide changes affecting reliability, and what levers may be perturbed to improve outcomes. However, the modeling framework in Reilly et al. (2017) is not well suited for providing insights into the optimal mix of resilience-enhancing measures, and does not consider the effect of the utility's decisions on retail electricity prices.

Finally, Eyer and Rose (2019) analyze the tradeoffs between preventive and corrective resilience-enhancing measures in a framework that includes consumer actions, such as investment in backup generation. Like MacKenzie and Zobel (2016), Eyer and Rose (2019) assume that a single benevolent social planner selects the optimal amount of resilience investments for the utility and the consumers. Additional assumptions (e.g., a Cobb-Douglas form for the damage function) allow for analytical solutions, but introduce some limitations in the analysis.

Our paper contributes to this strand of the literature by supporting analysis of resilience-enhancing investment decisions in a framework that accounts for potential distortions due to parties acting in their self interest and rate-of-return regulation.

2.2 Effect of rate-of-return regulation on the decisions of regulated monopolies

Rate-of-return regulation is the traditional method for regulating distribution utilities in the U.S. electric power industry (Kassakian et al., 2011). Under this form of regulation, state public utility commissions determine an allowed rate of return for the regulated firm, as well as the capital on which this return can be earned (known as the rate base). The allowed profit for the regulated utility is given by the product of rate of return and rate base. Given this profit level, the regulatory agency selects prices that result in the firm earning that profit (Viscusi et al., 2005). Rate-making occurs in proceedings known as rate cases, which are usually held every few years. Once prices are set, they remain fixed until the next rate case. By setting utility revenues equal to utility costs (including a return on investment in the rate base), rate-of-return regulation ensures full cost recovery. However, it creates minimal incentives for cost efficiency, because any profit gains are taken away by the regulator lowering prices in the next rate case.[1] Further, rate-of-return regulation may create perverse incentives to invest in capital beyond the cost-minimizing level, as shown by Averch and Johnson (1962). Their seminal paper presents an economic model of the effects of rate-of-return regulation on input choices of a profit-maximizing monopolist. Under some strong assumptions, they show that the regulated firm would choose too much capital relative to other inputs because its allowed profit is directly proportional to the rate base. Empirical tests of the Averch-Johnson (hereafter AJ) predicted bias toward capital intensity have yielded mixed results for the electric utility industry (Boyes, 1976; Spann, 1974; Courville, 1974; Petersen, 1975). Further, it has been argued that the AJ theory ignores attributes of real-world regulatory processes (Joskow, 1974; Joskow and Noll, 1981). As a result, some theoretical models analyze the efficiency of production and market decisions of regulated utilities in a setting where profits fluctuate within an error band, and regulatory review is triggered by zero profits (when the utility requests a review to raise the electricity price) or excessive profits (when customer groups request a review to lower the electricity price) (Burness et al., 1980; Braeutigam and Quirk, 1984; Teisberg, 1993). Other models using an AJ-type characterization examine the effect of relaxing model assumptions on the results. For example, Klevorick (1973) and Peles and Stein (1976) consider the effect of uncertainty, Bailey (1973) and Davis (1973) analyze regulatory lag, Gollop and Karlson (1978) and Joskow and MacAvoy (1975) discuss fuel adjustment clauses, and Douglas et al. (2009) account for regulatory cost disallowances on capital.

Our paper contributes to this literature by presenting an economic model of the AJ type to develop intuition about why regulated utilities in a rate-of-return regime may not be inclined to overinvest in capital that enhances grid resilience. If these expenses were allowed to become part of the rate base, the AJ theory would posit overinvestment in preventive measures, which contrasts with empirical evidence presented in Section 1. We build on the characterization of regulation offered by Douglas et al. (2009),

[1] As a result, regulatory practices have evolved to provide better incentives for cost reduction through regimes that decouple a utility's revenue from its actual costs, such as earnings sharing, price caps and yardstick regulation (Joskow, 2008).

who add some richness to the basic A-J model by considering regulatory cost disallowances on capital. Relative to their paper, we consider the effect of the risk of disallowances on the cost of capital of the regulated firm (i.e., we distinguish between the risk-free cost of capital, and the cost of capital that is required to compensate for the risk of regulatory cost disallowance). Further, we generalize their results by showing that overcapitalization bias does not always hold unless strong assumptions are made, and the regulated firm may underinvest in capital under some conditions.

2.3 Mathematical programs with equilibrium constraints

The Stackelberg model of duopoly (von Stackelberg, 1934) is appropriate for studying non-cooperative games with sequential moves in which a dominant player (or leader) chooses quantity first, and one or more subordinate players (or followers) choose their quantity after observing the leader's decision. The leader is aware that its actions influence the output choice of the followers, can anticipate their reaction, and uses this knowledge when selecting its own optimal strategy. The relevant equilibrium concept is the Stackelberg (subgame perfect Nash) equilibrium, which represents the only Nash equilibrium associated with the backwards induction outcome of the game (Gibbons, 1992). Stackelberg games are closely related to bi-level models in which (1) the optimization problem of the leader is presented at the upper level, (2) the optimization problems of the followers are given at the lower level, and (3) the upper level problem is constrained by the reaction of the followers. Considering the upper level problem and replacing the lower level problems by their Karush-Kuhn-Tucker (KKT) optimality conditions in the constraint set renders a mathematical program with equilibrium constraints (MPEC) (Luo et al., 1996).

The MPEC modeling framework has found wide application in areas like transportation (LeBlanc and Boyce, 1986; Labbé et al., 1998; Gao et al., 2004; Lawphongpanich and Hearn, 2004; Codina et al., 2006; Huang et al., 2016; Patriksson, 2008), facility location (Meng et al., 2009), and microbiology (Burgard et al., 2003; Zomorrodi and Maranas, 2012). In the energy sector, MPECs have been applied to study strategic behavior in day-ahead and real-time electricity markets (Kamat and Oren, 2004; Yao et al., 2008), transmission pricing in congested pricing of electric transmission (Hobbs and Kelly, 1992; Pepermans and Willems, 2005), generation capacity expansion decisions (Murphy and Smeers, 2005; Kazempour et al., 2011; Wogrin et al., 2011; Baringo and Conejo, 2012; Kazempour et al., 2012), bio-fuel production (Bard et al., 2000), and the natural gas market (Wolf and Smeers, 1997; Boots et al., 2004). Non-cooperative games that model restructured electricity markets over a network of generators and consumers have also adopted an MPEC structure (Cardell et al., 1997; Hobbs et al., 2000; Ruiz and Conejo, 2009; Gabriel and Leuthold, 2010). Chen et al. (2006) model the ability of the largest producer in an electricity market to exercise market power in the electricity and emission allowance markets. The largest producer plays the role of the Stackelberg leader in the MPEC, while medium-sized firms, the independent system operator and arbitrager are followers. Daxhelet and Smeers (2007) present MPECs to study the regulation on cross-border exchanges of electricity in the European Union: regional regulators from different countries (leaders) decide on the allocation of their network costs between generators and customers in order to maximize their country's net benefits, subject to the response of the electricity market (follower). Finally, Stackelberg games have been used to model the interactions between a utility company and its customers (Hobbs and Nelson, 1992; Maharjan et al., 2013; Yu and Hong, 2016). For example, Hobbs and Nelson (1992) present a bi-level model to study utility-sponsored energy conservation programs: the utility at the upper level (leader) seeks to maximize social welfare while setting electric rates and subsidizing energy conservation programs, while customers at the lower level (followers) maximize their net benefit by consuming electricity and investing in conservation.

Our paper contributes to this strand of the literature by applying bi-level models to utility spending on resilience-enhancing measures, which has emerged as a central policy concern in recent years, as highlighted by the Texas electricity crisis in February 2021.

3 ANALYTICAL MODEL

In this section, we present a simple analytical model to develop intuition about why electric utilities under traditional rate-of-return regulation may not be inclined to overinvest in capital that enhances grid resilience. As in Averch and Johnson (1962), we consider a monopolist that produces output using two resources, capital and labor. The firm maximizes profit, subject to a regulatory constraint on the allowed rate of return on capital s_K, and a technological constraint where output is bounded by a production function $F(L,K)$. The AJ theory posits that, if s_K exceeds the (risk-free) cost of capital P_K but is below the rate of return that would be enjoyed by the firm absent regulation, the firm will overinvest in capital stock. This result is derived in Appendix A, under the assumption that there is no regulatory cost disallowance.

Here, we assume instead that the regulator allows a share ϕ of the firm's capital expenditures to be included in the rate base, where $0 < \phi < 1$. This is supported by empirical evidence in our setting (Section 1) and, as noted by Mukhopadhyay and Hastak (2016), is expected to increase the riskiness of the firm's capital investments. As a result, the cost of capital would increase to r_K, where $r_K > P_K$. Let K denote the quantity of capital input chosen by the firm, L the quantity of labor input, P_L the cost of labor, and r_K be the cost of capital that is required to compensate for the risk of regulatory cost disallowance. The firm maximizes profit, defined as:

$$R(Y) - r_K \cdot K - P_L \cdot L \tag{1}$$

where $R(Y)$ is the revenue function. Assuming that depreciation is zero and the acquisition cost of capital is equal to 1, as in Averch and Johnson (1962), the regulatory constraint is:

$$R(Y) - P_L \cdot L - s_K \cdot \phi \cdot K \leq 0, \qquad (\lambda) \tag{2}$$

where the allowed rate of return s_K only applies to the share of capital expenditures included in the rate base, $\phi \cdot K$, and λ is the dual variable associated with the constraint. Finally, the technological constraint is:

$$Y \leq F(L, K), \qquad (\mu) \tag{3}$$

The Lagrangian function $\mathcal{L}$ is given by:

$$\mathcal{L} = [R(Y) - r_K \cdot K - P_L \cdot L] - \lambda \cdot [R(Y) - P_L \cdot L - s_K \cdot \phi \cdot K] - \mu \cdot [Y - F(L, K)] \tag{4}$$

and the first order conditions that result from maximizing equation (4) are:

$$\frac{\partial \mathcal{L}}{\partial L} = P_L \cdot (\lambda - 1) + \mu \cdot F_L = 0 \tag{5}$$

$$\frac{\partial \mathcal{L}}{\partial \mu} = F(L, K) - Y = 0 \tag{6}$$

$$\frac{\partial \mathcal{L}}{\partial K} = -r_K + \lambda \cdot s_K \cdot \phi + \mu \cdot F_K = 0 \tag{7}$$

$$\frac{\partial \mathcal{L}}{\partial Y} = (1 - \lambda) \cdot R^{'} - \mu = 0 \tag{8}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = -R(Y) + P_L \cdot L + s_K \cdot \phi \cdot K = 0 \tag{9}$$

where $F_K = \frac{\partial F(L,K)}{\partial K} > 0$, $F_L = \frac{\partial F(L,K)}{\partial L} > 0$ and $R' = \frac{\partial R(Y)}{\partial Y} > 0$. Next, assume that the firm produces an output level on the transformation frontier (i.e., $Y = F(K, L)$), implying that $\mu > 0$. Under the assumption that $s_K > P_K$,[2] it follows that $0 < \lambda < 1$ (Averch and Johnson, 1962). Finally, let $G = R(F(K, L))$ be concave to satisfy the second-order condition for maximization: thus, the marginal revenue product of capital is $G_K = R^{'} \cdot F_K$, and the marginal revenue product of labor is $G_L = R^{'} \cdot F_L$. Combining (5) and (8) we get:

$$P_L \cdot (\lambda - 1) + (1 - \lambda) \cdot G_L = 0 \tag{10}$$

This implies that the firm invests in labor L efficiently, because the marginal cost P_L is equal to the marginal revenue product G_L:

$$P_L = G_L \tag{11}$$

Similarly, combining (7) and (8) and using the definition of G_K, we have:

$$-r_K + \lambda \cdot s_K \cdot \phi + (1 - \lambda) \cdot G_K = 0 \tag{12}$$

To examine whether overcapitalization bias holds in the revised model, we consider two cases: $s_K > r_K > P_K$ or $r_K > s_K > P_K$.

[2] Averch and Johnson argue that $s_K > P_K$ is the interesting case in their static model. If $s_K < P_K$, the firm would prefer to shut down, while if $s_K = P_K$ the firm would be indifferent between the chosen quantities of capital and labor input.

Case I: $s_K > r_K > P_K$

Under the assumption that $s_K > r_K$, equation (12) becomes:

$$-r_K + \lambda \cdot r_K \cdot \phi + (1 - \lambda) \cdot G_K < 0 \tag{13}$$

or equivalently:

$$(1 - \lambda) \cdot G_K < (1 - \lambda \cdot \phi) \cdot r_K \tag{14}$$

Note that, while in the basic Averch-Johnson model $P_K > G_K$, we cannot conclusively compare r_K and G_K here. Further, totally differentiating equation (9) with respect to s_K yields:

$$-G_K \cdot \frac{dK}{ds_K} - G_L \cdot \frac{dL}{ds_K} + P_L \cdot \frac{dL}{ds_K} + \phi \cdot K + s_K \cdot \phi \cdot \frac{dK}{ds_K} = 0 \tag{15}$$

and substituting $P_L = G_L$ in equation (15) we find that:

$$\frac{dK}{ds_K} = \frac{\phi \cdot K}{G_K - \phi \cdot s_K} \tag{16}$$

In the AJ model, the ratio dK/ds_K is negative, as shown in Appendix A. In equation (16), the sign of dK/ds_K critically hinges upon the relation between $\phi \cdot s_K$ and G_K. Under the assumption that the post disallowance rate of return $\phi \cdot s_K$ exceeds the marginal revenue product of capital G_K (as in Douglas et al. (2009)), the ratio dK/ds_K is negative and the Averch-Johnson effect holds. However, this assumption does not hold in general, and has no empirical support in the context of capital investments that improve the resilience of the grid. Thus, overcapitalization bias does not hold conclusively under regulatory cost disallowances on capital, if $s_K > r_K$.

Case II: $r_K > s_K > P_K$

Under the assumption that $s_K < r_K$, equation (12) becomes:

$$-r_K + \lambda \cdot r_K \cdot \phi + (1 - \lambda) \cdot G_K > 0 \tag{17}$$

or equivalently:

$$(1 - \lambda) \cdot G_K > (1 - \lambda \cdot \phi) \cdot r_K \tag{18}$$

Since $s_K > P_K$, it follows that $0 < \lambda < 1$. Further, $0 < \phi < 1$. Hence, unlike Case I, we can infer that $r_K < G_K$. Totally differentiating equation (9) with respect to s_K and substituting $P_L = G_L$ in the result, we obtain equation (16). Since $s_K < G_K$ and the denominator of equation (16) is positive, the ratio dK/ds_K is positive. Thus, if the allowed rate of return exceeds the risk-free cost of capital but is below the cost of capital required to compensate for the risk of regulatory cost disallowance, the firm will underinvest in capital, yielding a "reverse Averch-Johnson effect" (Graves, 1982; Kolbe et al., 1993).

A comparison of assumptions and insights from the AJ model and the revised model in this section is presented in Table I. In sum, overcapitalization bias holds conclusively only if $\phi = 1$, as in the classic Averch-Johnson model. As noted by Mukhopadhyay and Hastak (2016), a regulator's denial of cost recovery for part of the firm's capital expenditures in preventive resilience might be expected to increase the riskiness of these investments, raising the cost of capital to r_K, where $r_K > P_K$. Under the assumption that the allowed rate of return s_K exceeds both the risk-free cost of capital P_K and r_K, we show that overcapitalization bias does not hold, *unless* the post disallowance rate of return exceeds the marginal revenue product of capital. Further, if s_K exceeds P_K but is below r_K, a profit-maximizing firm has incentives for *under*capitalization.

Assumption	ϕ	$\frac{dK}{ds_K}$	*Model*
$s_K > P_K$	$\phi = 1$	Negative	Averch and Johnson (1962)
$s_K > r_K > P_K$	$0 < \phi < 1$	Indeterminate	This paper
$r_K > s_K > P_K$	$0 < \phi < 1$	Positive	This paper

Table I. Insights from the analytical model and comparison with Averch and Johnson (1962)

4 BI-LEVEL OPTIMIZATION MODEL

4.1 Structure of the model

Our game-theoretic model is cast as a Stackelberg game between a utility regulated based on cost of service (leader) and utility customers with varying preferences for reliable power (followers). Figure 1 presents an overview of the static optimization model.

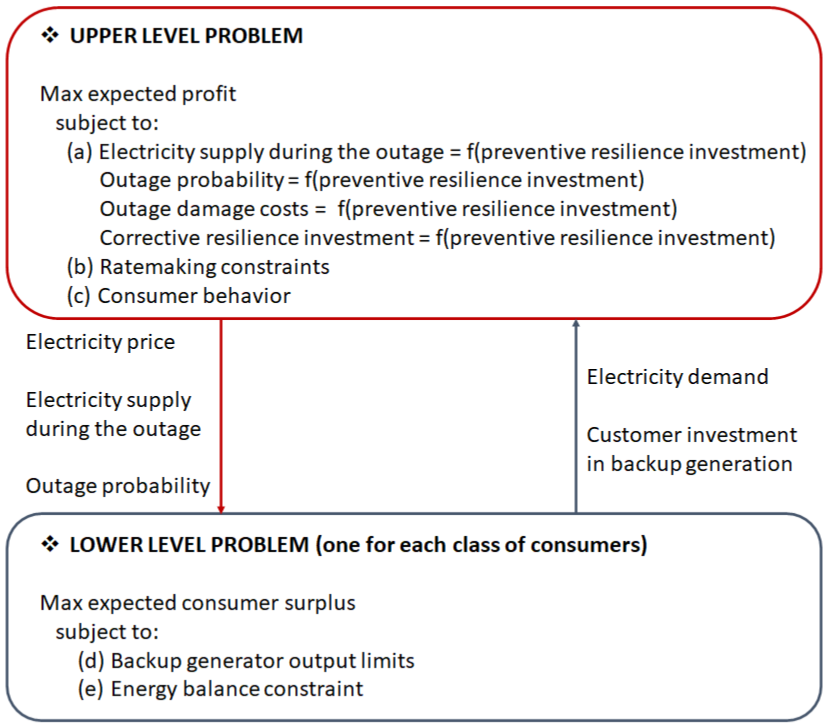

Figure 1. MPEC structure

At the upper level, given assumptions on (i) the probability of a long-duration outage, if no preventive measures are taken (π_{max}), (ii) the share of preventive expenditures that is likely to be approved for cost recovery by the regulator (ϕ), and (iii) the number of years over which recovery of outage damage costs is allowed (ρ), the utility maximizes expected annual profit subject to three sets of constraints. First, the outage probability in the system, outage damage costs and corrective resilience investments are determined as a function of preventive resilience investments. Second, the utility accounts for essential features of the rate-making process under traditional rate-of-return regulation. Third, the anticipated reaction of the consumers is given by the Karush-Kuhn-Tucker (KKT) conditions of the lower level problems. In line with the Stackelberg assumptions, the utility correctly anticipates backup generator investment decisions (and the resulting impact on electricity demand to be served during an outage) in response to changes in the utility's decisions. This would be possible, given detailed knowledge of customer load profiles and reasonable estimates for their value of lost load (or VOLL).

At the lower level, given the utility's storm hardening decisions and the resulting impact on electricity prices, outage probability and electricity supply during an outage, consumers maximize expected annual surplus subject to backup generator output limits and an energy balance constraint. In line with the Stackelberg assumptions, consumers make decisions naively assuming that the utility will not change the values of its decision variables. We consider two customer classes that place different value on reliable service: commercial customers $j \in J_H$ with high VOLL and residential customers $j \in J_L$ with low VOLL. There is no interconnection among the lower level models, except through the utility model in the upper level.

4.2 Formulation

In this section, we present the model formulation, starting from the last stage of the game. A list of sets, parameters and variables is provided in Appendix B.

4.2.1 Lower level problem

Given the electricity price p, the electricity supplied by the utility during the outage w_{jot}, and the probability of a long-duration outage π_{sys}, consumer $j \in J$ maximizes expected surplus over one year, under some constraints. Decision variables include investment in a backup generator r_j, the unserved energy due to supply interruptions u_{jot}, and the backup generator usage during the outage v_{jot}. The problem of consumer j is formulated as follows:

$$\max_{r_j, u_{jot}, v_{jot}} \quad \pi_{sys} \cdot \left[\sum_{o \in O} \sum_{t \in T_u} (VOLL_j - F_j) \cdot v_{jot} + \sum_{o \in O} \sum_{t \in T} (VOLL_j - p) \cdot w_{jot} - \sum_{o \in O} \sum_{t \in T} VOLL_j \cdot u_{jot} \right]$$

$$+ (1 - \pi_{sys}) \cdot \sum_{o \in O} \sum_{t \in T} (VOLL_j - p) \cdot L_{jot} + \sum_{n \in N} \sum_{t \in T} (VOLL_j - p) \cdot L_{jnt} - P^c_j \cdot r_j, \tag{19}$$

subject to:

$$0 \leq r_j \leq P_{max,j}, \qquad (\lambda^1_j) \tag{20}$$

$$0 \leq v_{jot} + w_{jot} \leq L_{jot}, \quad \forall o \in O, \forall t \in T \qquad (\lambda^2_{jot}) \tag{21}$$

$$0 \leq v_{jot} \leq r_j, \qquad \forall o \in O, \forall t \in T \qquad (\lambda^3_{jot}) \tag{22}$$

$$v_{jot} = 0, \qquad \forall o \in O, \forall t \in T_d \qquad (\mu^1_{jot}) \tag{23}$$

$$v_{jot} + w_{jot} + u_{jot} = L_{jot}, \quad \forall o \in O, \forall t \in T \qquad (\mu^2_{jot}) \tag{24}$$

$$u_{jot} \geq 0, \qquad \forall o \in O, \forall t \in T. \tag{25}$$

In equation (19), the consumer maximizes the expected surplus from power consumption (in \$ per year), which consists of several terms. If the outage does occur on days $o \in O$ with probability π_{sys}, the electric utility may serve all or part of consumer demand. If the utility is unable to supply electricity, backup generators may operate for a few consecutive hours, but would be unavailable during refueling breaks. Thus, a backup generator with capacity r_j may provide up to v_{jot} during the hours in which it is available. The first term in the objective represents the expected net benefit from power consumption if the outage occurs and the backup generator is used to serve load. Net benefit depends on the difference between the customer value of lost load, or $VOLL_j$, and the marginal cost of power generation for the backup generator F_j. The second term in the objective represents the expected net benefit from power consumption if the outage occurs and the utility supplies electricity. In this case, net benefit equals the difference between $VOLL_j$ and the electricity price, multiplied by the quantity supplied by the utility. The third term in the objective is the expected cost of unserved energy, if the outage occurs and both the backup generator and the utility are unable to supply electricity: this may occur during refueling breaks and hours in which backup generator capacity is not sufficient to satisfy demand.

If the outage does not occur on days $o \in O$ with probability $(1-\pi_{sys})$, the electric utility serves consumer demand. The fourth term in the objective represents the expected net benefit from power consumption in this case. Similarly, the net benefit from power consumption during normal operations (i.e., the fifth term in equation 19) is the difference between the consumer value of lost load and the regulated electricity price p, multiplied by consumer demand. Finally, the last term in (19) represents the annualized fixed cost of the backup generator.

In practice, consumers would make binary investment decisions in backup generators that are available on the market. This introduces computational challenges in a bi-level model, because sufficient optimality conditions cannot be derived for problems with discrete variables. Therefore, we assume that the consumer may invest in any continuous amount r_j, but r_j is bounded by $P_{max,j}$, the base rating of a backup generator satisfying the customer's hourly average consumption (equation (20)). In equation (21), the sum of backup generator output and power supplied by the utility during the outage cannot exceed consumer demand. Further, backup generator output cannot exceed capacity (equation (22)), and is equal to zero during downtime operations (equation (23)). Equation (24) ensures that consumer demand equals the sum of generator output, power supplied by the utility and unserved energy on the day(s) of the outage. Finally, unserved energy is non-negative (equation (25)).

Given the upper level decisions, the lower level consumer problems are linear.

4.2.2 Upper level problem

At the upper level, we assume that the probability of a long-duration outage if no preventive measures are taken, π_{max}, may be estimated based on historical data. Further, two additional parameters may be determined based on past rate cases: the share of preventive expenditures that is likely to be approved for cost recovery by the regulator, and the number of years over which recovery of outage damage costs is allowed. To enhance resilience to a severe storm the utility may invest in distribution feeder hardening before the storm (preventive measure), deployment of restoration crews after the event (corrective measure), or a combination of both. The utility's objective is given by:

$$\max_{\substack{cr_u, p, pr_u, q, w_{jot}, \pi_{sys},\\ r_j, u_{jot}, v_{jot}}} p \cdot q - VC \cdot q - \pi_{sys} \cdot d(pr_u) - (P_u^p + OM) \cdot pr_u, \tag{26}$$

In equation (26), expected profit (in \$ per year) is equal to expected revenue minus expected variable cost of electricity generation $VC \cdot q$, expected damage cost $\pi_{sys} \cdot d(pr_u)$, and hardening cost $(P_u^p + OM) \cdot pr_u$. Note that the investment in corrective measures is part of the damage costs, and is made only if the outage occurs. The primary decision variable for the utility is pr_u, the number of distribution feeders to harden. All other variables (cr_u, p, q, w_{jot} and π_{sys}) depend on pr_u, as discussed below.

As shown in Figure 1, the expected profit maximization is subject to three sets of constraints. Equations (27)-(31) represent the utility's internal constraints:

$$0 \leq pr_u \leq P_{max}, \tag{27}$$

$$w_{jot} = L_{jot} \cdot \frac{pr_u}{P_{max}}, \tag{28}$$

$$\pi_{sys} = \pi_{max} \cdot (1 - K \cdot \frac{pr_u}{P_{max}}), \tag{29}$$

$$d(pr_u) = \delta - \alpha \cdot ln(1 + \frac{pr_u}{P_{max}}), \tag{30}$$

$$cr_u = \frac{\gamma \cdot d(pr_u)}{P_u^c \cdot OD}, \tag{31}$$

Equation (27) limits the number of feeders that may be hardened to P_{max}, the ratio between the total number of customers in the network and the number of customers who are connected to each feeder. In equation (28), the quantity of electricity supplied by the utility during the outage is directly proportional to the number of feeders that are hardened. In equation (29), the outage probability π_{sys} depends on π_{max}, the probability of a long-duration outage *without hardening feeders*, and is inversely proportional to the number of hardened feeders, with sensitivity equal to K. Several functional forms may describe the relation between damage costs and investment in preventive measures. Following MacKenzie and Zobel (2016), who find that a logarithmic function provides the best fit to their empirical data, we assume a logarithmic damage function in equation (30), where δ represents the maximum damage costs incurred by the utility when there is no investment in preventive resilience-enhancing measures, and α is a positive scaling factor. Finally, equation (31) defines investment in corrective measures cr_u as a share of damage costs.

Equations (32)-(34) describe essential elements of the rate-making process for a utility subject to rate-of-return regulation:

$$q = \pi_{sys} \cdot \sum_{j \in J} \sum_{o \in O} \sum_{t \in T} w_{jot} + (1 - \pi_{sys}) \cdot \sum_{j \in J} \sum_{o \in O} \sum_{t \in T} L_{jot} + \sum_{j \in J} \sum_{n \in N} \sum_{t \in T} L_{jnt}, \tag{32}$$

$$rr = RB \cdot ROR + DE + VC \cdot q + \pi_{sys} \cdot d(pr_u) \cdot \rho + (P_u^p + OM) \cdot pr_u \cdot \phi, \tag{33}$$

$$p = \frac{rr}{q}, \tag{34}$$

In equation (32), annual expected electricity sales by the utility include electricity supply during the outage, served consumer demand if the outage does not occur on days $o \in O$, and consumer demand during normal operations. The utility's revenue requirement (i.e., the revenue amount considered necessary to cover expenses and the allowed rate of return) is defined in equation (33), and consists of five terms. The first three terms represent the product of the utility's rate base and the rate of return on shareholders' investment, the depreciation expenses for existing assets, and the expected variable costs of generation, respectively. Since damage costs for extreme events are typically recovered over several years (Platsky, 2018), the annual share of damage cost recovery is given by the fourth term in (33). The fifth term in (33) is the share of hardening investments that the utility expects to recover. Because regulators typically resist funding preventive activities that may not yield benefits for years, we assume that the regulator approves cost recovery for a share ϕ of hardening investments, where $0 \leq \phi \leq 1$. Finally, electricity retail prices for the regulated utility track its average costs and include a rate of return on shareholders' investment *ROR* that is deemed appropriate by the public utility commission. Therefore, in equation (34) the regulated retail electricity price is obtained as the ratio of the utility's revenue requirement and its electricity sales.[3]

Finally, the upper level problem is subject to a set of lower level problems, as shown in Figure 1. Since the lower level consumer problems are linear and thus convex, the KKT conditions are necessary and sufficient optimality conditions (Luenberger, 1973). As a result, each lower level problem can be replaced by its KKT conditions (35) - (40) and equality conditions (41) - (43), which in turn are included as additional constraints of the upper level problem:[4]

$$0 \leq P^c_j + \lambda^1_j - \sum_{o \in O} \sum_{t \in T} \lambda^3_{jot} \perp r_j \geq 0, \quad \forall j \in J \tag{35}$$

$$0 \leq \pi_{sys} \cdot VOLL_j + \mu^2_{jot} \perp u_{jot} \geq 0, \quad \forall j \in J, \forall o \in O, \forall t \in T \tag{36}$$

$$0 \leq -\pi_{sys} \cdot (VOLL_j - F_j) + \lambda^2_{jot} + \lambda^3_{jot} + \mu^1_{jot} + \mu^2_{jot} \perp v_{jot} \geq 0, \quad \forall j \in J, \forall o \in O, \forall t \in T \tag{37}$$

$$0 \leq P_{max,j} - r_j \perp \lambda^1_j \geq 0, \quad \forall j \in J \tag{38}$$

$$0 \leq L_{jot} - v_{jot} - w_{jot} \perp \lambda^2_{jot} \geq 0, \quad \forall j \in J, \forall o \in O, \forall t \in T \tag{39}$$

$$0 \leq r_j - v_{jot} \perp \lambda^3_{jot} \geq 0, \quad \forall j \in J, \forall o \in O, \forall t \in T \tag{40}$$

[3] We abstract from real-world complexities like price differentiation among customer classes and two-part tariffs, and assume that the same electricity price applies to all end users.

[4] The KKT conditions of the lower level problems are obtained by applying strong duality, as shown in Appendix C.

$$v_{jot} = 0, \quad \forall j \in J, \forall o \in O, \forall t \in T_d \tag{41}$$

$$\mu^1_{jot} = 0, \quad \forall j \in J, \forall o \in O, \forall t \in T_u \tag{42}$$

$$v_{jot} + w_{jot} + u_{jot} = L_{jot}, \quad \forall j \in J, \forall o \in O, \forall t \in T. \tag{43}$$

This yields a single-level problem (MPEC) given by equation (26), subject to the constraints in (27)-(43). The problem is non-linear non-convex, due to the inclusion of a logarithmic damage function in (30), the product of decision variables in the first term of (32), and the KKT conditions of the lower level problem in (35)-(40).

4.3 Solution approach

Due to its non-linearity, the problem in Section 4.2 cannot be solved using standard MPEC solvers, like KNITRO. Complementarity conditions in an MPEC may be easily linearized using the Fortuny-Amat and McCarl method (Fortuny-Amat and McCarl, 1981). In addition, the logarithmic damage function in (30) may be approximated by a piecewise linear function. However, the product of variables $\pi_{sys} \cdot \sum_{j \in J} \sum_{o \in O} \sum_{t \in T} w_{jot}$ in equation (32) cannot be easily linearized. Hence, we apply the solution method that involves penalization of the complementarity constraints to transform the MPEC into a non-linear program (NLP). In this approach, which was proposed by Dirkse et al. (2005) and is a common solution method for MPECs (Leyffer and Munson, 2010; Gabriel et al., 2013; Ruiz et al., 2014), the KKT conditions of the lower level problems are removed from the constraints of the upper level problem, and violations of the complementarity conditions are penalized in the upper level objective function.

To illustrate, consider a simple MPEC with one leader and one follower. The leader makes a decision x which minimizes its objective function $f(x, y)$, while anticipating the follower's reaction y. Non-convexity appears in the complementarity constraint (45), yielding a non-convex feasible set.

$$\min_{x,y} \quad f(x, y) \tag{44}$$

$$0 \leq \eta \perp g(x, y) \geq 0 \tag{45}$$

The MPEC is equivalent to the following single-level non-linear optimization problem:

$$\min_{x,y} \quad f(x, y) + M \cdot \eta \cdot g(x, y) \tag{46}$$

$$\eta \geq 0 \tag{47}$$

$$g(x, y) \geq 0 \tag{48}$$

where the parameter M in the objective represents a user-defined penalty on the violations of the KKT conditions of the lower level problem. The KKT conditions $\eta \geq 0$ and $g(x, y) \geq 0$ are automatically satisfied by any feasible solution to the non-linear optimization problem. Since the objective is to minimize equation (46) such that $\eta \geq 0$ and $g(x, y) \geq 0$ for a suitable value of M, we would obtain a solution that satisfies the third condition implied by (45), i.e. $\eta \cdot g(x, y) = 0$.

We apply the penalization approach to the MPEC in Section 4.2, and solve the equivalent NLP on a quad core machine with 16 GB RAM using the CONOPT4 solver in General Algebraic Modeling System (GAMS) version 28.2.0. The non-linear optimization problem has $1,314$ variables, and we set the parameter M equal to 1,000. Solution times range from 10.1 to 14.6 seconds, depending on parameter values. After solving the NLP, we verify that the complementarity conditions hold to ensure the optimality of the equilibrium solution. It is worth noting that NLP methods aim to find stationary points or, at best, local optima, rather than global optima. Since NLP solvers can be started from user-defined starting points in their search for a local optimum, we calculate solutions from several different starting points and find that the optimum is robust, as discussed in Appendix D1.

5 DATA

Severe storms are typically associated with electric power outages affecting at least 50,000 customers and lasting for more than one hour (U.S. Department of Energy, 2020a). Since Florida and Texas have sustained the highest amount of severe storms in recorded history in the United States (NOAA's Atlantic Oceanographic and Meteorological Laboratory, 2021), we rely on publicly available data for these states.

Lower level problem: We assume that the regulated utility serves 50,000 customers (88% residential and 12% commercial, based on the statistics reported by the Florida Public Service Commission

(2018b)). Each distribution feeder covers 2,500 customers (Baik et al., 2018). Typical hourly load profiles by customer type in a representative year in Houston, TX are obtained from the U.S. Department of Energy (2020b). The direct costs of interruption for a long-duration outage are $2.3/kWh for the residential customers (Baik et al., 2020) and $25/kWh for the commercial customers (Sullivan and Schellenberg, 2013). Sullivan and Schellenberg (2013) note that adding indirect costs would cause the total cost of the outage to be between 1.5 and 3 times the direct cost to the customers. Hence, we assume that the VOLL is equal to the direct costs of interruption by customer type, multiplied by 3. Table II presents the average hourly electricity consumption and estimated interruption costs by customer type.

Customer type	Number of customers	Average hourly power consumption (kW)	VOLL ($/kWh)
$j \in J_H$	6,000	8.76	75
$j \in J_L$	44,000	1.69	6.9

Table II. Average hourly power consumption and interruption costs by customer type

The characteristics of backup generators are presented in Table III. Among gasoline-fired backup generators available for sale at the largest U.S. home improvement retailer (Home Depot, 2020a,b), we select the closest base rating to the average hourly electricity consumption for each customer class. The annualized cost of each generator type is obtained assuming a 6.265% interest rate (equal to the utility's rate of return) and a 3-year lifetime. We consider a fuel cost of $2.63/gallon for the backup generators and 1-hour refueling breaks.

Customer type	Rating (kW)	Full load fuel consumption (gal/hr)	F_j ($/kWh)	Capital cost ($)	P^c_j ($/kW)	Refueling breaks in a day (#)
$j \in J_H$	10.5	2.08	0.52	1,299	46.51	4
$j \in J_L$	3.65	0.68	0.49	364	37.53	4

Table III. Backup generator characteristics by customer type

Upper level problem: The costs of specific resilience-enhancing measures vary significantly based on utility- and location-specific factors (Edison Electric Institute, 2014; U.S. Department of Energy, 2016). We do not have access to utility data. As a result, we consider two representative measures for which costs are available from the literature: hardening of electric distribution feeders (preventive measure), and deployment of restoration crews (corrective measure). The maximum number of feeders that may be hardened by the utility (P_{max}) is equal to the number of customers served by the utility (50,000), divided by the typical number of customers connected to a single distribution feeder (2,500) (Short, 2014). The capital and O&M costs per feeder in our analysis are from Baik et al. (2018). The utility's variable cost of electricity generation is based on a natural gas combined cycle plant with heat rate of 7,627 Btu/kWh and fuel cost of \$3.55/MMBtu (U.S. Energy Information Administration, 2020a,b). Finally, the cost of deploying restoration crews typically represents between 70% and 85% of the damage costs (North Carolina Utilities Commission, 2002; Downey, 2018; McNamara, 2019). In equation (31), we set the share of total damage costs spent on hiring restoration crews (γ) equal to 75%, and the per unit cost of restoration crews (P_u^c) to \$2,000/day.

In order to parameterize π_{max} in equation (29), we consider the number of outages due to extreme weather events affecting at least 50,000 customers and lasting for no less than one hour in Texas between 2002 and 2020 (U.S. Department of Energy, 2020a). Out of 89 events, 35 [11] {2} outages lasted less than 1 day [between 2 to 3 days] {between 19 and 20 days}. This yields an annual probability of 0.021 for a one-day outage, 0.006 for a three-day outage, and 0.001 for a twenty-day outage. Since Texas utilities harden only about 1% of their distribution structures (Quanta Technology, 2009), these probabilities proxy the likelihood of a long-duration outage when the utility does *not* harden electric distribution feeders. Thus, we use the probability of a three-day outage to parametrize π_{max} in our analysis.

A second key parameter in equation (29) is K, which measures the sensitivity of a reduction in the probability of a long-duration outage to the share of hardened feeders. We parametrize K based on feeder outage performance statistics for Hurricane Irma provided by Florida Power & Light (2018). In preparation for that storm, FP&L hardened 859 of its 3,287 distribution feeders, and the outage rate of hardened feeders was 13% lower than that of non-hardened feeders. Substituting these values into equation (29), we obtain a baseline value of K equal to 0.5.

Parameterization of the damage cost function $d(pr_u)$ in equation (30) is challenging due to the lack of publicly available data on resource allocation towards hardening and recovery activities made by the utilities for specific disruptive events. Quanta Technology (2009) reports damage data for hurricanes making landfall between 1999 and 2008, broken down by Texas utility. Entergy Texas was the utility most impacted by Hurricane Rita (Britt, 2017), which caused extensive damage to its distribution system ($373.2 million). This level of damage costs is in line with that reported by AEP Texas, which suffered the bulk of the damage from Hurricane Harvey in 2017 (North American Electric Reliability Corporation, 2018), and requested recovery of about $380 million in storm-related costs (Walton, 2018). In equation (30), we scale this cost based on the number of customers in our hypothetical system. Since 391,163 customers in Entergy Texas' territory were impacted by Hurricane Rita, the distribution-level damage costs per customer was about $954.1. Assuming 50,000 customers in our system, we set δ to $47,703,900 in our model.

The scaling factor α in equation (30) couples preventive investments made by the utility and damage costs incurred after the disruptive event. Based on FP&L's storm hardening plan filings, hardened feeders perform better than non-hardened feeders during severe storms (Florida Power & Light, 2020). In addition, upon review of the utilities' storm hardening and preparedness programs, the Florida Public Service Commission found that hardening reduces the length of outages: for example, hardened feeders required 50% less restoration time than non-hardened feeders after Hurricane Irma (Florida Public Service Commission, 2018a). As noted above, we set the cost of restoration crews equal to 75% of the utility's damage costs. Thus, we assume that these costs would be reduced by 37.5% (=75% $\times$ 50%), if all distribution feeders in the system were hardened (i.e., $pr_u = P_{max}$). Substituting these values into equation (30), we obtain a value of α equal to $25,808,317 in the baseline.

6 RESULTS

We simulate alternative scenarios to satisfy the annual electric power demand of the system, varying based on ϕ, ρ, and utility compensation to customers for extended outages. Table IV presents the scenarios, which are labeled using a combination of numbers and letters. Numbers 1-5 indicate changes in the value of ϕ, which ranges from 0 to 1 in increments of 0.25. Letters a-b indicate changes in the value of ρ (0.1 or 0.2). Finally, the subscript p indicates that the regulated utility is subject to a storm restoration incentive mechanism, and must pay compensation to customers in proportion to the amount of unserved energy during the outage. Annual results for a scenario are obtained by solving the model for 8,760 hours in a year.

Scenario	ϕ	ρ	Penalty for unserved energy	Section
1a	0	0.2	✗	6.1
2a	0.25	0.2	✗	6.2.1
3a	0.5	0.2	✗	
4a	0.75	0.2	✗	
5a	1	0.2	✗	
1b	0	0.1	✗	6.2.2
2b	0.25	0.1	✗	
3b	0.5	0.1	✗	
4b	0.75	0.1	✗	
5b	1	0.1	✗	
$1a_p$	0	0.2	✓	6.2.3
$2a_p$	0.25	0.2	✓	

Table IV. Scenarios

6.1 Baseline

Table V presents the parameter values in our baseline (Scenario 1a). We consider an outage duration of three days occurring from August 2 to August 4.[5] Since as noted above regulators typically resist funding preventive resilience measures, we assume that cost recovery of hardening investments is not allowed in the baseline ($\phi = 0$). Further, the utility expects that outage damage cost recovery is spread out over a five-year period ($\rho = 0.2$).

Tables VI and VII present the baseline results from the MPEC. The utility does not invest in preventive resilience measures; as a result, the probability of a three-day outage equals π_{max} and the damage cost is at its highest level ($47,703,900). The residential consumers do not invest in backup generation due to their low VOLL. In contrast, commercial customers, who may invest in up to 10.5 kW of backup generation, choose a 6.824 kW generator, incurring an annual cost of $3,155,520 if the outage occurs. This consists of a certain annualized investment cost of $1,904,157, and fuel costs to operate the generators that are only incurred in the event of an outage ($1,251,363). The occasional benefits to the

[5] According to NOAA, the official hurricane season for the Atlantic Basin is from June 1 to November 30, with a peak from mid August to late October (National Hurricane Center and Central Pacific Hurricane Center, 2021). Within this time frame, the three-day peak demand in our data is on August 2-4. Thus, we assume that the utility plans for a worst case outage occurring on this peak demand period.

Parameter	Value	Source
DE	80,000,000 [$ per year]	assumed
OD	3 [days]	assumed
OM	5,000 [$ per year]	O&M cost from Baik et al. (2018)
P_{max}	20 [feeders]	based on Baik et al. (2018)
P_u^c	2,000 [$ per person per day]	Arcos (2021)
P_u^p	8,907 [$ per year]	capital cost from Baik et al. (2018), assuming 3% interest rate and 20 year lifetime
RB	70,170,036 [$]	assumed
ROR	6.3 [%]	Florida Public Service Commission (2018b)
VC	0.027 [$/kWh]	based on U.S. Energy Information Administration (2020b) and U.S. Energy Information Administration (2020a)
α	25,808,317 [$]	assumed
γ	0.75	based on North Carolina Utilities Commission (2002), McNamara (2019)
δ	47,703,900 [$]	based on Quanta Technology (2009)
π_{max}	0.006	U.S. Department of Energy (2020a)
ρ	0.2	assumed
ϕ	0	assumed

Table V. Utility problem parameters (Baseline)

commercial customers in the event of an outage would be substantial ($359,032,735), and equal to the sum of the benefits from power consumption if backup generation is used to serve load ($178,890,686) and the avoided damage costs ($180,142,049).[6] Finally, the retail electricity price is about 10% higher if the outage occurs, because the damage costs incurred by the utility roll through to the ratepayers. Appendix sections D2-D4 test the robustness of the baseline results to alternate parameter values, including outage duration and beliefs about outage probability.

We compare the equilibrium results from the MPEC to the first best solution from a social planner problem (SPP). Recall that in the MPEC the utility and its customers act non-cooperatively and without coordination (i.e., each party maximizes their private objective). In the SPP, the utility acts instead as a benevolent social planner that chooses the mix of individual and system-level resilience measures that maximizes economic efficiency. Thus, the utility maximizes net expected social benefits, subject to own constraints and consumer constraints. The SPP is solved using the same parameter values in Table V,

[6]The benefits from power consumption are obtained by dividing the expected net benefit from backup generation (m in Table VI) by π_{sys}. The avoided damage costs are the difference between the damage costs without investing in backup generation and the actual customer damage costs (i.e., the product of VOLL and cumulative unserved energy).

	Scenario 1a MPEC	Scenario 1a Social planner problem (SPP)
Utility		
Preventive resilience:		
· hardened feeders (% of max)	0 (0%)	20 (100%)
· annual cost ($)	0	278,140
Corrective resilience, if the outage occurs:		
· restoration crews (% of max)	5,963 (100%)	3,727 (63%)
· annual cost ($)	35,777,925	22,361,203
Damage cost, if the outage occurs ($)	47,703,900	29,814,937
Avoided restoration cost, if the outage occurs ($)	0	13,416,722
Residential customers		
Backup generation:		
· kW per customer (% of max)	0 (0%)	0
· total kW in the system	0	0
· annual cost, if the outage occurs ($)	0	0
Damage cost, if the outage occurs ($)	48,612,891	0
Commercial customers		
Backup generation:		
· kW per customer (% of max)	6.824 (65%)	0
· total kW in the system	40,941	0
· annual cost, if the outage occurs ($)	3,155,520	0
Damage cost, if the outage occurs ($)	253,733,892	0
System		
Outage probability	0.006	0.003
Electricity price, if the outage occurs ($/kWh)	0.113	0.108
Electricity price, if the outage does not occur ($/kWh)	0.103	0.103

Notes: The annual cost of preventive resilience includes the annualized cost of feeder hardening and the annual O&M cost of the feeders. The avoided restoration cost is the difference between the restoration cost without hardening and the actual restoration cost. The annual cost of backup generation includes the annualized cost of investment and the operating cost, if the outage occurs. Customer damage costs are the product of VOLL and cumulative unserved energy.

Table VI. Resilience investments, costs, outage probability and prices (Baseline)

and yields the efficient mix of preventive, corrective and consumer resilience investments that would be achieved under perfect coordination in the game. Results are presented in Tables VI and VII. In contrast to the MPEC, the utility hardens the maximum number of feeders in the SPP. This has three effects. First, if the three-day outage occurs, the utility's damage costs are reduced by about 38%, relative to the MPEC.

	Scenario 1a MPEC	Scenario 1a Social planner problem (SPP)	(SPP - MPEC)
Utility			
· Expected revenue (*a*)	114,562,394	114,521,985	−40,409
· Expected generation cost (*b*)	30,104,178	30,106,438	2,260
· Expected damage cost (*c*)	310,315	96,973	−213,342
· Preventive resilience investment cost (*d*)	0	278,140	278,140
Expected net benefit to the utility (*e* = *a*-*b*-*c*-*d*)	84,147,901	84,040,434	−107,467
Residential customers			
Aug 2-4, outage occurs with probability π_{sys}			
· Expected net benefit from backup generation (*f*)	0	0	0
· Expected net benefit from utility generation (*g*)	0	155,754	155,754
· Expected cost of unserved energy (*h*)	316,228	0	−316,228
Aug 2-4, outage does not occur with probability (1-π_{sys})			
· Expected net benefit from utility generation (*i*)	47,575,469	47,731,531	156,062
Rest of the year			
· Expected net benefit from power consumption (*j*)	4,382,247,468	4,382,275,884	28,416
· Annualized backup generator investment costs (*k*)	0	0	0
Expected net benefit to residential customers (*l* = *f*+*g*-*h*+*i*+*j*-*k*)	4,429,506,709	4,430,163,169	656,460
Commercial customers			
Aug 2-4, outage occurs with probability π_{sys}			
· Expected net benefit from backup generation (*m*)	1,163,689	0	−1,163,689
· Expected net benefit from utility generation (*n*)	0	1,409,250	1,409,250
· Expected cost of unserved energy (*o*)	1,650,546	0	−1,650,546
Aug 2-4, outage does not occur with probability (1-π_{sys})			
· Expected net benefit from utility generation (*p*)	430,461,387	431,870,890	1,409,503
Rest of the year			
· Expected net benefit from power consumption (*q*)	34,033,046,573	34,033,066,599	20,026
· Annualized backup generator investment costs (*r*)	1,904,157	0	−1,904,157
Expected net benefit to commercial customers (*s* = *m*+*n*-*o*+*p*+*q*-*r*)	34,461,116,946	34,466,346,739	5,229,793
System			
Expected net benefit to all parties (*t* = *e*+*l*+*s*)	38,974,771,556	38,980,550,342	5,778,786

Notes: (a)-(d), (f)-(k) and (m)-(r) represent terms in the objective function of the utility, residential customers and commercial customers, respectively. All values are in $.

Table VII. Benefits and costs (Baseline)

Hence the utility incurs a certain cost of $4,000,000 (given by the sum of capital investment and O&M costs over 20 years for the feeders), and $29,814,937 in damage costs if the outage occurs. In contrast the utility's damage costs amount to $47,703,900, absent investment in preventive resilience. Second, feeder hardening reduces system vulnerability to a three-day outage, whose probability decreases by about 50%. Third, the investment in a preventive resilience measure reduces unserved energy in the system by 10.43 GWh relative to the MPEC, since the utility can supply electricity to all customers even during the outage. In particular, unserved energy for the commercial customers in the event of an outage decreases from 3.39 GWh in the MPEC to 0 GWh in the SPP. Recall that outage probability and electricity supply by the utility during the outage represent upper level decisions, which are taken as exogenous in the consumer problems. Given the reduction in outage probability and the lack of unserved energy, commercial customers do not invest in backup generation in the SPP.

Figure 2 compares the annualized investment cost in resilience measures, while Figure 3 shows the annual investment and operation cost in resilience measures, if the three-day outage occurs. Note that corrective measures after the outage represent the largest share of the resilience mix in both the MPEC and SPP, but the annual costs are about 40% lower in the SPP.

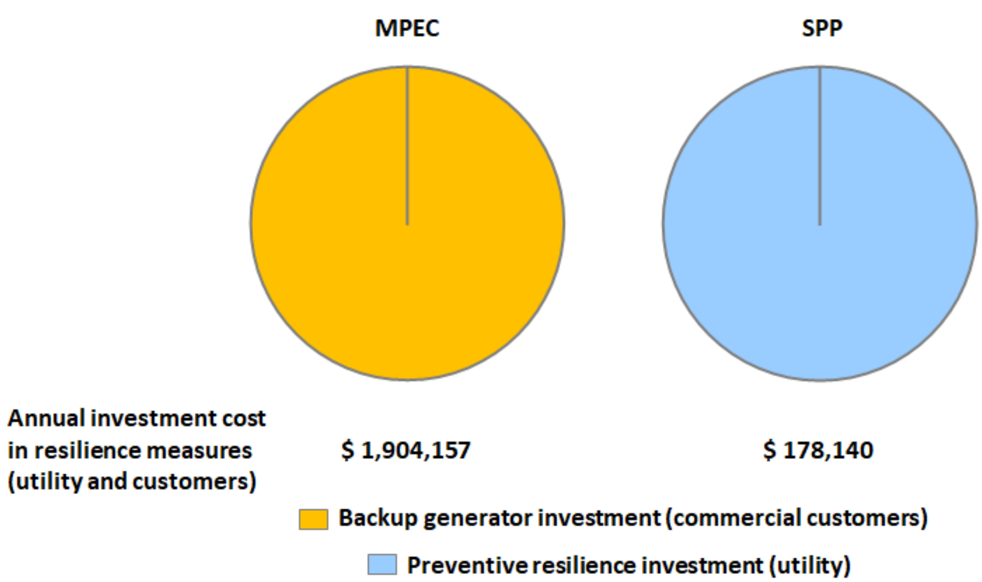

Figure 2. Investment in resilience measures (Baseline)

Although from a societal perspective it would be beneficial for the utility to invest in preventive resilience measures, the misalignment between social welfare maximization and private objectives, coupled

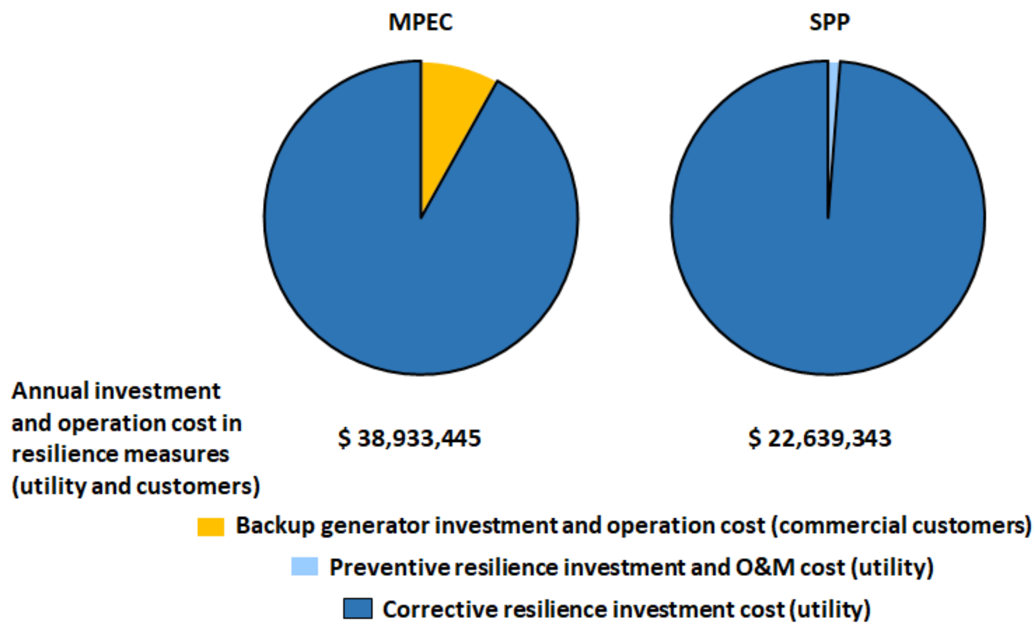

Figure 3. Resilience mix, if the outage occurs (Baseline)

with the regulator's denial of cost recovery for the utility's capital expenditures, results in an inefficient market outcome. Next, we examine conditions under which regulators may facilitate the realization of efficient market outcomes.

6.2 Sensitivity analyses

6.2.1 Share of preventive resilience investments that is approved for cost recovery

Our baseline results consider a scenario where the regulator does not approve cost recovery for hardening investments made by the utility ($\phi = 0$). In this section, we examine changes in resilience mix that result from increasing the share of preventive expenditures that is approved for cost recovery by the regulator.

Figure 4 shows the resilience investments made by the utility and the commercial customers (as a share of maximum investment) for increasing values of ϕ in Scenarios 1a-5a. To provide some context, on a national basis the value of ϕ is about one fifth or 0.2, as discussed in Section 1. In states like Arkansas, regulators are reluctant to approve major grid upgrades that would enhance resilience after a potential disaster, but raise costs for ratepayers in the near term (MacMillan and Englund, 2021). On the other end of the spectrum, regulators in Florida are more likely to allow cost recovery for preventive resilience measures (Dean, 2021).

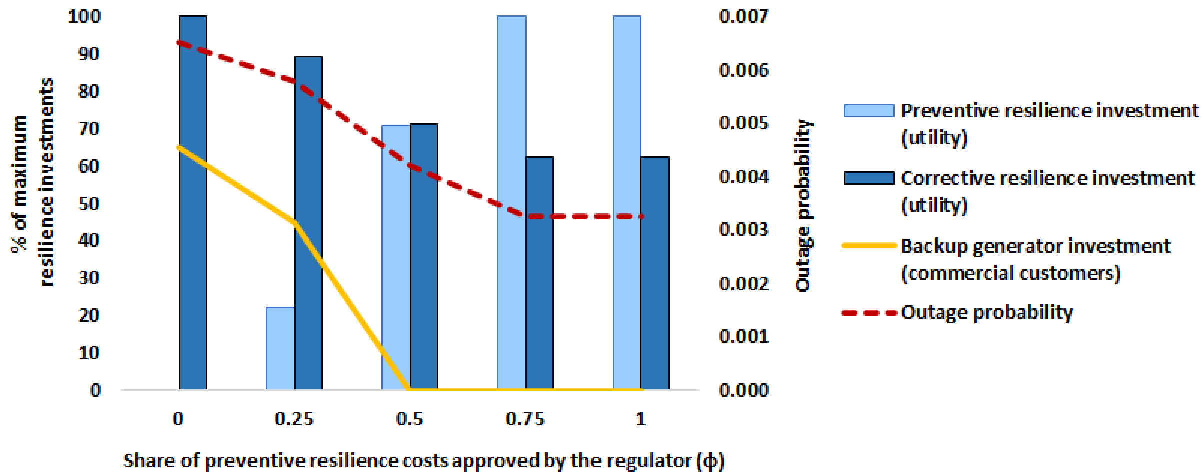

Figure 4. Resilience investments and outage probability (Scenarios 1a-5a)

Residential customers never invest in backup generation, hence they are not plotted on the graph. The utility invests more in preventive resilience measures for higher values of ϕ. As a result, the vulnerability of the system to the long-duration outage and restoration costs after the outage decrease, and commercial customers no longer invest in backup generation.

	Scenario 1a	Scenario 2a	Scenario 3a	Scenario 4a	Scenario 5a
ϕ	*0*	*0.25*	*0.5*	*0.75*	*1*
Utility					
Preventive resilience:					
· hardened feeders (% of max)	0 (0%)	4.415 (22%)	14.142 (71%)	20 (100%)	20 (100%)
· annual cost ($)	0	61,404	196,679	278,140	278,140
Corrective resilience, if the outage occurs:					
· restoration crews (% of max)	5,963 (100%)	5,320 (89%)	4,238 (71%)	3,729 (63%)	3,729 (63%)
· annual cost ($)	35,777,925	31,916,784	25,426,031	22,361,203	22,361,203
Damage cost, if the outage occurs ($)	47,703,900	42,555,712	33,901,375	29,814,937	29,814,937
Avoided restoration cost, if the outage occurs ($)	0	3,861,141	10,351,894	13,416,721	13,416,721
Residential customers					
Backup generation:					
· kW per customer (% of max)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
· total kW in the system	0	0	0	0	0
· annual cost ($)	0	0	0	0	0
Damage cost, if the outage occurs ($)	48,612,891	37,880,856	14,237,623	0	0
Commercial customers					
Backup generation:					
· kW per customer (% of max)	6.824 (65%)	4.697 (45%)	0 (0%)	0 (0%)	0 (0%)
· total kW in the system	40,941	28,182	0	0	0
· annual cost ($)	3,155,520	2,186,014	0	0	0
Damage cost, if the outage occurs ($)	253,733,892	212,091,218	127,072,512	0	0
System					
Outage probability	0.006	0.006	0.004	0.003	0.003
Electricity price, if the outage occurs ($/kWh)	0.113	0.111	0.110	0.109	0.109
Electricity price, if the outage does not occur ($/kWh)	0.103	0.103	0.103	0.103	0.103
Annual cost of resilience measures ($)	38,933,445	34,164,201.477	25,622,710	22,639,343	22,639,343
Damage cost, if the outage occurs ($)	350,050,683	292,527,786	175,211,509	29,814,937	29,814,937
Expected net benefit to all parties ($)	38,974,771,556	38,976,410,364	38,979,398,197	38,980,550,342	38,980,550,342

Notes: The annual cost of preventive resilience includes the annualized cost of feeder hardening and the annual O&M cost of the feeders. The avoided restoration cost is the difference between the restoration cost without hardening. and the actual restoration cost. The annual cost of backup generation includes the annualized of investment and the operating cost, if the outage occurs. Customer damage costs are the product of VOLL and cumulative unserved energy.

Table VIII. Resilience investments, costs, outage probability and prices (Scenarios 1a-5a)

Scenario	ϕ	Expected net benefit to the utility ($)	Expected net benefit to residential customers ($)	Expected net benefit to commercial customers ($)	Expected net benefit to all customers ($)	Expected net benefit to all parties ($)
1a	*0*	84,147,901	4,429,506,709	34,461,116,946	38,890,623,655	38,974,771,556
Change relative to Scenario 1a						
2a	*0.25*	*+5,184*	*+192,226*	*+1,441,398*	*+1,633,624*	*+1,638,808*
3a	*0.5*	*+35,865*	*+473,923*	*+4,116,853*	*+4,590,776*	*+4,626,641*
4a	*0.75*	*+101,138*	*+534,186*	*+5,143,462*	*+5,677,648*	*+5,778,786*
5a	*1*	*+170,673*	*+493,428*	*+5,114,685*	*+5,608,113*	*+5,778,786*

Table IX. Expected net benefits to all parties (Scenarios 2a-5a), relative to Scenario 1a

Table VIII presents the detailed MPEC results for increasing values of ϕ, while Table IX shows the change in expected net benefits to the parties for Scenarios 2a-5a, relative to the baseline. Scenarios 4a ($\phi = 0.75$) and 5a ($\phi = 1$) exhibit the highest expected net benefits to all parties, but the distribution of benefits differs in the two cases. Joint customer benefits are highest in Scenario 4a, as the utility's preventive resilience investments reduce the system's outage probability by 50%, but customers have to bear only 75% of the preventive resilience costs incurred by the utility. On the other hand, the utility obtains the highest benefit when it recovers all of its incurred preventive resilience costs in Scenario 5a ($\phi = 1$). Note that, while all parties benefit from an increase in ϕ, the utility prefers Scenario 5a (where it is allowed to fully recover the cost of hardening investments), while the customers prefer Scenario 4a (where the utility is only allowed to recover 75% of its hardening investments, yielding a lower increase in electricity rates). In sum, allowing cost recovery for a higher share of the utility's capital expenditures in preventive measures shifts the MPEC solution towards the first best solution from the SPP, enhancing system resilience despite lack of coordination among the parties.

6.2.2 Damage cost recovery period

Our baseline results assume that the recovery of outage damage costs is spread out over a five-year period ($\rho = 0.2$). Increasing the damage cost recovery period may affect the utility's resilience mix. Naturally, the utility would prefer a short cost recovery period. Thus, if cost recovery was spread out over a period longer than five years, the utility would seek to reduce damage costs, investing more in preventive resilience measures. In this section, we examine the utility's resilience investment decisions under increasing values of ϕ *and* a damage cost recovery period of 10 years (Scenarios 1b-5b).

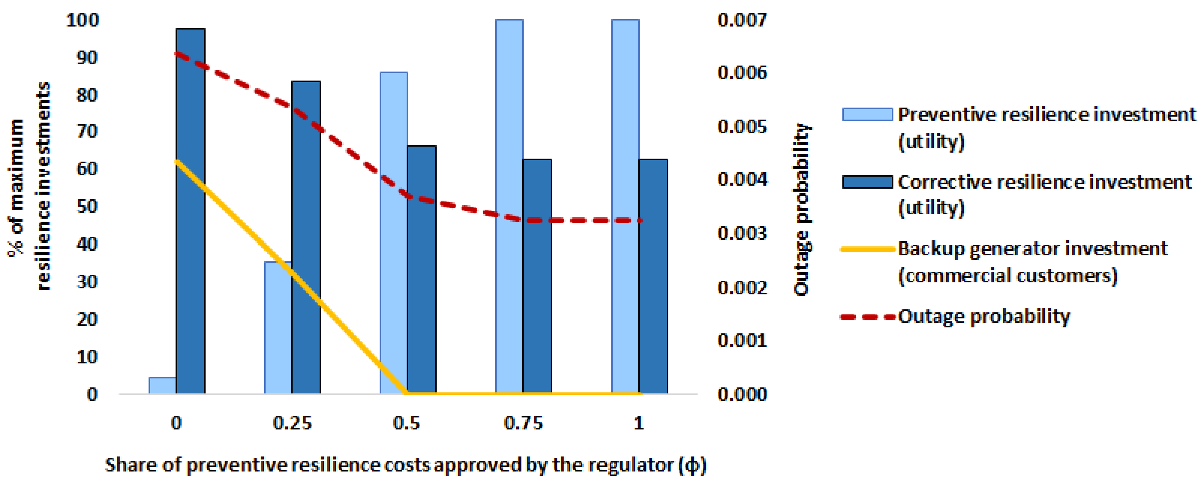

Figure 5. Resilience investments and outage probability (Scenarios 1b-5b)

Figure 5 presents the resilience investments made by the utility and the commercial customers (as a share of maximum investment). To analyze the changes in the utility's resilience investments that are solely due to the change in the cost recovery period, we compare results for the same value of ϕ in Figures 4 and 5. For example, the utility makes no preventive resilience investment in Scenario 1a, but hardens about 4% of the feeders in Scenario 1b. The utility invests more in preventive resilience when the time period over which damage costs can be recouped is extended. However, for a given value of ϕ, the utility is worse off (i.e., its expected profit is lower) if $\rho = 0.1$ than if $\rho = 0.2$, while customers are better off. To illustrate, consider the change in benefits in Scenario 1b relative to the baseline, shown in Table X. Although expected damage cost is reduced due to feeder hardening, expected revenues for the utility also decrease because a value of ρ equal to 0.1 yields lower annual expected damage costs in the revenue requirement, and thus a lower expected electricity price. In addition, the utility now incurs a cost for hardening feeders, but is not allowed to recover the cost through the rate-making process ($\phi = 0$). The combination of these effects makes the utility worse off in Scenario 1b, relative to the baseline. In contrast, due to the lower electricity price customers are better off when the time period associated with damage cost recovery increases. Similar insights may be drawn by comparing expected net benefits to the parties for the same (higher than zero) value of ϕ, but different values of ρ. In sum, increasing the time horizon associated with damage cost recovery incentivizes the utility to invest in preventive measures, shifting the MPEC solution towards the first best solution. Although total net benefit increases, the utility is worse off when the time period over which damage costs can be recouped is extended, while consumers are better off.

Scenario	ϕ	ρ	Expected net benefit to the utility ($)	Expected net benefit to residential customers ($)	Expected net benefit to commercial customers ($)	Expected net benefit to all customers ($)	Expected net benefit to all parties ($)
1a	*0*	*0.2*	84,147,901	4,429,506,709	34,461,116,946	38,890,623,655	38,974,771,556
Change relative to Scenario 1a							
1b	*0*	*0.1*	*−30,763*	*+59,374*	*+307,405*	*+366,779*	*+336,016*

Table X. Expected net benefits to all parties (Scenario 1b), relative to Scenario 1a

6.2.3 Utility compensation to customers for extended outages

Electric utilities across the U.S. typically do not offer any monetary compensation to their customers for long-duration outages. However, tying the utility's performance to losses incurred by the customers may provide incentives towards more efficient resilience investments. In this section, we examine the utility's resilience investment decisions under increasing values of ϕ *and* varying levels of customer compensation for long-duration outages.

The analysis considers two real-world incentive mechanisms as benchmarks. First, Pacific Gas & Electric (PGE) is one of the few electric utilities in the U.S. offering some monetary compensation to their customers for electricity outages lasting more than 48 hours. Compensation for a three-day outage (i.e., the duration in our baseline) ranges from $25 to $50 per customer (Pacific Gas & Electric, 2021). Given an average hourly residential load of 1.69 kW (Table II), $50 per customer for a three-day outage would translate to $0.411/kWh. As a second benchmark, we consider the incentive mechanism adopted by Ofgem, Great Britain's independent energy regulator. Electric utilities are required to offer compensation to their customers for long-duration outages, starting from £70 for an outage lasting 24 hours (Office of gas and electricity markets, 2021). If the outage lasts for more than 24 hours, the customer is paid an extra compensation of £70 for each additional 12 hours of power outage, up to a maximum compensation of £700. For a three-day outage, this compensation scheme would translate to £350 or \$465 per customer, using a conversion rate of 1.33 for sterling pounds to U.S. dollars. This is equivalent to a per unit compensation of \$3.825/kWh, which is more than 9 times the compensation offered by PGE.

We examine the effect of varying levels of monetary compensation for long-duration outages on the resilience investment decisions of the regulated utility. In line with current practice at Ofgem, we assume that the utility equally compensates residential and commercial customers. Let Θ be a penalty for unserved energy (in \$/kWh) paid by the utility to the customers. In the objective of the lower level problem (equation 19), $\sum_{o\in O}\sum_{t\in T} VOLL_j \cdot u_{jot}$ is replaced by $\sum_{o\in O}\sum_{t\in T}(VOLL_j - \Theta)\cdot u_{jot}$. Further, the term $\pi_{sys}\cdot\Theta\cdot\sum_{j\in J}\sum_{o\in O}\sum_{t\in T} u_{jot}$ is subtracted from in the objective of the upper level problem (equation 26). The constraints of the upper level problem are identical to those in Section 4.2.2, except for the revised KKT condition associated with u_{jot}.

Table XI shows the resilience investment mix for values of Θ ranging from 0 to \$5/kWh in increments of \$1/kWh. In addition, we consider the values of \$0.411/kWh and \$3.825/kWh referenced above. All other parameters are identical to Scenario 1a. We also present a similar comparison for a share of cost recovery for preventive measures that is close to the national average in the U.S. (ϕ = 0.25 in Table XII). Except for the penalty level, other parameters in Table XII are identical to Scenario 2a. The compensation per customer (in \$) represents the average compensation a residential customer would receive for a three-day outage, given the average hourly power consumption in our system.[7]

The resilience mix shifts towards the first best solution from the SPP, as the penalty for unserved energy increases. Note that, for $\phi = 0.25$, a low penalty like the one offered by PGE would significantly increase preventive resilience investments and avoid backup generation generation. Further, a penalty of \$3/kWh (slightly below the minimum compensation required by Ofgem, and about 7 times the compensation offered by PGE) would drive the utility towards efficient resilience investment decisions. In sum, given regulatory reluctance to approve cost recovery for preventive resilience investments, adopting an incentive mechanism requiring compensation of at least \$3/kWh for a three-day outage incentivizes the utility to invest in preventive measures, shifting the MPEC solution towards the first best solution.

[7]For example, for a three-day outage at a penalty of \$1/kWh, the residential customer would receive an average compensa-

Penalty for unserved energy ($/kWh) Θ	Compensation per customer ($)	Hardened feeders (% of max)	Restoration crews (% of max)	Commercial customer backup generation investment kW (% of max)
0	0	0 (0%)	5,963 (100%)	6.824 (65%)
0.411	50	1.591 (8%)	5,716 (96%)	6.209 (59%)
1	122	5.822 (29%)	5,139 (86%)	4.273 (41%)
2	243	13.657 (68%)	4,284 (72%)	0 (0%)
3	365	17.532 (88%)	3,932 (66%)	0 (0%)
3.825	465	19.635 (98%)	3,756 (63%)	0 (0%)
4	487	19.997 (100%)	3,727 (63%)	0 (0%)
5	608	20 (100%)	3,727 (63%)	0 (0%)

Table XI. Resilience investment mix in Scenario $1a_p$

Penalty for unserved energy ($/kWh) Θ	Compensation per customer ($)	Hardened feeders (% of max)	Restoration crews (% of max)	Commercial customer backup generation investment kW (% of max)
0	0	4.415 (22%)	5,319 (89%)	4.697 (45%)
0.411	50	8.816 (44%)	4,785 (80%)	0 (0%)
1	122	13.794 (69%)	4,271 (72%)	0 (0%)
2	243	18.893 (94%)	3,817 (64%)	0 (0%)
3	365	20 (100%)	3,727 (63%)	0 (0%)
3.825	465	20 (100%)	3,727 (63%)	0 (0%)
4	487	20 (100%)	3,727 (63%)	0 (0%)
5	608	20 (100%)	3,727 (63%)	0 (0%)

Table XII. Resilience investment mix in Scenario $2a_p$

7 CONCLUSIONS

Severe weather events, such as hurricanes, are the leading source of large-scale outages in the United States. Since these events disrupt lives and cost the economy billions of dollars, enhancing the resilience of the nation's electric power transmission and distribution system is a priority. However, because quantifying resilience is difficult, utilities do not have robust methods to allocate resources to measures that reduce vulnerability or improve recovery time in order to minimize expected outage costs. Further, state

tion of $1/kWh × 40.56 kWh × 3 days = $122.

regulators resist funding preventive measures that may only yield occasional benefits, while associated certain costs would be passed along to the ratepayers and increase electricity prices. As a result, utilities tend to spend heavily in corrective measures, as recovery of restoration costs from the ratepayers is generally allowed. Utility spending on resilience-enhancing measures has emerged as a central policy concern in recent years, as highlighted by the Texas electricity crisis in February 2021. In this paper, we present a simple analytical model to develop intuition about why electric utilities under traditional rate-of-return regulation may not be inclined to overinvest in capital that enhances grid resilience, in line with empirical evidence. This serves as a foundation for building a more detailed bi-level model to examine the mix of preventive and corrective measures that enhances grid resilience to a severe storm event. The bi-level model represents a Stackelberg game between a regulated utility (leader) that may harden distribution feeders before a long-duration outage and/or deploy restoration crews after the disruption, and utility customers with varying preferences for reliable power (followers) who may invest in backup generators. Unlike earlier work, we support analysis of resilience-enhancing investment decisions in a framework that accounts for potential distortions due to parties acting in their self interest and rate-of-return regulation. Our main findings can be summarized as follows.

First, the misalignment between social welfare maximization and private objectives, coupled with the regulator's denial of cost recovery for the utility's capital expenditures, yields an inefficient mix of resilience investments in the MPEC. This inefficient outcome is characterized by lack of investment in preventive measures by the utility and heavy reliance on backup generation by utility customers. If the outage occurs, utility damage costs are about 60% higher than in the first best solution under perfect coordination of the parties (i.e., the SPP benchmark). In addition, residential and commercial customers incur a substantial cost of unserved energy (about $300 million) in the MPEC, but no cost in the SPP. These distortions relative to the efficient benchmark raise serious concerns, as climate change is expected to increase the frequency and intensity of severe weather events.

Second, state regulators may promote more efficient resilience investments by the utility in several ways. Allowing cost recovery for a higher share of the utility's capital expenditures in preventive measures, increasing the time horizon associated with damage cost recovery, and adopting a storm restoration compensation mechanism incentivize the utility to invest in preventive measures, shifting the realized market outcome towards the efficient solution. In particular, on a national basis, about one fifth of preventive resilience investments is approved for cost recovery by state regulators in the U.S.. In this setting, we find that requiring utilities to pay compensation to customers of at least $3/kWh (equivalent to $365 to an average residential customer for a three-day outage, and about 7 times the level of compensation currently offered by U.S. utilities) provides significant incentives towards more efficient preventive resilience investments.

Our analysis has some limitations. The static optimization setup provides a snapshot of a representative year in the utility planning process. As a result, it may not adequately capture the long-term impacts of investment decisions, which span a multi-year time horizon. Further, we assume that all resource allocation decisions are made before the disruption; in fact, decisions to speed up recovery time are taken after the disruption and must be adapted based on factors like event intensity, possibly resulting in higher restoration costs than expected ex ante (and considered in our analysis). Finally, data limitations preclude the development of a version of our model in which the utility may determine the specific preventive and corrective measures to take, based on their cost effectiveness. Despite these limitations, our study provides meaningful insights to determine the optimal resource allocation to preventive and corrective resilience-enhancing measures, explore the inefficiencies that may arise in practice when self-interested parties make resilience investment decisions, and examine conditions under which regulators may facilitate the realization of efficient market outcomes.

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