

Techno-Economic Analysis of Data-driven and Transactive Approaches for Resilience Enhancement

Min Gyung Yu, *Member, IEEE*, Manisha Maharjan, *Member, IEEE*, Shiva Poudel, *Member, IEEE*, Monish Mukherjee, *Member, IEEE*, Sadie Bender *Member, IEEE*, Trevor D. Hardy, *Senior Member, IEEE*, and Hayden M. Reeve, *Member, IEEE*

Abstract—As extreme weather events lead to more frequent power outages, understanding and enhancing grid resilience is critical to mitigating economic losses and non-energy impacts from service disruptions. This study introduces a novel techno-economic analysis framework for evaluating resilience enhancement mechanisms. The framework combines grid response modeling with a co-simulation approach and valuation methodology to provide a comprehensive assessment. We apply this framework to a realistic case study of the Texas grid during Winter Storm Uri in February 2021. Two advanced resilience strategies are analyzed: a data-driven rolling outage mechanism and a transactive energy (TE) based allocation scheme. The rolling outage scheme selectively serves customers based on real-time curtailment needs, while the TE scheme allows customers to trade energy allocations according to their preferences. Our findings show that both the rolling outage and TE schemes significantly outperform conventional methods (*i.e.* controlled outages) by reducing the amount of energy not supplied to customers by 41% and 64%, respectively. These approaches also enhance flexibility and customer satisfaction, while improving energy utilization for greater resilience. Additionally, they maintain thermal comfort about 3.5 times better and substantially lower customer risk exposure. A key contribution of this study is addressing both utility and customer perspectives while considering both energy and non-energy impacts. The techno-economic analysis indicates that implementing these resilience enhancement strategies would incur an additional \$1.1B to \$1.6B in utility costs but has the potential to avoid \$17.3B to \$18B of customer losses as compared to existing solutions, thereby underscoring the value of investing in advanced resilience, as it provides significant societal benefits to customers.

Index Terms—Resilience, extreme temperatures, distribution grid resilience, intelligent automation, techno-economic analysis.

I. INTRODUCTION

IN recent years, there has been an increase in weather-related outages in power distribution grids, largely influenced by climate change—statistics have shown that the failures of distribution systems account for 90% of the customer outage minutes in the United States [1]. As it may be challenging to fully avoid extreme weather events given the increasing frequency, it becomes increasingly critical for utilities to identify resilience enhancement strategies such as critical load restoration, emergency resource allocation, and

repair crew dispatch [2]–[4]. While infrastructure damage typically requires short-term preparation and post-event restoration efforts, scarcity can occur during extreme temperature events such as heatwaves and cold-snaps due to sudden increase in demand as people use more cooling and heating systems, which stresses the grid [5]. Furthermore, the impact of extreme temperature events is exacerbated by the reduced grid performance due to aging infrastructure, which can lead to prolonged blackouts if not managed properly. For instance, (i) natural gas power plants and delivery systems failed during the winter storm Uri in Texas [6] and (ii) the infrastructure in the U.S. Pacific Northwest struggled to function as expected during prolonged heatwaves in July 2021 [7]). These incidents resulted in shortfall of available generation or supply. Therefore, increased electricity demand during extreme temperature-related events can significantly stress grid operations, leading to prolonged outages and widespread disruptions [8].

Although all service disruptions are associated with economic impacts, the concurrence of extreme temperature introduces additional risks and costs for all stakeholders; hence, enhancing resilience to such events is a growing priority for utilities. As it may not be feasible to maintain continuous supply to all customers during such events, utilities typically deploy non-voluntary load curtailment (*e.g.* blackouts) to manage scarcity during emergencies. While effective in reducing load, conventional schemes may lead to under-utilization of resources and wide disparities in the extent of economic losses and outage impacts across communities [9].

The recent advancement in information and communication technology (ICT), alongside the ongoing roll-out of smart meters (AMI) and advanced sensors (*e.g.* micro PMUs), provide strategic opportunities for utilities to enhance their outage management and restoration capabilities. Such sensors continuously collect large volumes of customer and network data, which can support developing effective outage management strategies by analytically predicting the impact of extreme temperatures on customer demand and network assets [10], [11]. They can also facilitate precise load shedding through remote disconnect/connect switches [12]. Our prior work in [13] demonstrated how AMI-based automation can improve the operational resilience of system as compared to conventional feeder-based or sectionalizer-based outage management. Although such data-driven outage management approaches are cost-effective, they are largely limited by the accuracy of the AMI meters and the availability of historical data during extreme conditions [13]. Moreover deploying such automation are costly and requires cost-benefit analysis to justify such

Min Gyung Yu, Manisha Maharjan, Shiva Poudel, Monish Mukherjee, Sadie Bender, Trevor D. Hardy, and Hayden M. Reeve are with the Pacific Northwest National Laboratory, Richland, WA, 99354 USA (e-mail: mingyung.yu@pnl.gov; manisha.maharjan@pnl.gov; shiva.poudel@pnl.gov; monish.mukherjee@pnl.gov; sadie.bender@pnl.gov; trevor.hardy@pnl.gov; hayden.reeve@pnl.gov).

investments. To complement the data availability limitations on AMI, the proliferation of distributed energy resources (DERs) provides synergistic opportunities for utilities to harness their flexibility during emergencies. Transactive energy (TE) is an emerging technique for incentivizing DERs to provide their flexibility fairly and equitably during extreme events [14]. TE mechanisms leverage physics-based models to accurately estimate DER flexibility and effectively optimize the limited available resources during emergencies. However, deploying such TE mechanisms may require new hardware and communication capabilities along with regulatory changes [15].

In order to determine the most effective solution and justify system investments for deploying such resilience mechanisms, stakeholders need to know not only the operational performance but also the impact on economic losses and customer safety. This necessitates a techno-economic evaluation approach that can capture the costs and economic consequences of such approaches based on their response and exposure analysis. Although it is clear that such resilience-oriented mechanisms are going to be pivotal in dealing with extreme temperature outages, at present, there are no standardized approaches to identify and value the impacts these investments have on resilience. Toward that goal, this paper introduces a comparative techno-economic analysis framework that evaluates two distinct schemes—data-driven outage management and TE-based allocation mechanism—to enhance resilience during extreme temperature-related outage events. The key contributions are summarized as follows:

- 1) A techno-economic analysis framework that facilitates evaluating the impact of resilience enhancement mechanisms from the perspective of customers and the system operator.
- 2) Evaluation of two different schemes—data-driven rolling outage and TE-based allocation—implemented using a modeling & co-simulation platform that emulates a real use-case of the Texas freeze event during winter storm Uri.
- 3) Identify relevant performance metrics that reflect energy utilization and socio-economic benefits along with the deployment cost for different resilience schemes under distribution automation (*e.g.* breakers, AMI, and IoT devices) to inform planning and investment decisions.

II. TECHNO-ECONOMIC ANALYSIS FRAMEWORK

The proposed techno-economic analysis framework comprises three key components: (1) high-fidelity distribution systems modeling to capture regional grid response, (2) design and implementation of resilience mechanisms, and (3) comprehensive valuation analysis to evaluate energy and non-energy impacts of the resilience approach during extreme temperature-related outage events. Fig. 1 provides an overview of the framework along with its key components.

A. Modeling and Simulation

This study leverages the Transactive Energy Simulation Platform (TESP) to emulate the response of distribution grids at scale [16]. The response models integrate detailed representations of the system’s physical elements, such as end-user load models, with associated dynamics and operational parameters under varying weather and grid scenarios. In this

work, we tailored the model to emulate the grid response in Texas further details of which are discussed in Section V.

B. Resilience Mechanism Design

This phase facilitates designing resilience mechanisms, prototyping algorithms, and implementing them with the grid models to observe the system- and customer-level response. In this work two resilience enhancement strategies, (1) an AMI-based rolling outage (*AMI-RO*) and (2) a TE-based allocation mechanism (*TE-Alloc*) are implemented and compared with legacy outage management schemes. It’s important to note that while two specific mechanisms were selected for demonstration, the proposed framework is flexible to integrate any resilience mechanism, ensuring its applicability across diverse scenarios. The details of these mechanisms, including underlying formulations, are discussed in Section III.

C. Valuation

The valuation methodology provides a holistic assessment of the resilience mechanisms from customers’ and system operators’ perspectives through metrics (See Section IV) that encompass some key dimensions, including:

a) Response & Exposure Analysis: This stage assesses the response capabilities and exposure levels of customers during extreme temperature-related outage events. Analyzing the effective utilization of available power indicates the potential for enhanced operational resilience. It evaluates resource utilization, such as the energy not served (ENS), along with the thermal stress level of customers [17] during outage events.

b) Damage and Loss Estimation: This aspect quantifies the impacts of outages events in terms of both energy- and non-energy-related damage and losses. Energy-related impacts include estimating costs such as power interruption. Non-energy-related customer impacts estimate their risk of mortality (Value of Statistical Life - VSL) along with the costs associated with medical expenses, and productivity losses. This highlights the customers’ human-centric damages associated with outages.

c) Cost of Deployment: This aspect compares the costs of deploying each method. It considers the capital and operational expenses (O&M) and the equipment required for implementation. Furthermore, the analysis will evaluate the opportunity costs, such as lost sales, by each approach.

With this framework, we aim in this paper to comprehensively assess the performance of two distinct approaches for managing scarcity to provide valuable insights into their technical effectiveness and economic viability for resilience enhancement during extreme-temperature outage events.

III. RESILIENCE ENHANCEMENT MECHANISMS

This section presents two strategies for resilience enhancement during scarcity developed in the authors’ prior work: 1) a data-driven approach to supply customers in a rolling fashion [13] and 2) an allocation-based transactive coordination approach based on operational physics [14]. This section describes the underlying formulations and highlights the required infrastructure to deploy such mechanisms.

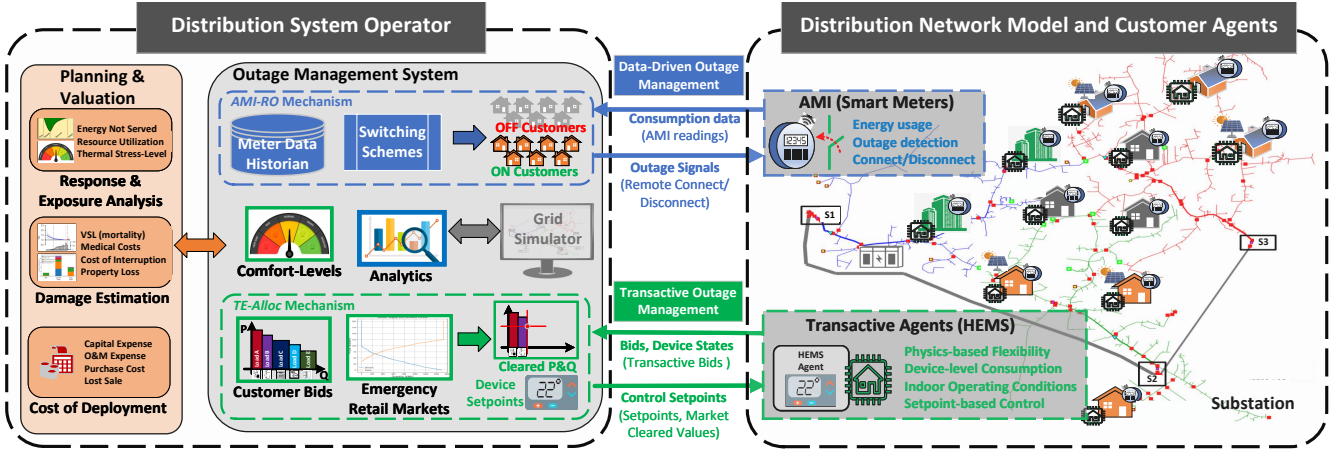


Fig. 1. Framework used to design, evaluate, and implement the performance of data-driven and transactive approaches for resilience enhancement.

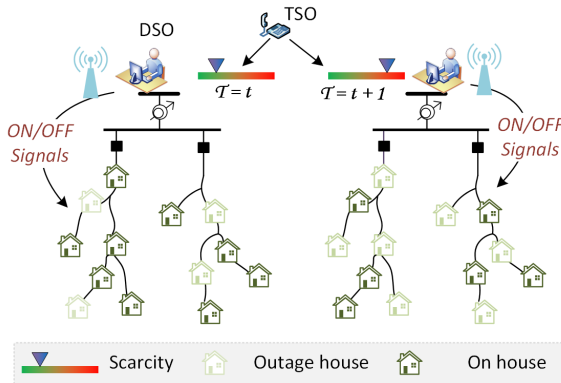


Fig. 2. Illustration of AMI-based rolling outage under varying levels of scarcity as communicated by TSO to DSO.

A. Data-Driven Rolling Outages using AMI systems (AMI-RO)

Typically, the independent system operator (ISO) monitors the electricity supply system and identifies potential issues that may lead to scarcity or grid instability. ISOs communicate this information to the Distribution System Operator (DSO), providing details about the nature of the problem, the expected duration, and any necessary actions to be taken. In this mechanism, the DSO closely monitors electricity demand across their distribution network and develops a schedule for rolling outages—systematically cutting off electricity supply to different areas or groups of customers for short periods, as shown in Fig. 2. These outages are typically rotated among different areas to distribute the impact fairly and minimize disruption. They may adjust the outage schedule based on real-time conditions and instructions from the ISO (see Fig. 2).

The main objective of the AMI-based rolling outage (AMI-RO) problem formulation is to ensure electricity supply to an evolving subset of customers to utilize the available power during extreme event conditions efficiently. This mechanism leverages past measurement data to estimate customer demand and presents an adaptive selection strategy based on the limited availability of power, as given by (1a) and (1b).

$$\min \sum_{i=1}^N -x_i^t W_i^t \quad (1a)$$

$$\text{subject to: } \sum_{i=1}^N x_i^t P_i^{max} \leq P_{avail}^t; x_i^t \in \{0, 1\} \quad (1b)$$

Where N is the total number of customers, x_i^t is the smart meter signal representing the connectivity status of a load, P_i^{max} is estimated undiversified demand, P_{avail}^t is available power, and W_i^t is the customer downtime severity index for the i^{th} customer that aims to capture the temporal power unavailability of a customer. W_i^t is continuously adjusted based on the duration of their power service in each state (“ON/OFF”) at the last instance t , as in (2). With the adaptive weighting scheme, where the weights are adjusted based on the state over time, the strategy aims to prioritize customers according to their downtime severity index (W_i^t).

$$W_i^{t+1} = \begin{cases} W_i^t \times \alpha^{T_i^{OFF}} & x_i^t = 0 \\ W_i^t & x_i^t = 1 \end{cases} \quad (2)$$

Where W_i^0 is the initial estimate of the severity index assigned for all the customers. Note that a significant expense is linked to the disruption of commercial loads, prompting a higher selection of W_i^0 for these customers. Moreover, W_i^0 can be set sufficiently high for other critical loads to ensure uninterrupted supply. Similarly, α is a constant that allows the accumulation of downtime leading to a higher value of severity index as customers are interrupted for longer intervals, and T_i^{OFF} represents the total number of time intervals the i^{th} customer has been out-of-service continuously. This mechanism requires AMI technology to report hourly consumption and assumes that smart meters allow for remote disconnect of customer supply by DSOs [18].

B. TE-based Allocation Mechanism (TE-Alloc)

Transactive Energy (TE) approaches facilitate the orchestration of DERs by providing coordination solutions that enable an effective balance between supply and demand. It relies on the technical needs of a system being formulated as price signals communicated to self-interested parties with the ability to respond and satisfy the system requirements. Prior studies [19], [20] have demonstrated the potential of TE mechanisms, through various customer-owned resources, such as heating, ventilation, and air conditioning (HVAC) systems, electric water heaters (WH), and energy storage devices.

This work implements an allocation-based TE coordination approach where the DSO uses a method intended to provide a fairer and more equitable distribution of energy to customers during emergencies [14]. Fig. 3 shows the architectural

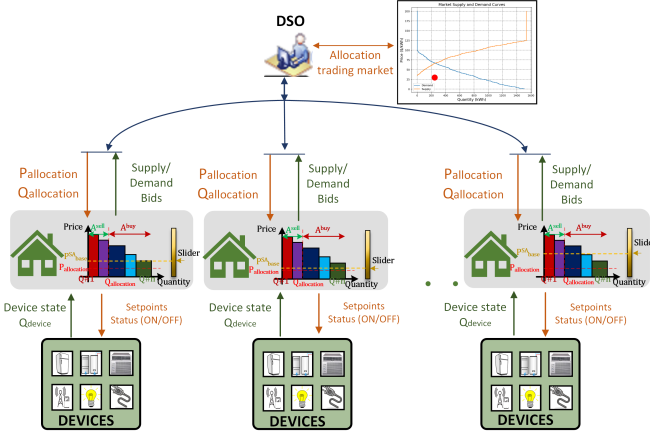


Fig. 3. Illustration of coordination architecture for TE-based allocation mechanism (TE-Alloc) during bidding and dispatch operations. overview of the TE-based allocation (*TE-Alloc*) mechanism among different entities during bidding and dispatch operations. Based on the availability, the DSO assigns an initial allocation to all participating customers. The mechanism also facilitates an allocation-trading market, enabling customers to voluntarily trade portions of their allocation with their peers. Customers provide the flexibility of the resources based on the operational dynamics, current state, and amenity preferences of the devices, such as HVAC, lighting, etc. Typically, higher-priority loads (e.g., medical devices) are priced higher and are most likely to fit under the allocation limit, whereas low-priority devices (e.g., lighting, plug devices) are made available in the allocation trading market as unmet demand. The customer's relative preference is expressed through baseline prices (P_{SA}^i) of their devices:

$$P_{SA}^i(t) = P_{min} + (P_{max} - P_{min}) * slider^i; slider^i \in (0, 1) \quad (3)$$

where $slider^i$ is the settings for customer i and P_{max} & P_{min} are the market price-limits. P_{SA}^i is used to form bid price ($P_{bid}^{i,n}$), characterized by device priority ($\pi^{i,n}$) and adjusted based on the relative need of energy, approximated through a discomfort parameter (T_{disc}). For instance, the bid price for HVAC devices would be calculated as (4a)–(4c).

$$T_{disc}^{i,hvac}(t) = T_{desired}^{i,hvac}(t) - T_{actual}^{i,hvac}(t) \quad (4a)$$

$$P_{bid}^{i,hvac}(t) = P_{SA}^i(t) \times \left[1 + \pi^{i,hvac} * T_{disc}^{i,hvac}(t) \right] \quad (4b)$$

$$\mathcal{B}_{bid}^{i,hvac} = \begin{cases} \langle P_{bid}^{i,hvac}(t), 0 \rangle; & \text{if } T_{disc}^{i,hvac}(t) \leq \Delta T \\ \langle P_{bid}^{i,hvac}(t), Q_{bid}^{i,hvac}(t) \rangle; & \text{if } T_{disc}^{i,hvac}(t) > \Delta T \end{cases} \quad (4c)$$

where ΔT is a threshold-tolerance for T_{disc} , $\pi^{i,hvac} \in (0, 1)$ is the relative priority for the HVAC & $\mathcal{B}_{bid}^{i,hvac}$ represents a block bid. Once the DSO clears the allocation-trading market, the customers' forgoing portions of the allocations are compensated, and customers willing to pay more for additional allocations have their devices dispatched. In this paradigm, the discomfort margin denotes the customer's preference to realize financial rewards while meeting their energy expectations with relatively small discomfort. This mechanism requires energy management systems at customer premises to communicate allocations or bids and control the operation of devices.

IV. VALUATION

This section presents the valuation assessment based on the grid and customer responses through the simulation under various outage mechanisms. We explore the dimensions of valuation from both customer and utility perspectives.

A. Customer Costs and Damages

The customer costs include energy procurements, installation expenses for the home energy management system (HEMS), and costs associated with damage/loss (e.g. risk of mortality, productivity, temperature-related building damage, power interruption) during the extreme temperature events. The valuation methodology estimates the damage levels experienced by each customer and converts them into dollar value losses, unifying all metrics into a single unit—dollars. Individual customer damages are then aggregated, and scaled to represent the total number of customers in the study region.

1) *Energy Procurement Costs*: This cost is calculated by multiplying the energy consumption by the retail energy price.

2) *Home Energy Management System Cost*: The calculation of the HEMS cost (C_{hems}) is determined as in (5).

$$C_{hems} = N_{zones} \cdot (C_{purch} + C_{cap} + (C_{labor} \cdot T_{labor})) \quad (5)$$

Here, N_{zones} represents the number of zones in the building. C_{purch} denotes the HEMS purchase cost, C_{cap} stands for the capital expenditure for HEMS materials installation, C_{labor} is the hourly wage for the electrician installing HEMS, and T_{labor} indicates the average installation time for HEMS. The determination of N_{zones} depends on the type of the building; for instance, residential structures are treated as a single zone, while commercial buildings are considered multiple zones.

3) *Customer Damage Estimation*: We consider the Value of Statistic Life (VSL) costs, medical costs, thermal-related productivity decrease costs, building damage repair costs, and power interruption costs as the impacts of extreme temperature events and quantify the loss associated with the damage [21].

a) *VSL and Medical Costs*: These are key metrics to quantify the potential human-related damage and loss caused by the extreme cold temperature outage since this is a significantly large value as like \$11.8M by the U.S. Department of Transportation [22] and \$11.6M by Federal Emergency Management Agency. Note that the VSL is not used to measure the value of human life but for a cost-benefit analysis to measure people's willingness to pay to reduce mortality risk.

Utilizing a location-specific metric for relative mortality risk associated with temperature (outlined by Gasparrini [23]) as in Fig. 4a, we map this information to assess potential occupant loss. Subsequently, a probability loss model, referenced [21], is employed to project the expected number of injuries and risk of mortality for calculating both VSL and medical cost estimations, as expressed in (6) – (10).

$$P_{mort} = (\overline{RR(Temp)} - 1) \quad (6)$$

$$N_{injured} = f(P_{mort}, P_{access}, P_{pre}, P_{sur}) \quad (7)$$

$$N_{death} = f(P_{mort}, P_{access}, P_{pre}, P_{sur}) \quad (8)$$

$$C_{vsl} = N_{death} VSL \quad (9)$$

$$C_{medical} = f(N_{injured}, P_{mort}, P_{heal,ins}) \quad (10)$$

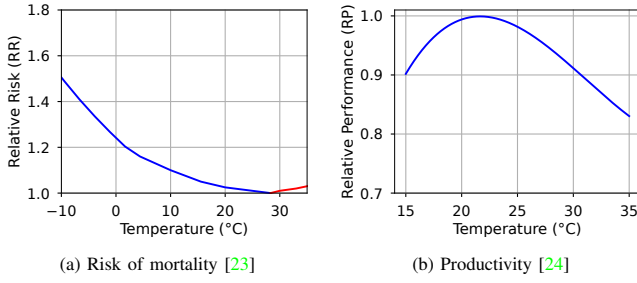


Fig. 4. Damage model as a function of temperature

where P_{mort} is based on the relative risk of mortality $RR(Temp)$ in Fig. 4a. $N_{injured}$ and N_{death} are the number of injuries and deaths estimated with the probability-based loss model [21], where healthcare accessibility P_{access} , pre-existing health conditions P_{pre} , and survivability P_{sur} are also used.

b) *Productivity Decrease Cost*: The productivity of occupants can be impacted by discomfort resulting from abnormal indoor temperatures during extreme temperature outages, with studies showing decreased performance outside the optimal temperature range (21°C to 23.5°C or 70°F to 74°F) [24]. The productivity level P_{prod} can be estimated using Fig. 4b. During power outages, productivity loss is assessed for non-power and intermittently powered jobs. Costs are calculated by multiplying productivity reduction by hourly wages. Total productivity loss costs are computed by summing the reduction across affected buildings and hours as in (11)

$$C_{prod} = N_{work}(1 - P_{prod})W_{avg} \quad (11)$$

where P_{prod} is the productivity level relative to indoor temperature, N_{work} is the number of workers in the building, and W_{avg} is the average hourly wage rate of affected workers.

c) *Property Damage Repair Cost*: Extreme temperature events, like cold spells, can lead to building damage, such as burst pipes. Our paper focuses on extreme cold temperature-related outage events, for which we utilize the Winter Index (WI) to evaluate the associated risk as in (12). This index considers both temperature and moisture levels, as outlined by Koci et al. [25]. Repair costs (C_{repair}) consider building insurance, labor, and material costs as in (13). Severity is factored in using the sum of WI over the outage period, mapped to a cost range specific to the repair item, as in (14).

$$WI_t = (T_L - T_t)(RH_t - RH_L) \quad (12)$$

$$C_{repair} = f(P_{damage}, P_{build,ins}, C_{labor}, C_{item}) \quad (13)$$

$$C_{item} = \alpha_{min} + (\alpha_{max} - \alpha_{min}) \left(\frac{\sum_t WI_t}{\beta_{WI}} \right) \quad (14)$$

where T_L and RH_L are critical values of temperature and moisture content and T_t and RH_t are temperature and moisture content at time t , respectively. WI is calculated only when both $T_t < T_L$ and $RH_t > RH_L$ are satisfied. α is the cost specific to a particular repair item, and β_{WI} is the maximum accumulated value of WI during the event.

d) *Power Interruption Costs*: We define the power interruption costs to assess losses due to service disruption, which are based on the customer types [26], as outlined in (15).

$$C_{cic} = f(e_{avg}, \Delta t_o, szn, inc, ind, c_{type}) \times S(\Delta t_o) \quad (15)$$

where C_{cic} represents the interruption cost, c_{type} is the customer type, e_{avg} is the average annual consumption of the customer, and Δt_o is the duration of the outage events which is determined by the actual power-off time for each building. szn is the season of interruption, ind denotes the customer business type, and inc is the annual household income. $S(\Delta t_o)$ is a scalability factor for outages beyond 16 hours based on outage duration to enhance the limitation of [26].

B. Utility Costs

1) *Operation Costs*: We implemented a parametric model to evaluate the operation costs related to expanded distribution automation equipment. Initially, an employee model estimates the necessary workforce for specific functions.

$$e_{op,da} = (a_t + b_t \cdot \frac{N_{cust}}{1000} + c \cdot \left\{ \frac{N_{cust}}{1000} \right\}^{\frac{1}{2}} + d_t \cdot N_{sub}) \times tf \quad (16)$$

Here, N_{cust} denotes the number of customers, a_t , b_t , c_t , and d_t represent base employee numbers for group t , and tf denotes the total employees to base-level ratio.

The total group cost is then computed using the following equation, incorporating yearly working hours ($HrYr$) and unburdened to fully burdened labor cost ratio (CR):

$$C_{op,da} = e_{op,da} \times tf \times \frac{HrYr}{CR} \quad (17)$$

This model is for estimating increased labor costs due to advanced cybersecurity and bi-directional communication infrastructure integration within grid automation strategies [27].

2) *AMI Network cost*: To evaluate investment costs for enhancing grid automation, we utilize a parametric cost model tailored to information technology systems [27], as in (18).

$$C_{inv,da} = \left(a + b \cdot \frac{N_{cust}}{1000} + c \cdot \left\{ \frac{N_{cust}}{1000} \right\}^{\frac{1}{3}} + d_t \cdot N_{sub} \right) \quad (18)$$

Here, N_{sub} signifies the number of substations in the service area, and coefficients a , b , c , and d are derived from overall costs reported by major utilities. This equation is adapted to account for two significant additional investments by utilities. These adjustments reflect their expansion in distribution automation infrastructure. Specifically, they include the cost of AMI meters for high granularity time interval load data collection and the cost of bi-directional communication between customers and utilities, which enables the exchange of outage instructions and load-shedding signals.

3) *Wholesale Purchases*: Typically, a DSO purchases energy through a mix of bilateral contracts with generators and direct energy purchases from the day-ahead (DAM) and real-time markets (RTM). Since only a small fraction of the energy is purchased through RTM, for the sake of simplicity the energy purchase cost is modeled via purchases through bilateral contracts and DAM as given by (19).

$$C_{wh} = \sum_{t=1}^T [f_{bi} \cdot Q_{bi}(t) \cdot P_{bi}(t) + f_{DA} \cdot Q_{DA}(t) \cdot P_{DA}(t)] \quad (19)$$

where f_{bi} & f_{DA} are the fraction of energy purchased through bilateral contracts and DAM and Q & P represents the respective price and quantity.

V. MODELING AND SIMULATION FRAMEWORK

Extreme weather events often lead to a surge in the electricity demand which along with the reduced performance of the infrastructure may cause the power grid to operate under high stress, and may potentially lead to prolonged outages. Therefore, predicting the system response during such extreme events with reasonable accuracy and resolution is crucial for evaluating the performance of resilience mechanisms. This work utilizes the TESP [16] for modeling at-scale distribution grid response during extreme events with high-fidelity. To reflect realistic grid response, the distribution grid models are developed using prototypical feeders populated with a region-specific mix of customers considering building design and operational characteristics based on detailed data from the U.S. Energy Information Administration (EIA). The resilience enhancement mechanisms are implemented using the response models for simulation-based evaluation. TESP integrates multiple tools to model transmission and distribution systems, enables time-synchronized message exchanging among modules, and supports realistic load models and transactive controls. The platform simulates extreme temperature events where the power grid faces severe scarcity due to a sudden spike in electricity demand and reduced generation and delivery performance. These simulations provide insights into the effectiveness of various outage mechanism effectiveness. Detailed modeling and co-simulation components of TESP are discussed below.

A. Distribution Grid Response Models

These models represent the distribution network’s physical components along with the operational parameters that guide the system’s performance with high fidelity. To generate a response model, the primary features of the region under consideration need to be identified and methodically integrated to configure the case study for the at-scale grid response simulation [16]. These features include 1) the geospatial location of the region, which determines the climate zone and consequent weather profile; 2) the type of utility - urban, suburban, or rural; 3) the number and mix of residential, commercial, and industrial customers; 4) regional characteristics of end-user loads for customers; and 5) the distribution system capacity constraints. Incorporating such detailed characteristics into the distribution models enables emulating the realistic regional grid response during extreme weather conditions and offers insights such as peak demand and cold load pick-up. Several aspects contributing to distribution grid response models are explained below:

1) *Feeder Backbone*: With the aforementioned features, the regional distribution grid is modeled using suitable prototypical feeders [28], which constitute the backbone infrastructure (e.g., network topology, equipment ratings, and power delivery elements). Then, the feeders are populated with end-user load models based on the customer’s uniqueness to the region.

2) *Customer Population Mix*: The backbone circuit for the network is acquired along with the customers’ mix and average consumption information. Next, the end-user loads for each customer are modeled through a combination of thermostatic devices (including HVACs, WHs, and refrigerators) and other end-use appliances (like lights, plug loads). The operational

and design features like building type, floor area, fuel source, and thermostat settings are attributed based on statistical distributions from the energy consumption survey conducted by the U.S. Energy Information Administration to appropriately model the customer’s response (further details can be found in [29]). Such a high-fidelity modeling approach ensures that the subsequent system demand and the distribution of energy usage among customers reflect the region under consideration.

3) *External Variables (Weather)*: The grid models need appropriate environmental variables to emulate extreme temperature conditions. This contains data on temperature, humidity, wind speed, solar insolation, and atmospheric pressure. These parameters serve as boundary conditions for buildings and their thermostatic devices and facilitate emulating the grid response under extreme conditions.

The distribution grid’s response, modeled from the given customer population, can realistically capture interactions between grid infrastructure, operational procedures, and external factors such as regional weather. This helps answer “what if all customers needed supply during an extreme event, given the existing grid infrastructure and load composition.” Such analysis provides insights into the need for flexibility to manage scarcity and paves the way for evaluating various resilience enhancement strategies.

B. Co-Simulation Platform

The proposed mechanism has been implemented on a co-simulation platform developed using HELICS, which facilitates large-scale co-simulations and enables information sharing between simulators during run-time [30]. Different layers of the mechanism are executed using the following simulators:

1) *Distribution Network*: is simulated using GridLAB-D [31]. The customer resources are modeled using different end-user loads and appliances with thermostatic loads, such as WH and HVAC systems, using the built-in functionality of GridLAB-D. The weather agent provides the simulator with real-time weather data like region-specific temperature, wind, and irradiance data, and the simulator updates the electrical and thermodynamic conditions of the devices.

2) *Site Agents (SA)*: are implemented as Python-based self-contained agents that facilitates the *TE-Alloc* mechanism by obtaining the current allocation, creating their device-specific blocks, and sending the bids to the DSO at each market cycle.

3) *DSO Agent*: runs an allocation-trading market and communicates the $P_{allocation}$ & $Q_{allocation}$ to the SA during each market cycle for the *TE-Alloc* mechanism. The final allocations and market-cleared pricing are returned to the SAs for dispatch. For *AMI-RO* case, the DSO agent runs an optimization problem to identify a set of outage customers and sends an outage signal to AMI meters.

Metrics are converted into dollar values, with performance estimates calculated for each individual customer. These individual estimates are then aggregated and scaled to represent the total number of customers in the study region.

VI. USE-CASE DEMONSTRATION

The proposed schemes are demonstrated and compared using the modeling & co-simulation platform configured to

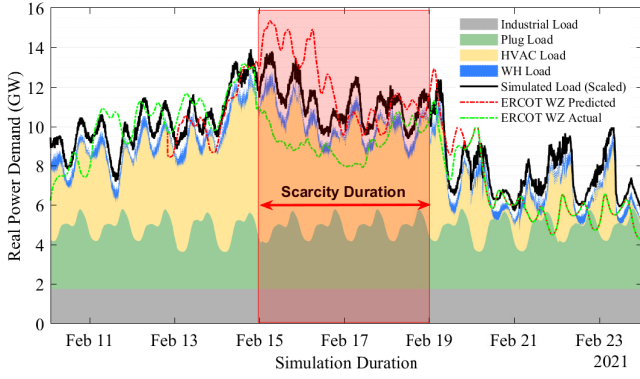


Fig. 5. Load decomposition obtained from the grid response models for Feb. 2021 calibrated against ERCOT load data for the SC weather zone. emulate the conditions during winter storm Uri in Texas to represent a realistic resilience use-case due to its severe impact and significant grid failure [8].

A. Response calibration

The use-case is configured to emulate the distribution grid response for the South Central (SC) weather zone (WZ) of Texas which is one of the eight ERCOT WZs [32]. The SC-WZ of Texas is mostly urban in demographics and its grid response was emulated using a distribution substation connected with two urban taxonomy feeders (R5-12.47-1 and R5-12.47-2) [28], with customer mix and end-user loads for SC-Texas based on EIA data. The configuration represents 1,308 residential houses and 61 commercial buildings (average of 2.09 average customers per building), scaled to represent 2,004,277 customers that are served within the WZ. The scaling factor is based on the business-as-usual (BAU) conditions of the WZ. Further details on the weather data and calibration are presented in [8]. Fig. 5 compares the simulated grid response with actual (with outages - sourced from [32]) and predicted demand (without outages - obtained from [33]) for the SC-WZ of ERCOT in Feb. 2021. The simulated response matches well with the predicted load during outage days and the actual loads during the non-outage days, respectively, presenting a baseline for the techno-economic analysis.

B. Scenarios

1) *Base (BAU)*: This scenario case defines a normal operational state in which all connected loads are served.

2) *Controlled Outage (CO)*: Extreme conditions during the winter storm Uri led to a widespread shortage of electricity due to a sudden increase in electricity demand along with generation deficiencies and equipment malfunctions. This scenario aims to implement a legacy strategy employed by utilities during emergency events, where they selectively deactivate the distribution feeders as a method of reducing load.

3) *Rolling Outage (AMI-RO)*: This case implements the AMI-RO strategy, with the DSO analyzing customers' historical data and consumption patterns during emergency events. The mechanism determines an evolving subset of specific customer groups for temporary disconnection based on the availability during scarcity events. The availability of power is determined based on the difference between actual and predicted loads for the SC-WZ as indicated in Fig. 5. In this study, these rolling outages are scheduled on an hourly

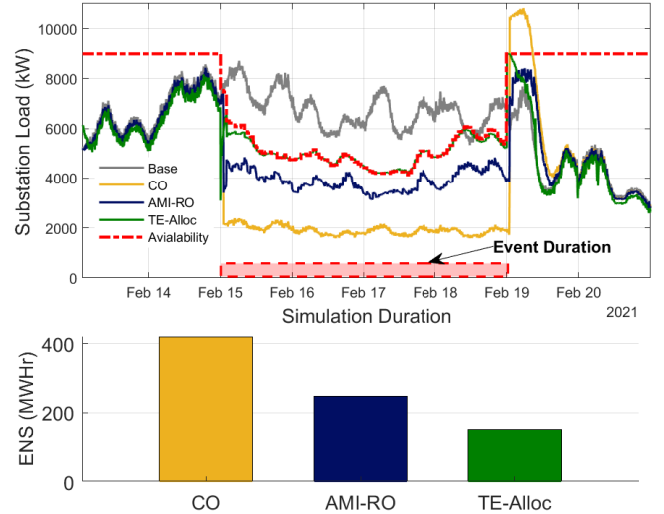


Fig. 6. Grid response during extreme temperature outage: Substation demand for resilience mechanisms (top), and the energy not served (ENS) (bottom).

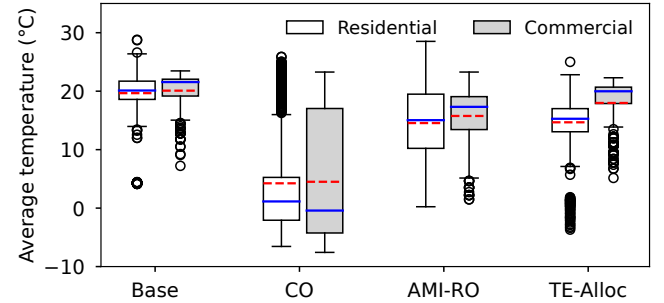


Fig. 7. Average indoor temperature during outage period

basis and commercial customers are provided higher priority as compared to residential customers.

4) *TE-based Allocation (TE-Alloc)*: The *TE-Alloc* mechanism serves as an alternative emergency scheme that provides equitable allocations to customers during the scarcity event. All customers receive base allocations and can trade portions of the allocations based on their preferences. The residential and commercial customers are provided with uniform energy allocations based on their average consumption and system's instantaneous availability (indicated by the red curve in Fig. 6). The commercial customers are configured with higher bidding prices indicating their willingness-to-pay more for services during extreme events. Moreover, the device priorities for all the customers are set similarly with thermostatic devices like HVAC, refrigerators, etc. having higher priorities.

VII. USE-CASE VALUATION

A. Response & Exposure Analysis

Fig. 6 illustrates grid response during extreme temperature outage. The top subplot shows the substation demand for resilience mechanisms, while the bottom subplot shows the energy not served (ENS). The *CO* scenario, akin to Texas winter storm Uri, showcases the simulated grid's response where affected customers are unable to operate building energy systems. In *AMI-RO* scenario, the ENS rate is lower than that of the *CO* case, as customers experience intermittent power interruptions for only a fraction of the total outage period.

TE-Alloc shows the best energy utilization rates, while the *CO* scenario demonstrates the lowest. This suggests that implementing *TE-Alloc* mechanism could lead to better allocation and utilization of energy resources during outage periods, thereby enhancing the system’s overall operational resilience.

We evaluated the indoor temperature of each customer to analyze how the building population responded to the extreme temperature-related outage and to assess the effectiveness of different outage management mechanisms in improving thermal resilience. Fig. 7 presents the average indoor temperatures during the extreme cold temperature-related outage period for our identified outage mechanisms compared to the baseline (*Base*) case and existing outage mechanism (*CO*). In the *CO* scenario, a large number of customers experienced power loss, resulting in indoor temperatures dropping below 10°C during the extreme cold temperature outage event. In contrast, other customers in the *CO* case maintained temperatures similar to the *Base* case, resulting in a wide range of variation in average temperature. For the Rolling Outage scenario, customers experienced intermittent power supply, thus they maintained significantly higher average indoor temperatures compared to the *CO* case on average. In the *TE-Alloc* scenario, we observed that the average indoor temperature was close to the *Base* case, with only a few outliers. Notably, commercial customers showed very similar average temperature compared to the *Base* case. This can be due to the characteristics of the outage mechanism that considers the customers’ preferences. The commercial customers’ strong willingness to maintain indoor thermal comfort during the outage event was clearly reflected and observed, as illustrated in Fig. 7.

To further evaluate customers’ thermal comfort, we determined the thermal stress level experienced by customers during the outage period. Specifically, cold thermal stress levels were estimated based on specific air temperature thresholds. Mild cold thermal stress falls within 15.5 to 10°C (60 to 50°F), moderate cold thermal stress within 10 to 4.5°C (50 to 40°F), and severe cold thermal stress below 4.5°C (40°F). Fig. 8 illustrates the number of customers across cold thermal stress levels for each case. In the *Base* case, most customers remained above the mild cold thermal stress threshold, with only a few experiencing cold thermal stress due to poor insulation. In the *CO* scenario, a significant number of customers experienced severe cold thermal stress during the extreme cold temperature outage event. However, the Rolling Outage and *TE-Alloc* scenarios showed remarkable improvement, with fewer customers experiencing moderate or severe cold thermal stress compared to the *CO* case. In comparison to the Rolling Outage scenario, the *TE-Alloc* scenario showed relatively better performance, with slightly more customers experiencing mild cold thermal stress rather than moderate or severe cold thermal stress. This observation is consistent with the trends found in Fig. 7.

B. Damage and Loss Estimation

We explored occupant and property damage in terms of mortality risk, building damage, and productivity level, as

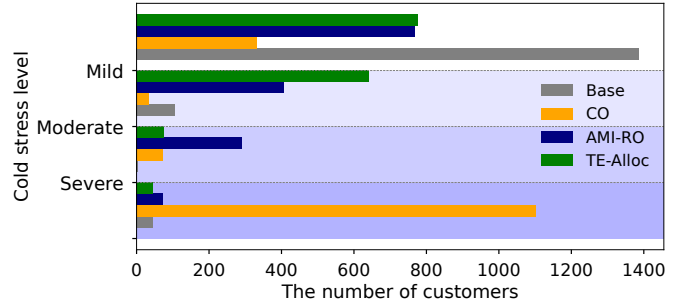


Fig. 8. The number of customers by cold thermal stress level

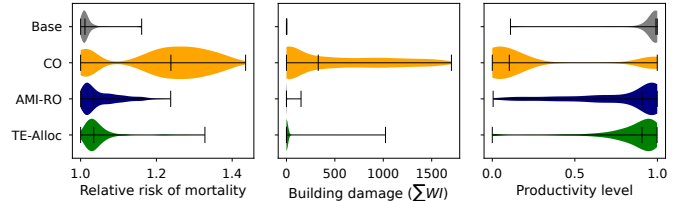


Fig. 9. Occupants and property damage level

illustrated in Fig. 9. The *CO* scenario shows two distinct density groups, reflecting their mechanism. Higher mortality risks were observed and building damage levels varied widely across the customers. Productivity levels drop significantly for large customers during extreme cold temperature outage events. Conversely, the *AMI-RO* and *TE-Alloc* scenarios show lower mortality risk and higher productivity levels.

Fig. 10 breaks down total costs associated with occupant and property damage during extreme-temperature outages, including the value of statistical life, medical costs, productivity losses, building maintenance expenses, and general power interruption costs, along with Table I. The outages lead to increased non-energy impacts, along with medical expenses and the value of statistical life due to health threats caused by the extreme cold. Implementing improved outage mechanisms like *AMI-RO* and *TE-Alloc* significantly reduces medical and VSL costs by maintaining acceptable indoor temperatures.

TE-Alloc shows slightly higher costs associated with productivity decrease costs compared to *AMI-RO* (i.e., \$ 1.78 billion for *TE-Alloc* versus \$ 1.43 billion for *AMI-RO*). This is due to the fundamental operational difference between the two mechanisms. *TE-Alloc* ensures a more consistent power supply to customers, while intermittent power supply is characterized by *AMI-RO*. In our analysis, the cost of decreased productivity is related to how indoor thermal conditions, are maintained when power is available in buildings.

An intriguing finding is observed when comparing Table I to Fig. 10, revealing further layers of complexity, through a detailed cost breakdown across residential and commercial customers. In Table I, productivity decrease costs for the residential customer under the *TE-Alloc* scenario are 1.4 times as costly as those under the *AMI-RO* scenario. This result aligns with the earlier rationale that we discussed. For commercial customers, on the other hand, a 1.8% reduction in productivity decrease costs is observed under the *TE-Alloc* compared to the *AMI-RO*. This reduction is due to the higher thermal comfort setting for commercial customers in the *TE-Alloc* case. These observations demonstrate that sophisticated strategies are required to optimize both cost-effectiveness and

TABLE I
CUSTOMER COSTS

Customer Costs	Residential			Commercial		
	CO	AMI-RO	TE-Alloc	CO	AMI-RO	TE-Alloc
Monthly Energy Costs						
Capital (HEMS) (\$)			1.5			7.9
Energy Procurement (\$)	160.4	175.1	258.9	724.8	763.6	884.0
Cost Per Customer (\$)	160.4	175.1	260.4	724.8	763.6	891.9
Total Cost (scaled) (\$M)	292.7	319.5	475.1	128.9	135.8	158.6
Damage / Loss Associated with the Event						
VSL (\$)	2706.0					
Medical (\$)	4602.0	738.0	732.2	0	0	0
Productivity Decrease (\$)	91.2	495.6	698.4	602.4	2878.8	2828.4
Building Maintenance (\$)	2637.6	26.4	67.2	5515.2	134.4	46.8
Power Interruption (\$)	130.6	108.36	56.64	14481.6	8917.2	4869.6
Loss per customer (\$K)	10.16	1.37	1.55	20.60	11.93	7.74
Total Loss (scaled) (\$B)	18.56	2.52	2.84	3.66	2.33	1.38

TABLE II
SYSTEM-LEVEL COST IMPACTS

Category	CO	AMI-RO	TE-Alloc
Utility's Change in Capital & O&M Costs from BAU-case			
Capital (\$M)	5.67	33.0	39.82
O&M (\$M)	2.26	15.24	18.71
Utility's Change in Energy Purchase & Sales from BAU-case			
Wholesale Purchases (\$M)	830.4	1764.0	2292.0
Revenue from Sale (\$M)	-74.52	-42.84	-26.28
Total Change in Utility's Costs from BAU-case			
Total Costs (\$M)	763.8	1855.1	2376.8
System-Level Impact of Resilience Enhancement			
Increased DSO costs (\$B)	-	1.09	1.61
Avoided customer damage (\$B)	-	17.32	18.00

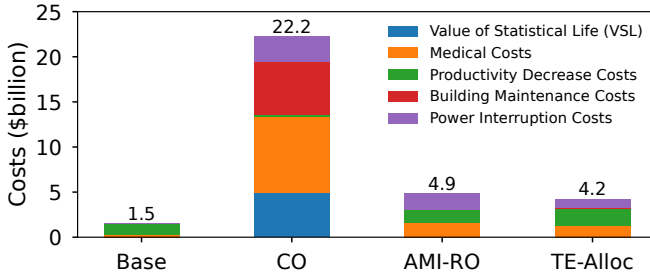


Fig. 10. Costs breakdown of the non-energy factors

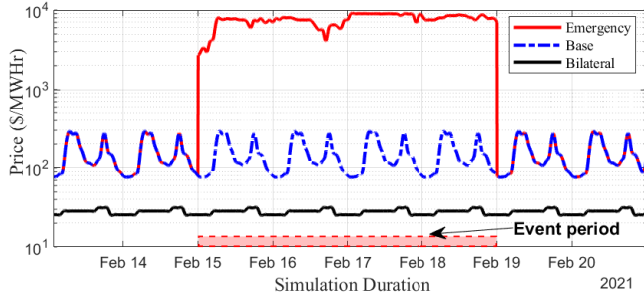


Fig. 11. Wholesale energy prices assumed for bilateral purchases along with DAM purchases for the BAU and emergency cases.

customer satisfaction across diverse customers.

C. Valuation

1) *Customer Costs*: Table I summarizes annual customer expenses in terms of total bills and losses associated with impact factors, categorized by customer type (i.e., residential and commercial). Total bill includes energy expenses and equipment installment costs, primarily for HEMS installations, annualized and distributed monthly. Damage-associated costs are also annualized, assuming a once-a-year occurrence of extreme temperature-related outages.

Energy procurement costs are relatively higher in *AMI-RO* and *TE-Alloc* cases compared to *CO* case due to better utilization in the former scenarios. For instance, in *AMI-RO* case, the intermittent power supply leads to increased electricity consumption when HVAC systems restart after outages. The

TE-Alloc case maximizes the available power for customers, thereby resulting in the highest energy procurements. Conversely, the *CO* allocates power based on the feeder allocation, leading to lower energy procurement.

The highest “Loss per customer” in *CO* case indicates that the customer damage might be the most severe, whereas *AMI-RO* and *TE-Alloc* cases result in lower customer damage due to more efficient energy utilization. Specifically, in the *TE-Alloc* scenario where more power is allocated to commercial customers, the losses are approximately 35.1% lower than *AMI-RO* case and 54.4% lower than *CO* case. For the residential customers, the *TE-Alloc* case shows an 84.7% reduction in the total costs compared to *CO* case but a 12.1% increase in the total costs compared to *AMI-RO* case. This demonstrates the importance of incorporating advanced metrics into the customer cost calculation. Assuming that the losses were not included in the calculations, the total bill would have increased by approximately 9.2% for *AMI-RO* and 62.3% for *TE-Alloc* in residential customers, and by 5.4% and 23.0% for *AMI-RO* and *TE-Alloc* cases respectively in commercial customers, compared to *CO* case.

2) *Utility Costs*: Table II presents a summary of utility expenses, encompassing capital, operations & maintenance (O&M), and energy purchase cost along with missed revenues for energy sold to customers. It is important to note that these expenses are additional to the standard investments and O&M of the grid. However, many of these investments are justified through broader value propositions during “blue sky operations” than just resilience. This analysis aims to capture the additional costs that would be imposed on utility as they aim to implement the resilience enhancement mechanisms. Thus, Table II presents this as the change in the monthly costs for utilities as compared to the BAU scenarios.

Each case has distinct infrastructure investments, as reflected in the capital costs. In the *CO* case, only basic distribution automation infrastructure investments are considered. The *AMI-RO* case includes the replacement of traditional meters with advanced meters by utility along with the cost of setting up and maintaining AMI networks. Lastly, the *TE-Alloc* scenario incorporates investments in bi-directional customer communication infrastructure, for reliable communication of

bids and allocations to individual customers. For further details on the parameters and value settings for these cost calculations, please refer to [27]. Due to the advanced infrastructure, the *TE-Alloc* case has the highest capital costs and O&M costs.

During the event, the wholesale electric prices reached \$9,000/MWhr which was the “system cap” set by ERCOT. This would impose additional costs on the DSO for every MWhr of energy purchased from wholesale markets. The BAU costs for energy purchases were estimated using ERCOT DAM prices from prior non-emergency but high-demand days as proxy prices (shown in Fig. 11) and considering 45% of the energy purchased from DAM and the remaining through bilateral agreements (see Fig. 11). The additional DSO purchase costs were estimated based on the differential cost of energy purchase from DAM at the emergency prices (see Fig. 11) during the event. Since the *AMI-RO* & *TE-Alloc* mechanism could achieve a higher degree of utilization as compared to the legacy *CO* mechanism, this would be associated with the additional purchase cost for the DSO as indicated in Table II. However, due to limited availability during the event, the DSO would also lose revenue as the lost opportunity for sales which are determined based on a retail blended rate of 12.4 ¢/kWh and the ENS values obtained from simulations.

Table II indicates that while implementing advanced resilience enhancement mechanisms would impose additional costs on utilities, \$1.85B for *AMI-RO* & \$2.37B for *TE-Alloc* cases as compared to \$0.763B for the legacy *CO* mechanism. This is mainly due to the energy purchases made at extremely high DAM prices to serve customers during the extreme event. However the economic viability of such prices is still an ongoing debate. Nonetheless, at such high prices, the avoided customer damages and societal benefits are huge (\$17.3B for *AMI-RO* & \$18B for *TE-Alloc* cases) and far exceeds the additional costs incurred by the DSO.

D. Key Takeaways

Extreme temperature-related outages may result in significant non-energy impact costs. Advanced resilience mechanisms are crucial for both energy supply stability and mitigating economic losses while ensuring customer thermal comfort.

Although it may not be feasible to provide continuous supply to all customers during such scarcity, efficient utilization of the available resources plays a very important roles in reducing the damages. Both the *AMI-RO* and *TE-Alloc* scenarios demonstrate lower customer damage compared to existing outage mechanisms, due to enhanced energy utilization. These more effective strategies lead to a reduction in total costs by extreme temperature outages and improve overall resilience.

Furthermore, there would be trade-offs in the damages experienced between customer groups. While the *TE-Alloc* scenario significantly decreases interruption costs for commercial customers, it results in higher interruption costs for residential customers compared to *AMI-RO* case. This highlights the need to balance energy allocation across customer groups considering the equitable service provision. Our analysis also emphasizes the importance of including metrics such as VSL and medical costs, in customer cost calculations. Failure to account for these non-energy impact factors could result in a significant underestimation of the true economic impact.

Finally the techno-economic analysis indicates that although additional costs (mainly associated with extremely high market prices) are incurred by the DSO to supply energy during extreme events, implementing advanced resilience enhancement mechanisms would lead to avoided customer damages and thereby societal benefits that far exceed the former.

VIII. CONCLUSION

This paper presents a comprehensive techno-economic analysis framework aimed at evaluating the resilience enhancement mechanisms from different stakeholders considering the operational performance along with the impact on economic losses and customer safety. This framework is tailored to address scarcity events related to extreme temperature, accounting for non-energy impacts and the associated customer losses.

By leveraging a co-simulation platform with a physics-based distribution grid simulator, the work implements two resilience mechanisms: a data-driven rolling outage (*AMI-RO*) and the TE-based allocation scheme (*TE-Alloc*). The techno-economic performance of the mechanism is evaluated through a realistic use-case emulating the responses of both the grid and individual customers during the winter storm Uri in Texas in 2021. Analysis on such a realistic use-case demonstrates the capability of the proposed framework towards enabling operators to understand potential vulnerabilities and the effectiveness of different approaches in avoiding customer loss during extreme events as compared to their cost of deployment. With the comparative analysis conducted for the ERCOT SC-WZ zone, both the *AMI-RO* and *TE-Alloc* cases demonstrated their effectiveness in maintaining a higher degree of thermal comfort (~ 3.4 - 3.5 times on average) as compared to the legacy outage mechanism (*CO*). The *TE-Alloc* scheme outperformed in terms of energy utilization, considering customer preferences, and reducing power interruption costs. The analysis also indicates that the DSO has to incur additional costs, in order of ~ 1.1 - 1.6 B, to deploy such a mechanism and supply energy during extreme events. However the avoided customer damages and thereby societal benefits of implementing such mechanisms are high, in the order of ~ 17 B - 18 B, and thereby far exceed the associated costs.

This study underscores the significance of implementing performance analysis of intelligent outage mechanisms for energy utilization and cost-benefit analysis, to provide insights crucial for informed planning and investment decisions. Although the proposed framework cannot predict events before they occur, the insights gained from the evaluation strongly suggest the need for resilience investments and improvements in outage management strategies, and their benefits far outweigh the additional costs associated with deployment. Future research will put particular effort into customer acceptance and effectiveness across diverse customer groups. It is imperative to refine the intelligent outage mechanisms to align more closely with the varied needs of customers, considering their preferences and behaviors during extreme temperature outage events. Moreover, while this paper primarily focused on evaluating the advanced outage mechanisms, the development of predictive outage mechanisms could be an area of future research.

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