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Final Technical Report (FTR)

Cover Page

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f. *Principal Investigator (PI)*	Name: Bala Natarajan Title: Professor Email address: bala@ksu.edu Phone number: 785-317-7010
g. *Business Contact (BC)*	Name: Paul R. Lowe Title: Associate Vice President for Research, Director, Office of PreAward Services Email address: plowe@ksu.edu Phone number: 785-532-6804

Signature of Certifying Official *Date*

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EXECUTIVE SUMMARY

The Stakeholder-guided holistic, Adaptive Framework for enhancing community Energy Resilience (SAFER) project advances resilience science and engineering by addressing challenges in rural Kansas communities where aging infrastructure, extreme weather, and socioeconomic disparities heighten vulnerability to energy disruptions. Traditional approaches often focus on technical performance while overlooking community concerns and priorities. SAFER responds by integrating community perspectives with advanced analytical frameworks to create a holistic model for measuring and improving resilience.

Project objectives included developing novel resilience metrics, advancing modeling frameworks that capture interdependencies across infrastructures, and embedding community-centric indicators directly into planning processes for distributed energy resources. The key technical innovations included the creation of self-organizing map (SOM)-based indices for objective resilience quantification, hetero-functional graph theory (HFGT) models linking power, water, transportation, and community assets, and graph neural network (GNN) tools for identifying critical nodes in complex systems. Community-centric energy planning was demonstrated through optimal siting and sizing of (photovoltaic) PV and battery storage, ensuring resilience enhancements also addressed energy burden and energy insecurity.

SAFER engaged community partners in Dodge City and Ford County through surveys, focus groups, and workshops, generating more than 600 responses that established baseline measures of energy burden, financial insecurity, and willingness-to-pay to avoid outages. This data, organized in terms of a community capitals framework, informed the development of weighted reliability indices that better reflect community costs than traditional utility metrics. SAFER's GNN-based critical node identification framework identified expert-labelled critical nodes with over 99% accuracy, while also uncovering additional functionalities essential for proactive resilience planning. The project's models demonstrated that optimal PV and storage deployment could improve resilience indices by over 11 percent, with dispatch strategies further enhancing outcomes, confirming both the technical effectiveness and economic feasibility of these approaches.

Through its combined emphasis on rigorous modeling, community-focused planning, and community engagement, SAFER advances the state of resilience research while delivering direct benefits to rural communities. The project provides tools, guidelines, and resilience heatmaps that help utilities, local governments, and residents better anticipate disruptions, prioritize investments, and strengthen the capacity to withstand and recover from energy-related hazards. Furthermore, the developed HFG and GNN frameworks are designed for transferability, allowing them to be adapted for resilience planning in other communities with minimal retraining. This inductive learning capability provides a scalable pathway to extend the SAFER project's impact. Thus, creating a foundation for a nationally applicable model of infrastructure resilience. Additionally, the HFG can also be extended to include other FEMA community lifelines.

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BACKGROUND

Community Resilience and Its Integration to Infrastructure Resilience

Improving community and energy resilience requires that we utilize a systems level approach that takes account of socioeconomic contexts [1]. The community capitals framework provides a holistic approach to capture assets and resources, including natural, built, human, cultural, political, human and financial capital, which provide a means to assess adaptive capacity of a community [2] and provide linkages to community vulnerabilities and assets to energy infrastructure and related services [3]. Assessments of community energy vulnerabilities have used several indicators (e.g., energy burden, insecurity and poverty) based on cost, ability to pay, and access = [4-5]. When these indicators are estimated at municipal or larger scales, they may underestimate actual energy situations in a community. Both secondary and primary data are needed to effectively gauge the energy situation of a community [4]. Much research using these measures, such as value of lost load, may not include current or adequate data for rural areas [6].

The current project extends this literature in a number of key ways. First, we engage communities through focus groups, community workshops, and primary survey data collection to understand rural communities' priorities with respect to community and energy resilience. Primary survey data is used to build models of energy burden, financial energy insecurity, and household value of loss load for a U.S. rural community that can capture heterogeneity of these measures across a rural community. Second, we identify community capital indicators for all of the community capitals using primary and secondary data to build community capital-based metrics for community resilience that connect with energy infrastructure. This builds on a small and growing literature trying to quantitatively measure community capitals [7]. These metrics and measures are examined at the household to community scale. Development is also driven by community input on how a community capitals influence community resilience using a community engagement approach [8].

Resilience Quantification Methods

Recent literature presents a wide range of definitions, metrics, and assessment techniques for power system resilience, generally focusing on a system's ability to prepare for, absorb, and recover from high-impact events [9]-[11]. Resilience is typically classified as short-term, capturing a system's dynamic response during an event, or long-term, involving infrastructure planning and mitigation [12]. Existing work quantifies resilience either probabilistically, using historical outage and restoration data to estimate indices such as restoration speed [13], or analytically, through simulations of event scenarios. Analytical studies further branch into complex-network approaches that apply graph theory and multi-criteria decision methods [14] and power-flow approaches that integrate stochastic optimization and system-hardening strategies [15]. Other research has explored community resilience metrics, including Conjoint Community Resiliency Assessment Measure (CCRAM) [16], self-assessment toolkits [17],[18], and indicators such as willingness to pay [19], as well as Sandia's Social Infrastructure Service Burden [20]. While these methods have advanced the understanding of resilience, they share several limitations: they often depend on post-event data, focus narrowly on infrastructure without integrating community vulnerabilities, and require subjective weight assignments or complex computations that hinder field adoption. A holistic resilience quantification framework must therefore capture both technical performance and community heterogeneity.

The SAFER project builds on and diverges from this body of work in key ways. Integrating socioeconomic vulnerability into resilience metrics can guide more equitable restoration strategies, inform distributed energy resource (DER) planning, and support policy interventions that protect at-risk populations. However, existing approaches to community resilience are often too complex, costly, or disconnected from utility planning processes, hindering their adoption in real-world decision-making. To address these gaps, SAFER develops community-centric resilience metrics that extend familiar utility indices to incorporate socioeconomic vulnerability in a computationally tractable manner by proposing a set of easy to compute, modified versions of reliability metrics typically used by utilities that can guide more sustainable and equitable resilient power system decisions. Further, it moves beyond the state of the art by introducing SomRes, a self-organizing-map-based, data-driven approach that estimates real-time, time-varying resilience from current and forecasted-system states without solely relying on historical event data or subjective weight assignments. Existing resilience quantification methods, such as weighted-sum or convolutional-integration-based methods, need a weight-assignment based on the perceived importance of resilience features being considered and, more so, on the system parameters, such as topology and size of the generating assets, which vary greatly from one system to another. Therefore, it becomes very difficult to assess which system parameters might be more dominant towards increasing/decreasing resilience, thereby making it difficult to assign weights to the multitude of resilience features that can be considered. Thus, weight-assignment methods are typically subjective and depend on the system operator's interpretation. On the other hand, SomRes is an unsupervised data-driven method that is used to aggregate a set of resilience features into an index using no input for weights. In SomRes, the neurons learn the various simulated system states and the corresponding resilience feature values, and then arrange themselves automatically in a one-dimensional array based on the learnt relative importance of those features. Furthermore, unlike most community-based metrics that are too generic or costly for integration into power-system operations, SomRes directly incorporates a broad set of infrastructure and operational features, while its offline training allows fast, on-demand assessment suitable for utility use.

By assimilating and extending these published methods, the project accelerates development and improves quality: existing probabilistic and analytical findings guide the selection of critical parameters for SOM training, and community-metric research informs the inclusion of demographic and service-access considerations. In doing so, the project situates itself squarely within ongoing R&D while delivering an objective, utility-ready tool that advances both the measurement and operational enhancement of power-system resilience.

Integrated Adaptive Resilience Analysis Framework

Recent research has explored modeling frameworks for electrical power distribution systems, focusing on interdependence with critical infrastructures like water, natural gas, transportation, and emergency services to enhance resilience against cascading failures. Simulation-based models have been used to effectively capture bidirectional dependencies between power and other infrastructure systems to simulate disruptions and identify mitigation strategies [21]. However, while these approaches provide higher accuracy, they are computationally intensive, making them infeasible for large systems. Component-level mapping and multi-layer frameworks have also been used to model interdependencies among power, water, gas, transportation, and/or communication infrastructures [22]-[25]. These approaches provide lightweight alternatives to simulation-based approaches. However, they often oversimplify the system physics. Socio-economic considerations have also been made in modeling interdependent infrastructure systems [26]. These allow stakeholder-oriented frameworks to evaluate and map modeling methodologies against specific decision-making contexts. Finally, hazard-specific models have also been incorporated into multi-infrastructure models [27]. However, these methods are not generalizable across other hazards or multi-hazard scenarios.

Therefore, no single existing framework ties together the benefits of having a light-weight approach that maps functionalities across multiple infrastructures and takes into consideration socio-economic factors while being general across multiple hazard types. This necessitated the development of SAFER's Integrated Adaptive Resilience Analysis Framework, which uses a hetero-functional graph theoretic (HFGT) approach to model critical interdependent infrastructure systems. It enables rapid scenario analyses and integrates community metrics like social vulnerability for community-focused interventions and critical node identification via graph neural networks, addressing rural community challenges.

Resilience Enhancement Approaches

Power distribution systems are rapidly evolving with high levels of distributed generation (DG) such as solar PV, wind, and biomass. Traditional DG planning uses optimal power flow to minimize losses, improve voltage profiles, and reduce energy costs [36], and studies show networks can host 10–15% DG penetration without major upgrades. At the same time, recent research has begun to incorporate community considerations [37], [38]: e.g., hosting capacity and outage reliability for disadvantaged versus non-disadvantaged communities [39], and game-theoretic coordination of microgrids with fairness [40]. These studies are like the current project in that they recognize the need to embed community aspects into distribution system decision-making and use advanced optimization or analytic tools to inform DG deployment.

However, important differences remain. Most existing efforts emphasize operational flexibility or incremental hosting-capacity analysis and generally treat community perspectives qualitatively or as a post-processing step, rather than as a primary design constraint. In contrast, the present project embeds community metrics directly in the DG planning process by using optimal transport theory to transform the statistical distribution of consumer energy burdens toward an “equal distribution equivalent.” This approach determines the optimal siting and sizing of rooftop solar PV while balancing cost-effectiveness and community objectives, and it supports both revenue-neutral and revenue-agnostic modes of implementation. These capabilities go beyond the operational or policy-translation focus of prior work.

The project fully leverages published methods to accelerate development and improve quality. Established DG optimization and hosting-capacity studies inform the technical constraints and cost models used in the optimal-transport formulation, ensuring that the proposed algorithm aligns with proven power-flow and economic principles. Insights from community-focused research guide the selection of demographic and socioeconomic indicators and validate metrics for measuring reductions in community energy burden. By synthesizing these advances into a single optimization framework, the project situates itself within ongoing R&D on equitable distributed energy resources while delivering a rigorous, utility-ready planning tool that moves the state of the art from descriptive community-benefit analysis to actionable, system-wide DG planning.

PROJECT OBJECTIVES

The objective of the proposed project is to enhance community energy resilience of rural regions of Kansas via the development of a one-of-a-kind SAFER framework that incorporates novel resilience quantification, analysis and enhancement technologies. The SAFER framework involves key technology innovations (summarized in Fig. 1) which will be pursued in collaboration with our city/county/utility partners. These include co-designing novel power system performance and non-performance-based community resilience metrics and integrating them via a unique self-organizing map (SOM) approach. To effectively compute community resilience metrics, SAFER will explore the use of a hetero-functional graph theoretic (HFGT) modeling framework to capture interdependencies between energy and other critical infrastructures. The holistic and adaptive graph theoretic framework will also

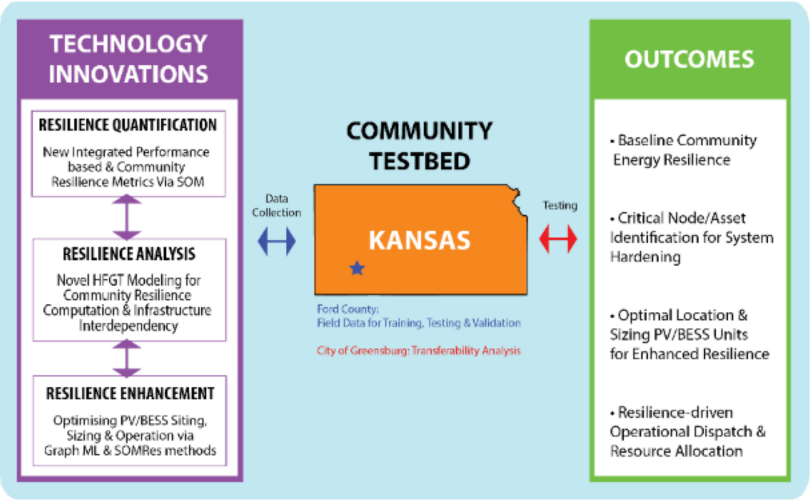


Figure 1. Proposed SAFER approach to quantify, analyze and enhance community energy resilience

be used for effective scenario analyses to (1) identify system vulnerabilities and critical assets via a novel graph neural network (GNN) based approach; (2) effective restoration strategies that emphasize community welfare (e.g. energy security and resilience, social vulnerability); (3) demonstrate impact of optimal renewable energy and storage integration on resilience enhancement, and (4) assist in updating stakeholders' energy and community resilience planning efforts.

Table 1. Project milestones, status, and success measures

Milestone	**Milestone Description**	**Percent Complete**	**Assessment Tool / Method of Measuring Success Value**
1.1.1	Human Subject Training, IRB provided by the Collaborative Institutional Training Initiative (CITI) Community-Engaged & Community-Based Research training provided by the Collaborative Institutional Training Initiative (CITI)	***100%***	Training organized. Completion of Human Subject and Community Engagement modules.
1.2.1	Establish NDA and Data sharing agreements, (IRB) protocols	***100%***	NDA negotiation process and language aligned with project needs and goals and amenable to all parties
1.3.1	Stakeholder Advisory Council Kickoff Meeting	***100%***	StAC kickoff meeting organized
1.3.2	Stakeholder Advisory Yearly Meeting	***100%***	The StAC meeting at the end of year 1 will be used to update all partners on the project progress. Feedback will be used to guide the follow-on efforts in year 2.
2.1.1	Representative Community Sample for Survey	***100%***	We will assess representatives of survey response overall and for different community sub-populations using community secondary-data and census-tract data. We will also assess the representativeness of underrepresented groups (DEI).
2.2.1	Community Focus Group Interviews	***100%***	Community focus group interviews organized and completed with community members and organizations participating.
2.3.1	Collection of Power System Related Data and Other Socio-Economic Data	***100%***	Summary of collected data provided to DOE in quarterly reporting.
3.1.1	Define Community Resilience Metrics Based on Community Capitals	***100%***	We will cross-check with community stakeholders and partners on the suite of metrics defined. Summary of findings and metrics shared with DOE as part of quarterly review/report
3.2.1	SOM resilience index validation based on power system performance-based resilience metrics	***100%***	Results and report sent to DOE as part of quarterly review/report
4.1.1	Equivalent HFGT model for Dodge city power distribution system	***100%***	The HFG model will be shared with DOE as part of the quarterly review/report
4.2.1	Integrated HFGT model with socio-economic factors and physical infrastructure models completed	***100%***	Modeling framework will be shared with DOE as part of the quarterly review/report
4.3.1	Baseline community energy resilience index	***100%***	Results and report sent to DOE as part of quarterly review/report and also shared with stakeholders

5.0.1	Identifying the critical nodes/functionalities/assets	***100%***	Simulation results and report sent to DOE and utility partners for verification.
6.1.1	Community energy resilience index with the proposed holistic resilience focused optimal PV/BESS sizing and siting	***100%***	Simulation results and report sent to DOE and stakeholders for verification
6.2.1	Community resilience index when the proposed optimal resource allocation and dispatch strategy is employed on top of optimal siting	***100%***	Simulation results and report sent to DOE and stakeholders for verification
7.0.1	Resilience Heatmap for Ford County	***100%***	Simulation data and Report sent to DOE and utility for verification.
8.1.1	Planning and Assessment Guideline Tool	***100%***	Planning and assessment guideline report submitted in quarterly report to DOE
8.1.2	Community Resilience Workshop	***10%***	Summary of workshop report provided to DOE in quarterly reporting. This engagement activity is planned for Fall 2025
8.2.2	Project Web Page	***100%***	Summary of web page development and access to DOE and links to original source code provided in quarterly reporting.

PROJECT RESULTS AND DISCUSSION

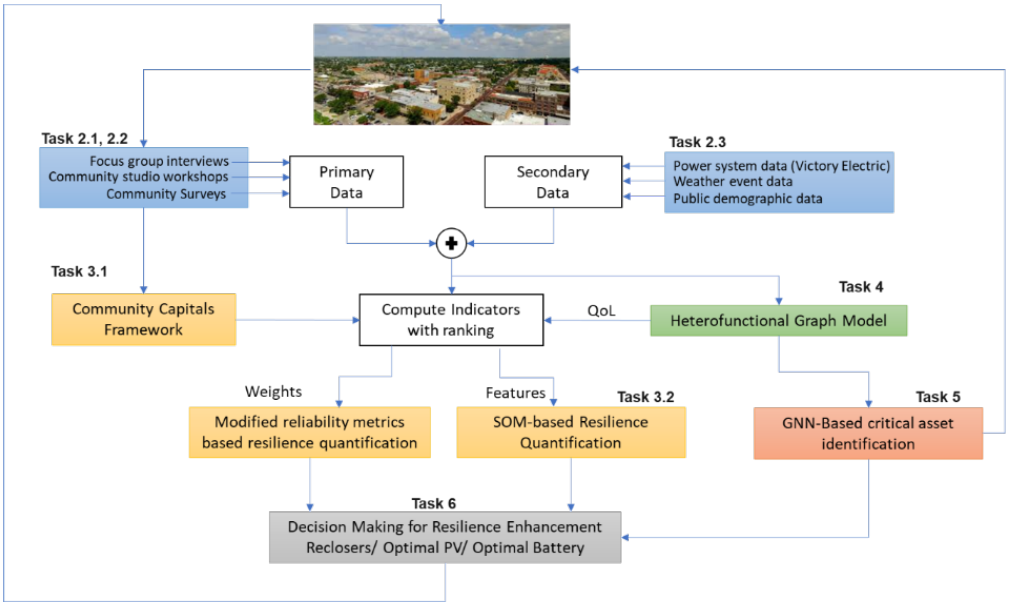


Figure 2. Project and Tasks Overview

Fig. 2 gives the overall flow of various tasks associated with this project. The first task of the project was to collect primary and secondary data needed for downstream tasks. The primary data was obtained using *Community Stakeholder Engagement* and secondary data was obtained from the utility and various other data sources. Since one of the major goals of the project was to involve the community in the decision-making process, community workshops and interviews were also utilized to understand priorities of the community to select the indicators and rank them based on importance. These indicators, along with appropriate rankings, were then used for *Resilience Metrics Quantification* using approaches such as modified reliability metrics and Self-Organizing Maps (SOM). Other indirect Quality of Life (QoL) indicators and their changes during disruption events were obtained using a *Novel Integrated Adaptive Resilience Analysis Framework* using heterofunctional graph theory (HFGT). This integrated approach supports analyzing various cascading impacts considering socio-economic factors, community assets, and multiple infrastructure systems. A GNN based framework was then implemented on this HFG to identify the critical nodes, functionalities and assets that could support recovery from the disruptions. The resilience metrics and the HFGT outputs were then used for *Enhancing Resilience via Placement of Renewables and Reclosers.* The resilience decisions, along with the metrics and important assets, were finally reported back to the community to help local governments and partners identify, assess, and implement resilience initiatives using the SAFER project outcomes. Each of these different tasks are explained in detail in the sections below.

TASK 1.0: WORK PLAN AND PROJECT MANAGEMENT

Task Summary

This task focused on establishing project management structures, building partnerships, and engaging stakeholders to guide the SAFER project. Together, these activities provided the foundation for all other project milestones by ensuring strong project management, trusted utility partnerships, and engaged community stakeholders. The kickoff and quarterly meetings helped inform survey design, resilience metrics, and workforce development efforts. The Non-Disclosure Agreement (NDA) process with our utility partners secured the data access necessary for technical analysis. This helped ensure that subsequent milestones would be built on solid community relationships, reliable data, and a well-prepared research team.

A summary of accomplishments include:

- Established project management processes and team training.
- Executed NDA process with utility partners.
- Held StAC kickoff, quarterly, and end-of-year meetings.
- Strengthened utility and community partnerships.
- Supported workforce development.

Task Outcomes

Stakeholder Advisory Committee Kickoff and Quarterly Meeting

We held a kickoff event on August 14, 2023, with our Stakeholder Advisory Committee (StAC) in attendance, including members from Victory Electric, City of Dodge, Dodge City, and Ford County Development Corporation, Emergency Management of Ford County, Catholic Charities, Dodge City Community College, and local businesses. We presented an overview of the project, including our mission and goals, building community partnerships, benefits to the community, working with our partners, and a question-and-answer session. We conducted a facilitated activity and discussion around several topics related to community and energy resilience. We continued to meet with the StAC members regularly. These meetings provided input and feedback to disseminate findings and educate our community partners on what we learned. We learned that community resilience in Ford County and Dodge City spans disaster response and recovery, preparation, adaptation, and mitigation; economic and political factors; leadership and communication; community vitality and survivability; and access to services such as power. Attendees emphasized energy's role in growth, reliability, affordability, daily operations, safety, and health. Perceptions of energy resilience included safety, variety, sustainability, affordability, reliability, vulnerability to weather, sound infrastructure, and adaptability of systems. When asked to identify top factors that shape community resilience, attendees indicated employment and wages, cooperation, leadership, energy affordability, weather, aging infrastructure, migration, supply chain dynamics, economic conditions, education, social networks, food security, and community planning. While many potential data sources were identified, not all are public, requiring SAFER to conduct surveys and focus groups. In addition, few attendees were directly measuring or collecting data specifically about community resilience. This information provided the necessary background for survey development.

Figure 3: Community and Stakeholder Engagement Event in Dodge City, KS on August 14, 2023.

We continued to meet with StAC members at least quarterly, both virtually and in-person, to share project updates and further feedback. These meetings provided valuable insights, including the importance of obtaining quantifiable measures that clearly demonstrate the value of resilience investments to community members. Attendees expressed strong interest in survey results (see attached SAFER Summary Report). We also collaborated with our utility partner, who received funding to install reclosers, to quantify the potential benefits of this investment for both the community and the utility. Workforce development was another recurring priority, with the StAC supporting efforts to engage local students in resilience-related research. Through the K-State Research Immersion: Pathways to STEM (RiPS) program, SAFER worked with two undergraduate students from under-represented groups on predicting power outages based on weather data for the Dodge City/Ford County area. One student from Dodge City Community College will be transferring to K-State to pursue an engineering degree. The StAC welcomed this and encouraged continued student opportunities.

Impact

Through our StAC meeting and community engagement, we have built lasting partnerships in the Ford County and Dodge City community. As seen above, we have worked with our partners to help provide needed data about the community, assess benefits working directly with partners of investments to build energy resilience, built relationships with local colleges to educate students and facilitate pathways for STEM learning, and provide needed resilience metrics and information to help inform the community and explain why resilience investments are extremely valuable. Our partnerships help to build needed bridges to disseminate our research findings and project outputs and for future energy research in order to have on-the-ground impacts.

Table 2: Task 1 milestones and status

Task #	Performance Metric	Success Value	Assessment Tool / Method of Measuring Success Value	Progress Notes
1.1.1	Participation rate for training for SAFER research team	>90%	Training organized. Completion of Human Subject and Community Engagement modules.	100% Complete (All team members have completed training)
1.2.1	NDA process with utility partners to allow access to power system data in Dodge City/Ford County area.	NDA signed and executed	NDA negotiation process and language aligned with project needs and goals and amenable to all parties	100% Complete (Multiparty NDA Executed with Victory Electric Cooperative, Sunflower electric corporation, NREL and KSU)
1.3.1	Participation rate in StAC kickoff meeting	> 70% of committed members	StAC kickoff meeting organized	100% Complete
1.3.2	End-of-year StAC meeting participation	>70% of committed members	The StAC meeting at the end of year 1 will be used to update all partners on the project progress. Feedback will be used to guide the follow-on efforts in year 2.	100% Complete (we had 80% of StAC members participate and we shared a presentation to those who were unable to join due to schedule conflicts)

TASK 2.0: COMMUNITY STAKEHOLDER ENGAGEMENT AND DATA COLLECTION

Task Summary

The milestones in this task focused on gathering community-level data through surveys, focus groups, workshops, and secondary datasets to better understand resilience, energy burden, and energy insecurity in Dodge City and Ford County. The data collected through surveys, focus groups, and workshops provided the foundation for measuring and modeling community resilience. By establishing baseline metrics for energy burden, energy insecurity, and willingness-to-pay to avoid outages, Task 2 enabled the project to quantify community needs and prioritize resilience investments. The secondary datasets and direct community input ensured that subsequent analyses, modeling tasks, and resilience planning efforts are both data-driven and grounded in community experiences.

A summary of accomplishments includes:

- Completed a representative community survey and focus group interviews with local households and businesses to capture disaster experiences, resilience perceptions, and challenges.
- Developed a baseline for resilience by determining and validating metrics for energy burden and energy insecurity.
- Quantified value of lost load through a stated choice experiment to estimate households' willingness-to-pay.
- Hosted a community workshop to identify resilience indicators using the community capitals framework.
- Collected and cleaned secondary datasets for integration into resilience modeling.

Task Outcomes

Community Survey (Subtask 2.1.1)

We conducted a community survey of residents within Dodge City, Ford County, and rural Kansas, working with our community partners and stakeholders (StAC). The community survey was administered online, by mail, and in-person in the Summer and Fall of 2024 in both English and Spanish. IRB approval was obtained prior to sending out the survey. We obtained 613 total survey responses from our survey efforts. The survey asked about community resilience, hazard risks, recent extreme weather events, household characteristics, household demographics, household vulnerabilities, energy burden, energy insecurity, a willingness-to-pay to avoid a power outage during a natural disaster or extreme weather event, and renewable energy support and perceptions. Based on the community demographics that we can match from the Census to our survey responses in Dodge City, Ford County, and rural Kansas, we found that the survey respondents were relatively representative (> 75% representative) of the local county population for the characteristics examined. A copy of the mail survey sent is attached as a supplementary document to this report.

The survey collected primary data to assess financial energy insecurity, energy burden, access to power, and ability to sustain a household in the absence of power and impacts from power outages using designed metrics motivated from literature. We followed metric development for energy insecurity following methods from the Department of Health and Human Services. We developed a stated choice experiment in the survey to assess residents' and businesses' willingness to pay for energy services during an outage (household value of lost load) from an extreme weather event or natural disaster.

Using the survey data, we estimated the average energy burden for electric power in Ford County is 3.1% with a standard deviation of 0.040%. About 9.2% of those surveyed had an energy burden of 6% or higher. Survey data was then used to assess financial energy insecurity for electric power. We developed a categorical scale that had 5 categories: Thriving, Capable, Stable, Vulnerable and In Crisis. Table 3 maps the energy insecurity questions from the survey to the energy insecurity categories. Once a threshold for a given energy insecurity category is met for a given question, a respondent is always placed in that energy insecurity category overall. For example, if a respondent meets the category for Vulnerable for any question, then they will always be in the Vulnerable category, even if they do not meet that threshold for other questions.

Table 3: Energy Insecurity Survey Questions and Mapping to Energy Security Index

Energy Insecurity Question	**Category**	**Threshold**
We were worried that our energy bill would become overdue before we had money to pay it.	Financial Strain	Thriving = (1); Capable = (2) to (5)
Our monthly home energy bill became overdue.	Outside Assistance	Thriving = (1); Capable = (2); Stable = (3) to (4); Vulnerable = (5)
We needed somebody's help or had to reduce our spending on other basic necessities to pay our energy bill.	Outside Assistance Household Necessities	Thriving = Never; Stable = (2); Vulnerable = (3) to (4); In Crisis = (5)
We could not pay our energy bill.	Non-payment of energy bills	Thriving = (1); Stable = (2); Vulnerable = (3) to (5)
We received a notice threatening to disconnect our energy service.	Non-payment of energy bills	Thriving = (1); Stable = (2); Vulnerable = (3) to (5)
We had our energy service disconnected due to an inability to pay our energy bill.	Non-payment of energy bills	Thriving = (1); Vulnerable = (2); In Crisis = (3) to (5)

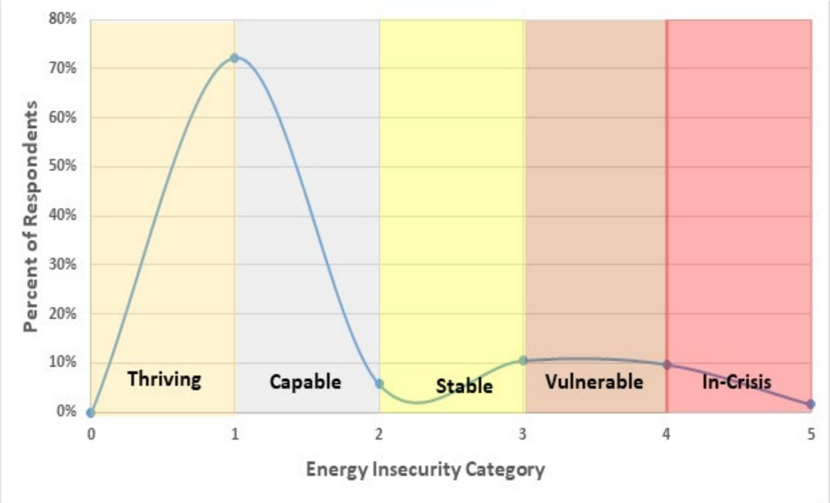


Figure 4: Energy Insecurity of Survey Respondents in Ford County, KS

Figure 4 shows the percentage of survey respondents that fall in the different energy insecurity categories. About 12% of respondents are energy insecure in the Vulnerable or In-Crisis categories. The vulnerable category is based on comfort, convenience, and basic household energy needs. The household may have arrears and be threatened with losing energy services. In addition, they may experience occasional service disconnections and routinely rely on external assistance to pay energy bills. The in-crisis category is households that experience frequent loss of energy services and engage in energy bill payment strategies that adversely affect the provision of basic household needs. These households can live without energy and consistently sacrifice basic necessities to reduce energy use or maintain energy use, but compromise on other non-energy basic necessities.

We determined statistically significant predictors that influence energy insecurity using an ordered logistic regression. We found that higher monthly income, being over 65, owning your home, and having a college degree reduced the likelihood of being in the vulnerable or in-crisis energy insecurity categories. In contrast, higher energy bills, living in a rural area, living in a condo or townhouse, having electric heating, and having electricity dependent medical needs increased the likelihood of being in the vulnerable or in-crisis energy insecurity categories. These factors connect to multiple community capitals, including built, social, human, cultural and financial. We developed a stated choice experiment in the survey to assess residents' and businesses' willingness to pay (WTP) for energy services during an extreme weather event or disaster outage. A focus on rural areas and extreme weather is a novel contribution. An example of the question asked in the survey is provided below in Figure 5. From the experiment, we estimated the cost of outage curves for households, which determines household willing-to-pay to forgo an outage of a particular length, during a given time of day, and time of year. This measure is also referred to as (household) value of lost load. The curves provide a way to measure the indirect cost of power outages to residents and businesses [7].

Power Outages: Please consider three different situations where your power goes out during a severe weather event.

	Situation 1	**Situation 2**	**Situation 3**
Duration of the power outage (hours)	1 day (24 hours)	1 hour	3 days (72 hours)
Part of the week the outage occurs	Weekend	Weekday	Weekend
Starting time of the outage	4:00 p.m.	10:00 a.m.	10:00 p.m.
Season when the outage occurs	Winter	Summer	Summer
User fee charged	$100	$10	$5
Would you be willing to pay for this service?	○Yes ○No	○Yes ○No	○Yes ○No

Figure 5. Sample survey question

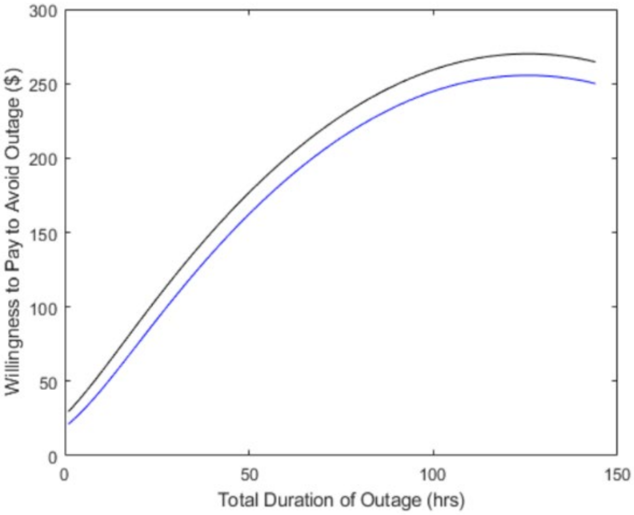


Figure 6: Overall Willingness-to-Pay to Avoid a Power Outage for Different Durations (in hours). Scenario is for a weekday starting at 4 pm. The black curve represents an outage in winter. The blue curve an outage in summer.

The most significant attributes that led to a high willingness to pay (WTP) to avoid an energy outage where the user fee charged, duration of the outage, and having an outage later in the day. The average marginal WTP to avoid an hour of outage was $3.21 across survey respondents within Ford County across all durations of outage. Figure 6 provides a graph showing the overall willingness to pay (WTP) by a household on average for an outage of different durations during summer and winter, assuming it occurs on a weekday starting at 4 p.m. Of interest is that the overall WTP is nonlinear and begins to decrease around 120 hours or a 5-day outage. It peaks at just over $250 for at a 120-hour or 5-day outage. Of value is that this can be used to capture impacts of power outages and reliability across seasons, time of outage, and duration. In addition, this can relate to other community capitals to assess differences across households within a community.

Focused Group Interviews/ Workshop **(Subtask 2.2.1)**

Business Focus Group: We conducted a focused group interview with local businesses on August 14, 2023, with 4 participants (local mechanic, bank, rental agency, and nonprofit organization). Copies of the focus group instrument and questionnaire are provided as an attachment to this report. Attendees had very positive experiences about Dodge City and Ford County, but the businesses did face challenges. Significant challenges identified were economic impacts, such as closing of a beef processor or significant disruption to agricultural production, as well as weather impacts, such as wind and tornadoes. Each business indicated potentially significant impacts from losing power for an extended period, but these varied from loss of business, loss of production, and food security issues. Often, local businesses were not fully prepared for severe weather or a natural disaster, but participants think they and the community would survive and rebound. We also collected information on perceptions about community resilience.

Household Focus Group: We conducted a focus group interview with local households on December 4, 2023, with 8 participants from a group of residents from different backgrounds, parts of the city, employment tracts, and experiences. A copy of the focus group instrument is provided as an attachment to this report. Participants indicated that Dodge City has good “quality of life and quality of people”; had a good education system; a strong investment in culture and local history; good pay and low unemployment; but had issues with healthcare and medical access and lower access to certain markets; The riskiest natural hazards faced included ice storms, high winds, tornados, and drought. Participants felt the power system is relatively reliable, and longer outages are faced by people who are farther out from town. Residents could experience outages for days at a time. Most participants felt power was usually restored relatively quickly. Some participants, but not all, had 1 to 3 days of emergency supplies and only a couple had power generators. Many did not have what they felt were adequate financial savings if a disaster or extreme weather event severely disrupted their lives. Members indicated household resilience depends on availability of services and repair; sources of income; having a reliable vehicle, cost of and availability of insurance; access to health care; cost of childcare and other amenities; among other items.

Community Studio Workshop: We conducted a community studio workshop on February 28, 2024, in Dodge City to further assist with defining community resilience with our research team using the community capitals framework. We had 16 participants across municipal government, civic organizations, non-profit organizations, local businesses, power and utilities, economic development corporations, education, and community members. The community studios helped to identify community capital indicators that can be used to construct and develop resilience metrics that are applicable.

The objectives for the workshop were to (1) help identify important aspects and characteristics of community resilience to shape a community-centric definition of community resilience for each ARISE community; (2) identify community assets based on the community capitals framework and how these community assets interlink with each other; and (3) identify which community assets influence community resilience and balanced representation. The community studio comprised a set of directed activities that tied into each other to meet our objectives, following methods developed by Emery et al., (2006) [8]. All attendees signed an informed consent form to allow us to assess data and information collected, as well as audio record sessions and discussions.

We completed an exercise examining different guiding principles or aspects of community resilience that have been used in literature and planning efforts using a ranking type of experiment known as Best-Worst Scaling. Table 4 shows the high, middle and lower ranked aspects of community resilience identified by participants. Of interest is that reliable access to infrastructure services and reliable and hardened infrastructure ranked among the top five.

Table 4. Relative importance of alternative guiding principles & aspects of community resilience for Dodge City.

Relative Ranking	Guiding Principle
Higher Ranked Aspects	Effective leadership. Reliable access to infrastructure services (water, energy, and transportation). Reliable and hardened infrastructure (water, energy, transportation). Disaster and hazard preparedness plans and resources developed and ready. Balanced access to community services (health, education, housing, child-care).
Aspects Ranked in the Middle	Strong and balanced emergency response. Good communication between infrastructure services (water, energy, transportation) during emergencies. Strong and reliable communication networks Reliable access to community services (health, education, housing, child-care). Balanced access to infrastructure services (water, energy, and transportation).
Lower Ranked Aspects	All community members can easily access information about their water, energy and transportation services. Reliable and sufficient labor force. Community sticks together. Effective early warning. Actively building capacity to withstand future hazards.

We also conducted a mapping of community capitals for Dodge City. An illustration of the mapped capitals is provided in Figure 7. In addition, we asked participants to indicate their perception of how "each community capital influences community resilience and balanced representation for their community." There were four options: "No influence currently and needs a lot of work" (Red) (1), "Lower influence and we need to work on this" (Yellow) (2), "Positive influence but there is room to improve" (Blue) (3), "Strong positive influence and it's moving in the right direction" (Green) (4). We coded these options 1 to 4 and were able to determine the impact of different categories of community capitals on community resilience by averaging across the relevant impact of different identified assets and resources on community resilience.

Figure 7. Dodge City, KS Community Capitals. For full image see Appendix 1.

The community capitals had the following average ratings on a 4-point scale: Political - 3.5, Social - 3.1, Cultural - 2.8, Natural - 2.9, Financial - 3.3, Built - 3.4, and Human - 2.5. The lower the score, the less influence the capital stock had in improving community resilience in Dodge City. Thus, we were able to assess all 7 community capitals and obtained valuable information about how each of the community capitals influences community resilience from the community's perspective.

***Secondary Data Collection* (Subtask 2.1.3).** We developed a database of secondary data for use on project tasks by working with community and utility partners. Table 5 gives a summary of the various secondary data that were collected for Ford County, along with the sources from which these data were obtained. These data were all at multiple spatial and temporal resolutions and some of these data were corrupted. The data was checked and corrected for missing values and errors, and was further spatio-temporally correlated to obtain a cohesive dataset to be used for various tasks as described in the further sections. Fig. 8 shows the combined data indicating the distribution system and county block groups. The county block groups are color-coded based on their social vulnerability index as defined by the generalized community vulnerability score (GCVS) explained further in Task 3.

Table 5. Secondary data sources collected for Ford County.

Dataset	**Information extracted**	**Source**	**Type**
Outage management system data	Outage time, restore time, #Customers, section of distribution system	Victory Electric	Private
Distribution system data	Location (lat-long) of elements (substation, transformer, lines, meters etc.), critical loads	Victory Electric	Private
Wind event data	Location (lat-long), type, magnitude	National Centers for Environmental Information.	Public
Demographic data	Location (FIPS), race & ethnicity, housing tenure, poverty level, education level, age, disability status	American Community Survey	Public

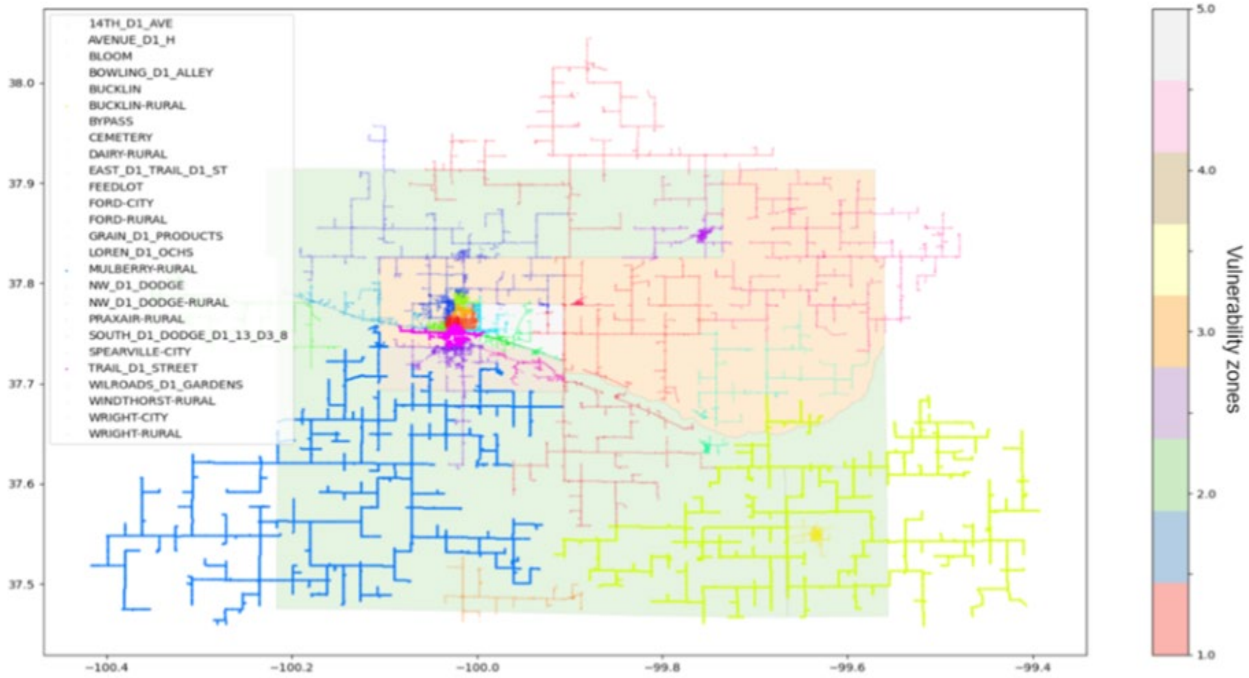


Figure 8. Distribution system overlayed on Ford County with vulnerability zones

Impact

Focus groups with local businesses and residents helped with development of the community survey, understanding community context and local disaster experiences, and helped to assess community perceptions about resilience for metric development. The community survey provided needed data for understanding the energy situation (e.g. energy burden, energy insecurity, and impacts from energy outages from disasters and severe weather) in the community that helps to establish a baseline, provided a primary household level dataset for modeling efforts, and helped with development of household scale resilience and vulnerability metrics, including value of loss load and energy insecurity. Research findings have helped to advance assessment and understanding of value of loss load for households across space at a community scale for a more rural community, as well as understand the prevalence and predictors of energy insecurity in rural areas in the Great Plains of the U.S. Community engagement activities have had impacts by helping to educate partners and residents on energy resilience (through our kickoff meeting, community engagement workshop, survey summary report, and StAC meetings) and provide needed information at a household, community and county scale on household energy situation in the study region. The secondary data was used for various analyses like Self-Organizing Map (SOM) based resilience quantification, heterofunctional graph-based resilience analysis, and resiliency improvement using recloser placement and PV planning. The cleaned secondary data and the cohesive dataset will be shared back with the utility partners for future use cases.

Table 6: Task 2 milestones and status

Task #	Performance Metric	Success Value	Assessment Tool / Method of Measuring Success Value	Progress Notes
2.1.1	Community survey representativeness	>75%	We will assess representatives of survey response overall and for different community sub-populations using community secondary-data and census-tract data. We will also assess the representativeness of underrepresented groups.	100% Complete
2.2.1	Completed focus group interviews with community members and organizations.	At least 1 interview completed.	Community focus group interviews organized and completed with community members and organizations participating.	100% Complete
2.3.1	Collection of power system related data and other socio-economic data.	Data collected adequately to simulate power system behavior during weather events and feed into SOM and HFGT	Critical data needs for utility, SOM and HFGT modeling, and resilience metric estimation have been obtained.	100% Complete

TASK 3.0: RESILIENCE METRICS AND QUANTIFICATION

Task Summary

Task 3 built on the community survey and focus group data from Task 2 to develop and validate resilience metrics that integrate both community capitals and power system performance. This provided the baseline metrics and analytical tools needed to measure and track resilience at multiple scales, bridging community-level social indicators with technical energy system performance. By combining household survey results with optimization and dispatch modeling, Task 3 validated methods to quantify resilience improvements and enables utilities and communities to evaluate the effectiveness of resilience investments.

A summary of accomplishments include:

- Defined community resilience metrics tailored to local priorities using all seven community capitals.
- Developed household and community-scale measures, including energy burden, energy insecurity index, and value of lost load.
- Made spatially explicit maps of resilience metrics for Dodge City and Ford County
- Implemented and validated SOM-based resilience quantification, linking community indices to power system performance.
- Demonstrated that optimal PV/battery siting increased resilience by 11.53% while optimal dispatch improved resilience by 11.01% and load served by 4.69%.

- Established baseline resilience indices for use in modeling, reporting, and future resilience planning.

Task Outcomes

Indicators Based on Community Capitals

We collected a database of indicators for all seven community capitals for development of community and non-performance-based resilience metrics, allowing for resilience metrics to be systematically designed and customized based on community preferences and needs. A list of indicators is included in an EXCEL spreadsheet accompanying this report. Fig. 9 provides an example of community capital indicators that were used to develop a community capital-based resilience capacity metric. Indicators for each community capital were used to estimate community capital indices using factor analysis. The factor loadings are provided along each arc in Fig. 9 between the indicators and community capitals. The resilience capacity metric is the weighted linear combination of the community capital indices. The weights are based on the average standardized rankings of community capitals identified by the community studio participants for each category (discussed on page 16 in the community studio workshop section). These weights are shown along the arcs connecting the community capital factors to the community capital resilience capacity metric in Fig 9. The metric captures a community's overall community capital capacity for enhancing community resilience. For interpretability, the metric is then divided by the number of households (thousands of households) in the county. We compute the same metric with the same weighting for neighboring counties for comparison purposes. Ford County had a rating of 0.10, compared with 0.11 for Finney County and 0.35 for Seward County, two comparable rural counties in southwest Kansas. The comparison indicates that Dodge County has less

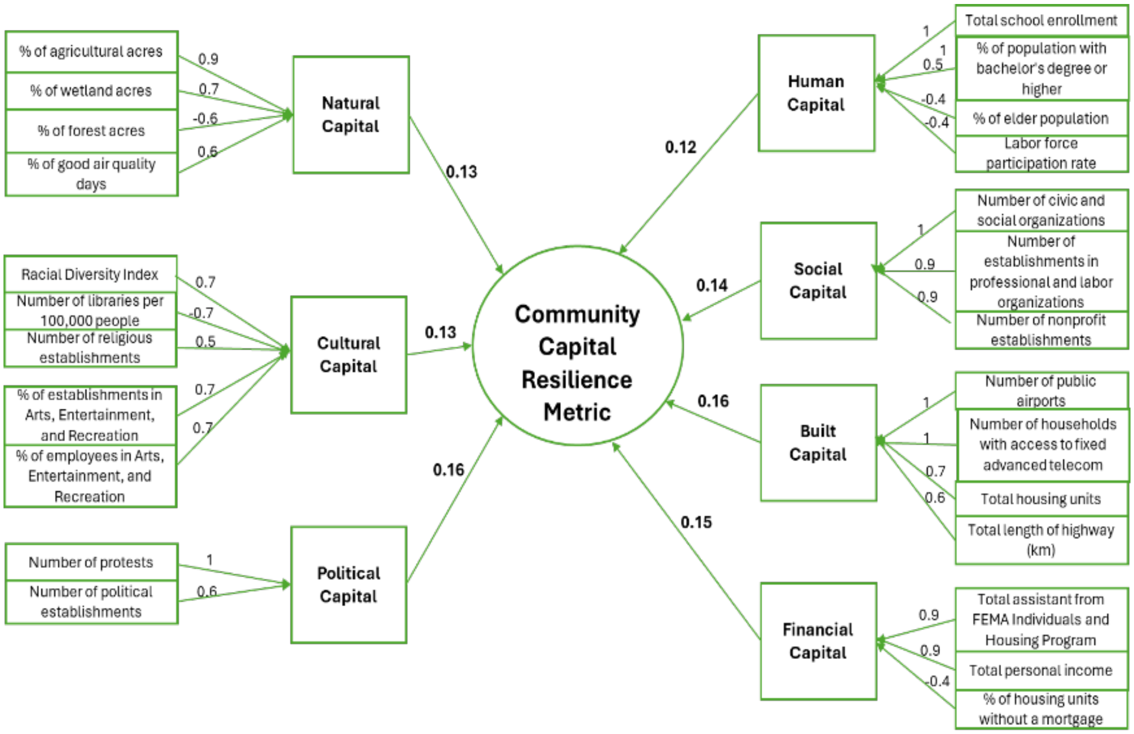


Figure 9. Community-Capital based community resilience metric development framework.

asset and resource capacity for community resilience from a community capital perspective relative to the other two counties. Rural areas are often less resilient than more urban communities [4].

We added several community resilience metrics that are derived from primary community survey data. Results for all three of these were presented earlier under Task 2, Subtask 2.1.1, with survey results. We developed spatially explicit estimates for Ford County and Dodge City from the survey data. These include: **(1)** ***Energy Burden*** – Ratio of monthly energy costs (only for electricity) to monthly household/business income, tied directly to energy price changes, and financial and built capital. **(2)** ***Energy Insecurity*** – Energy insecurity captures the financial strain and ability to pay of households for access to energy. Regression results indicate energy security is influenced by multiple community capitals, including built (electric bill, household, electric service), human (employment, education), social and cultural (demographics), natural (geography) and financial (income). We matched these predictors to secondary data that is publicly available, then used the secondary indicators and ordered logistic regression results to estimate an energy insecurity index at the county level across Kansas. The index represents the predicted percentage of households in the vulnerable or in-crisis energy insecurity categories for a county. Ford County was estimated to be 19.5%, with a survey rate given at 12%. With lower response rates for some more vulnerable segments of the community, we expect that survey estimates may be somewhat underestimated. For comparison, similar counties, such as Finney and Seward counties, had much closer estimates, at 14.4% vs. 14.3% and 14.1% vs 8.6%, respectively. Statewide estimates indicate 18% of the Kansas population is in the vulnerable and in-crisis categories, with our metric estimating it to be about 16.1%. **(3)** ***Value of Loss Load for a Household*** – As described when presenting findings from the survey, another useful measure collected is the indirect economic impact (or cost) of a power outage to a household (e.g., from lost access to services, household amenities, etc.). This is measured using the choice experiment in the survey and can be measured at different spatial scales from household to community level.

Power system resilience metrics: Performance and non-performance

The impact of an event on the power system is not limited just to the duration of the event. There can be multiple outages that are an impact of the same event which may happen over a period in a cascade, and we call this series of outages and restorations an outage event. An outage event can be identified from a performance curve (number of unrestored outages $U(t)$ vs time). The performance curve is shown by the green curve in Figure 10.

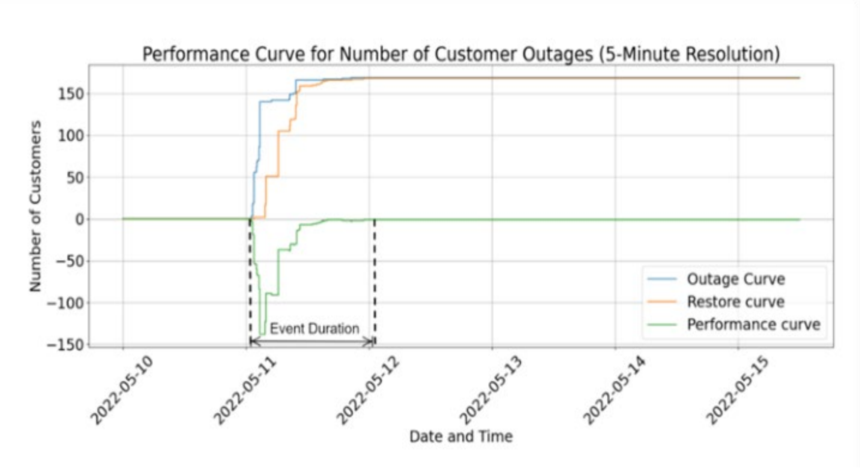


Figure 10. Outage, Restoration and Performance curves for a thunderstorm event

Currently, operators use reliability indices to capture the performance of the system. These indices consider an averaged value over an entire year. However, resilience metrics should be able to better capture the High Impact Low Frequency Events. We propose resilience metrics that utilize the definitions of reliability metrics and compute these for the duration of outage events. In this regard, we look at two resilience metrics:

Event Customer Minutes of Interruption (E-CMI): E-CMI is defined as $A_0 = \int_{t_1}^{t_n} U(t)\ dt$ where, $t_1$and t_n the start and end times of the outage event and U(t) is the performance curve. This metric is indicative of system wide impacts of an outage. Events like tornadoes could lead to a large number of outages in a single area, but events like thunderstorms can extend over larger regions and for longer times. These impacts are captured well by E-CMI. A higher value of E-CMI indicates that the system is less resilient to the event being considered.

Event Customer Average Interruption Duration Index (E-CAIDI): We confine the popular CAIDI metric to the duration of the outage and propose a resilience metric called E-CAIDI obtained as $C_0 = \frac{\sum t_i N_i}{\sum N_i}$. The numerator in the equation above gives the sum of all customer interruption durations during the event. The table below shows the results for the performance metrics for the distribution system spanning Ford County:

Table 7. Performance Metrics for Ford County Distribution System

Metric	Annual Reliability Metrics	Event Based Reliability metric (Resilience metric)		
		High Wind	Thunderstorm	Tornado
E-CMI (customer hours)	3263	40	6439	2383
E-CAIDI (hours	2.83	3	0.5	1.3

From the table, it can be observed that the event-based metrics encapsulate the spatial and temporal impacts of different events. For example, high winds (especially gusts) are more common, have more impacts on the distribution system and are localized. Thus, the average outage time per customer (E-CAIDI) due to a high wind event is higher than thunderstorms or tornadoes. These variations due to different events are adequately represented in the E-CMI and E-CAIDI and not in the annual averages.

The impact of an outage on different communities could be different. Assuming the varied cost of outage for different communities, we further expand the above metrics to weighted E-CMI (wE-CMI) and weighted E-CAIDI (wE-CAIDI) that take into account the socioeconomic factors of the region experiencing the outage. The wE-CAIDI is defined as: $C_0^w = \frac{\sum t_i N_i w_i}{\sum N_i}$ where, w_i is the weight that integrates the community vulnerability. To introduce the idea of integrating non-performance measures within the weighted metrics, we proposed a well-defined and generalized method to calculate the weights called the Generalized Community Vulnerability Score (GCVS). The GCVS can be extended to multiple social and economic indicators, and it is a combination of:

1. Social vulnerability indicators: inspired by the Social Vulnerability Score.
2. Economic vulnerability indicators: inspired from the Lawrence Berkeley National Laboratory report on cost of sustained power interruptions.
3. QoL indicators: The community capitals framework can be used to derive other QoL indicators based on the indicators and factor analysis presented above.

The overview of the above approach is shown in Figure 11:

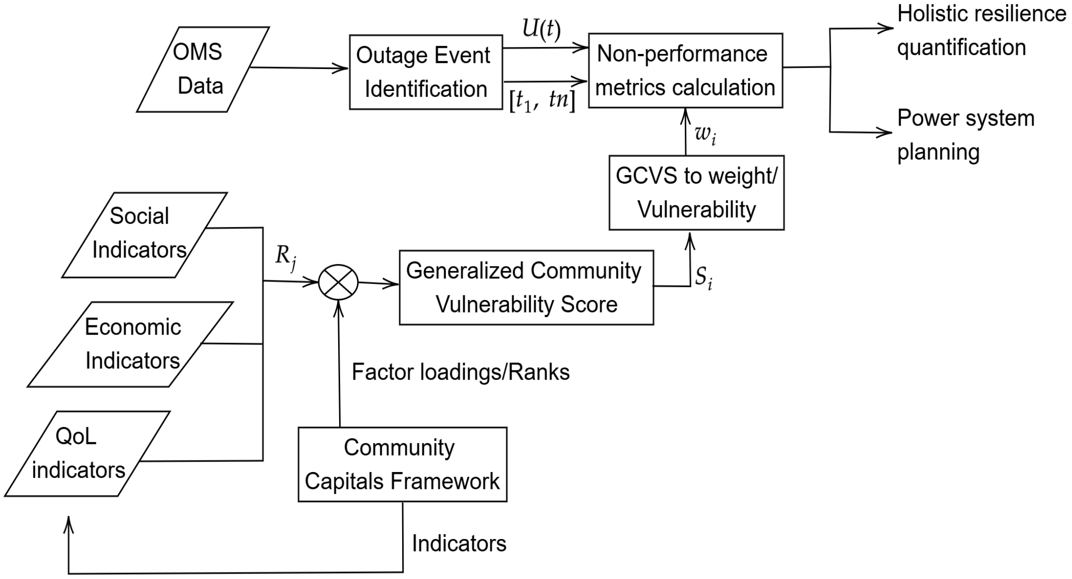


Figure 11. Overview of development of socioeconomic resilience metric for power distribution systems

Table 8 gives the comparison between the performance (non-weighted) and non-performance (weighted) metrics.

Table 8. Weighted and Non-Weighted CAIDI

Metric	High wind	Thunderstorm	Tornado
E-CAIDI	*3*	*0.5*	*1.3*
Weighted E-CAIDI	*6.2*	*1.54*	*4.16*

From Table 8, it can be observed that the wE-CAIDI for a tornado event is around twice that of E-CAIDI. This is because the area affected by the tornado was in vulnerability zone 2. Thus, the higher the weighted resilience metric, the higher the community's cost of outage. Thus, it can be concluded that the weighted resilience metrics are better indicators of resilience as they consider community demographics.

SOM-based Resilience Quantification Approach

Our approach to quantifying system resilience involves the following steps:

- Determining relevant features to capture static & dynamic topological/operational features along with relevant community-capitals-based features
- Developing mathematical formulations for each of these indices
- Aggregating these indices to determine a holistic community-based resilience index

For aggregating features, we use self-organizing maps (SOM) to obtain a final resilience index:

- SOMs belong to the category of competitive learning neural networks and are based on unsupervised learning.
- They can be used for clustering data without having prior knowledge of class memberships of the input data.

There are several advantages of using SOM. Existing resilience quantification methods are mostly applicable after an event has occurred and use the post-event data. However, this post-event resilience quantification can inform only future planning decisions. Instead, estimating resilience of a system without depending solely on historical event data is critical to inform both planning and real-time operations before and during an event. Existing resilience quantification methods need a weight-assignment method based on the resilience features being considered. Therefore, it becomes very difficult to assess which system parameters might be more dominant towards increasing/decreasing resilience, thereby making it difficult to assign weights to the multitude of resilience features that can be considered. Weight-assignment methods are typically subjective and depend on the system operator's interpretation. On the other hand, the SOM-based method is a step towards objective quantification of a system's resilience by removing any subjective weight assignment requirement. The SOM automatically rearranges its neuron weights based on the learnt importance of the features. The SOM development and usage processes are shown in Fig 12.

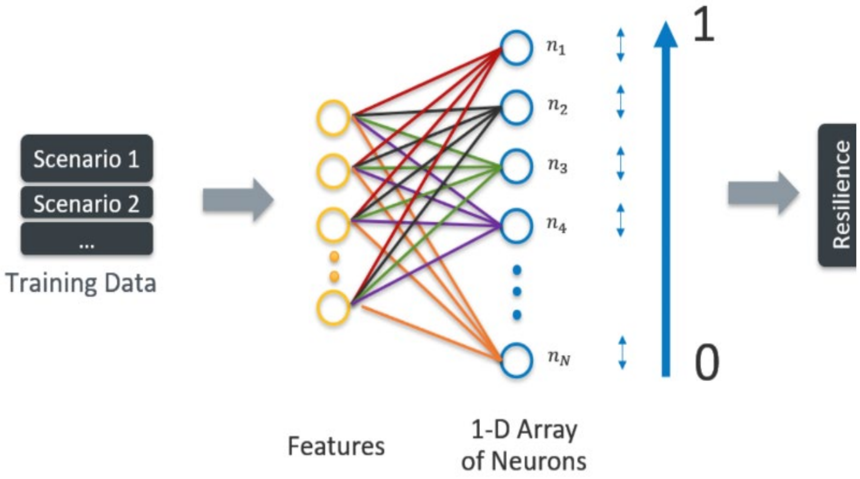


Figure 12: SOM development and usage process.

Offline Learning

- Generate training data.
- Generate multiple event scenarios (different paths of an event and its intensity)
- Each training data point is equivalent to an event scenario.
- Determine availability of assets as the event propagates.
- Based on the available assets, a load-shedding minimization OPF problem is solved.
- Calculate values for all features (corresponding to the generated event scenario).
- Run the SOM learning algorithm.
- Store SOM weights.
- $\mathcal{R}_{state} = \mathbb{SOM}(F_i^s, \dots \forall\, i \in Set\ of\ Features, s \in Set\ of\ Scenarios)$

Online Usage

- Determine current availability of assets.
- Calculate feature values based on the dispatch strategy.

- Input the feature values into SOM to get a resilience index.

To determine availability of assets, the following steps were performed to process the outage data provided by Victory Electric. (1) Events which corresponded to causes other than "Weather" were discarded. (2) The asset type was then filtered to consider line sections and transformers. (3) Outage data was separated for different weather events – namely, "Ice, Sleet, Frost", "Wind", "Lightning", and "Other". (4) New event begins if there is at least a 1-hour gap between the time stamp of complete restoration of all assets that previously were under outage and the next asset outage. (5) If an asset goes under outage while there is at least 1 asset left to be restored, then it will be considered a part of the previous event. (6) Events where an asset's restoration took more than 1 week were considered anomalies and discarded. (7) It is assumed that the first asset outage occurs after the event has been going on for 5 minutes.

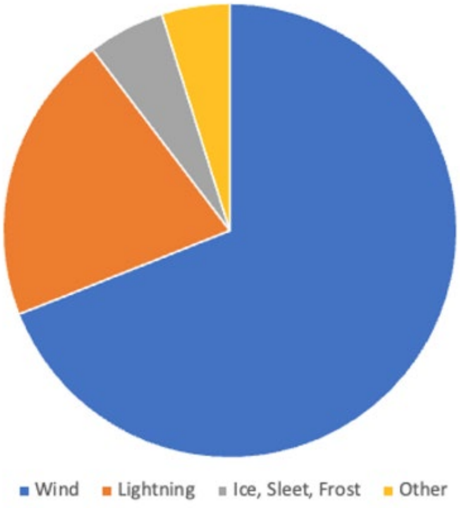


Figure 13: Line & transformer outages due to weather events.

The following performance and non-performance metrics were developed:

Sustainability

This feature considers whether the existing generation capability inside the system is enough to enable survival of critical loads for at least T time steps by ensuring power flow constraints are not violated.

Availability of energy reserves

During and after an extreme event, the presence of enough energy reserves, such as state of charge (SOC) of BESS, will ensure that the system can sustain its critical loads until the damaged assets are repaired by utility field crew.

Feasible islands

If an event strikes inside the system, the ability of the assets within that system to further form multiple feasible microgrids will significantly improve the system's overall resilience. The feasibility of such microgrids can be described in terms of sufficient generation capacity available in each microgrid with respect to critical load requirements, voltage limits, etc.

Path redundancy

The higher the number of possible paths from generation to critical and customer loads is, the higher the likelihood of ensuring power supply to such loads under varied damage scenarios of an event. Thus, the number of possible parallel paths available from a generator node to a load node is considered in this feature.

Social burden under outage

This aims to capture the difference in effects of customer demand not met based on their vulnerability to health, preparedness, and demographics → Social Vulnerability Score (SV). Essentially, it calculates the normalized load demand not met weighted by the social vulnerability score of the customers.

Energy poverty under outage

This aims to capture the lack of access to basic, life-sustaining energy needed by a household under extreme event infrastructure damage scenarios. Essentially, it determines whether a vulnerable household has access to electricity or not and at what times during outage.

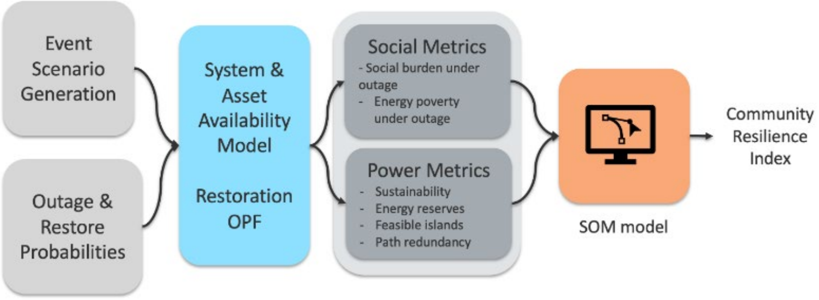


Figure 14: Energy poverty under outage scenario

The following steps were performed to generate the training data: (1) Create 10,000 event scenarios – each event scenario means a weather event of a certain normalized intensity is moving across the distribution system over time and in varying directions. (2) Determine the availability of line/transformer assets as each event propagates (based on outage/restoration probability determined from Victory Electric's outage data). (3) Based on the available line and transformer statuses, three subsets of cases were simulated:

- Baseline case – No additional DERs & existing restoration approach
- Intermediate case – Additional DERs & basic FLISR
- Advanced case – Additional DERs & advanced FLISR

(4) For each event scenario, the resilience features are calculated and the set of these features for an event scenario constitute a data point. Three different scenarios were also considered:

- Baseline case – No additional DERs & existing restoration approach
    - System model: Use existing system model without any additional DER placement.

Restoration approach: If an event has caused damage to the system, the affected loads will remain de-energized until the restoration of the affected lines and transformers happens.

- Intermediate case – Additional DERs & basic FLISR
    - System model: Use existing system model with additional utility-scale DERs placed randomly across 3-ph nodes.
    - Restoration approach: Implement a basic FLISR.

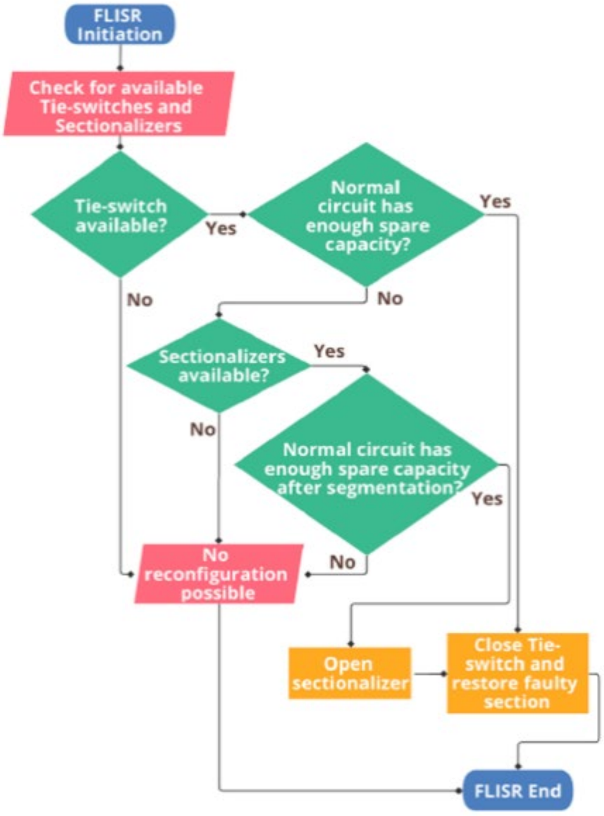


Figure 15: Basic FLISR logic used in the intermediate case.

- Advanced case – Additional DERs & advanced FLISR
    - System model: Use existing system model with additional DERs placed randomly across 3-ph nodes.
    - Restoration approach: Implement an advanced FLISR where utility-scale DERs are controlled optimally in addition to network switching.

To validate the SOM approach, we compare the average energy served across multiple test scenarios, as shown in Fig 16. The performance validation results of the SOM approach are in Fig 17. As can be seen, the performance-based resilience metric as well as the community-resilience metric follow closely with the normalized energy supplied, with the former having a higher correlation.

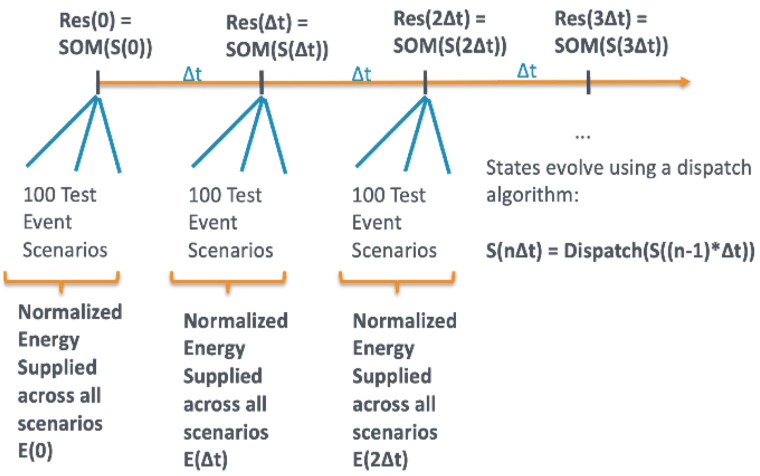


Figure 16: Average energy scenarios

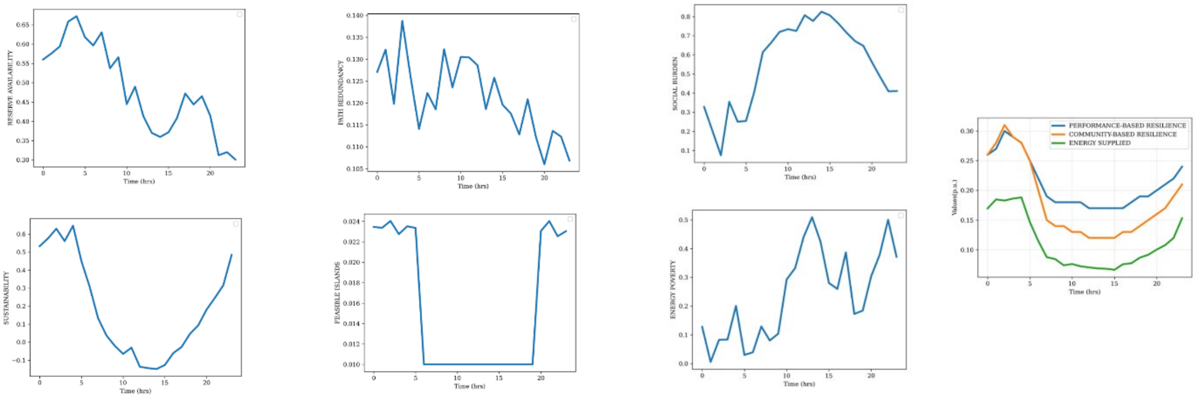


Figure 17: SOM performance validation. For full image see Appendix 2.

Impact

The proposed resilience metrics can be used to define the baseline resilience index of the community and can be incorporated into resilience planning and analysis to analyze the overall improvement, both for the community and the utility. The community and household metrics and approaches allow for resilience quantification at different spatial scales for modeling and reporting purposes.

Table 9: Task 3 milestones and status.

Task #	Performance Metric	Success Value	Assessment Tool / Method of Measuring Success Value	Progress Notes
3.1.1	Defined Community Resilience	At least 5 indicators that holistically define	We will elicit community and utility partners' and stakeholders'	100% Complete – We have extended our list of community capitals and resilience metrics

	Metrics based on community capitals	community resilience according to the community capitals framework.	assessment of the defined community resilience metrics based on the needs of the project and the testbed community.	that can be defined using them, which include
3.2.1	SOM resilience index validation based on power system performance-based resilience metrics	Pearson correlation coefficient between the SOM-based resilience index output versus critical load served under multiple test scenarios > 0.1	The SOM resilience output will be benchmarked with the critical load served under a set of event scenarios, and the Pearson correlation coefficient will be computed to see the correlation and to validate the SOM-based approach.	100% Completed

TASK 4.0: NOVEL INTEGRATED ADAPTIVE RESILIENCE ANALYSIS

Task Summary

Utilizing the community and utility data from Task 2, Task 4 created a novel heterofunctional graph (HFG)-based framework that allows a richer characterization of "Quality of Life" (QoL) indicators that includes both primary and secondary impacts of disaster related disruptions to the power infrastructure. These QoL indicators can be directly fed into resilience metric computation as weights/features as described in Task 3. The HFG framework enables lightweight but detailed simulations of power system disruptions and their cascading impacts on water, transportation, stormwater, and critical services such as hospitals, fire stations, and grocery stores. By incorporating stochastic recovery processes and accessibility measures, Task 4 established a baseline energy resilience index and developed tools for evaluating investment and operational strategies. This framework sets the stage for future tasks by providing the modeling backbone for critical node identification, scenario testing, and resilience planning.

A summary of accomplishments include:

- Built an equivalent HFG model or Dodge City's power system and expanded it to a multi-infrastructure Ford County model with 322K nodes and 1M+ edges.
- Automated HFG generation enabling scalable modeling of power, water, transportation, stormwater, and community assets.
- Integrated socio-economic factors and resilience metrics to establish a baseline energy resilience index.
- Developed the Access Degradation Factor (ADF) to measure community access to critical services during disruptions.
- Validated HFG models and demonstrated their use in testing resilience investments such as PV siting and asset hardening.

Task Outcomes

Integrated Adaptive Resilience Analysis Framework

Disruptions in power infrastructure can cause secondary impacts on interdependent infrastructures, affecting the quality of life of the community. Therefore, we developed a novel graphical modeling framework that involves heterofunctional graphs to capture interdependencies between infrastructures from a functionality standpoint. Specifically, heterofunctional graph (HFG) representations of critical infrastructure systems that provide lightweight alternatives to standard (slow) power system simulators were developed. This lightweight graphical representation provides significant speed-ups in computational performance. For example, a study to assess outages due to a tornado event using HFGs for Ford County (322,000 nodes, one million edges) was 80 times faster than equivalent analysis performed using a multi-infrastructure co-simulator. Such approximation enables rapid assessment of investment and response strategies. HFGs consist of directed edges between functionalities of the system's assets. Unlike traditional graph representations of multi-infrastructure systems, these representations allow a fine-grained view of their dependencies. Traditional HFGs are represented by binary adjacency matrices that encode functionality dependencies (say, with 1s representing the functionalities that work appropriately and 0s representing functionalities that do not work). The adjacent matrices can be used to simulate the evolution of system states through transient or disaster scenarios. Non-binary HFG frameworks allow the characterization of functionalities through vector functions.

Initial HFGs for Dodge City were developed using Python-based tools that operate on OpenDSS models. The developed HFGs consisted of limited functionalities, such as "generate power," "transport power," and "consume power". The initial model consisted of 1651 nodes (functionalities) and was mapped to specific community metrics such as Social Vulnerability Score (SVS), Social Vulnerability Zone (SVZ), and Criticality. To provide contingencies for the scenarios in which the binary HFG model may not satisfy the high-resolution requirements of certain simulation scenarios, we developed a non-binary HFG framework in which each functionality is characterized by a vector function (in general) that expresses the output of a given functionality when the functionalities on which the given functionality depends are functioning at arbitrary capacities. For example, suppose a power transmission line, providing a transport functionality, functions at 50% and transports power to a consumer from a generator that functions at 20% of its full capacity; then, the transported power is no more than 20% of the regular full-capacity available power (these constructs become quite a bit more involved when dealing with functionalities characterized by vector inputs and outputs).

Additionally, a stochastic recovery framework was developed, in which our set of functionalities is endowed with a partial order, denoting logical priority, which is then enhanced to a full order by additional operational priority decisions. These priority decisions represent our optimization variables and are the source of equitable interventions. Specifically, the damaged functionalities will be ordered according to this order, and repair resources will be allocated in this order until all damages have been fixed. Once the required repair resources are allocated, the amount of time it takes to fix a specific damage is a random variable. Our enhanced HFG framework enables us to more closely approximate the actual performance curves in disaster scenarios and has the ability to integrate both investment and operational decisions, as well as specific consumer-oriented metrics (also represented as functionalities), towards optimizing community resilience.

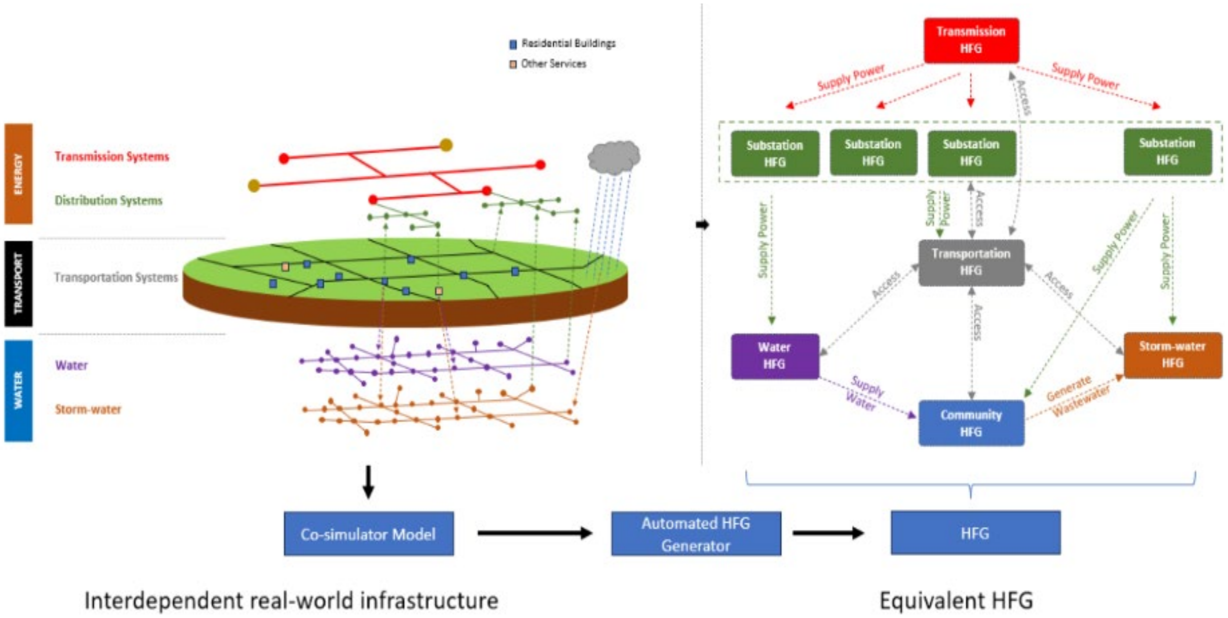


Figure 18. Overview of HFG Generation

Further, an automatic heterofunctional graph generation tool was developed to operate on multi-infrastructure systems and community asset models to automate the HFG generation process, as shown in Fig. 18. This tool reduces the tedious and error-prone process of manual generation of heterofunctional graphs for large systems. The developed tool also expands the number of functionalities from three in the initial HFG to 126 different functionalities spanning across all infrastructure systems and community assets. The initial HFGs were refined by using the automated tool, expanding to the entirety of Ford County, adding assets from multiple infrastructure systems (power, water, stormwater, and transportation) and community assets (hospitals, police stations, fire stations, grocery stores, and gas stations, to name a few). The HFG developed on this data resulted in a highly detailed heterofunctional graph for Ford County, which contains 322k nodes and 1.04 million edges, significantly improving the interactions between the functionalities compared to the initial models. Further, accessibility-based features, such as time and distance to the nearest emergency services, such as hospitals, fire stations, and police stations, were added as node features.

We also validated the heterofunctional graphs for structural accuracy. Fig 19 shows an example of building functionalities connected to various services and resource functionalities up to a 2-hop neighborhood of the building operations functionality. The updated models were shared with Task 5.0.1 for critical node identification. The multi-infrastructure heterofunctional graph model for Ford County, integrated with community assets such as police stations, fire stations, hospitals, groceries, gas stations, and other assets can also be used to quantify degradation in access to services during disruptions. Functionalities were defined for each community asset to model the resource requirements and services provided. These functionalities were mapped to infrastructure system functionalities based on geographical locations. For example, each community asset has a functionality requiring power. These functionalities are connected to the

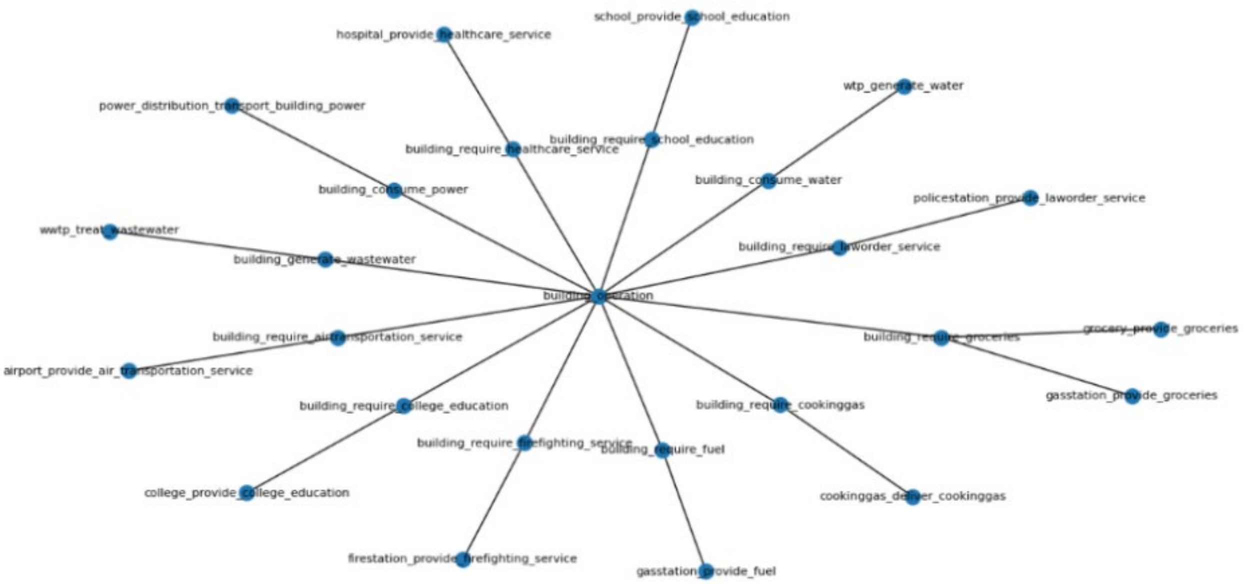


Figure 19. Validation of HFG structural accuracy - 2-hop neighborhood functionalities of "building operation" functionality.

nearest power system functionality for delivering power based on geographical location. The transportation network model for Ford County was used to generate distance and time matrices during normal operation conditions (all assets operative), also referred to as the baseline distance and time required to access resources. During disruption events, changes in access distance or time with respect to their baselines serve as a quantitative measure of access degradation. We define this measure as Access Degradation Factor (ADF). Figure 20 shows the degradation in access to an asset in the case of a power failure. This metric can be used to inform asset hardening and assess baseline resilience for communities.

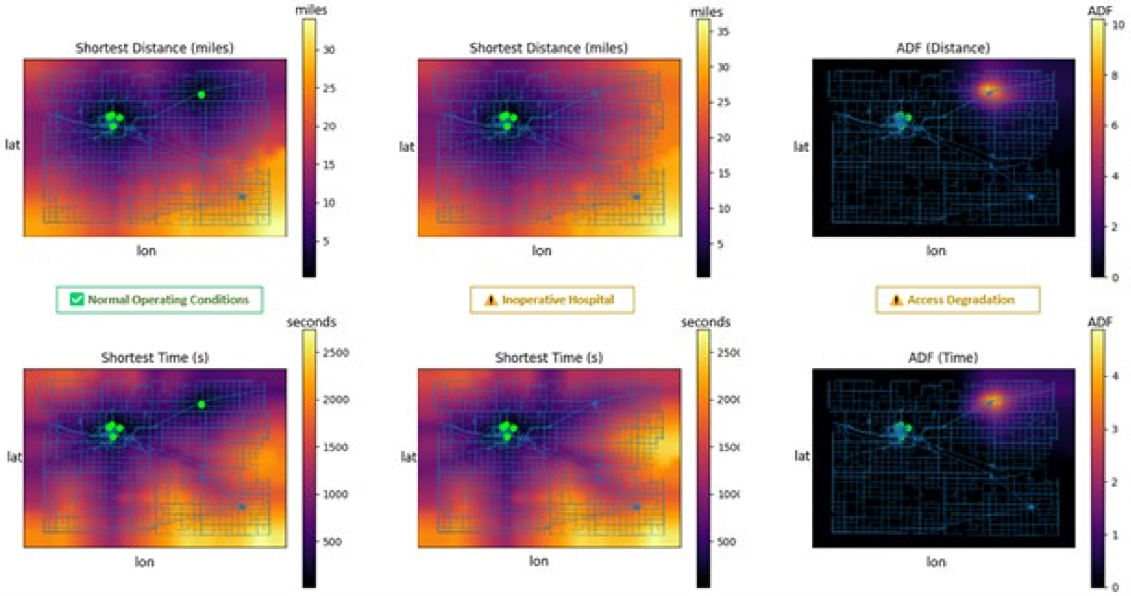


Figure 20. Degradation in access due to power failure

Impact

This work developed a framework to create and analyze fine-grained models of critical interdependent infrastructure systems and communities. For example, the HFG developed on the obtained data resulted in a highly detailed heterofunctional graph for Ford County, which contains 322k nodes and 1.04 million edges. The data was also used to map accessibility-based features, such as time and distance to the nearest emergency services. Furthermore, the access degradation factor metric was developed which enables the quantification of impacts of disruptions in terms of accessibility to services. Additionally, the developed models can also be extended to other applications such as asset hardening and critical node identification.

Table 10: Task 4 milestones and status.

Task #	Performance Metric	Success Value	Assessment Tool / Method of Measuring Success Value	Progress Notes
4.1.1	Equivalent HFG model for Dodge City power distribution system	Accuracy of HFG model simulations and physical power system simulations match with at least 90% accuracy as it relates to lost loads	Simulate multiple failure scenarios to evaluate impact on power network and the equivalent HFG model to compare number of lost loads.	100% complete. Automated algorithms for the creation of HFG models from simulation files are completed. Framework for stochastic HFG evolution was completed. A HFG consisting of roughly 322k nodes (functionalities), modeling the Dodge City's infrastructures, has been completed
4.2.1	Integrated HFGT model with socio-economic factors and physical infrastructure models completed	At least 1 method to integrate socio-economic factors in HFGT model is designed	Based on the available data, appropriate ways to define and integrate socio-economic factors will be studied and implemented. Preliminary tests on impact of failures/disruptions will be used to measure and assess the integration methods.	100% complete. Power distribution system equivalent HFG model is complete. HFG validated for structural accuracy. All functionality nodes have been associated with social vulnerability scores and resource generation, requirements, and accessibility-based features.
4.3.1	Baseline Energy resilience index	Community energy resilience index considering only performance-based metrics versus the case with both performance and community resilience metrics should be different from each other by at least 10%	With the determined baseline values, percentage difference between the resilience index considering both performance-based and community-oriented resilience metrics to the resilience index considering only performance-based resilience metrics	100% - We have completed this analysis for the weighted event-based metrics and the SOM approach.

TASK 5.0: IDENTIFYING THE CRITICAL NODES/FUNCTIONALITIES/ASSETS

Task Summary

Task 5 built on the heterofunctional graph (HFG) framework from Task 4 to identify the most critical nodes, functionalities, and assets in the Dodge City and Ford County infrastructure systems. We trained GNN models on heterofunctional graph models developed in Task 4 to classify nodes as critical/ non-critical based on features and dependencies with other functionalities. This analysis provides a scalable method for pinpointing essential assets that, if hardened or prioritized, will maximize overall resilience. Task 5 work enabled data-driven planning, system hardening, and transferring learning applications for resilience assessment in other networks.

A summary of accomplishments includes:

- Developed and validated a GNN-based framework to identify critical nodes in heterofunctional graphs.
- Applied the model to Dodge City and Ford County HFGs, identifying essential services and power delivery nodes critical to resilience.
- Demonstrated that HFGs capture fine-grained interdependencies missed by traditional graph models.
- Established a scalable method for system hardening and maintenance planning based on criticality.
- Created a foundation for applying transfer learning to resilience assessments in new communities and networks.

Task Outcomes

Critical Node Identification – HFG

The heterofunctional graph theoretical framework allows the fine-grained modeling of interdependent infrastructure systems. Unlike conventional graph modeling, the developed modeling framework identifies all asset dependencies. Therefore, the critical functionality identification of these graphs enables criticality assessment at the resource and service levels. A graph neural network (GNN)-based strategy was formulated that operates on the heterofunctional graphs (HFG) constructed in the previous tasks to identify critical functionalities and, thereby, critical assets of the power systems. This inductive graph learning-based approach enables us to utilize node embeddings and features to learn the criticality of all assets in the network. These inputs allow strategic system hardening or updated system maintenance and planning processes.

The developed GNN framework uses a two-step process for inductive learning-based approximation of the criticality of nodes in a graph, referred to as Inductive Learner for Graph Robustness (ILGR). The algorithm uses GraphSAGE to first learn node embeddings from node features and neighborhood sub-graphs, which are then used to calculate the criticality scores. The approach is scalable because the GNN model learns the node/link criticality score on a small representative subset of nodes/links. Then, the trained model is employed to predict the scores of unseen nodes/links in large graphs and consequently identify the most critical nodes. Once the critical nodes are identified, strategic system hardening or updated system maintenance and planning processes can be put in place to protect those assets, thereby enhancing overall system resilience.

In our model, the critical functionality identification problem is posed as a node classification task. Power delivery functionalities to community assets that provide essential services, and the functionalities providing essential services were tagged as critical during the training of the GNN-based model. The GNN is trained to predict the critical/non-critical label for each node in the training set based on node features and graph structure. The GNN framework employs two fundamental mechanisms: message passing and aggregation. Here, each node's importance is captured along with aggregated information from its neighbors up to k-hops, updating its representation to capture local and global graph properties. This process allows GNNs to learn complex relationships between a node's attributes, neighbors, and the graph structure. For each node v in the graph, we aggregate the features from its neighbors $N(v)$:

$$m_{\mathcal{N}(v)}^{(l)} = \text{AGGREGATE}^{(l)}\left(\{h_u^{(l-1)}, \forall u \in \mathcal{N}(v)\}\right)$$

where,

- $m_{\mathcal{N}(v)}^{(l)}$ Is the aggregate message from the neighborhood of node v at layer l .
- $AGGREGATE^{(l)}$ is a differentiable aggregator function (e.g., mean, max, sum) at layer l . In our implementation we use the mean aggregator.
- $h_u^{(l-1)}$ is the hidden representation of neighbor u at the previous layer $(l-1)$.
- $N(v)$ is the set of neighbors of node v .

The aggregated message is then combined with the node's own previous hidden representation and passed through a non-linear activation function.

$$h_v^{(l)} = \sigma\left(W^{(l)} \cdot \text{CONCAT}\left(h_v^{(l-1)}, m_{\mathcal{N}(v)}^{(l)}\right)\right)$$

Where,

- $h_v^{(l)}$ Is the hidden representation of node v at layer l .
- σ is the non-linear activation function (e.g., ReLU).
- $W^{(l)}$ is the trainable weight matrix at layer l .
- $CONCAT$ denotes the concatenation operation.

The trained model identified more functionalities than the seed nodes, using only functionality connectivity and node features (which consist of resource and service requirements and generation). Therefore, HFGs provided greater utility than the traditional graph models by identifying fine-grained essential network interactions. The developed framework also enables future possibilities of incorporating transfer learning that utilizes graph neural networks' inductive capabilities to apply to new networks.

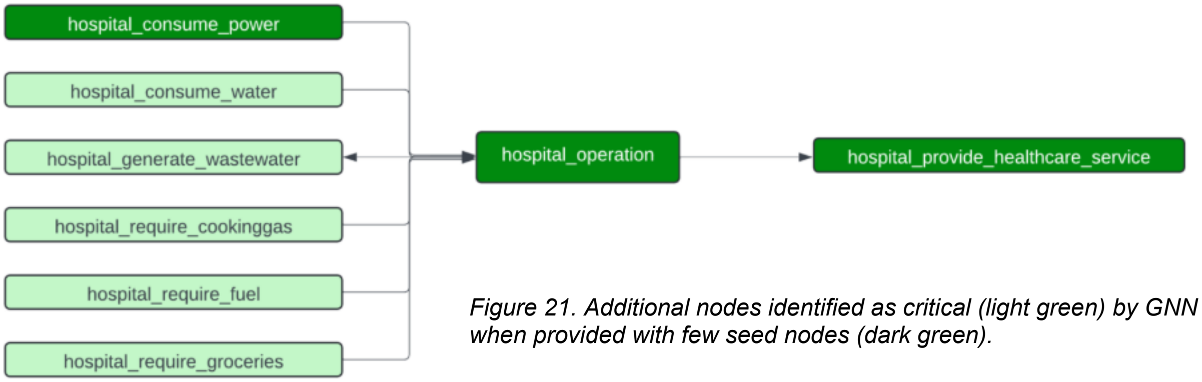


Figure 21. Additional nodes identified as critical (light green) by GNN when provided with few seed nodes (dark green).

Impact

The critical functionalities identified by the GNN-based framework on the HFGs were mapped to their corresponding assets. These results were compared with the list of nodes identified as critical by running the framework on the system graph. The results showed that the framework provides the same set of critical nodes in both cases. However, the benefit of utilizing HFGs is the potential to identify critical functionalities of assets, which is not possible with traditional power system graph analysis. For example, while a traditional analysis on a system graph would identify a fire station as a critical load, the GNN-based model identified the underlying functionalities essential for its operations, such as ’firestation_consume_water’ as critical, even though it was not included in the original seed set, Therefore, the GNN-based framework was able to generalize and extend the critical node set beyond its initial seed set by utilizing node features and network structures. Therefore, the developed HFG and critical node identification framework provide fine-grained information on critical assets and functionalities.

Table 11: Task 5 milestones and status.

Task #	Performance Metric	Success Value	Assessment Tool / Method of Measuring Success Value	Progress Notes
5.0.1	GNN-based critical node/functionality/ asset identification in HFGT and regular power distribution network.	Top 5 critical assets accurately identified in both cases.	Simulate multiple failure scenarios to evaluate criticality. This will also be guided by likely weather events specific to Ford County.	100% - Validated critical nodes identified by HFG against those identified on the asset graph. Critical node analysis on HFG was able to identify functionality-level critical nodes for assets. Further, the framework was able to identify additional functionalities initially not considered critical.

TASK 6.0: ENHANCING RESILIENCE VIA PLACEMENT OF RENEWABLES AND THEIR DISPATCH STRATEGY

Task Summary

Task 6 utilizes the work on resilience metrics from Task 3, the integrated HFG framework from Task 4, and critical node identification from Task 5 to evaluate how renewable energy and storage can be optimally developed to improve community resilience. We developed optimization frameworks for strategic recloser placement and PV siting/sizing to reduce outage impacts, improve reliability, and lower community energy burden. We also compared optimal dispatch strategies for distributed resources against naive approaches to assess community-wide resilience gains. This task sets the stage for future work by providing utilities and communities with actionable, data-driven strategies for resilience-focused energy planning.

A summary of accomplishments include:

- Developed and validated optimization frameworks for recloser placement, improving both reliability and cost-effectiveness.
- Demonstrated that optimal recloser siting reduced CENS and VENS by about 30% compared to traditional placement strategies.

- Applied optimal transport (OT)-based methods to PV siting and sizing, improving the energy burden distribution across households.
- Enhanced PV planning models by incorporating power flow and network loss constraints, making siting recommendations more realistic and impactful.
- Compared optimal versus naive dispatch strategies, showing improvements in the community resilience index when optimal resource allocation is employed.

Task Outcomes

Resilience Enhancement

The aims of this task are to provide local stakeholder groups with information on where the deployment of distributed photovoltaics (PV) and energy storage systems could enhance the community's resilience the most, and to provide optimal recloser placement locations to improve the overall system reliability.

We develop two methods to improve the system reliability, namely,

1. Optimal recloser placement to reduce the outage duration and improve the system reliability, considering both cost and value of energy not served.
2. PV placement in the grid to improve the energy burden distribution of Ford County.

Recloser Placement for Resilience Enhancement

Modern power distribution systems face the challenge of balancing reliability, cost, and fair service delivery. One key aspect of this is the strategic placement of reclosers, which help restore power after faults. Traditionally, utilities install a few expensive three-phase reclosers on main feeders, but this approach overlooks the cost-benefit trade-offs and the different types of power interruptions. Momentary outages, which last only a few seconds, can disrupt industrial operations, while sustained outages require manual repairs and lead to major economic losses. Single-phase reclosers, which are significantly cheaper, offer a better solution by isolating faults on lateral branches without causing widespread disruptions. In the last quarter, this study introduced a new framework for recloser placement that considers both utility and consumer impacts. In this quarter, we designed an optimal algorithm that uses probabilistic fault modeling to assess reliability and incorporate economic factors like the cost of energy not supplied (CENS) and the value of lost load (VoLL) for different sectors. By distinguishing between failure rates and repair times across different parts of the grid, the approach enables more effective reliability assessments. The proposed method is scalable and helps utilities make data-driven decisions to improve service reliability while managing costs more efficiently.

To quantify the impact of interruptions, a multi-objective optimization framework is introduced, considering different types of service disruptions:

1. **Momentary Interruptions** – Measures the number of affected customers.
2. **Sustained Interruptions (CENS)** – Assesses financial losses incurred by utility.
3. **Sustained Interruptions (VENS)** – Estimates customer economic losses.
4. **Combined Impact** – A weighted combination of the above three objectives.

An Interruption Impact Function evaluates the effect of a fault at a feeder segment on load points, with different formulations based on the chosen objective function.

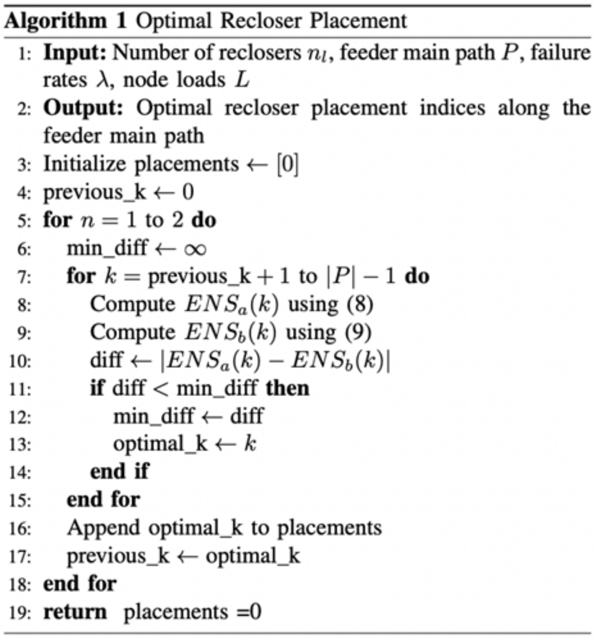
$$f^{(m,s)} = \begin{cases} \frac{N_j}{\lambda_{ij} r_{ij} L_j}, & \text{if} \quad \textit{Obj 1}, \\ C_j, & \text{if} \quad \textit{Obj 2}, \\ V_j, & \text{if} \quad \textit{Obj 3}, \\ \gamma_1 \frac{N_j}{\lambda_{ij} r_{ij} L_{aj}} + \gamma_2 C_j + \gamma_3 V_j, & \text{if} \quad \textit{Obj 4}. \end{cases}$$

The methodology employs a graph-theoretic model where the distribution network is represented as a directed graph G=(N,E), with N denoting nodes and E edges. The core objective is to minimize energy not served (ENS), a critical reliability metric reflecting financial losses from outages. For a recloser placed at node k, the cumulative upstream reliability impact ENSa (k) and downstream impact ENSb (k) are derived as:

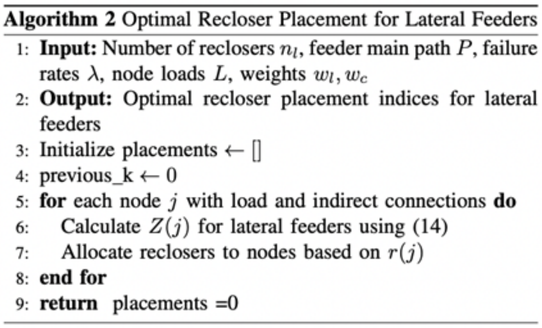
$$\mathrm{ENS}_a(k) = \left(\sum_{i=1}^{k} \lambda_i \cdot r_i \right) \times L_{total} \cdot f^{(m,s)} \qquad \mathrm{ENS}_b(k) = \sum_{i=k+1}^{B} \sum_{j=k+1}^{B} (\lambda_i \cdot r_i) \times \mathrm{L}_j \cdot f^{(m,s)}$$

where λi and ri are the failure rate and repair time of edge i, Ltotal is the total system load, Lj is the load downstream of node j, and f(m,s) is the interruption impact function. The optimal recloser location k∗ is determined by balancing these impacts, ensuring that reliability improvements are equitably distributed across upstream and downstream sections.

For three-phase recloser placement (Algorithm 1), the framework iteratively evaluates candidate positions along the main feeder, minimizing the ENS difference. The algorithm prioritizes locations where reclosers maximize fault isolation and auto-reclosing benefits, particularly temporary faults. Single-phase trip saver placement requires an additional allocation step to address lateral feeders (Algorithm 2). A weighted scoring system assigns reclosers based on load distribution and network complexity. The composite score guides proportional allocation of reclosers, ensuring integer distributions via remainder of adjustments.



```
Algorithm 1 Optimal Recloser Placement
Input: Number of reclosers $n_l$, feeder main path $P$, failure rates $\lambda$, node loads $L$
Output: Optimal recloser placement indices along the feeder main path
Initialize placements ← [0]
previous_k ← 0
for $n = 1$ to 2 do
    min_diff ← $\infty$
    for $k$ = previous_k + 1 to $|P| - 1$ do
        Compute $ENS_a(k)$ using (8)
        Compute $ENS_b(k)$ using (9)
        diff ← $|ENS_a(k) - ENS_b(k)|$
        if diff < min_diff then
            min_diff ← diff
            optimal_k ← $k$
        end if
    end for
    Append optimal_k to placements
    previous_k ← optimal_k
end for
return placements =0
```

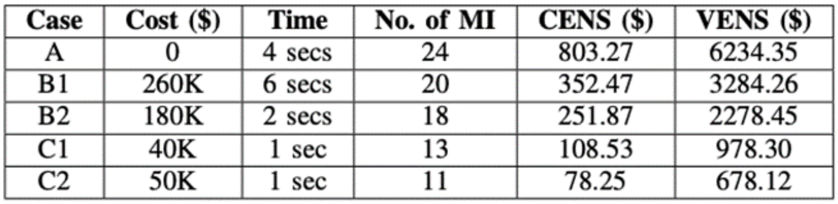


```
Algorithm 2 Optimal Recloser Placement for Lateral Feeders
Input: Number of reclosers $n_l$, feeder main path $P$, failure rates $\lambda$, node loads $L$, weights $w_l, w_c$
Output: Optimal recloser placement indices for lateral feeders
Initialize placements ← []
previous_k ← 0
for each node $j$ with load and indirect connections do
    Calculate $Z(j)$ for lateral feeders using (14)
    Allocate reclosers to nodes based on $r(j)$
end for
return placements =0
```

The framework's scalability stems from its O(N·B) time complexity, accommodating diverse network configurations. For three-phase reclosers, strategic placement reduces prolonged outages by enabling auto-reclosing for transient faults and targeted isolation for permanent faults. For lateral feeders, single-phase trip savers localize disruptions, preventing cascading outages. This dual approach harmonizes cost-effectiveness (leveraging cheaper single-phase devices) and reliability (prioritizing high-impact main feeder nodes), offering utilities an adaptable solution for grid resilience.

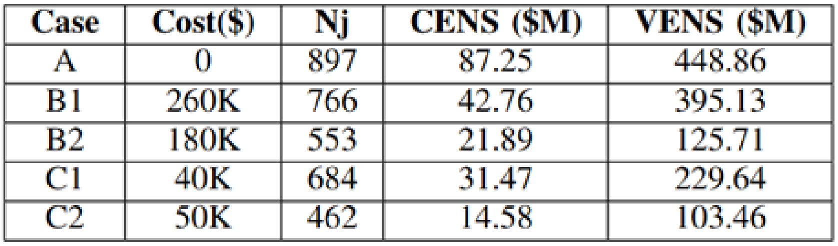
This study evaluated recloser placement strategies through a structured scenario analysis framework, comparing five cases across three impact functions. The cases include a baseline with no reclosers (Case A), predefined placements of three-phase reclosers on the main feeder (B1) and single-phase trip savers on laterals (C1), and optimized placements using the proposed algorithm for three-phase (B2) and single-phase reclosers (C2). The optimization framework demonstrates adaptability, generating distinct recloser locations depending on whether MI, CENS, or VENS is prioritized, thereby enabling utilities to align placements with specific reliability or economic goals.
The methodology is further validated through comparative case studies, demonstrating significant reductions in ENS and operational costs across varying network topologies. Results from the IEEE-37 bus test system and the Ford County system reveal significant improvements with optimal placements. For three-phase reclosers, as compared to predefined placements (B1), Case B2 reduces CENS by 29% ($100) for the test system and by 48% ($21,000,000) for the Ford County distribution system and VENS by 31% ($1000 for test system and $270,000,000 for Ford County system). Single-phase reclosers in Case C2 achieve even greater efficiency, lowering CENS to a 28% ($30 for test and $17,000,000 for Ford County) and 31% ($300 for test and $126,000,000 for Ford improvement over Case C1, respectively. The computational superiority of the proposed method is evident, solving optimal placements in seconds versus hours for exhaustive search (e.g., 4 seconds vs. 39 minutes for B2 on the test system). In large-scale networks, the method remains efficient (9–11 seconds for actual systems), while exhaustive search becomes infeasible.

Table 12. 5 case studies across three impact functions for IEEE 37-bus test system.

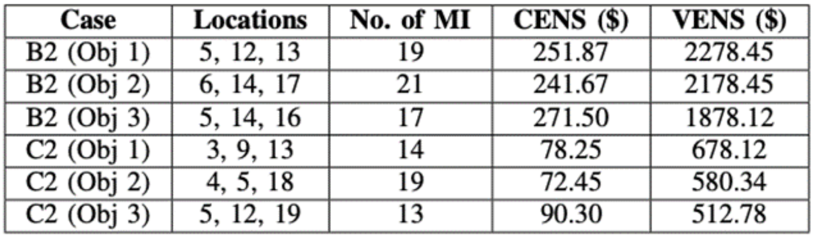


Case	Cost ($)	Time	No. of MI	CENS ($)	VENS ($)
A	0	4 secs	24	803.27	6234.35
B1	260K	6 secs	20	352.47	3284.26
B2	180K	2 secs	18	251.87	2278.45
C1	40K	1 sec	13	108.53	978.30
C2	50K	1 sec	11	78.25	678.12

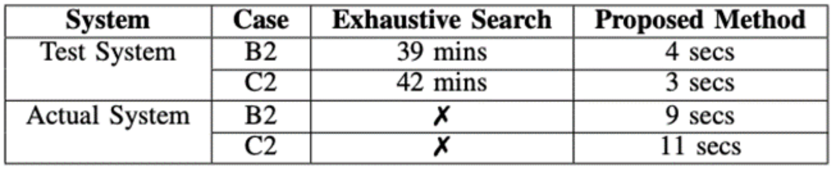
Table 13. 5 case studies across three impact functions for Ford County Distribution system



Case	Cost($)	Nj	CENS ($M)	VENS ($M)
A	0	897	87.25	448.86
B1	260K	766	42.76	395.13
B2	180K	553	21.89	125.71
C1	40K	684	31.47	229.64
C2	50K	462	14.58	103.46



Case	Locations	No. of MI	CENS ($)	VENS ($)
B2 (Obj 1)	5, 12, 13	19	251.87	2278.45
B2 (Obj 2)	6, 14, 17	21	241.67	2178.45
B2 (Obj 3)	5, 14, 16	17	271.50	1878.12
C2 (Obj 1)	3, 9, 13	14	78.25	678.12
C2 (Obj 2)	4, 5, 18	19	72.45	580.34
C2 (Obj 3)	5, 12, 19	13	90.30	512.78



System	Case	Exhaustive Search	Proposed Method
Test System	B2	39 mins	4 secs
	C2	42 mins	3 secs
Actual System	B2	✗	9 secs
	C2	✗	11 secs

The study highlights the necessity of optimization-driven strategies. Optimal reclosers on laterals (C2) yield the lowest MI, CENS, and VENS, underscoring the critical role of lateral protection. The framework’s flexibility allows utilities to prioritize objectives: minimizing MI favors recloser placements near high-failure zones, while CENS/VENS reduction prioritizes load-heavy regions. For instance, prioritizing VENS in Case B2 reduces consumer losses by 18% compared to prioritizing CENS. These findings validate the framework’s ability to balance reliability and cost-effectiveness, offering utilities a scalable solution for enhancing grid resilience. The results, summarized in the tables given above, demonstrate that strategic recloser placement not only mitigates outages but also aligns operational decisions with economic and reliability targets.

Balanced PV Planning

Power distribution system planning processes usually consider efficiency and reliability as the main objectives. However, it is also crucial to incorporate community-centric metrics while making important investments related to distributed generation (DG). We proposed a novel method based on the principles of optimal transport (OT) theory to improve the distribution of Quality-of-life indicators among consumers while enhancing the efficiency of the distribution system network. The approach involves the strategic siting and sizing of Distributed Energy Resources (DERs) like solar PV, and battery to improve the Quality-of-Life metrics for the consumers. This approach supports customers by improving overall quality of life distributions while minimizing network active power losses. While the proposed approach is applicable to multiple DERs and quality of life indicators, we focus on PV siting and sizing to improve the energy burden distribution in this work. Specifically, an OT-based formulation is used to estimate the capacity of distributed solar PV to be installed at various locations and to determine the necessary tariff adjustments.

Since income and electricity consumption vary across loads, the distribution of energy burden can be used to characterize the community’s capacity to access electricity service. Assume that the energy burden distribution, denoted as μ, is given for a community. By investing in solar PV generation at various locations in the distribution system, the power is consumed from the grid.

P_{gi} can be reduced, thereby reducing the energy burden of the customers by changing the energy burden distribution μ. The objective of this work is to transform the base energy burden distribution μ to a more equitable/favorable distribution ν so that low-income customers are not overburdened. The overall methodology can be divided into 3 stages:

1. Defining Target Distribution: The target energy burden distribution ν is defined based on the idea of equal distribution equivalent (EDE), which is a measure of the central location of a distribution, adjusted for inequality based on a social welfare function.
2. Optimal Transport plan: We use OT theory to obtain the desired energy burden distribution, ν, which ensures the most cost-effective transformation of the initial distribution, μ. The resulting optimal transport plan is then used to determine the locations and ratings of solar PV installations on the rooftops of households within the distribution system.
3. Solar PV capacity and Tariff estimation: The size of PV and cost of electricity is determined using a feasibility problem.

We applied the proposed approach to the Dodge City substation area of the Ford County distribution system to site the PV locations such that the energy burden of the community is improved. Figure 22 shows the PV-locations overlay on the county map. Based on these PV locations, the current and improved energy burden distribution is shown in Figure 22.

It can be observed from Figure 22 that all the PV sites are concentrated near the Dodge City area. This can also be observed in the resilience heatmap, i.e., the resilience improvement can only be observed in the areas near Dodge City. This is because the populations with high energy burden are concentrated in those areas, and the algorithm did not consider any network parameters.

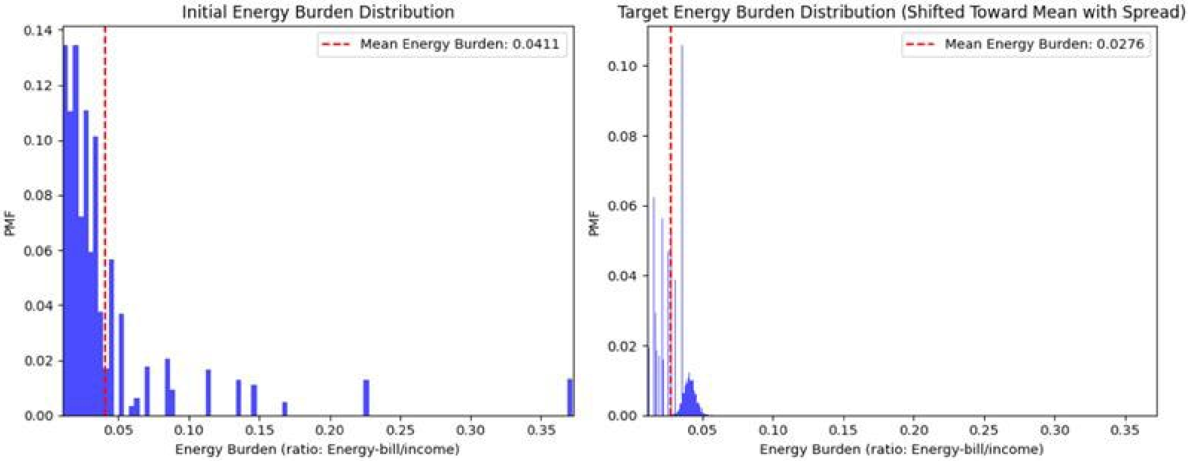


Figure 22. Current and improved energy burden distribution from PV locations.

Based on this observation, we improved the PV siting algorithm to a constrained OT problem by incorporating power flow and network losses. The mathematical formulation for entropy-regularized constrained OT-based distributed generation planning is as follows:

$$\min_{\gamma\in\pi(\mu,\nu)} \sum_{x,y} \gamma(x,y)c(x,y) + \sum_{x,y} \gamma(x,y)(\log\, \gamma(x,y)-1)\quad ,$$

$$c(x,y) = f\left(\phi_{x,y}, \delta_{x,y}\right) = \phi(x,y) + \alpha\delta(x,y)$$
$$\phi(x,y) = \|x-y\|^2$$
$$\delta(x,y) = \left\|\delta_x - \delta_y\right\|^2$$
$$\sum_{y} \gamma(x,y) = \mu_x\ \forall\, x$$
$$\sum_{x}^{y} \gamma(x,y) = \nu_y\ \forall\, y$$
$$\gamma \geq 0\ \forall\, x, y$$
$$\delta_x = \sum_{i=1}^{k} \frac{\partial P^{loss}}{\partial P_i^{pv}} = 2\sum_{i=1}^{k}\sum_{j=1}^{n} B_{ij}P_j^{pv}\ \forall\, E_i^x$$

where, $\gamma(x,y)$ is the optimal transport plan; $\phi_{x,y}$ is Euclidean cost; (x,y) is transportation cost; λ is regularization parameter; $\delta_{x,y}$ is cost proportional to network loss sensitivity factor; α is weight parameter; δ_x is sum of loss sensitivity factors of consumers corresponds to E_x; B_{ij} is loss coefficient matrix; P_{pvi} is solar PV generation at i_{th} location in the network. The above formulation considers both energy burden and loss sensitivity for PV placement. We tested the above algorithm on a 559-bus test system, and the results indicate an EB distribution that is still very close to the target distribution.

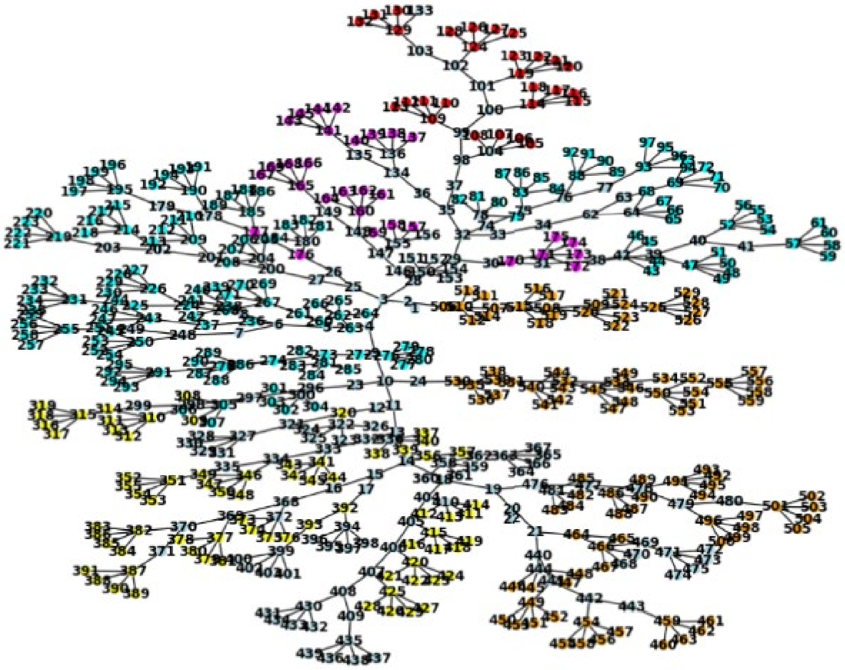
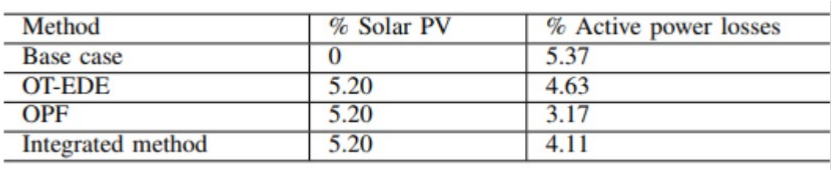


Figure 23. 559-Bus test system

Table 14 shows the results for locations obtained using multiple methods. For the same solar PV percentage, the active power losses are the lowest for the improved formulation integrating EDE and loss sensitivities.

Table 14: Results for locations using multiple methods



Method	% Solar PV	% Active power losses
Base case	0	5.37
OT-EDE	5.20	4.63
OPF	5.20	3.17
Integrated method	5.20	4.11

The proposed approach can be extended to include other constraints such as other resilience indicators (E-CAIDI, E-SAIDI), DERs (battery, mobile generators, DGs etc.), business models (community solar, off-grid solar etc.), and quality of life indicators and distributions (energy insecurity).

Resilience Metric Quantification for Optimal PV/Battery siting vs Naïve siting

This section provides details about the comparison of community resilience index obtained after optimal siting of PVs and batteries with that obtained after a naïve siting approach. The optimal PV sites were obtained from the study done by KSU, and the following modifications were made on top of those optimal PV sites: For the naïve siting approach, the same number of optimal sites are assumed to be randomly distributed across the distribution system. The PV capacities were scaled from 1kW peak to 10kW peak. A PV irradiance profile was applied to all such PVs. A Battery system is assumed to be installed at each PV location corresponding to the scenario. Each Battery system is assumed to be of the rating 5kW/50kWh. A load profile was associated with each load. A time-varying event is simulated to be moving across the distribution system and its multiple feeders from midnight to noon. This event causes several line/transformer damage, and their probabilities of outage are calculated based on the techniques described in previous reports. A control time-step of 1 hour is assumed; therefore, total simulated time-steps are 12. A naïve control algorithm is assumed to be in place, which essentially aims to utilize as much PV generation as possible, while utilizing the batteries proportionally as needed to aim to supply as much load as possible.

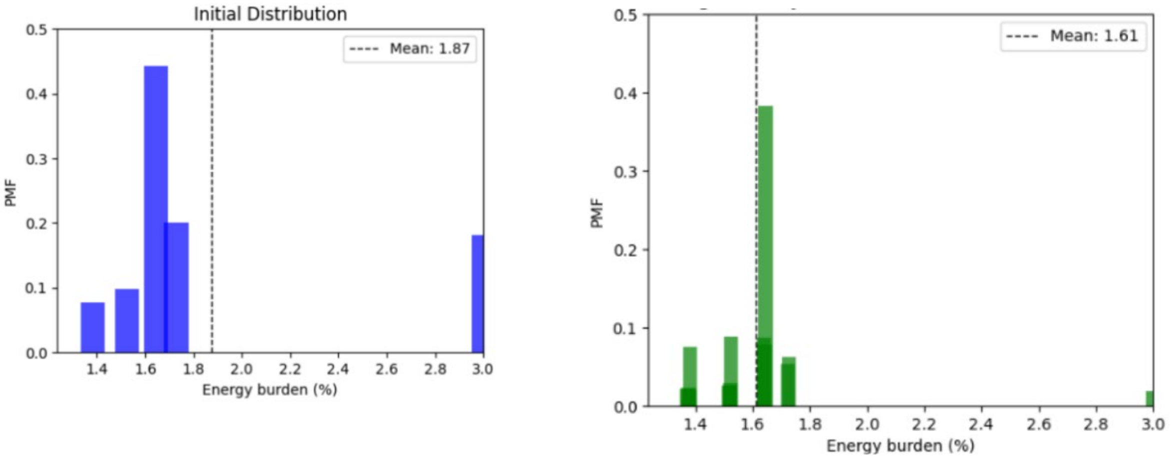


Figure 24. Initial and improved energy burden distribution from PV locations for 559 bus test system

The PV shape and the Loadshape used are shown in Figure 25.

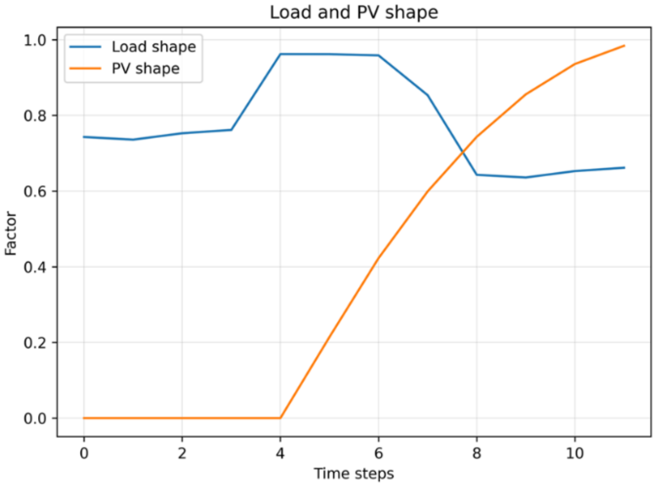


Figure 25. Load and PV irradiance shapes.

The optimal PV/Battery locations are shown overlaid on the topology map below:

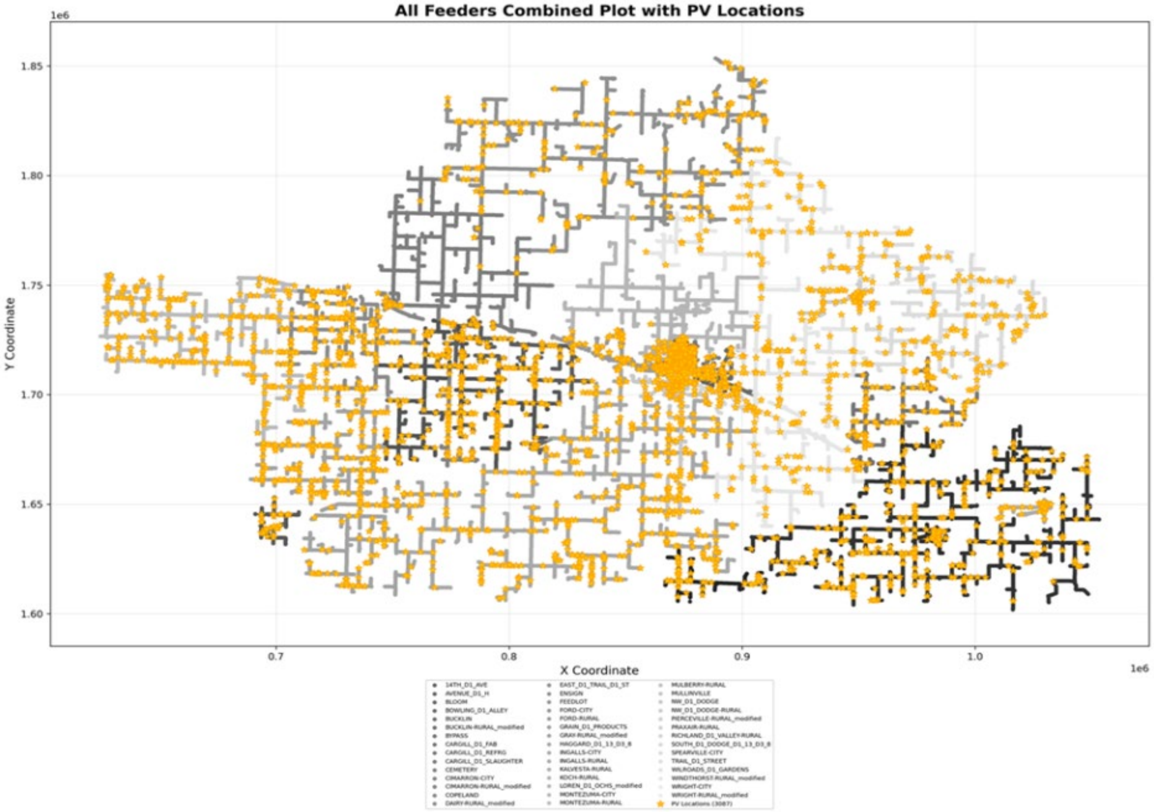
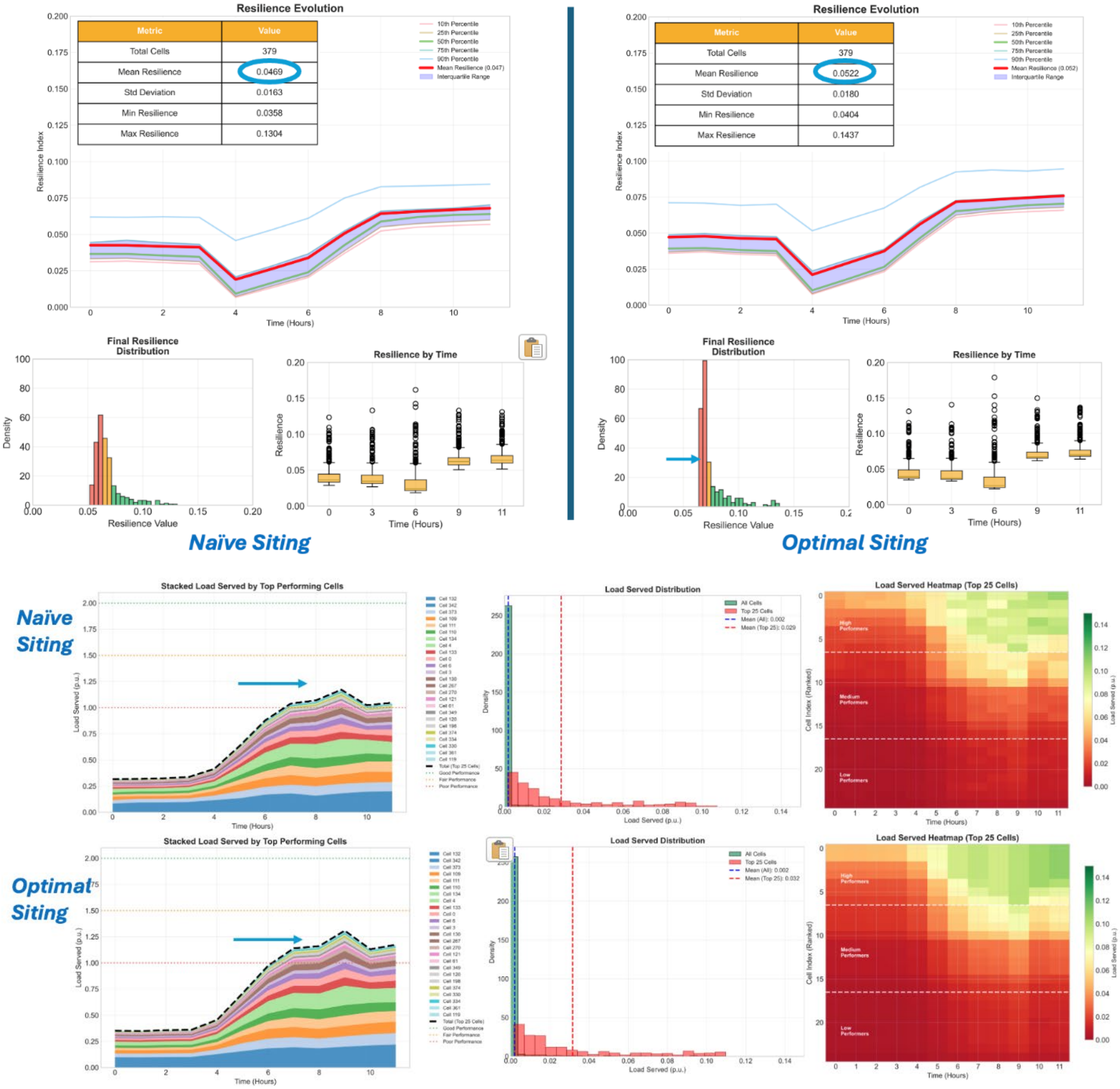


Figure 26. Locations of PV/Battery systems. For full image see Appendix 3.

With these assumptions, a naïve control algorithm is assumed to be in place which essentially aims to utilize as much PV generation as possible while utilizing the batteries proportionally as needed to aim to supply as much load as possible. The results comparing the community resilience and overall load served for both scenarios are shown next. It is noted that each of the lines in the plots below represents the subnetwork (or cell) that is formed after the event has completely passed through the system and has damaged multiple lines and transformers.



Naïve Siting:

Metric	Value
Total Cells	379
Mean Resilience	0.0469
Std Deviation	0.0163
Min Resilience	0.0358
Max Resilience	0.1304

Optimal Siting:

Metric	Value
Total Cells	379
Mean Resilience	0.0522
Std Deviation	0.0180
Min Resilience	0.0404
Max Resilience	0.1437

Figure 27: Results comparing the community resilience and overall load served for both scenarios. For full image see Appendix 4.

It can be seen from the above figures that the community resilience index and the load served for optimal siting scenario is slightly better than the naïve siting scenario. An interesting thing to note here is that even though the PVs are starting to generate more power during the later time-steps, resilience does not increase much because the batteries have been almost fully depleted and all the solar power being generated is going towards the loads as the total PV installation is much smaller than the load requirement.

Resilience Metric Quantification for Optimal PV/Battery Dispatch vs Naïve Dispatch
This section provides a comparison of the community resilience index obtained after optimal dispatch of PVs and batteries sited using the optimal siting approach from Task 6 with a naïve dispatch of PVs and batteries sited using the optimal siting approach. The control setup is similar to the previous section, except in the optimal dispatch scenario, where we employ the SomRes algorithm to dispatch PVs and batteries optimally. The SomRes algorithm tries to continuously adjust the level of storage reserves (battery state-of-charge in this case) to maximize the predicted resilience in the next time-step. Results comparing the community resilience, overall load served, and state-of-charge of batteries for both of these scenarios are shown next.

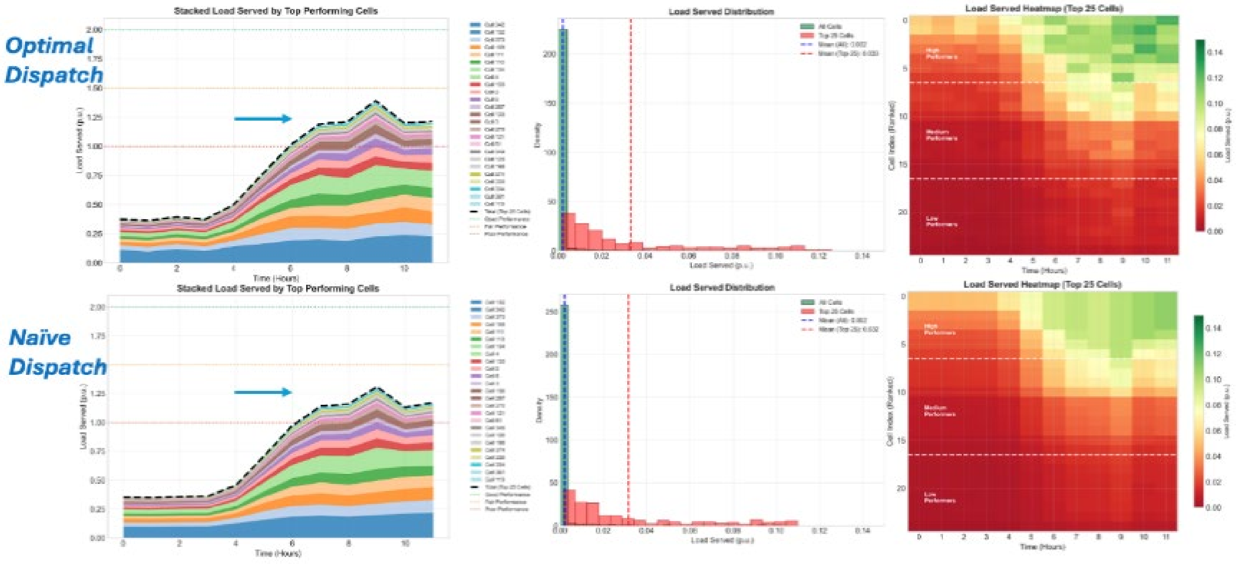
Naïve dispatch approach

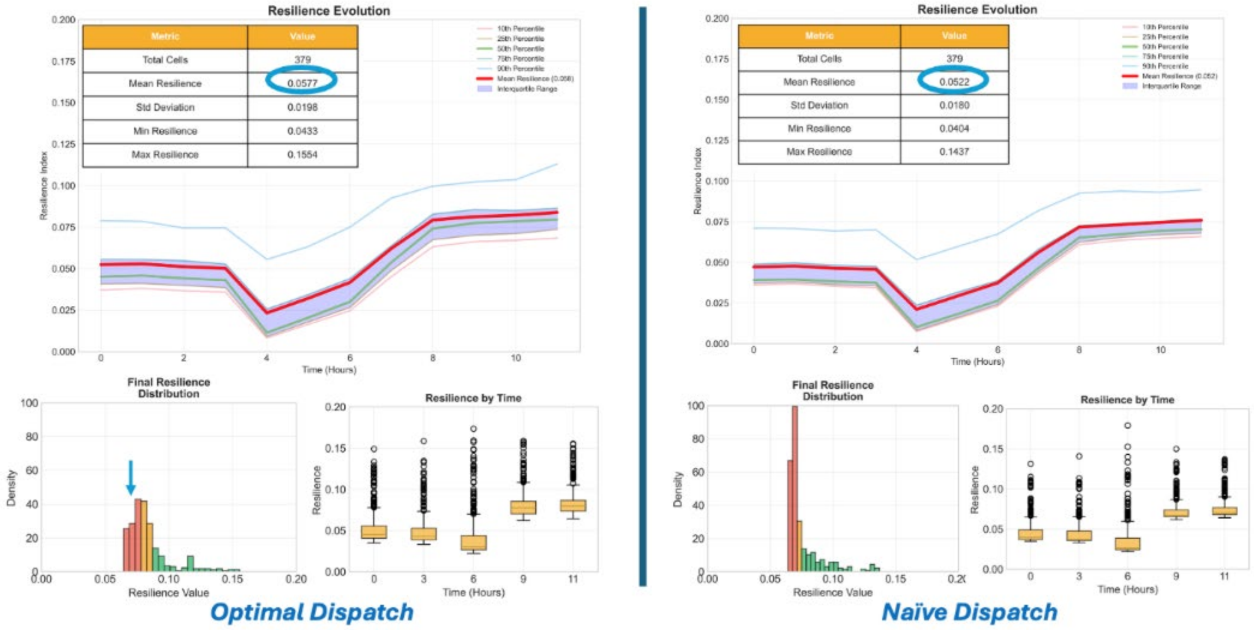
- ✓ Aims to utilize as much PV generation as possible
- ✓ Utilizes the batteries proportional to available SOC as needed
- ✓ Aims to supply as much load as possible within each isolated cell at the current time-step

vs

SomRes dispatch approach

- ✓ Aims to utilize as much PV generation as possible
- ✓ Continuously adjusts the SOC level of batteries
- ✓ Aims to maximize load supplied at the current time-step
- ✓ Aims to maximize the predicted resilience in the next few time-steps





Metric	Value
Total Cells	379
Mean Resilience	0.0577
Std Deviation	0.0198
Min Resilience	0.0433
Max Resilience	0.1554

Metric	Value
Total Cells	379
Mean Resilience	0.0522
Std Deviation	0.0180
Min Resilience	0.0404
Max Resilience	0.1437

Figure 28: Results comparing community resilience, overall load served, and state-of-charge of batteries for both scenarios. For full image see Appendix 5.

First, it can be observed from the above figures that the community resilience index and the load served for optimal dispatch scenario is better than the naïve dispatch scenario, with the average increase in resilience as 11.01%, and the average increase in normalized load supplied as 4.69%. These improvements are not only technical but also reflect survey-informed weighting, as household energy insecurity categories and willingness-to-pay values were incorporated into the optimization framework. Secondly, it can be observed that there is a lot more variation in the available battery SOC of the cells. This is because the SomRes algorithm is continuously charging batteries that are anticipated to have low resilience in the next step, while discharging those that are not because of the absence of grid power and a fixed availability of generation.

Impact

The proposed recloser placement approach and locations will be shared with Victory Electric to support them in their single-phase recloser project to improve the system's resilience. The overall method can be further used by various utilities to prioritize the locations based on their budget.

The PV location results will also be shared with utility and community stakeholders to support decision making on investing in solar PV projects. The utilities can further integrate their tariff and business models into the optimal transport formulation to make investment and incentivization decisions.

Table 15: Task 6 milestones and status

Task #	Performance Metric	Success Value	Assessment Tool / Method of Measuring Success Value	Progress Notes
6.1.1	Community energy resilience index with the proposed holistic resilience focused optimal PV/BESS sizing and siting versus existing performance-based metrics method used by utilities	Ratio of community resilience index with optimal PV/BESS siting/sizing based on performance & non-performance-based metrics versus a performance-based metrics method currently used by utilities >1.1	Simulate multiple disaster scenarios to train and optimize PV/BESS siting. Evaluate the resilience index for optimal versus naïve siting and sizing.	100%
6.2.1	Community resilience index when the proposed optimal resource allocation and dispatch strategy is employed on top of optimal siting, compared to a scenario where a naïve resource dispatch strategy is employed on top of optimal siting.	Ratio of resilience index of the system with optimal resource allocation and dispatch versus a naïve resource dispatch strategy >1.1	Simulate multiple disaster scenarios to evaluate the resilience index with optimal resource allocation and dispatch and a naïve dispatch.	100%

TASK 7.0: RESILIENCE HEATMAP FOR FORD COUNTY

Task Summary

As part of the broader testing and validation efforts in Task 7, this section focuses on generating a resiliency heatmap for Ford County to visually demonstrate the SAFER framework's impact on community energy resilience. The heatmaps were developed using fragility curves for assets and various contingency scenarios (tornadoes and high winds that are the primary disasters of interest in Ford County), but is general to expand to other weather events as well. These results can further be mapped with resilience indices. We compared two key cases: (1) baseline resilience without PV, and (2) enhanced resilience incorporating optimal siting and sizing of Solar PV and Battery Energy Storage Systems (BESS) derived from Task 6.

A summary of accomplishments include: (1) Demonstrated the application of HFGs for visualizing the impact of weather-related outages. (2) Demonstrated the application of HFGs for comparing resilience enhancement investments.

Task Outcomes

The developed heterofunctional graph models from Task 4, along with fragility curves, can also be used to compare investment options for their effectiveness in reducing the impacts of disruptions. Utilities can utilize their network models to simulate various weather event scenarios and also compare the outage impacts of disruption events for various investment options. Figures 29 and 30 show the application of HFGs along with fragility curves to assess weather induced impacts on power systems.

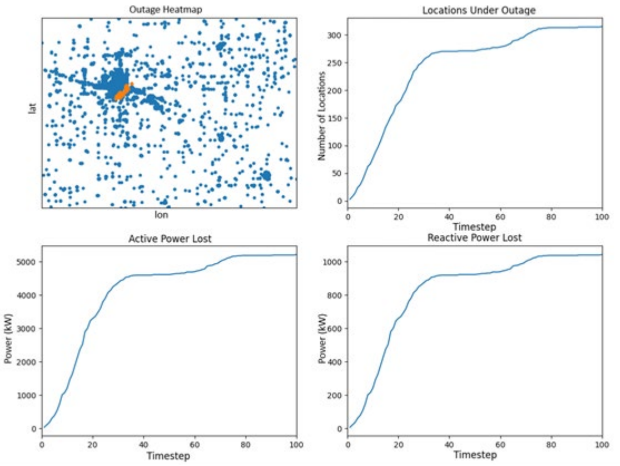


Figure 29. HFGs for weather impact analysis (Tornado scenario). For full image see Appendix 6.

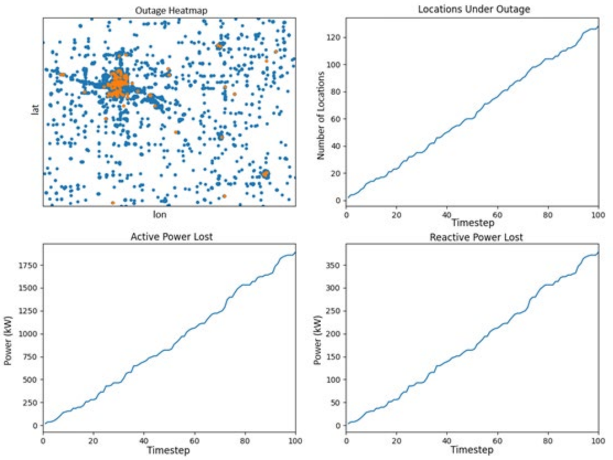


Figure 30. HFGs for weather impact analysis (High Winds scenario). For full image see Appendix 7.

By introducing PV into these systems, resilience enhancement impacts of PV investments can be studied. For example, Figure 31 shows the same disruption event for two cases of solar PV installations. It can be observed that Option B results in lower lost load during disruptions. They also show the baseline scenario with no PV and how both investment strategies improve upon the baseline.

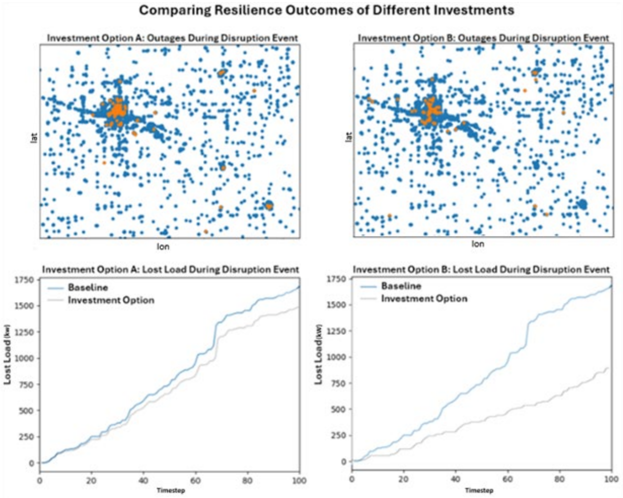


Figure 31. Comparison of investment options using the HFG framework. For full image see Appendix 8.

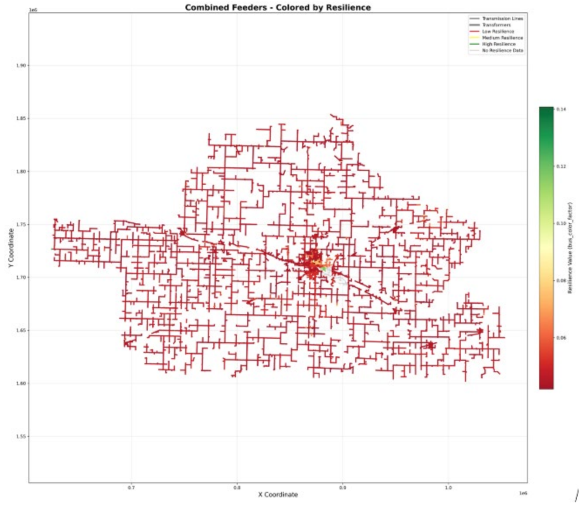


Figure 32: Ford County resilience heatmap. For full image see Appendix 9.

Resilience heatmap of Ford County

The resilience heatmap of Ford County is shown in Figure 32 represented by different colors for individual possible subnetworks.

Impact

The developed HFG framework can be used to study the progression of outages under various weather scenarios. This can be achieved by augmenting them with fragility curves for assets. This also enables the evaluation of various resilience enhancement investments. Further, unlike computationally intensive simulation-based studies, the HFG-based approaches provide lightweight alternatives and enable a wider range of scenarios to be tested within the same time frame as simulation-based studies.

Table 16: Task 7 milestones and status.

Task #	Performance Metric	Success Value	Assessment Tool / Method of Measuring Success Value	Progress Notes
7.0.1	Resilience heatmap for Ford County	Resilience index of vulnerable communities with PV/BESS > Baseline resilience index for those communities	Simulate multiple scenarios and test cases to determine survivability of subnetworks within Ford County grid.	100% - Utilized HFGs to estimate baseline distances and times to access resources. These results were used to assess degradation in access to resources during disruptions.

TASK 8.0: TECHNOLOGY TRANSFERABILITY AND OUTREACH

Task Summary

Task 8 focused on utilizing the research outputs from previous tasks to translate findings into practical tools and resources for communities. The team developed a Community Energy Resilience Planning Guide, designed to help local governments and partners identify, assess, and implement resilience initiatives using the SAFER project outcomes. The guide breaks the planning process into clear, adaptable steps and provides examples, frameworks, and responsible parties for implementation. The website provides an overview of the SAFER project and outcomes for stakeholders and communities. The achievements from this task ensure the project's research is transferable, accessible, and actionable for both Ford County and other communities.

A summary of accomplishments include:

- Developed a Community Energy Resilience Planning Guide, outlining a step-by-step framework for resilience projects.
- Made guide and supporting materials (e.g., survey instruments, summary reports) accessible to partner and non-partner communities.
- Completed the project webpage and provided open access to source codes for transparency and replication.
- Disseminated project findings through an outreach-oriented toolkit that integrates examples and best practices.
- Established a foundation for scaling and refining resilience planning across diverse communities.

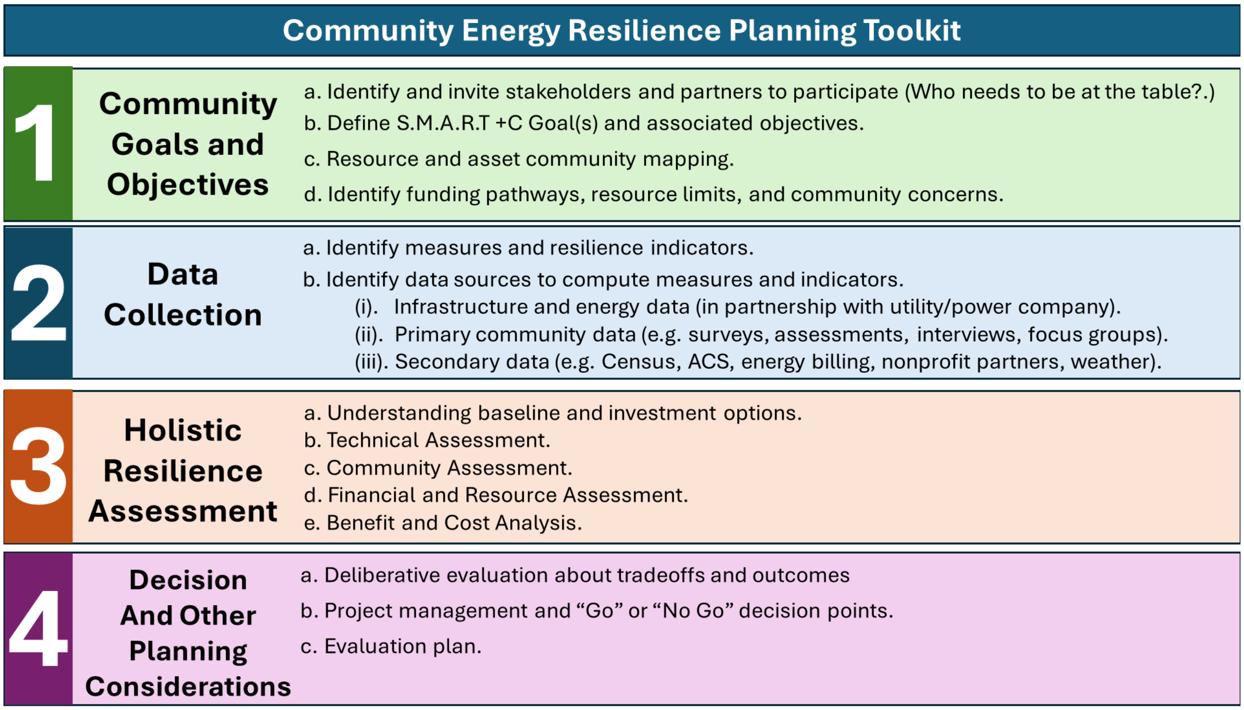
Task Outcomes

Community Energy Resilience Planning Guide

We developed a planning and assessment guideline tool kit for our partnering community that is accessible to other communities as well. Our aim in preparing a community energy resilience planning guide is to help communities identify, assess, and solve issues related to energy resilience using outcomes from the SAFER research project. The purpose of the guide is to provide a planning framework that communities can follow and apply when making decisions about energy challenges they face. Figure 33 shows how the guide is organized and breaks down the process of developing community energy resilience projects and initiatives into four components or steps. These steps are listed in the order we envision the planning process taking place, but the components may overlap and be done in the order best suited for a community's planning purposes. Each section of the guide provides an overview, approach, examples and/or identifies potential responsible parties for different steps and their components in the planning process. The guide provides a comprehensive framework for helping communities plan community energy resilience projects with examples, links and important considerations for the planning process. A copy of the community energy resilience planning guide accompanies this report.

Impact

The community planning guide will help to guide community energy resilience project planning on the ground and be refined as it is used and implemented in the field. The guide provides one outlet for disseminating and educating communities about the SAFER project. In addition, it is supplemented with additional documentation, including our survey and survey summary.



Community Energy Resilience Planning Toolkit		
1	Community Goals and Objectives	a. Identify and invite stakeholders and partners to participate (Who needs to be at the table?.) b. Define S.M.A.R.T +C Goal(s) and associated objectives. c. Resource and asset community mapping. d. Identify funding pathways, resource limits, and community concerns.
2	Data Collection	a. Identify measures and resilience indicators. b. Identify data sources to compute measures and indicators. (i). Infrastructure and energy data (in partnership with utility/power company). (ii). Primary community data (e.g. surveys, assessments, interviews, focus groups). (iii). Secondary data (e.g. Census, ACS, energy billing, nonprofit partners, weather).
3	Holistic Resilience Assessment	a. Understanding baseline and investment options. b. Technical Assessment. c. Community Assessment. d. Financial and Resource Assessment. e. Benefit and Cost Analysis.
4	Decision And Other Planning Considerations	a. Deliberative evaluation about tradeoffs and outcomes b. Project management and "Go" or "No Go" decision points. c. Evaluation plan.

Figure 33: Community Energy Resilience Planning Toolkit

Table 17: Task 8 milestones and status

Task #	**Performance Metric**	**Success Value**	**Assessment Tool / Method of Measuring Success Value**	**Progress Notes**
8.1.1	Planning and Assessment Guideline Tool Kits Available	Completion of toolkit for dissemination	Completion and distribution to partners and online.	100%
8.1.2	Participation rate in community Resilience Workshop	70% of committed stakeholders participated.	Completion of a community resilience workshop in Year 2 of the project to help with dissemination and outreach	10% We have contacted our StAC members and partners to begin to inquire about potential dates for holding our final community resilience workshop.
8.2.2	Completed Project Web Page and Open Access to Original Source Codes	Active project web page online and original source codes posted to accessible open and secure site.	A project webpage for dissemination of project materials is completed and has been made available online. Original Source codes will be posted on an open and secure site (e.g. GitHub)	100%

SIGNIFICANT ACCOMPLISHMENTS AND CONCLUSIONS

The SAFER project successfully advanced both the science and practice of community energy resilience by combining stakeholder engagement, community-informed data collection, technical modeling, and outreach. Together, the project's eight tasks built a stepwise foundation where community voices shaped technical approaches, and technical advances were translated back into actionable tools for communities and utilities.

We began by establishing strong partnerships through the Stakeholder Advisory Committee (Task 1), which included utilities, local governments, and community organizations. These partnerships were essential in shaping project goals, ensuring access to utility data, and fostering community trust that underpins all subsequent tasks. Building on that foundation, we collected a robust and representative dataset on household resilience through surveys, focus groups, and workshops (Task 2). This dataset provided rare and critical insights into energy burden, energy insecurity, and lived experiences of rural communities, ensuring that resilience models and metrics were grounded in real community needs. Using these inputs, we developed new resilience metrics such as community capital-based resilience capacity, energy burden, energy insecurity indices, and value of lost load that link household vulnerability to infrastructure performance. The latter three use primary survey data (Task 3). These metrics/features integrated through Self-Organizing Map (SOM) modeling established quantifiable baselines for resilience across Ford County, enabling both community-scale and system-scale planning.

We then advanced technical modeling through the development of a novel heterofunctional graph (HFG) framework (Task 4). This framework enabled fine-grained modeling of interdependent systems including power, water, transportation, and community assets at an unprecedented scale, with over 322,000 nodes. Importantly, we introduced the Access Degradation Factor (ADF), which translates infrastructure disruptions into tangible community impacts/QoL metrics, such as loss of access to hospitals or groceries. To prioritize where investments matter most, we applied graph neural networks (Task 5) to identify critical nodes and functionalities within the HFG framework. This allowed utilities and planners to pinpoint and protect the most essential services, maximizing resilience benefits with limited resources.

Task 6 moved from analysis to solutions by developing optimization frameworks for both recloser placement and PV siting. The recloser optimization framework reduced outage-related costs and customer losses by nearly 30%, while the community-focused PV siting approach improved the distribution of energy burden, ensuring that resilience investments directly benefited low-income and vulnerable households. Task 7 produced resilience heatmaps for Ford County that visually demonstrate resilience strengths and vulnerabilities across the county. These heatmaps will provide a powerful decision-support tool for policymakers and community leaders to target future resilience investments. Finally, Task 8 ensured that all this work would extend beyond the research team by producing a Community Energy Resilience Planning Guide, an open-access project webpage, and openly available source codes. These resources make the project's technical and community-based findings accessible and actionable for communities far beyond Ford County, ensuring lasting impact and scalability.

In summary, the SAFER project's accomplishments are significant because they:

- Built deep community partnerships to ensure relevance and trust.
- Created the first comprehensive dataset on household energy resilience in rural Kansas.
- Developed new, quantifiable resilience metrics that connect households to infrastructure systems.
- Advanced cutting-edge modeling tools that capture interdependencies across infrastructures.
- Identified the most critical nodes and assets to guide efficient resilience investments.
- Produced practical strategies such as recloser optimization and community-centric PV siting methodologies that utilities can act on immediately.
- Generated transferable tools and guides to empower communities nationwide.

Together, these outcomes position the SAFER project as a model for integrating community engagement with technical innovation, producing resilience solutions that are both scientifically rigorous and socially meaningful.

PATH FORWARD

While there are many outstanding challenges to address in the broad area of resilience science and engineering, we describe a few logical next steps that build off of SAFER research. First, we want to enhance the holistic community capitals framework based on initial SAFER research on community-capital-based community and energy resilience metrics using secondary data at the community and county scale. We want to expand the development of community capital indices, the interrelationships between different community capital indices, the effects of natural disasters and shocks on community capital stocks, and the influence of community capital indices on community wellbeing, economic situation, and vulnerability. Secondly, we want to determine how to operationalize resilience metrics that we have developed with community input. This will involve discussions with all stakeholders and possible refinement of the metrics and development of software tools to enable efficient computation by non-experts. The heterofunctional graph-modeling framework will be expanded to include more FEMA community lifelines, such as communication and shelters. Leveraging the graph neural network (GNN)-based critical node identification technique from Task 5, future work will involve applying transfer learning techniques to use the pre-trained models from Ford County HFG to new, unseen infrastructure networks with minimal retraining. The idea of using Optimal Transport to guide community-centric DER planning (Task 6) can be extended to include EV charger planning as well as more advanced business models to make PV/BESS investments appealing to all stakeholders. Resilience heatmap visualization tools will be integrated into interactive web-based dashboards that allow stakeholders to simulate custom scenarios, such as varying weather intensities or investment options like additional DER placements. We also would like to develop an AI-chatbot interface for city administrators and emergency management staff to easily use the core SAFER modeling and impact analyses tools with minimal technical training.

PRODUCTS

Journals/Conferences

a. Published

1. P. Gautam, A. Sreejith and B. Natarajan, "A Transductive Graph Neural Network learning for Grid Resilience Analysis," 2023 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm), Glasgow, United Kingdom, 2023, pp. 1-6, doi: 10.1109/SmartGridComm57358.2023.10333912
2. Dhanapala, Prudhviraj, Amulya Sreejith, Balasubramaniam Natarajan, and Anil Pahwa. "Equity-driven Planning of Distributed Solar PV using Optimal Transport," *2025 IEEE Power and Energy Society General Meeting (PESGM)*, Austin, TX, USA, 2025.

b. Planned/In Development/Under Review

1. A. Sreejith, R. Madbhavi, P. Dhanapala, B. Natarajan, A. Pahwa, J. Bergtold, “Socioeconomic Vulnerability based Resilience Assessment Metric for Power Distribution Systems” IEEE Access (under review)
2. A. Pradeep, A. Sreejith, B. Natarajan, A. Pahwa, “A Flexible and Scalable Multi-Objective Optimization Framework for Recloser Placement in Power Distribution Systems” IEEE Transactions on Reliability
3. Gautam, P., Madbhavi, R., and Natarajan, B. "Scalable Criticality Analysis in Interdependent Infrastructure Systems using Functionality Graphs." Submitted to IEEE Systems Journal, 2025.
4. P. Gautam; R. Madbhavi; B. Natarajan, “Critical Asset and Functionality Identification in Interdependent Infrastructure Systems”
5. R. Madbhavi, B. Natarajan, “HFG-TK: A Toolkit for Modeling Critical Interdependent Infrastructure Systems using Heterofunctional Graphs”
6. E. Osman, J.S. Bergtold, E.J. Sutley, M. Graham, A. Guacin, Y. Ren, R. Sharmin, “Extreme Weather Events, Community Resilience, and Energy Insecurity in Kansas”
7. J.S. Bergtold, Y. Ren, E. Osman, M. Gharib, M. Graham, E. Sutley, “Households’ Willingness-to-Pay to Avoid Power Outages in Rural Areas”

Presentations

1. R. Madbhavi, B. Natarajan, “Disruption Propagation in Interdependent Infrastructures: A Heterofunctional Graph Theoretic Approach,” NHERI Computational Symposium, 2025
2. Gautam, P., Natarajan, B., Munikoti, S., Ferdous, S. M., Halappanavar, M. "GNN-Based Candidate Node Predictor for Influence Maximization in Temporal Graphs." AAAI Workshop, 2025.

Other Media

1. Project website: https://www.k-state.edu/safer/
2. Press release: https://www.k-state.edu/news/newsreleases/2023-08/Natarajan-energy-resilience-grant82823.html

Thesis/Dissertations

1. D. Wesseler, “Community Solar: Resident’s Willingness-to-Pay and the Role of Values, Beliefs and Energy Situation,” MS Thesis, Department of Agricultural Economics, Kansas State University, Manhattan, Kansas, USA, 2024.

PROJECT TEAM AND ROLES

Table 18: Project members, expertise, and roles

Investigator	Organization	Expertise	Roles
1. Bala Natarajan	Professor, KSU ECE[a]	Cyber-physical-social-systems modeling, ML with graphs, resilience analysis of complex systems.	T1, T2, T3, T4 9.6 months
2. Anil Pahwa	Professor, KSU ECE[a]	Power distribution system analysis, system level impacts of integration of renewables	T2, T3, T4, 6 months
3. Jason Bergtold	Professor, KSU AE[b]	Bio- and renewable energy, sustainable agriculture, technology adoption, land use economics.	T1, T2, T3, T8 6 months
4. Marcellus M. Caldas	Professor, KSU GGSOIP[c]	Geographic Information System, geospatial analysis and applications, and economic geography.	T1, T3, 6 months
6. George Amariucai	Associate Professor, KSU CS[e]	Privacy, privacy metrics, cybersecurity, social network modelling and machine learning.	T1, T2, T4, 6 months
7. Fei Ding	Distinguished Member of Research Staff, NREL	Renewable energy grid integration, grid resilience, cybersecurity.	T2, T3, T4 2 months
8. Utkarsh Kumar	Senior Research Engineer, NREL	System-resilience quantification metrics and strategies, DER integration	T1, T2, T3, 2 months
9. Rahul Madbhavi	Postdoctoral Scholar, Kansas State University	Critical interdependent infrastructure systems research: modeling, simulation, critical assets identification, cascading failures and resilience analyses.	T4, T5, T7
10. Amulya Sreejith	Postdoctoral Scholar, Kansas State University	Holistic-resilience quantification metrics, Recloser and OT-based DER planning.	T2, T3, T6
11. Adwaitha Pradeep	GRA, Kansas State University	Recloser planning and resilience analysis.	T6
13. David Wesseler	GRA, Kansas State University	Renewable energy, community solar and agricultural economics.	T2, T3
14. Niranjana Unnithan	GRA, Kansas State University	HFGT development	T5

Community/Utility/Industry Partners - Stakeholder advisory council (StAC)			
1. Nick Hernandez	City Manager, Dodge City	5. Stacy Barnes	City Administrator, City of Greensburg
2. JoAnn Knight	Dodge City/Ford County Development Corp.	6. Andrea Burns	Ford County Extension Office
3. Rex Beemer	Ford County Emergency Management	7. Robert Reichenberger	Solar Prime LLC
4. Al Tamimi	Sunflower Electric	8. Shane Laws	Victory Cooperative

REFERENCES

[1] Elms D. 2015. Improving community resilience to natural events. Civil Engineering and Environmental Systems. 32 (1-2): 77 – 89. https://doi.org/10.1080/10286608.2015.1011626.

[2] Cafer A, Green J, Goreham G. 2019. A community resilience framework for community development practitioners building equity and adaptive capacity. Community Development 50(2): 201 – 216. https://doi.org/10.1080/15575330.2019.1575442.

[3] Daniel L, Mazumder RK, Enderami SA, Sutley EJ and Lequesne RD. 2022. Community capitals framework for linking buildings and organizations for enhancing community resilience through the built environment. Journal of Infrastructure Systems 28(1): https://doi.org/10.1061/(ASCE)IS.1943-555X.0000668.

[4] Brown MA, Kale S, and Anthony, R. 2023. Rescaling energy burden: using household surveys to examine vulnerabilities and consequences in the Southeastern U.S. Energy Research and Social Science. 106: 103308. https://doi.org/10.1016/j.erss.2023.103308.

[5] Ren J and Sovacool BK. 2014. Quantifying, measuring, and strategizing energy security: determining the most meaningful dimension and metrics. Energy. 76(1): 838 – 849. https://doi.org/10.1016/j.energy.2014.08.083.

[6] Sullivan, MJ, Schellenberg J and Blundell M. 2015. Updated value of service reliability estimates for electric utility customers in the United States. Energy Analysis and Environmental Impacts Division, Energy Markets and Policy Department, Energy Storage and Distributed Resources Division, Grid Integration Group, Consortium for Electric Reliability Technology Solutions (CERTS), LBNL-6941E. Available at: https://eta-publications.lbl.gov/sites/default/files/lbnl-6941e.pdf.

[7] Mueller D, Hoard S, Roemer K, Sanders C and Rijkhoff SAM. 2020. Quantifying the community capitals framework: strategic application of the community assets and attributes model. Community Development. 51(5): 535 – 555. https://doi.org/10.1080/15575330.2020.1801785.

[8] Emery M, Fey S and Flora C. 2006. Using community capitals to develop assets for positive community change. CD Practice. 13: 1 – 19.

[9] B. Chiu, A. Bose, S. Brown, B. Chalamala, D. Immerman, A. Khodaei, J. Liu, J. Mazurek, D. Novosel, A. Paaso, F. Rahmatian, J. R. Agüero, and M. Vaiman, ‘‘Resilience framework, methods, and metrics for the electricity sector,’’ tech. rep., IEEE Power and Energy Society, 2020.

[10] L. Das, S. Munikoti, B. Natarajan, and B. Srinivasan, ‘‘Measuring smart grid resilience: Methods, challenges and opportunities,” Renewable and Sustainable Energy Reviews, vol. 130, p. 109918, 2020.

[11] M. Panteli, P. Mancarella, D. N. Trakas, E. Kyriakides, and N. D. Hatziargyriou, ‘‘Metrics and quantification of operational and infrastructure resilience in power systems,’’ IEEE Transactions on Power Systems, vol. 32, no. 6, pp. 4732–4742, 2017.

[12] E. D. Vugrin, A. R. Castillo, and C. A. Silva-Monroy, “Resilience metrics for the electric power system: A performance-based approach,” Sandia Nat. Lab., Albuquerque, NM, USA, Rep. SAND2017-1493, 2017.

[13] P. Bajpai, S. Chanda, and A. K. Srivastava, “A novel metric to quantify and enable resilient distribution system using graph theory and Choquet integral,” IEEE Trans. Smart Grid, vol. 9, no. 4, pp. 2918–2929, Jul. 2018.

[14] A. Kwasinski, “Quantitative model and metrics of electrical grids’ resilience evaluated at a power distribution level,” Energies, vol. 9, no. 2, p. 93, 2019.

[15] K. Anderson et al., “Integrating the value of electricity resilience in energy planning and operations decisions,” IEEE Syst. J., vol. 15, no. 1, pp. 204–214, Mar. 2021.

[16] D. Leykin, M. Lahad, O. Cohen, A. Goldberg, and L. Aharonson Daniel, ‘‘Conjoint community resiliency assessment measure: a self-report tool for assessing community resilience,’’ American Journal of Community Psychology, vol. 52, pp. 313-323, 2013.

[17] A. Walton, J. Marr, M. Cahillane, and K. Bush, ‘‘Building community resilience to disasters: a review of interventions to improve and measure public health outcomes in the northeastern united states,’’ Sustainability, vol. 13, p. 11699, 2021.

[18] M. Schoch-Spana, K. Gill, D. Hosangadi, C. Slemp, R. Burhans, J. Zeis, E. Carbone, and J. Links, ‘‘The copewell rubric: a self-assessment toolkit to strengthen community resilience to disasters,’’ International Journal of Environmental Research and Public Health, vol. 16, p. 2372, 2019.

[19] M. Sullivan, M. T. Collins, J. Schellenberg, and P. H. Larsen, ‘Estimating power system interruption costs: A guidebook for electric utilities,’ 2018.

[20] A. Wachtel, D. Melander, and R. Jeffers, ‘‘Measuring societal infrastructure service burden.,’’ tech. rep., Sandia National Lab. (SNL-NM), Albuquerque, NM (United States), 2022.

[21] Edgar C. Portante, James A. Kavicky, Brian A. Craig, Leah E. Talaber, & Stephen M. Folga (2017). Modeling Electric Power and Natural Gas System Interdependencies. Journal of Infrastructure Systems, 23(4), 04017035.

[22] A. Momeni, V. Prasad, H. I. Dharmawardena, K. R. Piratla and K. Venayagamoorthy, "Mapping and Modeling Interdependent Power, Water, and Gas Infrastructures," 2018 Clemson University Power Systems Conference (PSC), Charleston, SC, USA, 2018, pp. 1-8, doi: 10.1109/PSC.2018.8664050.

[23] Zuloaga, S., Khatavkar, P., Vittal, V. and Mays, L.W. (2020), Interdependent electric and water infrastructure modelling, optimisation and control. IET Energy Syst. Integr., 2: 9-21. https://doi.org/10.1049/iet-esi.2019.0039

[24] X. Lu et al., "An Open Source Modeling Framework for Interdependent Energy-Transportation-Communication Infrastructure in Smart and Connected Communities," in IEEE Access, vol. 7, pp. 55458-55476, 2019, doi: 10.1109/ACCESS.2019.2913630.

[25] Pengcheng Zhang, & Srinivas Peeta (2011). A generalized modeling framework to analyze interdependencies among infrastructure systems. Transportation Research Part B: Methodological, 45(3), 553-579.

[26] Hasan, S., Foliente, G. Modeling infrastructure system interdependencies and socioeconomic impacts of failure in extreme events: emerging R&D challenges. Nat Hazards 78, 2143–2168 (2015). https://doi.org/10.1007/s11069-015-1814-7

[27] A. Cardoni, G.P. Cimellaro, M. Domaneschi, S. Sordo, & A. Mazza (2020). Modeling the interdependency between buildings and the electrical distribution system for seismic resilience assessment. International Journal of Disaster Risk Reduction, 42, 101315.

[28] C. Paulsen, J. M. Boyens, N. Bartol, and K. Winkler, “Criticality analysis process model: Prioritizing systems and components,” 2018.

[29] C. Alcaraz and S. Zeadally, “Critical infrastructure protection: Requirements and challenges for the 21st century,” International Journal of Critical Infrastructure Protection, vol. 8, pp. 53–66, 01 2015.

[30] W. Ellens and R. E. Kooij, “Graph measures and network robustness,” CoRR, vol. abs/1311.5064, 2013.

[31] P. Gautam and B. Natarajan, “Gnn-based criticality analysis in inter-connected infrastructure networks,” in 2024 IEEE Green Technologies Conference (GreenTech), pp. 213–217, 2024.

[32] P. S. Hegde, W. C. H. Schoonenberg, D. J. Thompson, and A. M. Farid, “The hetero-functional graph theory toolbox,” ArXiv, vol. abs/2005.10006, 2020.

[33] P. Acheson, C. Dagli, and N. Kilicay-Ergin, “Model based systems engineering for system of systems using agent-based modeling,” Procedia Computer Science, vol. 16, pp. 11–19, 2013. 2013 Conference on Systems Engineering Research.

[34] M. Tariverdi, M. Nunez-del Prado, N. Leonova, and J. Rentschler, “Measuring accessibility to public services and infrastructure criticality for disasters risk management,” Scientific Reports, vol. 13, p. 1569, Jan. 2023.

[35] K. D. A. Susan L. Cutter and C. T. Emrich, “Urban–rural differences in disaster resilience,” Annals of the American Association of Geographers, vol. 106, no. 6, pp. 1236–1252, 2016.

[36] S. Bandyopadhyay, G. R. C. Mouli, Z. Qin, L. R. Elizondo, and P. Bauer, “Techno-economical model based optimal sizing of pv-battery systems for microgrids,” IEEE Transactions on Sustainable Energy, vol. 11, no. 3, pp. 1657–1668, 2019.

[37] T. M. Logan, M. J. Anderson, T. G. Williams, and L. Conrow, “Measuring inequalities in urban systems: An approach for evaluating the distribution of amenities and burdens,” Computers, Environment and Urban Systems, vol. 86, p. 101590, 2021.

[38] J. Barlow, R. Tapio, and B. Tarekegne, “Advancing the state of energy equity metrics,” The Electricity Journal, vol. 35, no. 10, p. 107208, 2022.

[39] A. K. Bharati, A. Singhal, R. Jinsiwale, K. Kazimierczuk, J. Yoshimura, and B. Tarekegne, “Advancing energy equity considerations in distribution systems planning,” in 2023 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), pp. 1–5, IEEE, 2023.

[40] P. Dhanapala, A. Sreejith, B. Natarajan, and A. Pahwa, “Game theoretic coordination of microgrids with equity considerations,” in 2024 IEEE Kansas Power and Energy Conference (KPEC), pp. 1–6, 2024.

APPENDIX 1

- Electrical Infrastructure
- Equipment (e.g. Bobcats)
- Waste Water Treatment
- Wind Farms
- Solar Farms
- Broadband Access/Internet
- Medical/Health Infrastructure
- Gas Infrastructure
- Water Recycling
- Biogas Plant
- Transportation Services

- Why Not Dodge Projects
- Protein Industry & Plants
- Banks
- External Grants
- FEMA Funds
- Casino and Resort
- Tourism
- Contractors & Services
- Charity Access for Resources
- In-Kind Support
- Packing Plants
- Loans
- Credit Unions
- Salex Tax

- "Dodge City" Name
- Boot Hill Museum
- Dodge City Days
- Mexican Village
- International Festival
- Ethic Mindset Culture
- Farmers' Community
- Main Street Festival
- Multi-Cultural Committees
- Library Events
- Agriculture Culture
- Local Fundraisers
- Cattle Drive
- Religious Events
- Cinco De Mayo

- Neighborhood Parks
- Access to Land
- Horse Thief Reservoir
- Farms/Ranches
- Agricultural Resources (Soil)
- Stewardship Commitments
- Hunting
- Natural Landscape

- Disaster Declaration
- City Council
- County Commission
- Leadership and City Administration
- Dodge City/Ford County Development Corporation
- Mutual Trust
- STAR Bond Districts
- RHID Program
- Community Will (Can Do)
- Civic Organizations
- Emergency Management Planning
- Police & Fire Department
- Chamber of Commerce
- Advisory Boards
- UFCW2
- Emergency Management Planning

- Social Media Groups
- YMCA
- Diverse Culture
- Community Communication
- Church Community
- Community Volunteers
- Community Member Connections
- DC Chamber of Commerce
- Women's Chamber
- Community Foundation of SW Kansas
- Public-Private Partnerships
- Catholic Charities
- Main Street Organizations
- Water Park

- Labor Force/Job Creation
- Experienced Experts
- Library
- Community College
- Community Volunteers
- Public-Private Partnerships
- USD 443
- Leadership Dodge
- Adult Enrichment Programs/Groups
- Willingness to Help
- Community Fundraising Events
- YMCA Sport Programs
- University Training Center

Figure 7. Dodge City, KS Community Capitals.

APPENDIX 2

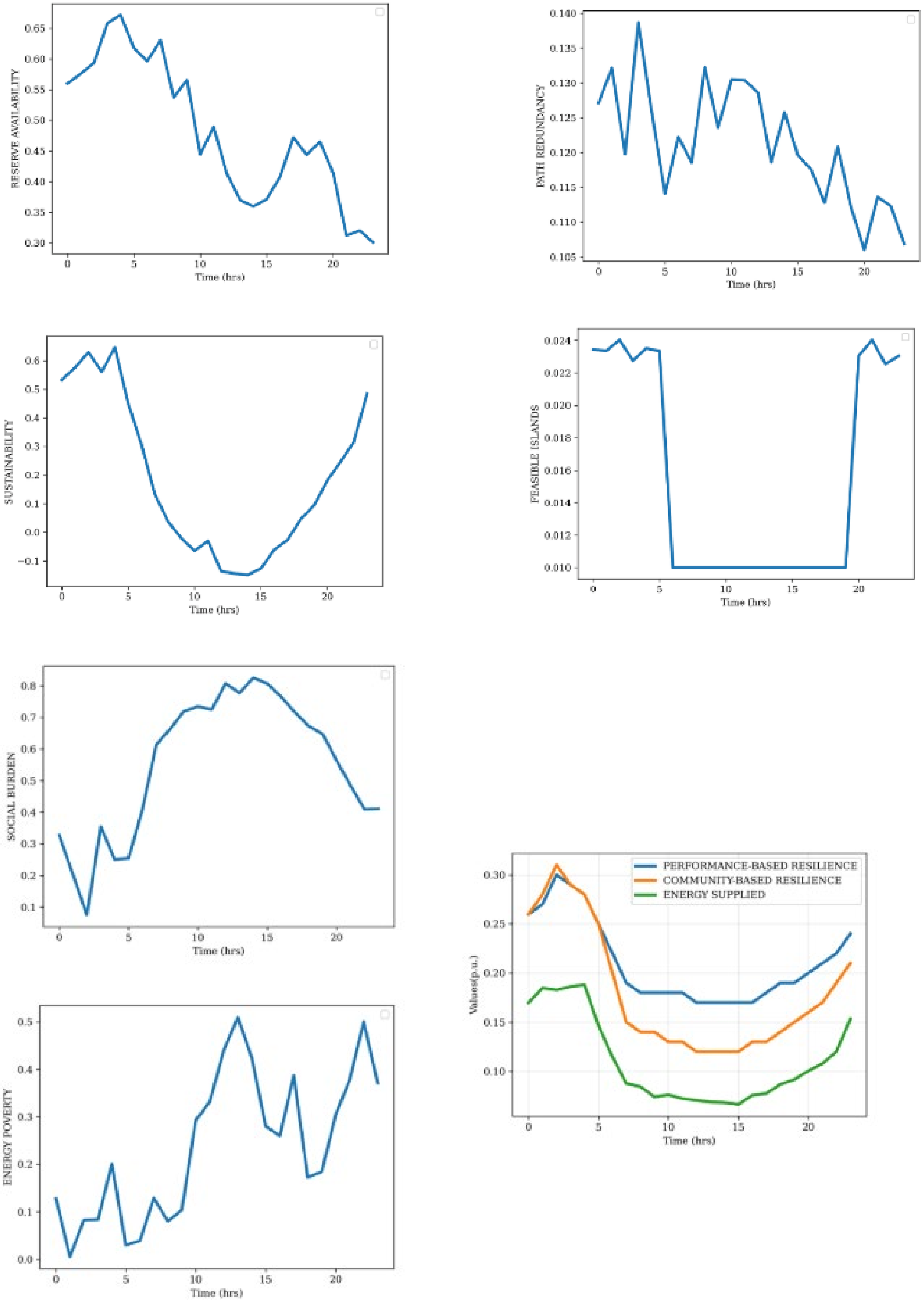


Figure 17: SOM performance validation.

APPENDIX 3

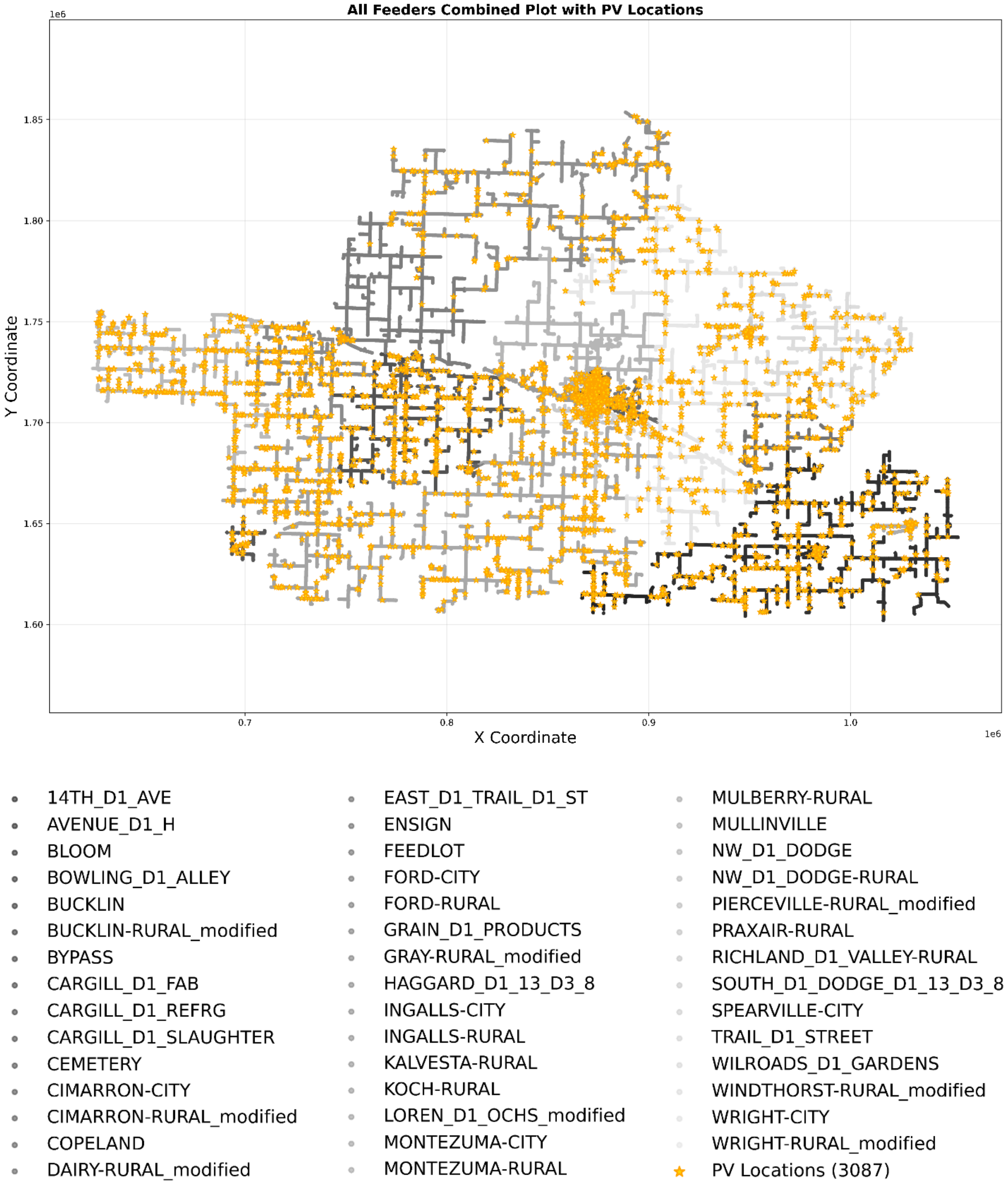
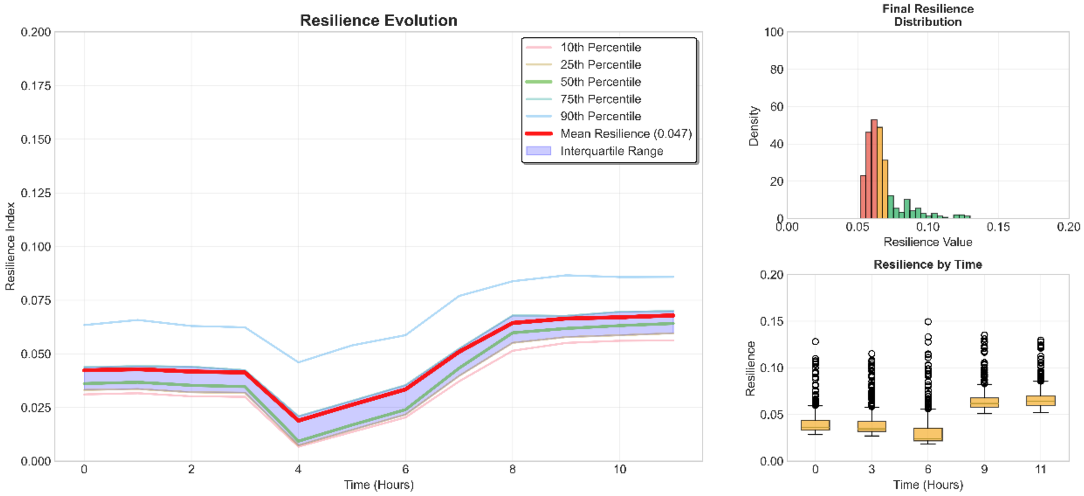
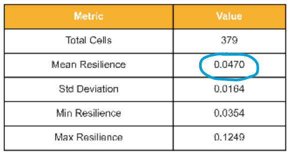

All Feeders Combined Plot with PV Locations

Figure 26. Locations of PV/Battery systems

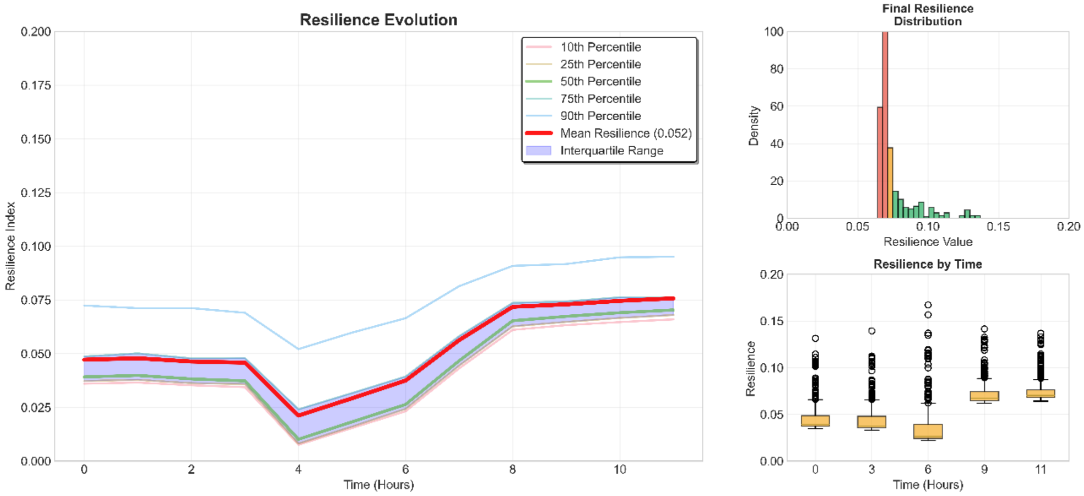
APPENDIX 4



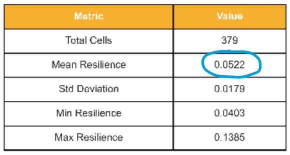
Naïve Siting



Metric	Value
Total Cells	379
Mean Resilience	0.0470
Std Deviation	0.0164
Min Resilience	0.0354
Max Resilience	0.1249

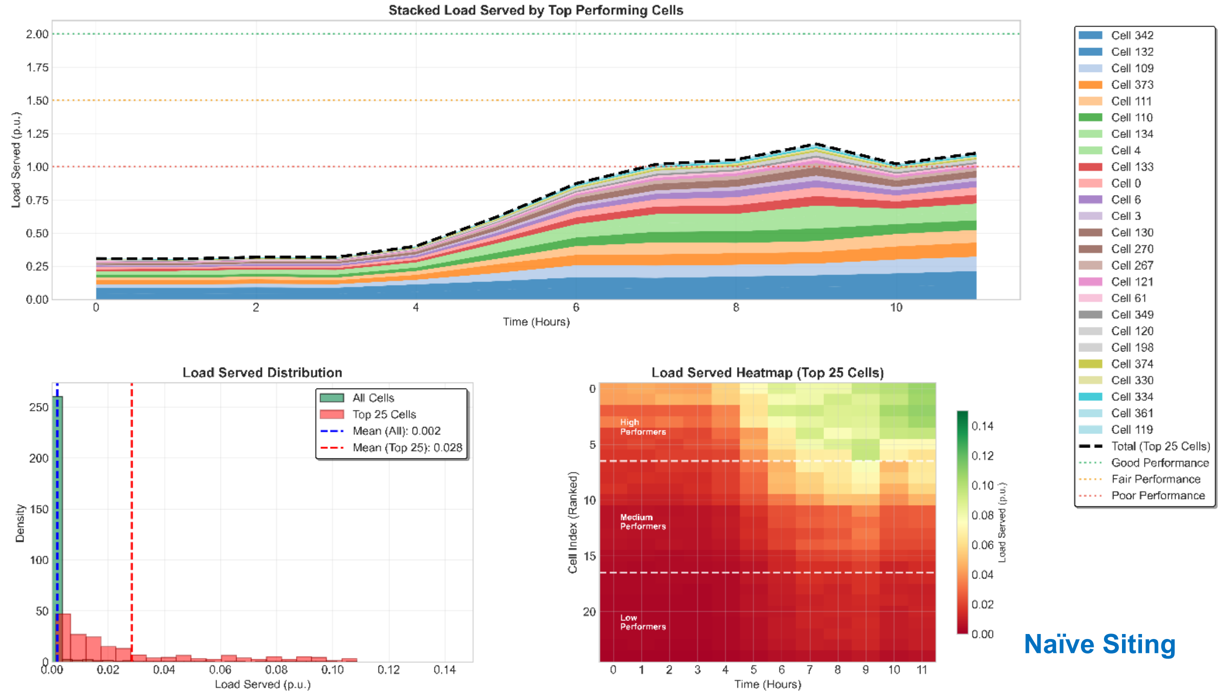


Optimal

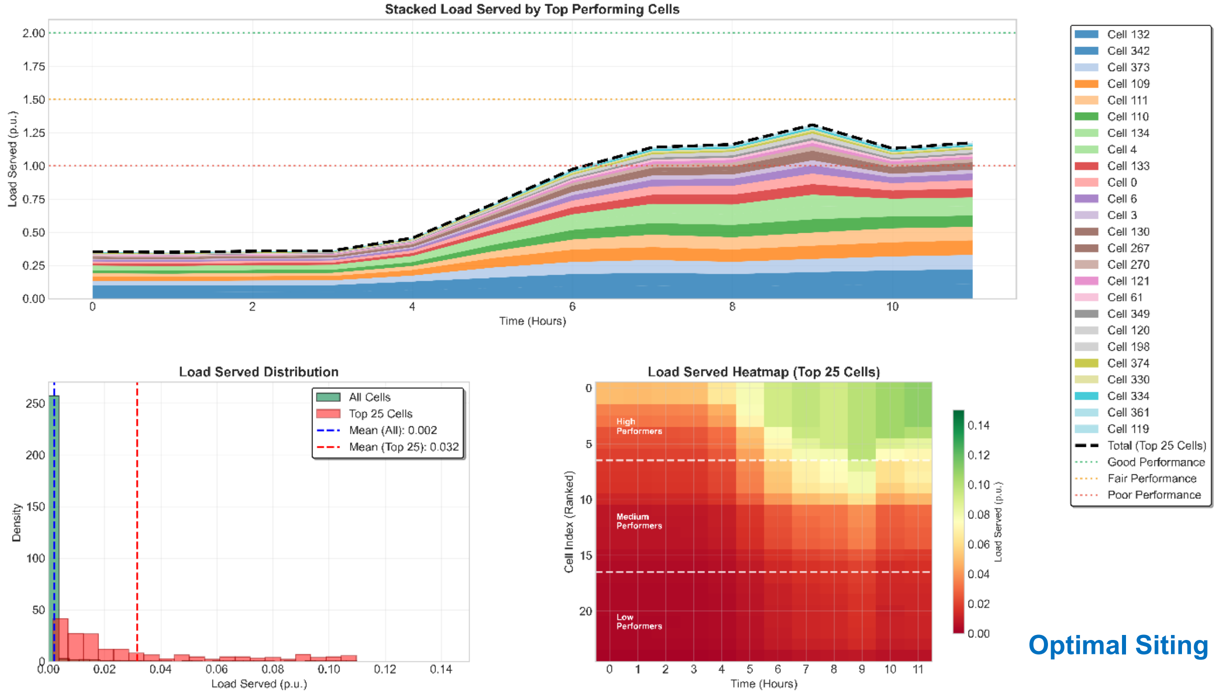


Metric	Value
Total Cells	379
Mean Resilience	0.0522
Std Deviation	0.0179
Min Resilience	0.0403
Max Resilience	0.1385

Figure 27: Results comparing the community resilience served for both scenarios



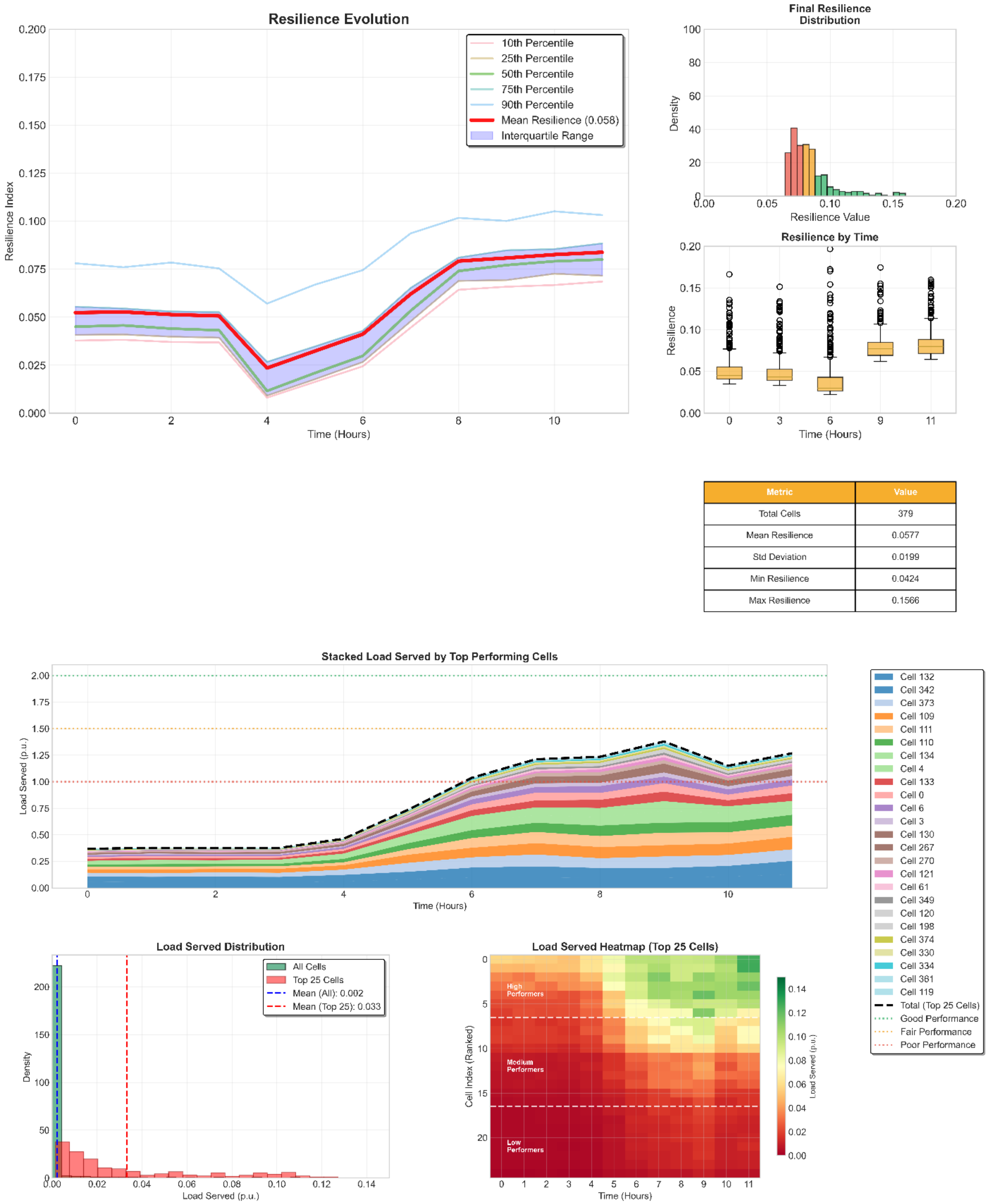
Naïve Siting



Optimal Siting

Figure 27: Results comparing the overall load served for both scenarios.

APPENDIX 5



Metric	Value
Total Cells	379
Mean Resilience	0.0577
Std Deviation	0.0199
Min Resilience	0.0424
Max Resilience	0.1566

Figure 28: Results comparing community resilience, overall load served, and state-of-charge of batteries for both scenarios.

APPENDIX 6

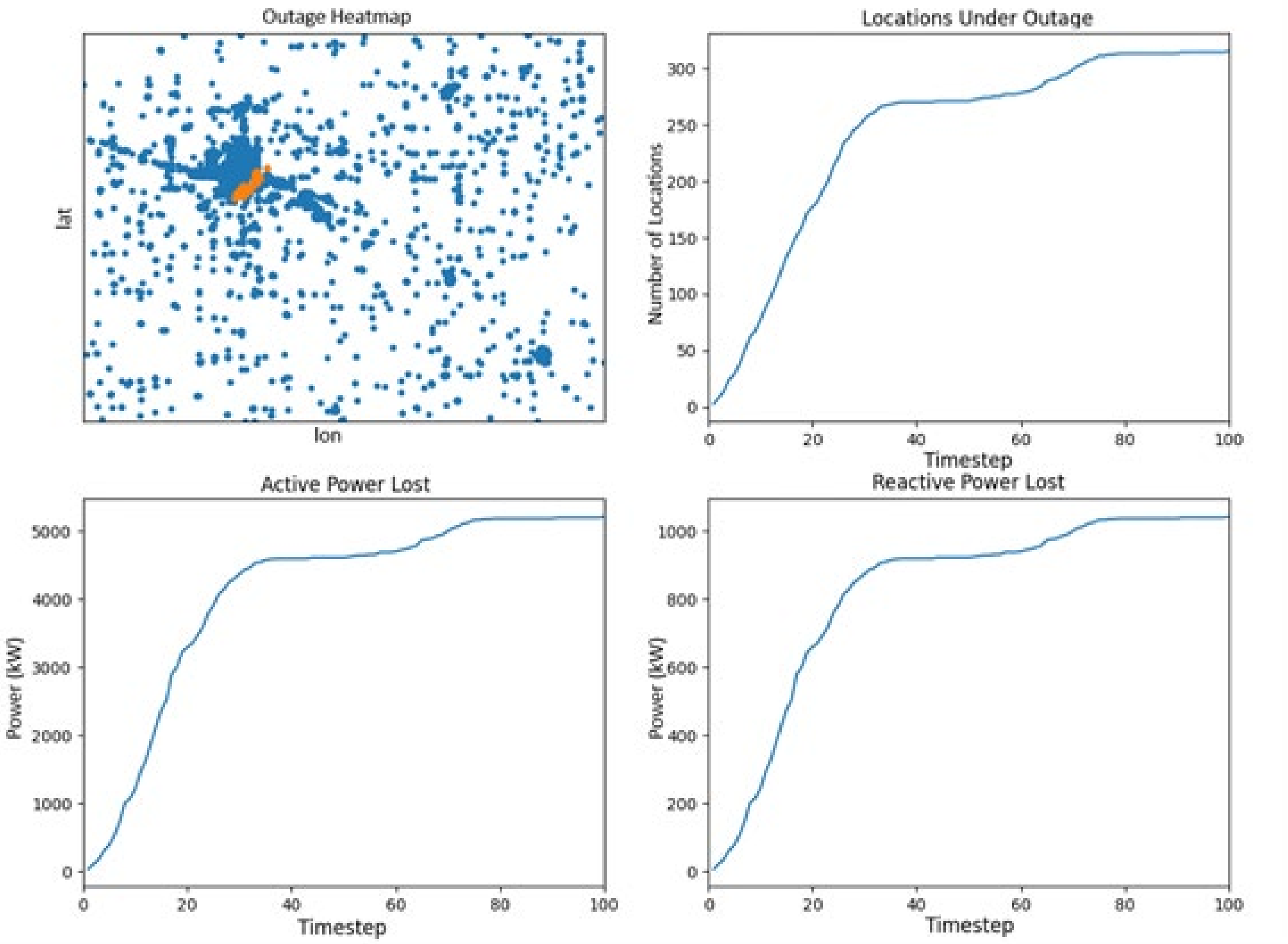


Figure 29. HFGs for weather impact analysis (Tornado scenario).

APPENDIX 7

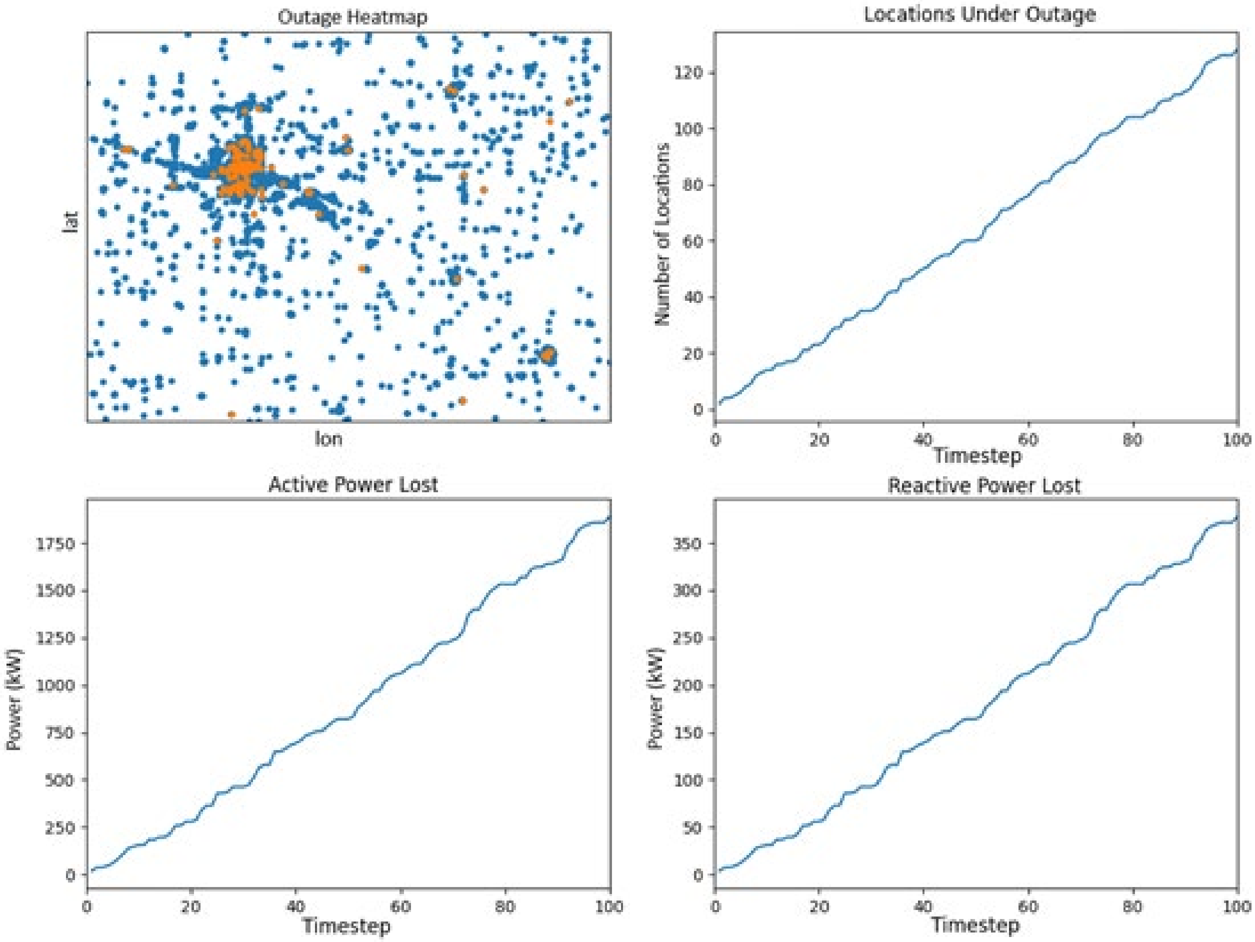


Figure 30. HFGs for weather impact analysis (High Winds scenario).

APPENDIX 8

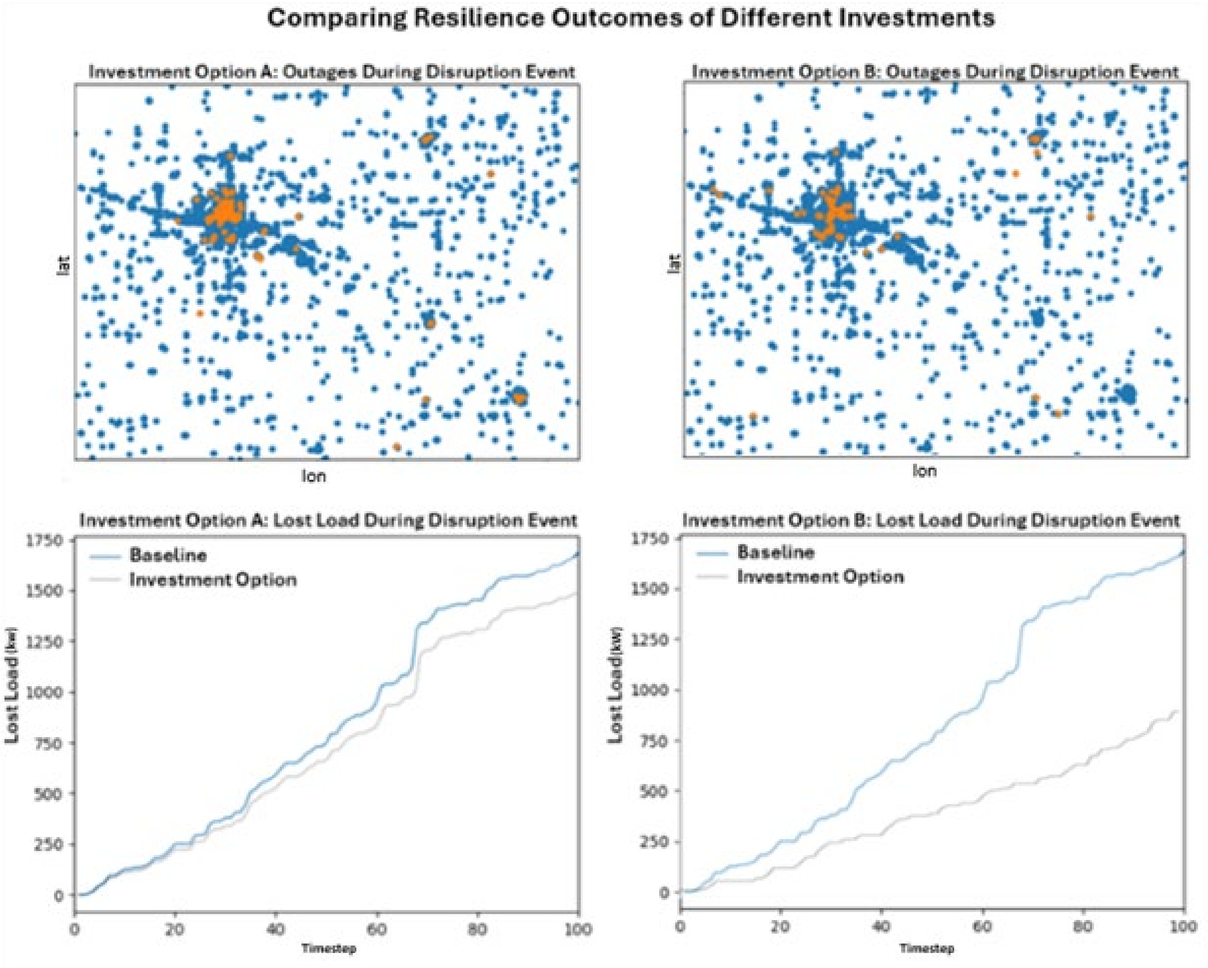


Figure 31. Comparison of investment options using the HFG framework.

APPENDIX 9

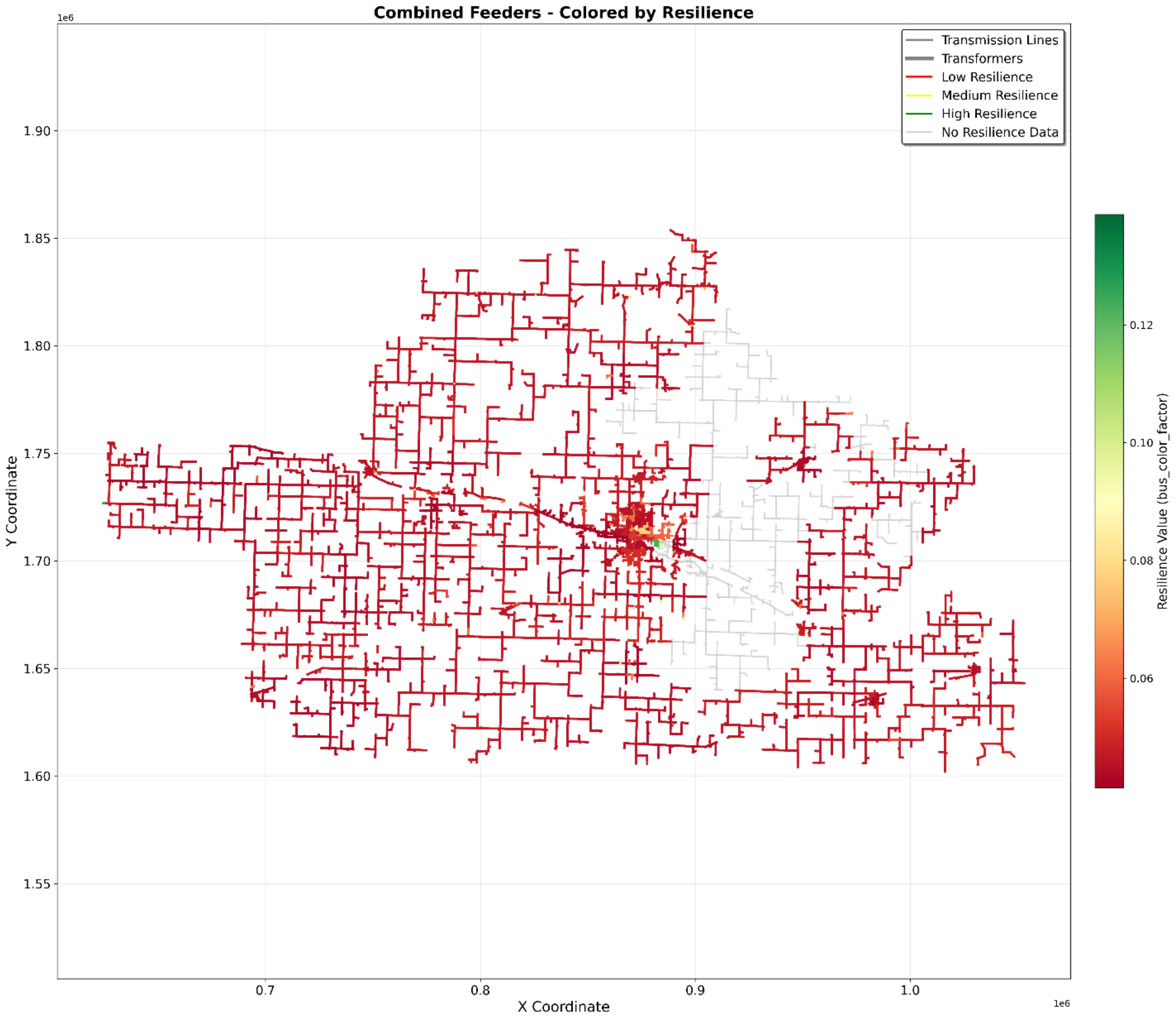


Figure 32: Ford County resilience heatmap.