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Game Theory Approaches for System-level Incentive Design

September 2025

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U.S. DEPARTMENT of ENERGY
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Abstract

This report presents a generalized Stackelberg game framework for designing and evaluating financial incentives that enhance power system resilience through strategic deployment of distributed energy resources (DERs) under various contingencies. The proposed approach addresses the challenge of coordinating individual community investment decisions to meet system-wide resilience objectives. The framework is demonstrated in a three-community test system subjected to two transmission contingency scenarios: inter-community line failure (Scenario one) and complete main grid disconnection (Scenario two). In both scenarios, three incentive levels are compared: a Base case with no financial incentives, and low- and high-incentive cases. In Scenario one, the Base case (no incentives) results in a total installed DER capacity of 217.1 MW, with no load shedding due to alternative routing and the highest community costs. Increasing incentives raises DER deployment to 432.5 MW, lowers total aggregate community costs by $63.8M (7.13%), and completely avoids the need for costly new transmission line construction. In Scenario two, the Base case results in 24.3 MWh of unserved load. With the introduction of incentives, all load shedding is eliminated, and the communities maintain up to 177.6 MWh of battery storage as an emergency reserve. These results demonstrate that targeted incentives can dramatically improve grid resilience and cost-effectiveness. This framework therefore provides policymakers and system planners with a practical tool to design and evaluate financial incentive programs that simultaneously optimize system resilience, community investment behavior, and economic efficiency across multi-community transmission networks.

Acronyms and Abbreviations

BESS	battery energy storage system
DER	distributed energy resource(s)
KKT	Karush-Kuhn-Tucker
MW	megawatt(s)
MWh	megawatt-hour(s)
PNNL	Pacific Northwest National Laboratory
PV	photovoltaic(s)
SoC	state-of-charge

Notation

Sets

c(s)	A set of disconnected transmission lines in contingency scenario s
$\mathcal{L}$	A set of transmission lines
$\mathcal{N}$	A set of communities
$\mathcal{S}$	A set of contingency scenarios
$\mathcal{T}$	A set contains all time steps
$\mathcal{T}_s^{\text{cont}}$	A set contains all time steps in contingency scenario s
$t(n)$	A set of transmission lines going into community n
$f(n)$	A set of transmission lines going out from community n

Indices

l	Transmission line index
n	Community index
s	Contingency scenario index
t	Time step index

Parameters

B	Total budget of the system operator
C^{Batt}	Unit cost of BESS
C^{PV}	Unit cost of PV
$C_{n,t,s}^{\text{cont}}$	Electricity price for community n at time t in contingency scenario s
$C_{n,t}^{\text{norm}}$	Electricity price for community n at time t under normal condition
$C_{n,t,s}^{\text{shed}}$	Unserved load cost for community n at time t in contingency scenario s
C_l^{line}	Unit variable cost for increasing the capacity of line l
$D_{n,t}$	Load of community n at time t
D^{Batt}	BESS duration
F_l^{line}	Fixed cost for increasing the capacity of line l
M	A sufficiently large number
$r_{n,t}$	Solar irradiance level at community n at time t
$\hat{t}_s$	Start time of contingency scenario s
α^{ann}	Annuity factor
η^{ch}	BESS charging efficiency
η^{dis}	BESS discharging efficiency
θ^{lim}	BESS cycle limit
$\omega_{n,t}^{\text{norm}}$	Probability of normal condition at time t
$\omega_{n,t,s}^{\text{cont}}$	Probability of contingency scenario s at time t

Decision Variables of the System Operator

C^{E}	Credit for emergency reserve (Fixed parameter for incentive evaluation)
$p^{\text{cont}}_{l,t,s}$	Power flow through line l at time t in contingency scenario s
$p^{\text{norm}}_{l,t}$	Power flow through line l at time t under normal condition
$\underline{P}^{\text{cont}}_{n,t,s}$	Lower purchase limit of community n at time t in contingency scenario s
$\overline{P}^{\text{cont}}_{n,t,s}$	Upper purchase limit of community n at time t in contingency scenario s
I^{PV}	Incentive for PV (Fixed parameter for incentive evaluation)
I^{Batt}	Incentive for BESS (Fixed parameter for incentive evaluation)
$\hat{p}_l$	Increased capacity of line l (Fixed parameter for incentive evaluation)
x_l	Binary variable indicating the expansion decision on line l

Decision Variables of Community n

$e^{\text{batt,c}}_{n,t,s}$	BESS SoC at time t in contingency scenario s
$e^{\text{batt,n}}_{n,t}$	BESS SoC at time t under normal condition
$p^{\text{ch,c}}_{n,t,s}$	BESS charged power at time t in contingency scenario s
$p^{\text{ch,n}}_{n,t}$	BESS charged power at time t under normal condition
$p^{\text{dis,c}}_{n,t,s}$	BESS discharged power at time t in contingency scenario s
$p^{\text{dis,n}}_{n,t}$	BESS discharged power at time t under normal condition
$p^{\text{cont}}_{n,t,s}$	Power purchased at time t in contingency scenario s
$p^{\text{norm}}_{n,t}$	Power purchased at time t under normal condition
$p^{\text{pv,c}}_{n,t,s}$	PV generation at time t in contingency scenario s
$p^{\text{pv,n}}_{n,t}$	PV generation at time t under normal condition
$p^{\text{shed}}_{n,t,s}$	Load shedding at time t in contingency scenario s

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1.0 Introduction

Historical blackout events highlight the critical need to enhance grid resilience through improved policymaking and coordinated planning and investment in distributed energy resources (DERs), given the increasing frequency of power system disruptions. Busby et al. (2021) conducted a comprehensive analysis of the 2021 Texas winter blackout, employing interdisciplinary methods combining meteorological data, grid operations analysis, and policy evaluation. Their findings showed how interdependent failures in electricity and natural gas systems led to prolonged, cascading outages affecting over 4.5 million customers. Similarly, California's implementation of Public Safety Power Shutoffs to mitigate wildfire risk underscores the operational and regulatory challenges utilities are facing in maintaining reliability amid natural hazards (Guliasi 2021). Both cases demonstrate how current incentive structures and regulatory frameworks may fail to prevent large-scale supply interruptions, highlighting the necessity for more adaptive and coordinated approaches to resilience planning—especially as transmission contingencies become more frequent and severe.

Furthermore, Ganz, Duan, and Ji (2023) carried out econometric analysis of outage data from major U.S. metropolitan areas to study how severe weather-induced power outages affect different communities. Their results showed that restoration times and outage impacts vary significantly across regions and customer segments and that the importance of analytical frameworks' capability to capture heterogeneity in system response and recovery during extreme events is underscored.

The fundamental challenge in designing incentive mechanisms is to align individual community investment decisions with system-wide resilience objectives when communities are confronted with a range of possible contingencies, including but not limited to, inter-community line disconnections, main grid outages, and other disruptions that may isolate or constrain regions. Addressing this coordination problem requires systematic design and evaluation of how financial incentive programs influence community investment behaviors and resulting system performance across different contingency scenarios.

Foundational research on incentive regulation has provided the theoretical and empirical basis for designing mechanisms that coordinate decentralized investment behaviors with system wide objectives in electricity systems (Joskow 2014). This literature finds that well-designed incentive structures, such as price-cap and revenue-cap regulation, can effectively improve efficiency and service reliability across network industries. A practical application of this theory to electricity transmission and networks is shown in Joskow (2008). This empirical case study illustrates significant efficiency improvements when price-cap and revenue-cap mechanisms are properly calibrated.

Alvarez and Rudnick (2010) analyzed the impact of several regulatory schemes and financial incentives aimed at reconciling the objectives of planners and distribution companies while promoting energy efficiency in the power sector. White certificates, also known as energy efficiency certificates or tradable white certificates, are market-based instruments that create tradable credits for verified energy savings achieved through efficiency measures. Under this mechanism, utilities or other obligated parties must achieve specified energy savings targets and can trade certificates to meet these obligations cost-effectively. By employing a data envelope analysis framework on the distribution system in Chile, the authors conclude that white certificates for energy efficiency best address the disincentive problems with minimal economic stress of only 8-12% distribution loss. Revenue decoupling also performs well, surpassing direct investment requirements when efficiency targets are modest; however direct investment is more effective for ambitious targets. Complementing these insights, Khonakdar-Tarsi et al. (2021) propose a reliability incentive regulation based on reward-penalty mechanisms, which is tailored to account for local reliability characteristics. By grouping distribution feeders based on uncontrollable parameters such as geographic and environmental factors, the authors design cluster-specific reward-penalty structures where the magnitude of financial rewards and penalties varies based on each group's baseline reliability challenges. Rather than applying uniform incentive rates across all feeders, this approach recognizes that feeders facing different inherent reliability constraints should have differentiated performance targets and corresponding financial consequences. Application to a real-world 194-feeder system demonstrates that such differentiated, cluster-based regulation can improve reliability by incentivizing utilities to compete for higher service quality while accounting for varying operational conditions.

Recent developments in incentive design mechanisms for DERs have shifted focus to addressing coordination challenges among multiple stakeholders. Wang et al. (2019) present a comprehensive sharing mechanism for DERs that leverages cooperative game theory and mechanism design. Their analysis of multi-community systems shows that effective collaboration among communities requires substantial incentives to overcome self-interested optimization behaviors. Brown and Sappington (2018) study optimal procurement strategies of DERs using mechanism design theory. Their findings demonstrate that menu-based contracts with screening mechanisms can yield efficient, cost-effective procurement outcomes for utilities. Bhattacharya et al. (2022) conducted a systematic review of over 150 studies on incentive mechanisms for smart grids, including demand response, renewable integration, and grid modernization. Their studies summarize key design principles and implementation challenges with various effectiveness across different application areas. Xu et al. (2024) experimentally assess incentive mechanisms in a multi-community microgrid testbed. Their results show that properly designed incentives increase resilience investments by 25-40% while maintaining cost-effectiveness for participants. Alternatively, Yuli Astriani (2021) propose an optimization-based approach for microgrid demand response that achieves both targeted system cost-effectiveness and high participant satisfaction.

Distribution system planning approaches increasingly integrate incentive designs within their optimization frameworks. Alotaibi and Salama (2018) propose a multi-stage expansion planning model incorporating mixed-integer linear programming and uncertainty considerations. Their case study on a 33-bus distribution system shows that coordinated incentives reduce system costs by 15-20% compared to uncoordinated planning. Fattaheian-Dehkordi et al. (2021) develop bilevel optimization strategies to alleviate active power congestion in multi-agent distribution systems by capturing agents' strategic behaviors. Simulation results on a modified IEEE test system show significant congestion reduction and improved system efficiency. Tian et al. (2020) propose a joint planning framework to integrate financial incentives with stochastic planning and operation for renewable-storage systems. Their case study results show that feed-in tariffs and investment tax credits significantly influence optimal system sizing and operational strategies, with benefit-cost ratios varying from 1.1 to 2.8 depending on the incentive structure.

At the residential and community scale, DERs have been increasingly adopted for their potential to provide local resilience benefits. Gorman et al. (2024) analyze the backup capabilities of solar-plus-storage systems across the U.S. using geospatial and techno-economic modeling, concluding that such hybrid systems can provide 3-7 days of backup power for typical households, with economic viability improving significantly under current federal incentive programs. Li and Okur (2023) present a game-theoretic and empirical analysis of European energy communities, finding that significant variation in investment responses comes from local resource characteristics and regulatory environments, with benefit-cost ratios ranging from 1.2 to 3.8 across different community types.

Explaining this heterogeneity requires a deeper understanding of behavioral and contextual drivers. Vibrans et al. (2023) analyze data from nearly 1,200 German households, identifying distinct photovoltaic (PV) adopter profiles because households vary substantially in price sensitivities and non-economic motivations, supporting the need for differentiated incentive approaches. Masini and Menichetti (2012) demonstrate, through empirical analysis of 265 renewable energy investors, that behavioral factors significantly impact choices beyond pure economic optimization. Their survey shows that risk perception, social norms, and policy uncertainty substantially influence investment timing and scale, highlighting the limitations of strictly economic models.

Community energy planning methodologies have also evolved to account for varying organizational structures and resource constraints. Gui and MacGill (2018) use scenario analysis and stakeholder consultations to explore typologies of future clean energy communities and identify structural opportunities and challenges across different community configurations. Gui, Diesendorf, and MacGill (2017) examine infrastructure paradigms for DERs using institutional economics analysis, focusing on community microgrids and factors such as transaction costs, governance, and regulatory barriers. Ross and Day (2022) summarize the best practices from NREL's technical assistance work with over 100 communities, using comparative case study analysis to identify success factors in community energy planning, which include the importance of local leadership, stakeholder engagement, and technical capacity building in achieving planning objectives.

Methods for power system expansion planning provide the foundation for integrating DERs into grid transmission and distribution system development. Vahidinasab et al. (2020) review over 200 studies on distribution network expansion across deterministic, stochastic, and robust optimization frameworks, covering key challenges such as uncertainty management and multi-objective trade-offs. Resener et al. (2019) develop detailed MILP models for distribution system expansion planning, incorporating load growth uncertainty, distributed generation integration, and reliability constraints. Their two-part framework addresses both strategic investment timing and operational flexibility requirements. Aschidamini et al. (2022) provide a systematic review of expansion planning approaches considering reliability, based on over 120 studies across different uncertainty modeling and solution methodologies. Their classification framework highlights key trade-offs between computational complexity and solution quality across different problem formulations. Saberi et al. (2023) develop multi-objective optimization approaches that prioritize both reliability and resilience. A case study analysis of an 84-bus distribution system shows substantial resilience improvements through strategic capacity investments, with load shedding reductions of 25-40% under various contingency scenarios.

Sophisticated mathematical frameworks have greatly advanced the modeling of multi-stakeholder decisions and strategic interactions in energy systems. The seminal work of Fortuny-Amat and McCarl (1981) establishes the canonical mathematical formulation for two-level (bilevel) programming problems, providing the foundation for the leader–follower modeling structures that underpin much of the subsequent literature on hierarchical and strategic decision-making in energy systems. Furthermore, Dempe and Zemkoho (2020) provide a comprehensive theoretical approach for bilevel optimization problems, while Ruiz et al. (2014) provide comprehensive tutorial review of complementarity-based approaches for energy market modeling. Recent studies by Steriotis et al. (2023) and Dehghan and Amjady (2015) leverage these advances, developing robust and bilevel frameworks for co-optimizing investments and operations under uncertainty, and demonstrate practical benefits for coordinated resource planning in complex transmission and distribution systems.

While reliability-based models emphasize maintaining consistent service quality under standard operating conditions, recent research in resilience-oriented planning has focused on strategic system adaptation to extreme, low-probability, and high-impact disruptions. For example, Khodaei (2014) propose a resiliency-oriented microgrid optimal scheduling framework to reduce load shedding during severe contingencies via adaptive resource dispatch using scenario-based stochastic optimization. Similarly, Wang, Rousis, and Strbac (2022) develop models for optimally sizing and pre-positioning mobile energy storage in decentralized microgrids, concluding that coordinated storage deployment can achieve 30–50% reductions in load shedding during major outages compared to fixed assets.

Economic valuation methodologies are fundamental for quantifying and justifying investments in resilience. Sullivan, Schellenberg, and Blundell (2015) conduct an extensive survey on over 3,000 commercial and industrial electricity customers, and provide updated value-of-service reliability estimates for electric utility customers across the United States. Their findings conclude that the cost of load shedding typically ranges $10,000 and $50,000 per MWh depending on customer class and outage duration. Furthermore, Schröder and Kuckshinrichs (2015) conduct a systematic international literature review of value of lost load studies, identifying methodological challenges and variations in valuation estimates, yet consistently affirming the substantial economic benefits of reducing outages.

While this extensive literature provides valuable theoretical and methodological foundations, there are several methodological limitations that constrain multi-community transmission resilience planning. Regulatory and mechanism design approaches, including Joskow (2014, 2008), Alvarez and Rudnick (2010), and Khonakdar-Tarsi et al. (2021), typically focus on utility-level coordination without capturing strategic interactions and decentralized investment responses of multiple independent communities facing transmission contingencies. Distribution system planning studies, including Alotaibi and Salama (2018), Fattaheian-Dehkordi et al. (2021), Tian et al. (2020), Saberi et al. (2023), and Resener et al. (2019), usually assume a single, centralized decision-making authority and do not consider cross-community coordination effects or transmission-level contingency scenarios. Bilevel optimization has emerged as a standard approach for modeling hierarchical interactions in power systems, supporting the analysis of strategic behavior among diverse stakeholders under regulatory or market-based coordination (Steriotis et al. 2023; Dehghan and Amjady 2015; Ruiz et al. 2014). However, prior applications emphasize primarily transmission and distribution coordination, market equilibrium, or single-entity investment problems rather than investment planning across multiple autonomous communities. Similarly, most resilience-oriented approaches, such as Khodaei (2014) and Wang, Rousis, and Strbac (2022), consider microgrid scheduling or operational resource management for individual entities, rather than integrated, long-term investment coordination among heterogeneous communities linked by the transmission network.

In this report, we extend the application of Stackelberg (bilevel) optimization frameworks to evaluate the effectiveness of various incentive designs for resilience investment across multiple interconnected communities under various contingency scenarios. While the model can, in principle, optimize incentive levels by treating them as upper-level variables, the current analysis focuses on sensitivity analysis and policy evaluation for different fixed incentive scenarios, due to computational and practical constraints. This approach demonstrates the evaluation capability of the framework, while recognizing that future extensions could integrate true incentive optimization within the bilevel structure.

2.0 Model Formulation

This section presents our one-leader multiple-follower Stackelberg game model where a system operator (leader) provides incentives to influence community investment decisions toward achieving societal benefits, while communities (followers) optimize their individual objectives given these incentives and available resources. The framework is formulated as a bilevel optimization problem, with the system operator's decisions modeled in the upper level and each community's response represented as a distinct lower-level problem.

2.1 Lower-Level Problems: Community Optimization

We assume there are N communities in the system. Each community $n \in \mathcal{N} = \{1, 2, \cdots, N\}$, acting as an independent follower, responds to the system operator's incentive and minimizes its total cost, including net investment costs and expected operational costs across normal and contingency scenarios:

$$\begin{aligned} \min \quad & \left(C^{\text{PV}} - I^{\text{PV}}\right) P_n^{\text{PV}} + \left(C^{\text{Batt}} - I^{\text{Batt}}\right) P_n^{\text{Batt}} - C^{\text{E}} E_n^{\text{min}} \\ & + \alpha^{\text{ann}} \left[\sum_{t \in \mathcal{T}} \omega_t^{\text{norm}} C_{n,t}^{\text{norm}} p_{n,t}^{\text{norm}} + \sum_{s \in \mathcal{S}} \sum_{t \in \mathcal{T}_s^{\text{cont}}} \omega_{t,s}^{\text{cont}} \left(C_{n,t,s}^{\text{cont}} p_{n,t,s}^{\text{cont}} + C_{n,t,s}^{\text{shed}} p_{n,t,s}^{\text{shed}} \right) \right]. \end{aligned} \tag{1}$$

The first line of (1) calculates the net investment costs incurred by community n for installing new devices. C^{PV} and C^{Batt} represent the unit costs of PV and BESS, respectively; I^{PV}, I^{Batt}, and C^{E} denote the incentives provided for PV, BESS, and emergency reserve, respectively; P_n^{PV}, P_n^{Batt}, and E_n^{min} are the size of PV, the size of BESS, and the amount of emergency reserve for community n, respectively.

The second line of the objective function evaluates the operational costs of community n over a typical time period (e.g., a day, week, month, or year), where the set $\mathcal{T} = \{1, 2, \cdots, T\}$ representing the time indices. Annuity factor α^{ann} converts the total operational cost over the lifespan of PV and BESS to equivalent current values.

The set $\mathcal{S}$ includes all contingency scenarios. For each scenarios $s \in \mathcal{S}$, which begins at time $\hat{t}_s$, the corresponding time steps are collected as $\mathcal{T}_s^{\text{cont}} = \{\hat{t}_s, \hat{t}_s + 1, \cdots, T\} \subseteq \mathcal{T}$. Parameters ω_t^{norm} and $\omega_{t,s}^{\text{cont}}$ denote the probability of normal condition and contingency scenario s at time t, respectively; $C_{n,t}^{\text{norm}}$, $C_{n,t,s}^{\text{cont}}$, and $C_{n,t,s}^{\text{shed}}$ represent the electricity price under normal condition, electricity price during contingency scenario s, and the cost of unserved load, respectively. The decision variables $p_{n,t}^{\text{norm}}$, $p_{n,t,s}^{\text{cont}}$, and $p_{n,t,s}^{\text{shed}}$ represent the amount of power purchased under normal condition, purchased power during contingency scenario s, and the amount of load shedding, respectively.

The behavior of each community is described by a series of decision variables and constraints. The following constraints are for all $n \in \mathcal{N}$.

PV generation is limited by solar irradiance and installed capacity under normal condition and contingency scenarios:

$$0 \le p_{n,t}^{\text{pv,n}} \le r_{n,t}^{\text{pv}} P_n^{\text{pv}} \quad \forall t \in \mathcal{T}, \tag{2}$$

$$0 \le p_{n,t,s}^{\text{pv,c}} \le r_{n,t}^{\text{pv}} P_n^{\text{pv}} \quad \forall s \in \mathcal{S},\ t \in \mathcal{T}_s^{\text{cont}}, \tag{3}$$

where $p_{n,t}^{\text{pv,n}}$ and $p_{n,t,s}^{\text{pv,c}}$ are decision variables for the PV generation in normal condition and contingency scenario s, respectively, and $r_{n,t}$ represents the solar irradiance level.

BESS operation should satisfy power and energy limits:

$$0 \le p_{n,t}^{\text{ch,n}},\ p_{n,t}^{\text{dis,n}} \le P_n^{\text{Batt}} \quad \forall t \in \mathcal{T}, \tag{4}$$

$$0 \le p_{n,t,s}^{\text{ch,c}},\ p_{n,t,s}^{\text{dis,c}} \le P_n^{\text{Batt}} \quad \forall s \in \mathcal{S},\ t \in \mathcal{T}_s^{\text{cont}}, \tag{5}$$

$$E_n^{\text{min}} \le e_{n,t}^{\text{batt,n}} \le P_n^{\text{Batt}} D^{\text{Batt}} \quad \forall t \in \mathcal{T}, \tag{6}$$

$$0 \le e_{n,t,s}^{\text{batt,c}} \le P_n^{\text{Batt}} D^{\text{Batt}} \quad \forall s \in \mathcal{S},\ t \in \mathcal{T}_s^{\text{cont}}, \tag{7}$$

where D^{Batt} is BESS duration; $p_{n,t}^{\text{ch,n}}$, $p_{n,t}^{\text{dis,n}}$, and $e_{n,t}^{\text{batt,n}}$ are decision variables for BESS charged power, discharged power, and state of charge (SoC) at time t under normal condition; $p_{n,t,s}^{\text{ch,c}}$, $p_{n,t,s}^{\text{dis,c}}$, and $e_{n,t,s}^{\text{batt,c}}$ are the corresponding ones for contingency scenario s.

The dynamics of the BESS SoC can be modeled as:

$$e_{n,t}^{\text{batt,n}} = e_{n,t-1}^{\text{batt,n}} - \left(\eta^{\text{dis}} p_{n,t}^{\text{dis,n}} - \eta^{\text{ch}} p_{n,t}^{\text{ch,n}}\right) \Delta T \quad \forall t \in \mathcal{T} \backslash \{1\}, \tag{8}$$

$$e_{n,t,s}^{\text{batt,c}} = e_{n,t-1,s}^{\text{batt,c}} - \left(\eta^{\text{dis}} p_{n,t,s}^{\text{dis,c}} - \eta^{\text{ch}} p_{n,t,s}^{\text{ch,c}}\right) \Delta T \quad \forall s \in \mathcal{S},\ t \in \mathcal{T}_s^{\text{cont}} \backslash \{\hat{t}_s\}, \tag{9}$$

where η^{ch} and η^{dis} are BESS charging and discharging efficiencies, respectively; ΔT represents time step length. In addition, we assume the BESS is half charged at both the beginning and end of the operational time horizon under normal condition. The initial SoC in each contingency scenario depends on the corresponding BESS state under normal condition. The SoC at the final time step in contingency scenarios is left unrestricted. Such boundary conditions are formulated as:

$$e_{n,1}^{\text{batt,n}} = 0.5 P_n^{\text{Batt}} D^{\text{Batt}} - \left(\eta^{\text{dis}} p_{n,1}^{\text{dis,n}} - \eta^{\text{ch}} p_{n,1}^{\text{ch,n}}\right) \Delta T, \tag{10}$$

$$e_{n,\hat{t},s}^{\text{batt,c}} = e_{n,\hat{t}-1}^{\text{batt,n}} - \left(\eta^{\text{dis}} p_{n,\hat{t},s}^{\text{dis,c}} - \eta^{\text{ch}} p_{n,\hat{t},s}^{\text{ch,c}}\right) \Delta T \quad \forall s \in \mathcal{S}, \tag{11}$$

$$e_{n,T}^{\text{batt,n}} = 0.5 P_n^{\text{Batt}} D^{\text{Batt}}. \tag{12}$$

BESS cycling limit is imposed by restricting total discharged energy under normal condition:

$$\sum_{t \in \mathcal{T}} e_{n,t}^{\text{batt,n}} \le \theta^{\text{lim}} P_n^{\text{Batt}} D^{\text{Batt}}, \tag{13}$$

where θ^{lim} is the number of cycle limit. The BESS operation in contingency scenarios is not restricted because such events typically have a low probability of occurrence, and the BESS serves as a critical resource for meeting load demands when they happen.

Power should be balanced to satisfy demand under normal condition and in contingency scenarios:

$$p_{n,t}^{\text{pv,n}} + p_{n,t}^{\text{dis,n}} - p_{n,t}^{\text{ch,n}} + p_{n,t}^{\text{norm}} = D_{n,t} \quad \forall t \in \mathcal{T}, \tag{14}$$

$$p_{n,t,s}^{\text{pv,c}} + p_{n,t,s}^{\text{dis,c}} - p_{n,t,s}^{\text{ch,c}} + p_{n,t,s}^{\text{cont}} + p_{n,t,s}^{\text{shed}} = D_{n,t} \quad \forall s \in \mathcal{S},\ t \in \mathcal{T}_s^{\text{cont}}, \tag{15}$$

where $D_{n,t}$ represents the load at time t.

We assume that each community can only purchase power under normal condition but is permitted to sell power to other communities during contingency scenarios. While the system typically has sufficient transmission capacity to meet the load demands of all communities, limits on power purchases may be imposed during contingency scenarios to prevent overloading the remaining operational transmission lines. The related variables have the following bounds:

$$p^{\text{norm}}_{n,t} \geq 0 \quad \forall t \in \mathcal{T}, \tag{16}$$

$$\underline{P}^{\text{cont}}_{n,t,s} \leq p^{\text{cont}}_{n,t,s} \leq \overline{P}^{\text{cont}}_{n,t,s} \quad \forall s \in \mathcal{S},\ t \in \mathcal{T}^{\text{cont}}_s, \tag{17}$$

$$0 \leq p^{\text{shed}}_{n,t,s} \leq D_{n,t} \quad \forall s \in \mathcal{S},\ t \in \mathcal{T}^{\text{cont}}_s, \tag{18}$$

where $\underline{P}^{\text{cont}}_{n,t,s}$ and $\overline{P}^{\text{cont}}_{n,t,s}$ are lower and upper limits for power purchase in contingency scenario s, respectively.

2.2 Upper-Level Problem: System Operator

To enhance the resilience of the system, the system operator aims to minimize the total load shedding across all communities during contingency scenarios. This objective is formulated as:

$$\text{min} \quad \sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}} \sum_{t\in\mathcal{T}^{\text{cont}}_s} \omega^{\text{cont}}_{t,s} p^{\text{shed}}_{n,t,s}. \tag{19}$$

In this objective, alternative metrics, such as the total system energy cost, can also be considered and formulated easily.

The system operator is subject to a budget constraint that accounts for the total incentives provided and the investment in transmission capacity expansion. This constraint is formulated as:

$$I^{\text{PV}} P^{\text{PV}}_n + I^{\text{Batt}} P^{\text{Batt}}_n + C^{\text{E}} E^{\text{min}}_n + \sum_{l\in\mathcal{L}} \left(F^{\text{line}}_l x_l + C^{\text{line}}_l \hat{p}_l \right) \leq B, \tag{20}$$

where $\mathcal{L}$ is the set of all transmission lines, F^{line}_l and C^{line}_l represent the fixed cost and unit variable cost associated with increasing the capacity of line l, and B denotes the total budget of the system operator. The binary variable x_l indicates whether line l is expended ($x_l = 1$) or not ($x_l = 0$), while the continuous variable $\hat{p}_l$ specifies the amount of increased capacity. They have the following relationship with M being a sufficiently large number:

$$0 \leq \hat{p}_l \leq \text{M} x_l \quad \forall l \in \mathcal{L}. \tag{21}$$

Power flow through transmission lines should be balanced at each community and within line capacity:

$$\sum_{l\in t(n)} p^{\text{norm}}_{l,t} - \sum_{l\in f(n)} p^{\text{norm}}_{l,t} = p^{\text{norm}}_{n,t} \quad \forall n \in \mathcal{N},\ t \in \mathcal{T}, \tag{22}$$

$$\sum_{l\in t(n)} p^{\text{cont}}_{l,t,s} - \sum_{l\in f(n)} p^{\text{cont}}_{l,t,s} = p^{\text{cont}}_{n,t,s} \quad \forall n \in \mathcal{N},\ s \in \mathcal{S},\ t \in \mathcal{T}^{\text{cont}}_s, \tag{23}$$

$$-P_l - \hat{p}_l \leq p^{\text{norm}}_{l,t} \leq P_l + \hat{p}_l, \quad \forall l \in \mathcal{L},\ t \in \mathcal{T} \tag{24}$$

$$-\mathbb{I}_{l\in \text{c}(s)} P_l - \hat{p}_l \leq p^{\text{cont}}_{l,t,s} \leq \mathbb{I}_{l\in \text{c}(s)} P_l + \hat{p}_l, \quad \forall l \in \mathcal{L},\ s \in \mathcal{S},\ t \in \mathcal{T}^{\text{cont}}_s \tag{25}$$

$$\tag{26}$$

where $t(n)$ and $f(n)$ are the sets of transmission lines going into and out from community n, respectively; $\text{c}(s)$ is the set of lines disconnected in contingency scenario s; P_l represents the original capacity of line l. Variables $p_{l,t}^{\text{norm}}$ and $p_{l,t,s}^{\text{cont}}$ denote the power flow through line l at time t under normal condition and in contingency scenarios, respectively. $\mathbb{I}_{l\in\mathsf{c}(s)}$ is an indicator function that takes 1 if $l \in \mathsf{c}(s)$ and 0 otherwise.

The power purchase limits for each community have the following bounds:

$$\underline{P}_{n,t,s}^{\text{cont}} \leq 0 \quad \forall n \in \mathcal{N},\ s \in \mathcal{S},\ t \in \mathcal{T}_s^{\text{cont}}, \tag{27}$$

$$\overline{P}_{n,t,s}^{\text{cont}} \geq 0 \quad \forall n \in \mathcal{N},\ s \in \mathcal{S},\ t \in \mathcal{T}_s^{\text{cont}}. \tag{28}$$

2.3 Integrated Model Formulation and Solution Approach Discussion

With both leader's and Followers' problem defined, they can be integrated as the following Stackelberg game model for incentive evaluation and design:

$$\begin{aligned} \text{min} \quad & (19) \\ \text{s.t.} \quad & (20-28) \\ & \mathbf{p}_{n,\cdot,\cdot}^{\text{shed}} \in \text{argmin}\{(1)_n|(2-18)_n\} \quad \forall n \in \mathcal{N}. \end{aligned} \tag{29}$$

where the subscript n of the equations numbers indicates the corresponding index in the referenced objective function and constraints.

This bilevel optimization problem can be reformulated as a single-level problem by replacing the lower-level problems with their Karush-Kuhn-Tucker (KKT) conditions. When applied to incentive design, the incentive values are treated as upper-level decision variables. The product of these variables with lower-level variables, representing the sizes of PV, BESS, and emergency reserves, causes the single-level reformulation to remain nonconvex and nonlinear—even if the complementary slackness constraints are linearized using the big-M approach. Additionally, upper-level variables appear as both objective function coefficients and right-hand-side constants in the lower-level problems, while lower-level variables are also present in upper-level constraints. These interdependencies make it challenging to directly apply decomposition algorithms. Advanced solution approaches are needed to solve the general form of this problem.

When the incentives are fixed and treated as parameters, the proposed Stackelberg game model can simulate community responses and evaluate their outcomes. In this context, the single-level reformulation can be converted into a mixed-integer linear programming problem, which offers better scalability and can be efficiently solved using open-source or commercial solvers. By testing and analyzing different incentive combinations, this framework can support and enhance decision-making processes. A case study is presented and analyzed in the following section.

3.0 Case Study

3.1 Case Settings

We analyze incentives for a three-community system under various transmission contingency scenarios. The structure of the system is illustrated in Figure 1. Community 1 is connected to the power market as well as to the other two communities.

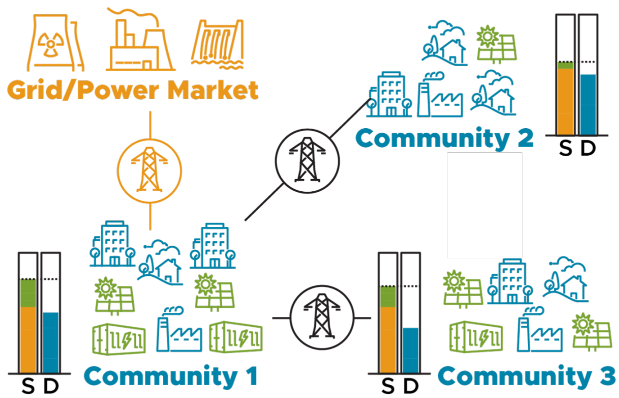


Figure 1: Structure of the three-community system.

A 5% discount rate is applied over a 16-year lifespan of the equipment. The average electricity price, load profiles and solar capacity factors for three regions in August 2024 are extracted from CAISO to represent a typical day in the analysis. Each region corresponds to one community in the system. The load is scaled to reach a peak demand of 100 MW, assuming similar load levels across all three communities. The cost of unserved demand is set to be 10 times the electricity price. The data are visualized in Figure 2.

Two contingency scenarios, shown in Figure 3, are analyzed. In the first scenario, the transmission line between Community 1 and Community 3 is disconnected, causing community 3 to be isolated. A new transmission line between Community 2 and Community 3 can be constructed to maintain the power supply to Community 3 during the contingency. In the second scenario, the transmission line connecting Community 1 to the power market is disconnected, causing the entire three-community system to be isolated from the main grid. Since the communities remain connected to each other, no additional transmission line is required. The contingency scenarios are assumed to begin at 10 a.m. and last for 6 hours, with a 5% probability of occurrence.

For each scenario analyzed, three incentive levels are considered: a base case with no incentives, and low- and high-incentive cases for comparison. Detailed information on the incentive values and cost parameters for PV and BESS is summarized in Table 1. All BESS used are assumed to have 4-hour duration.

3.2 Results and Analysis for Contingency Scenario One

The investment decisions of all three communities under different incentive levels in contingency scenario one are illustrated in Figure 4. The investment costs, power purchase costs, total received incentives, and total unserved load for each community are summarized in Table 2. Additionally, the power flow through the new transmission line is depicted in Figure 5.

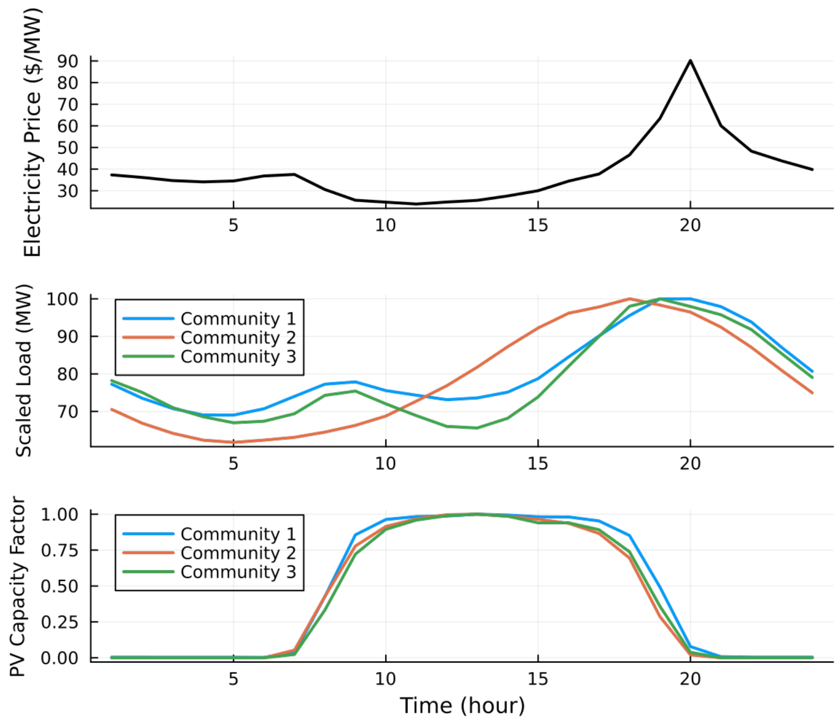


Figure 2: Input parameters of the use case, including power price, scaled load and solar capacity factor of each community in a typical day.

With DERs and the new transmission line, there is no unserved load in any of the three cases. In the absence of incentives, only PV systems are installed by the communities, as they can directly provide additional power. The sizes of the PV systems range from 66 MW to 76 MW, with an investment cost of $80M–$90M per community. Additionally, each community incurs power purchase costs ranging from $207M to $220M. The total cost, combining device investments and power purchases, is approximately $300M. During the contingency, up to 12 MW of power flows through the new transmission line between Communities 2 and 3 to meet the load demand in Community 3.

In the low-incentive case, the installed PV capacities at the communities increase to 80 MW–91 MW. Additionally, each community installs a 20 MW–32 MW BESS, with approximately half of the energy capacity allocated for emergency reserves. Due to the incentives, the total investment cost for each community slightly increases to $92M–$108M. However, these new devices reduce power purchase costs to $178M–$197M, bringing the total combined cost down to $186M–$289M. This reduction of approximately $10M per community requires a total incentive of $128M. Furthermore, the power flow through the new transmission line drops from over 12 MW to below 1 MW. By offering these incentives, the costs associated with the new transmission line can be significantly reduced.

In the high-incentive case, the installed PV capacities further increase to 92MW–98 MW, and the BESS capacities rise to 27MW–65 MW. As in the low-incentive case, about half of the BESS energy capacity is allocated for emergency reserves. With the higher incentives, the total investment cost for each community increases to $96M–$121M, while power purchase costs decrease to $160M–$178M. The total combined cost is reduced to $275M–$281M, representing approximately a $10M reduction compared to the low-incentive case. The total incentives provided amount to $264M. Since there is no power flow through the new transmission line, its

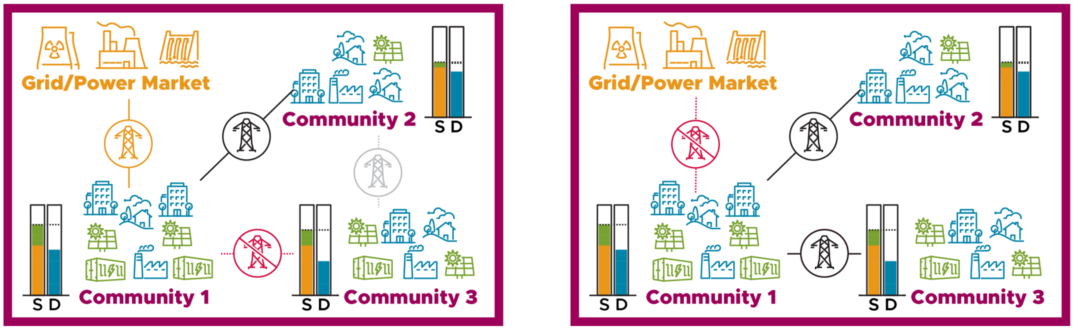


Figure 3: Two contingency scenarios analyzed in the case study.

Table 1: Cost and incentive values for each scenario

		Cost		Incentive		
		PV ($M/MW)	BESS ($M/MW)	PV ($M/MW)	BESS ($M/MW)	Emergency Reserve ($M/MWh)
Scenario 1	Base	1.2	1.6	0	0	0
	Low Incentive	1.2	1.6	0.2	0.4	0.3
	High Incentive	1.2	1.6	0.3	0.5	0.3
Scenario 2	Base	1.2	1.6	0	0	0
	Low Incentive	1.2	1.6	0.2	0.4	0.3
	High Incentive	1.2	1.6	0.3	0.5	0.3

construction cost is completely avoided.

Figure 6 illustrates the net power purchases of each community across all cases under normal and contingency scenarios. In the Base case, the purchased power during normal and contingency scenarios remains nearly identical due to the availability of the new transmission line. During solar peak hours, Community 1 supplies a small amount of power to the other communities. In the low-incentive case, with increased PV capacity and BESS deployment, no power is purchased during the contingency scenario. Since the emergency reserve is discharged to meet demand during and after outages, power purchases during high-price hours are also reduced, lowering overall energy costs. In the high-incentive case, similar behaviors are observed as in the low-incentive case.

3.3 Results and Analysis for Contingency Scenario Two

The same figures and tables are used to analyze scenario two as in scenario one, except for the power flow plot, since no new transmission line is considered in this case. In the Base case, the solution is suboptimal because the solver failed to converge after several hours of computation.

Similar behaviors are observed in scenario two as in scenario one. In the Base case, only PV systems are installed. As incentives increase, the installed capacities of both PV and BESS

Table 2: Community costs, incentives, and load shedding in scenario one

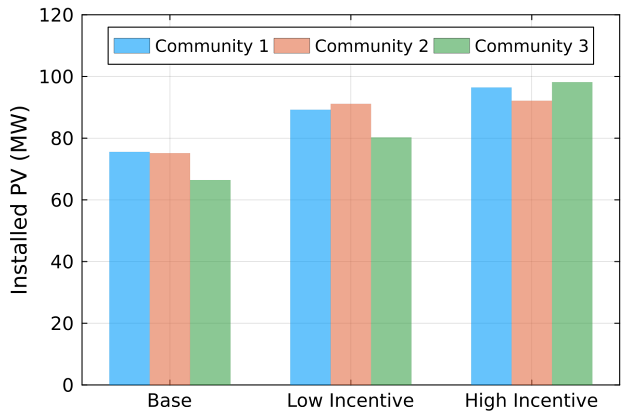
	Community	Investment Cost ($M)	Power Purchase Cost ($M)	Total Cost ($M)	Total Incentive ($M)	Load Shedding (MWh)
Base	1	90.7	206.6	297.2	0	0
	2	90.2	207.7	297.9	0	0
	3	79.7	219.8	299.6	0	0
Low Incentive	1	108.4	177.6	286.0	49.8	0
	2	105.7	180.4	286.1	42.5	0
	3	92.0	196.7	288.7	35.6	0
High Incentive	1	114.0	161.0	275.0	88.8	0
	2	96.2	178.3	274.5	56.8	0
	3	120.8	160.6	281.4	100.8	0

grow, with approximately half of the BESS energy capacity allocated for emergency reserves. The total cost for the communities decreases as higher incentives are provided.

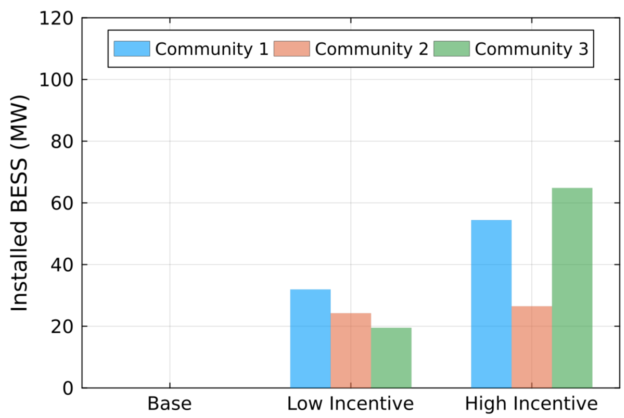
There are some differences between the two scenarios. In scenario two, all three communities are isolated from the market during the contingency, resulting in positive unserved load in the Base case, even though larger PV systems are installed compared to the Base case in scenario one. For the low- and high-incentive cases, the installed sizes of PV and BESS are smaller than those in scenario one. One possible explanation is the total isolation of the system. Since the BESS loses the ability to perform market arbitrage during the contingency, only smaller BESS capacities are financially viable, as their costs can be covered by the limited revenue.

Table 3: Community costs, incentives, and load shedding in scenario two

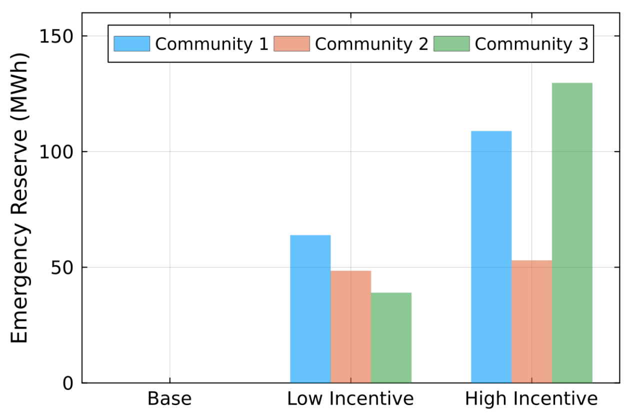
	Community	Investment Cost ($M)	Power Purchase Cost ($M)	Total Cost ($M)	Total Incentive ($M)	Load Shedding (MWh)
Base	1	94.1	203.9	298.0	0	1.7
	2	98.2	202.1	300.2	0	14.5
	3	86.2	215.0	301.2	0	8.1
Low Incentive	1	83.2	199.3	282.5	22.8	0
	2	105.4	180.6	286.0	42.2	0
	3	96.5	192.9	289.4	40.3	0
High Incentive	1	89.3	184.3	273.6	51.7	0
	2	90.7	183.7	274.4	49.3	0
	3	104.1	175.9	280.0	76.6	0



(a) PV



(b) BESS



(c) Emergency Reserve

Figure 4: Community investment decisions under different incentive values in scenario one.

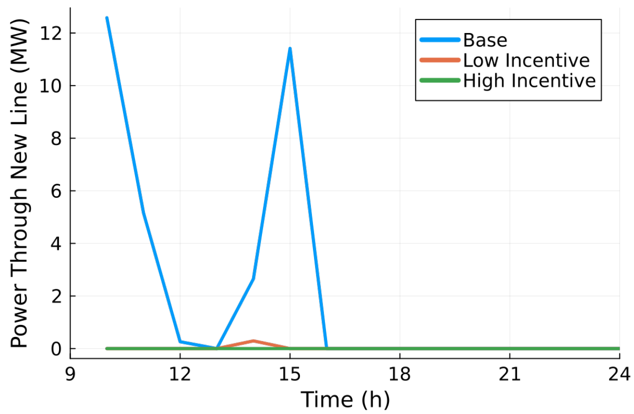
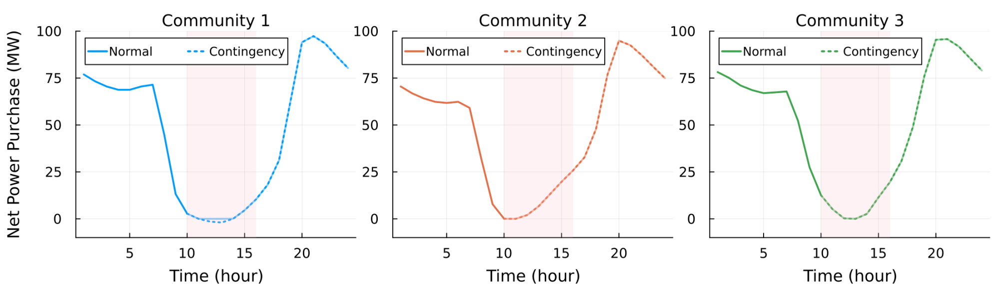
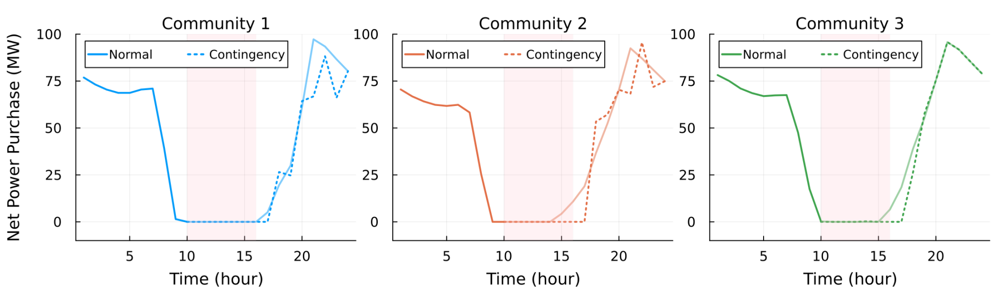


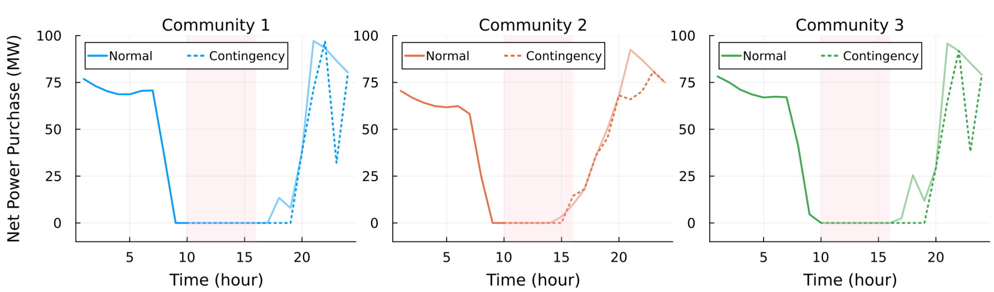
Figure 5: Power flow through the new transmission line.



(a) Base

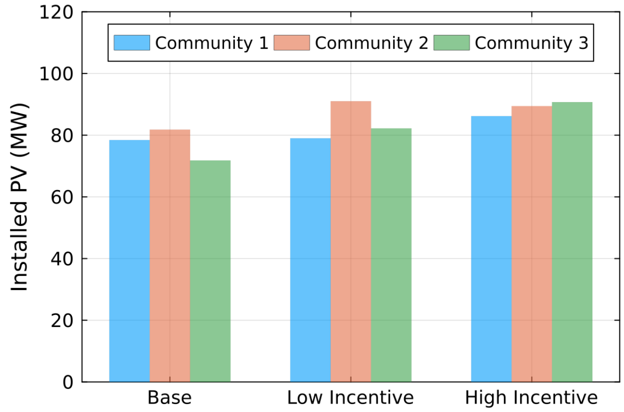


(b) Low Incentive

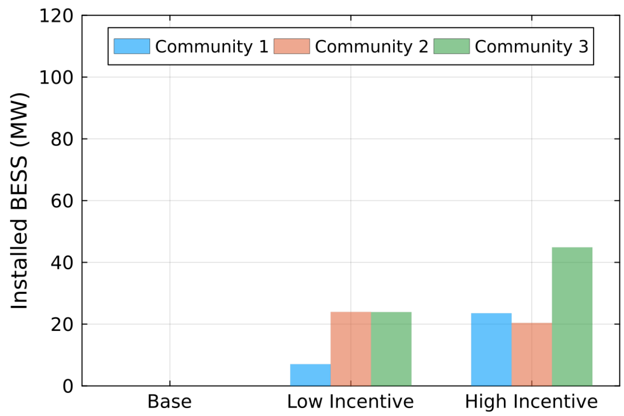


(c) High Incentive

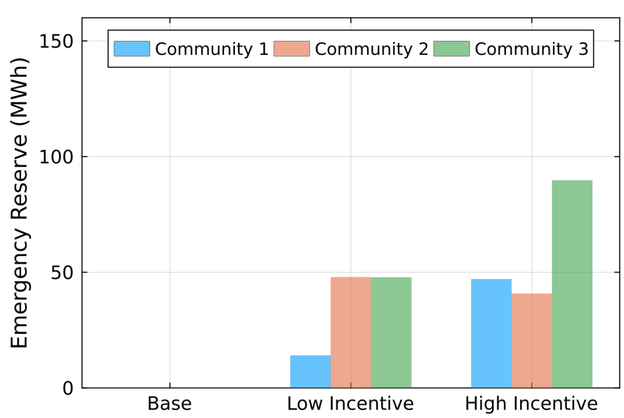
Figure 6: Net power purchase of each community under different incentive values in scenario one.



(a) PV

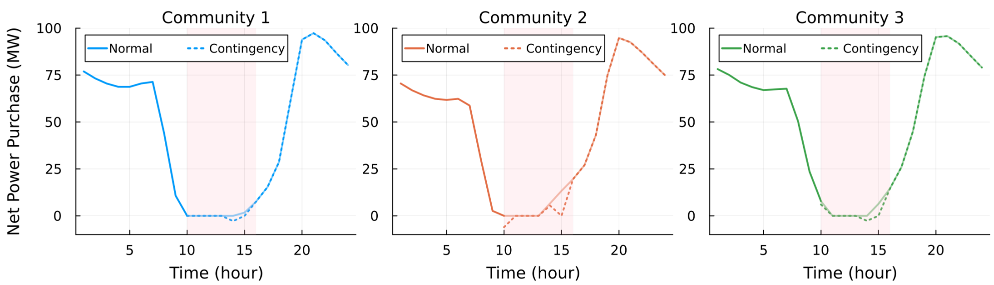


(b) BESS

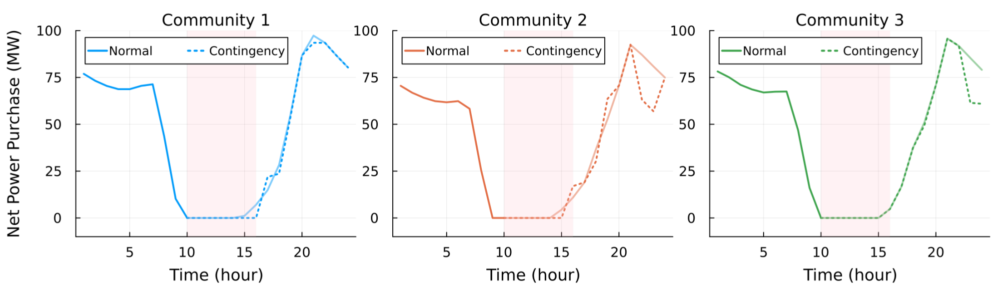


(c) Emergency Reserve

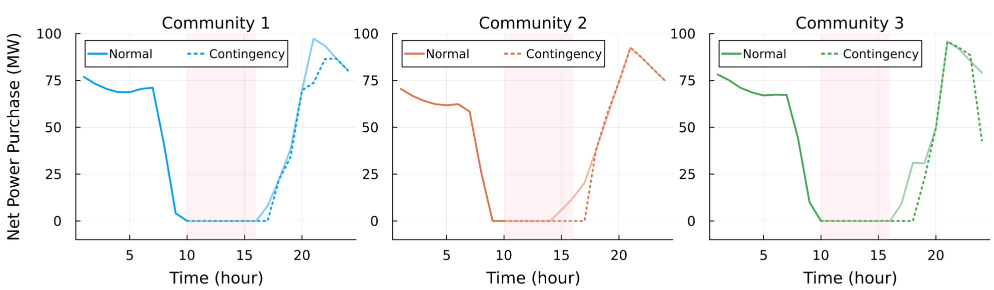
Figure 7: Community investment decisions under different incentive values in scenario two.



(a) Base



(b) Low Incentive



(c) High Incentive

Figure 8: Net power purchase of each community under different incentive values in scenario two.

4.0 Conclusions

This project constructs a Stackelberg game model as a systematic framework for designing and evaluating financial incentives that enhance power system resilience through strategic deployment of distributed energy resources. The methodology successfully addresses the fundamental challenge of aligning individual community investment decisions with system-wide resilience objectives under extreme contingency scenarios.

A three-community test system is constructed and analyzed to validate the proposed model and framework. In this use case, one community is connected to the main grid and the other two communities. Two contingency scenarios are tested across three incentive levels. In scenario one, an internal transmission line connecting two communities fails causing the isolation of one community. A new transmission line reconnecting this community is considered. In scenario two, the entire three-community system is isolated from the main grid. The system operator provides incentive to encourage the communities to install PV and BESS as well as holding energy as emergency reserve for outage events. The three incentive levels include a Base case with no incentives, as well as low- and high-incentive cases for comparison.

For both scenarios, only PV systems are installed when there is no incentive. As incentives increase, the installed capacities of both PV and BESS grow, with approximately half of the BESS energy capacity allocated for emergency reserves. The total cost for the communities, including invest ment cost for DER facilities and power purchase cost, decreases as higher incentives are provided.

In scenario one, a relatively high power flow through the new transmission line is observed in the Base case. This flow decreases significantly when low incentives are provided and drops to zero with high incentives. By offering incentives to communities, the construction cost for new transmission lines can be avoided, as the incentives encourage communities to become self-sufficient and support one another during outage events. In scenario two, unserved load is observed in the Base case, even with the installation of PV systems. However, when incentives are provided, the combination of PV systems and BESS is sufficient to meet the total load during the contingency.

In conclusion, the bilevel optimization framework provides policymakers with a systematic tool for designing and evaluating incentive programs that prepare communities for contingency scenarios while maintaining economic efficiency. The methodology coordinates the decentralized decision-making among individual communities toward societal benefits and enhanced resilience.

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