Bilevel Optimization for Optimal Incentive Design in Resilient Power System Planning with Distributed Energy Resources

Wei Wang, Liping Li, Brittany Tarufelli, Sarah Newman, and Thiagarajan Ramachandran
Parcific Northwest National Laboratory, Richland, WA 99352
{w.wang, liping.li, brittany.tarufelli, sarah.newman, thiagarajan.ramachandran}@pnnl.gov

***Abstract*—This paper introduces a one-leader, multiple-follower Stackelberg game framework for designing incentives to enhance power system resilience through the strategic deployment of distributed energy resources (DERs) under contingency events. The framework models a system operator (leader) who provides incentives to influence community investment decisions toward achieving societal benefits, while communities (followers) optimize their individual objectives based on the given incentives and available resources. The proposed model addresses the critical challenge of aligning community-level investment decisions with system-wide resilience objectives. A case study involving a three-community system is conducted to validate the model. The results demonstrate that financial incentives effectively stimulate communities to invest in DERs, mitigating contingency events and significantly reducing total system load shedding. This framework provides policymakers and system planners with a practical tool to design financial incentive programs that simultaneously optimize system resilience, community investment behavior, and economic efficiency across multi-community networks.**

***Index Terms*—Stackelberg game theory, bilevel optimization, power system resilience, distributed energy resources, incentive design, transmission contingencies**

I. Introduction

The increasing frequency of power system disruptions, exemplified by the 2021 Texas winter storm [1] and California's Public Safety Power Shutoffs [2], highlights the critical need for enhanced grid reliability and resilience. Historical blackout events showed that restoration times and outage impacts vary significantly across regions and customer segments [3]. Distributed energy resources (DERs), such as solar panels and battery storage, offer a promising solution to enhance reliability and resilience at community level. By decentralizing energy generation and storage, DERs reduce reliance on centralized infrastructure and enable faster recovery during outages, while providing critical backup power to vulnerable regions.

Despite the potential benefits of DERs, microgrids and communities often face significant barriers to investment, including limited financial resources and insufficient motivation to prioritize resilience enhancements over other essential needs. This disconnect stems from the fact that individual communities tend to base their investment decisions on private costs and benefits, while the broader social value of resilience,such as system-wide reliability and reduced losses from outages, is often overlooked. This misalignment results in a market failure that necessitates policy intervention to bridge the gap between private interests and public objectives. While various policies and regulatory approaches have attempted to address this issue, many rely on ad-hoc, non-systematic incentive structures that may not fully account for the nuances of optimizing financial mechanisms for DER adoption to enhance resilience [4]. To ensure efficient outcomes, a systematic framework is required to determine optimized incentive parameters tailored across different incentive types.

The design of effective incentive mechanisms to promote DER investments and utilization has been extensively studied in recent years. For instance, Huang and Söder proposed a modeling framework to assess how incentive regulations impact distribution network investments [5]. Wang et al. developed mechanisms for sharing DERs, aiming to minimize energy costs for users [6]. Brown and Sappington examined cost-sharing policies for DER projects, highlighting their sensitivity to specific elements within the implementation environment [7], [8]. Similarly, García-García et al. assessed the financial feasibility of microgrid projects under four distinct tax incentives [9]. Further discussions on various incentive policy approaches can be found in works such as [10]–[13].

While these studies provide valuable insights into the economic feasibility and profitability of incentives for DER adoption, they often prioritize cost optimization and financial performance over resilience enhancement. Few of them have specifically addressed how incentive design can explicitly align with the goal of improving power system reliability and resilience. Given the increasing threats to grid stability, a key challenge lies in understanding how to structure incentives that optimize both resilience outcomes and economic efficiency. Filling this research gap is a prerequisite for ensuring that DER deployments effectively blend economic viability with vital system-wide resilience and reliability enhancements.

This work tackles the critical challenge of integrating resilience enhancement into incentive design by proposing a comprehensive Stackelberg game framework. It is formulated as a bilevel optimization model with multiple lower-level problems to account for the diverse responses of individual communities. Stackelberg game theory provides a powerful

This work is funded by the Laboratory Directed Research and Development (LDRD) at the Pacific Northwest National Laboratory (PNNL) as part of the E-COMP initiative. PNNL is operated by Battelle for the DOE under Contract DOE-AC05-76RL01830.

979-8-3315-8138-1

tool for modeling the hierarchical interaction between strategic decision-makers, where the leader determines the incentive structure first, and the followers react accordingly.

In the upper level of the framework, the system operator optimizes incentive parameters to minimize system-wide load shedding under contingency scenarios, placing resilience outcomes at the forefront of decision-making. In the lower level, the model captures the heterogeneous responses of communities to the incentives, reflecting varied investment behaviors influenced by local conditions and resource availability. By explicitly connecting the overarching resilience objectives of the system operator with the individual investment decisions of communities, this bilevel framework ensures a systematic and cohesive approach to incentive design. It provides a pathway to align community-level actions with the broader goals of enhancing grid reliability and resilience in an efficient manner.

The remainder of the paper is organized as follow. Section II presents our one-leader multiple follower Stackelberg game model for incentive design. A case study is analyzed in Section III. Finally, the paper is concluded in Section IV.

II. Model Formulation

We formulate a one-leader multiple-follower Stackelberg game 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 communities' response represented as distinct lower-level problems. The incentives include the subsidies for installing photovoltaic (PV) devices, battery energy storage systems (BESS), and the credit for holding energy at the BESS as emergency reserve to be used in contingency events.

A. 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.

$$\begin{aligned}\min_{\mathbf{y}_n} \quad & C^{\text{pv}} P_n^{\text{pv}} + C^{\text{batt}} P_n^{\text{batt}} - I_n^{\text{pv}} - I_n^{\text{batt}} - I_n^{\text{E}} \\ & + \alpha^{\text{ann}} \Bigg[\sum_{t \in \mathcal{T}} \omega^{\text{n}} C_{n,t}^{\text{n}} p_{n,t}^{\text{n}} \\ & + \sum_{t \in \mathcal{T}^{\text{c}}} \omega^{\text{c}} \left(C_{n,t}^{\text{c}} p_{n,t}^{\text{c}} + C_{n,t}^{\text{shed}} p_{n,t}^{\text{shed}} \right) \Bigg] \qquad (1) \\ \text{s.t.} \quad & (2-18)\end{aligned}$$

where $\mathbf{y}_n = (P_n^{\text{pv}}, P_n^{\text{batt}}, E_n^{\min}, I_n^{\text{pv}}, I_n^{\text{batt}}, I_n^{\text{E}}, \mathbf{p}_n^{\text{n}}, \mathbf{p}_n^{\text{c}}, \mathbf{p}_n^{\text{shed}}, \mathbf{p}_n^{\text{pv},\cdot}, \mathbf{p}_n^{\text{ch},\cdot}, \mathbf{p}_n^{\text{dis},\cdot}, \mathbf{e}_n^{\text{batt},\cdot})$ represents all decision variables for community n.

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 battery, respectively; I^{pv}, I^{batt}, and I^{E} denote the total 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 held in the battery to be used in contingency for community n, respectively.

The following constraints are defined for all $n \in \mathcal{N}$. To avoid duplication, we introduce $\mathcal{S} = \{\text{n}, \text{c}\}$ to represent the set of normal and contingency scenarios, with n and c being superscripts to distinguish parameters and decisions variables associated with different scenarios. The set of time indices is represented as $\mathcal{T} = \{1, 2, \cdots, T\}$ with $\mathcal{T}^{\text{n}} = \mathcal{T}$.

The subsidies provided by the system operator for unit size of PV and battery investments are S^{pv} and S^{batt}, respectively, and the credit for holding unit energy at the battery for use during contingency is C^{E}. The upper limit for each type of subsidy and credit can be received by the communities are I^{pv}, I^{batt}, and I^{E}, respectively. Then we have

$$I_n^{\text{pv}} \leq S^{\text{pv}} P_n^{\text{pv}}, \; I_n^{\text{pv}} \leq I^{\text{pv}}, \tag{2}$$

$$I_n^{\text{batt}} \leq S^{\text{batt}} P_n^{\text{batt}}, \; I_n^{\text{batt}} \leq I^{\text{batt}}, \tag{3}$$

$$I_n^{\text{E}} \leq C^{\text{E}} E_n^{\min}, \; I_n^{\text{E}} \leq I^{\text{E}}. \tag{4}$$

Contingency event starts at time $\hat{t}$, and all the time steps are collected as $\mathcal{T}^{\text{c}} = \{\hat{t}, \hat{t}+1, \cdots, T\} \subseteq \mathcal{T}$. Parameters ω^{n} and ω^{c} denote the probability of normal condition and contingency event, respectively; $C_{n,t}^{\text{n}}$, $C_{n,t}^{\text{c}}$, and $C_{n,t}^{\text{shed}}$ represent the electricity price under normal condition, electricity price during contingency, and the cost of unserved load, respectively. The decision variables $p_{n,t}^{\text{n}}$, $p_{n,t}^{\text{c}}$, and $p_{n,t}^{\text{shed}}$ represent the amount of power purchased under normal condition, purchased power during contingency, and the amount of load shedding, respectively.

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

$$0 \leq p_{n,t}^{\text{pv,s}} \leq r_{n,t}^{\text{pv}} P_n^{\text{pv}} \quad \forall \text{s} \in \mathcal{S}, \; t \in \mathcal{T}^{s}, \tag{5}$$

Battery operation should satisfy power and energy limits:

$$0 \leq p_{n,t}^{\text{ch,s}}, \; p_{n,t}^{\text{dis,n}} \leq P_n^{\text{batt}} \quad \forall \text{s} \in \mathcal{S}, \; t \in \mathcal{T}^{s}, \tag{6}$$

$$E_n^{\min} \leq e_{n,t}^{\text{batt,n}} \leq P_n^{\text{batt}} D^{\text{batt}} \quad \forall t \in \mathcal{T}, \tag{7}$$

$$0 \leq e_{n,t}^{\text{batt,c}} \leq P_n^{\text{batt}} D^{\text{batt}} \quad \forall t \in \mathcal{T}^{\text{c}}, \tag{8}$$

where D^{batt} is battery duration; $p_{n,t}^{\text{ch,s}}$, $p_{n,t}^{\text{dis,s}}$, and $e_{n,t}^{\text{batt,s}}$ are decision variables for BESS charged power, discharged power, and state of charge (SoC) at time t.

The dynamics of the BESS SoC can be modeled as follow for all $\text{s} \in \mathcal{S}, \; t \in \mathcal{T}^{s}$:

$$e_{n,t}^{\text{batt,s}} = e_{n,t-1}^{\text{batt,s}} - \left(\eta^{\text{dis}} p_{n,t}^{\text{dis,s}} - \eta^{\text{ch}} p_{n,t}^{\text{ch,s}} \right) \Delta T, \tag{9}$$

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

$$e^{\text{batt,n}}_{n,1} = 0.5P^{\text{batt}}_{n}D^{\text{batt}} - \left(\eta^{\text{dis}}p^{\text{dis,n}}_{n,1} - \eta^{\text{ch}}p^{\text{ch,n}}_{n,1}\right)\Delta T, \tag{10}$$

$$e^{\text{batt,c}}_{n,\hat{t}} = e^{\text{batt,n}}_{n,\hat{t}-1} - \left(\eta^{\text{dis}}p^{\text{dis,c}}_{n,\hat{t}} - \eta^{\text{ch}}p^{\text{ch,c}}_{n,\hat{t}}\right)\Delta T, \tag{11}$$

$$e^{\text{batt,n}}_{n,T} = 0.5P^{\text{batt}}_{n}D^{\text{batt}}. \tag{12}$$

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

$$\sum_{t\in\mathcal{T}} e^{\text{batt,n}}_{n,t} \leq \theta^{\text{lim}}P^{\text{Batt}}_{n}D^{\text{Batt}}, \tag{13}$$

where θ^{lim} is the number of cycle limit. The battery operation in contingency is not restricted because such events typically have a low probability of occurrence.

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

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

$$p^{\text{pv,c}}_{n,t} + p^{\text{dis,c}}_{n,t} - p^{\text{ch,c}}_{n,t} + p^{\text{cont}}_{n,t} + p^{\text{shed}}_{n,t} = D_{n,t}\ \forall t \in \mathcal{T}^{\text{c}}, \tag{15}$$

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. While the system has sufficient transmission capacity to meet the load demands of all communities, limits on power purchases may be imposed by the system operator during contingency. The related variables have the following bounds:

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

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

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

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

B. Upper-Level Problem: System Operator

As the leader in the Stackelberg game, the system operator selects the optimal incentive parameters $\mathbf{x} = (S^{\text{pv}}, S^{\text{batt}}, C^{E}, I^{\text{pv}}, I^{\text{batt}}, I^{E}, \underline{\mathbf{P}}^{\text{c}}, \overline{\mathbf{P}}^{\text{c}})$ to minimize total load shedding of all communities during contingency. With the lower-level community model presented in the previous section, the upper-level problem is formulated as follow:

$$\min_{\mathbf{x}} \quad \sum_{n\in N}\sum_{t\in T^{\text{c}}} p^{\text{shed}}_{n,t} \tag{19}$$

$$\text{s.t.} \quad (21-26)$$

$$\mathbf{p}^{\text{shed}}_{n} \in \arg\min\{(1)_n | (2-18)_n\} \quad \forall n \in \mathcal{N}. \tag{20}$$

The system operator is subject to a budget constraint that accounts for the total incentives provided:

$$N(I^{\text{pv}} + I^{\text{batt}} + I^{\text{E}}) \leq B, \tag{21}$$

where B denotes the total budget of the system operator.

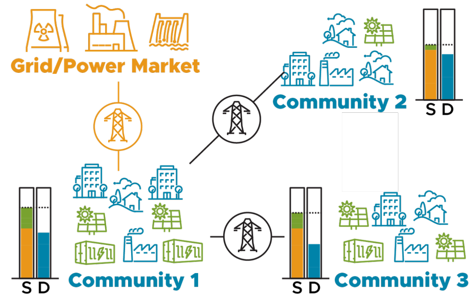


Fig. 1: Three-community system with transmission network. Community 1 is connected to the power market as well as to the other two communities.

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

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

$$-P_l \leq p^{\text{s}}_{l,t} \leq P_l, \quad \forall l \in \mathcal{L},\ \text{s} \in \mathcal{S},\ t \in \mathcal{T}^{\text{s}}, \tag{23}$$

$$-\mathbb{I}_{l\in\mathcal{C}}P_l \leq p^{\text{c}}_{l,t,s} \leq \mathbb{I}_{l\in\mathcal{C}}P_l, \quad \forall l \in \mathcal{L},\ t \in \mathcal{T}^{\text{f}}, \tag{24}$$

where $t(n)$ and $f(n)$ are the sets of transmission lines going into and out from community n, respectively; $\mathcal{C}$ is the set of lines disconnected in the contingency event; P_l represents the capacity of line l. Variables $p^{\text{n}}_{l,t}$ and $p^{\text{c}}_{l,t}$ denote the power flow through line l at time t under normal and contingency conditions, respectively. $\mathbb{I}_{l\in\mathcal{C}}$ is an indicator function that takes 1 if $l \in \mathcal{C}$ and 0 otherwise. $\mathcal{T}^{\text{f}}$ is the set of all time indices during which the lines are disconnected.

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

$$\underline{P}^{\text{c}}_{n,t} \leq 0 \quad \forall n \in \mathcal{N},\ t \in \mathcal{T}^{\text{c}}, \tag{25}$$

$$\overline{P}^{\text{c}}_{n,t} \geq 0 \quad \forall n \in \mathcal{N},\ t \in \mathcal{T}^{\text{c}}. \tag{26}$$

III. Case Study

A. Case Setting

We analyze optimal incentive design for a three-community system illustrated in Fig. 1. Community 1 is connected to the power market as well as to the other two communities.

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 Fig. 2.

Installation costs for PV and BESS are \$1.2 M/MW and \$1.6 M/MW, respectively. The BESS is assumed to have a 4-hour duration. To enhance realism, we discretize incentive values and PV/BESS sizes using integer variables. The PV and BESS sizes range from 0 to 100 MW, in increments of 10 MW.

979-8-3315-8138-1

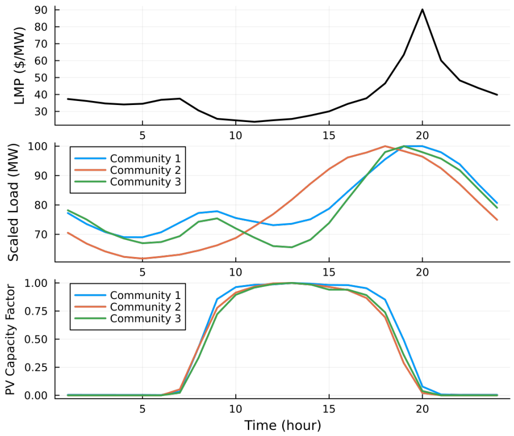


Fig. 2: Input parameters of the use case, including power price, scaled load and solar capacity factor of each community in a typical day.

Fig. 3: The contingency event analyzed in the case study. The transmission line connecting Community 1 to the power market is disconnected.

Incentives for PV and BESS range from 0 to \$0.4 M/MW and \$0.5 M/MW, respectively, with increments of \$0.1 M/MW. At most, half of the BESS energy capacity can be designated for emergency reserve, with a credit capped between 0 and \$0.4 M/MWh, in increments of \$0.1 M/MWh. The total budget of the system operator for providing incentives ranges from 0 to \$300 M.

The contingency event analyzed in the case study is shown in Fig. 3. 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. The contingency scenario is assumed to begin at 2 p.m. and last for 6 hours, with a 5% probability of occurrence.

B. System Load Shedding and Detailed Incentives

Fig. 4 illustrates the load shedding experienced by each community during the contingency event under various incentive levels. Without any incentives, the total load shedding across all communities is 423.4 MW. This is significantly reduced to 210.8 MW when a \$50 M incentive is provided. Further increasing the incentive to \$100 M lowers the total load shedding to 114.9 MW. To bring total load shedding below 50 MW, an incentive of \$200 M is required. With an incentive budget of \$300 M, all loads can be fully satisfied during the contingency event.

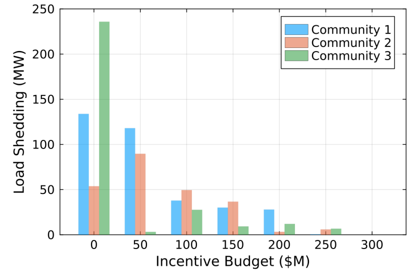
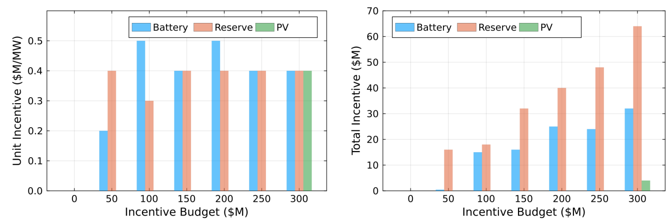


Fig. 4: Load shedding of each community under different incentive budgets.



(a) Unit incentives

(b) Total incentives

Fig. 5: Unit and Total incentives for battery, emergency reserve, and PV under different incentive budgets.

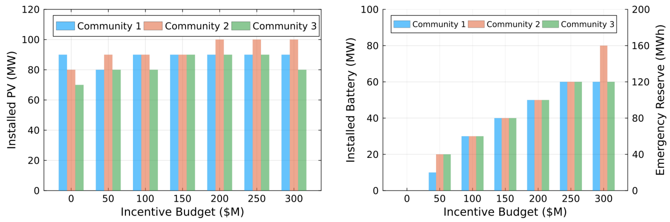
The marginal benefit of total incentives diminishes as the budget increases. The first \$150 M reduces over 80% of the total load shedding, whereas achieving the remaining 20% requires an additional \$150 M.

The contingency event leads to varying levels of load shedding across communities, with incentives affecting each community differently. When comparing the \$50 M incentive budget to the case with no incentive, the load shedding in community 2 is even higher. This outcome may be attributed to the fact that the communities prioritize minimizing their total costs over solely reducing unserved load.

Fig. 5 illustrates the detailed unit and total incentives allocated to BESS, emergency reserve, and PV under various incentive budgets. Notably, incentives for PV are only provided at the highest budget level, suggesting that communities are more inclined to self-finance PV installations due to their ability to generate cost-free power once installed.

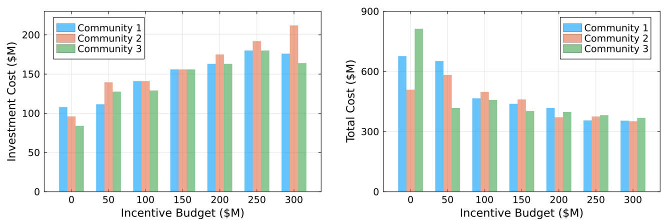
The unit incentives for BESS and emergency reserves increase as the total budget grows, particularly when the budget is low. However, these incentives stabilize once the budget reaches \$100 M. As shown in Fig. 5b, a larger portion of the incentives is allocated to encourage communities to maintain emergency reserves, as this energy is crucial for sustaining operations during contingency events when other power sources are unavailable.

979-8-3315-8138-1



(a) Installed PV (b) Installed battery and reserve

Fig. 6: Installed PV, battery and emergency reserve by each community under different incentive budgets.



(a) Investment cost (b) Total cost

Fig. 7: Investment cost and total cost by each community under different incentive budgets.

C. Community Investment Response

Fig. 6 illustrates communities' investment decisions in response to system incentives as the incentive budgets increase. Without any incentives, communities install between 70 MW and 90 MW of PV devices, which remains at no less than 80 MW once incentives are provided. Although no direct incentives are allocated for PV installation when the budget is below $300 M, PV investment decisions are still indirectly influenced by incentives for other resources. The consistently high levels of PV installation support our earlier hypothesis that communities are more inclined to self-finance PV installations due to their long-term benefits.

Across all incentive budget scenarios, communities consistently allocate half of the battery's energy capacity as emergency reserves, which represents the upper limit set by our model. This high proportion of emergency reserves aligns with the substantial incentives provided by the system. Notably, higher credit for emergency reserves indirectly motivates communities to install larger BESS. As a result, we observe that battery sizes increase as the incentive budget grows.

Fig. 7 illustrates each community's total investment costs for PV and BESS, as well as their total costs over the 16-year lifespan of the equipment. Higher incentives clearly encourage greater investment in distributed resources. Although the installation costs for PV and BESS increase with higher incentives, each community's total cost decreases overall. Similar to the system's load shedding behavior, the marginal impact of incentives diminishes as the total incentive budget increases.

IV. Conclusion

This paper develops a generic bilevel optimization model to design financial incentives that enhance power system resilience through the strategic deployment of distributed energy resources (DERs). The proposed methodology effectively tackles the critical challenge of aligning individual community investment decisions with system-wide resilience objectives under normal and contingency events.

A case study involving a three-community system is conducted to validate the proposed model. Incentives are offered to communities to encourage investment in DERs and the allocation of emergency reserves to mitigate contingency events. As the incentives increase, the total system load shedding decreases, community investment in DERs rises, and overall total costs decline. However, the marginal effectiveness of the incentives diminishes as the total incentive budget grows.

Future research could expand the framework to account for multiple contingency scenarios with varying durations and seasonal conditions. For large-scale problems, developing advanced solution techniques will be essential to efficiently solve the optimization model.

References

[1] J. W. Busby, K. Baker, M. D. Bazilian *et al.*, "Cascading risks: Understanding the 2021 winter blackout in Texas," *Energy Research & Social Science*, vol. 77, p. 102106, 2021.

[2] L. Guliasi, "Toward a political economy of public safety power shutoff: Politics, ideology, and the limits of regulatory choice in California," *Energy Research & Social Science*, vol. 71, p. 101842, 2021.

[3] S. C. Ganz, C. Duan, and C. Ji, "Socioeconomic vulnerability and differential impact of severe weather-induced power outages," *PNAS Nexus*, vol. 2, pp. 1–10, 2023.

[4] Synapse Energy Economics, "Regulatory mechanisms to enable investments in electric utility resilience," Sandia National Laboratories, Tech. Rep. SAND2021-6781, 2021.

[5] Y. Huang and L. Söder, "Assessing the impact of incentive regulation on distribution network investment considering distributed generation integration," *International Journal of Electrical Power & Energy Systems*, vol. 89, pp. 126–135, 2017.

[6] J. Wang, H. Zhong, J. Qin, W. Tang, R. Rajagopal, Q. Xia, and C. Kang, "Incentive mechanism for sharing distributed energy resources," *Journal of Modern Power Systems and Clean Energy*, vol. 7, pp. 837–850, 2019.

[7] D. P. Brown and D. E. M. Sappington, "Optimal procurement of distributed energy resources," *Energy Journal*, vol. 39, no. 5, pp. 131–154, 2018.

[8] D. P. Brown and D. E. Sappington, "Employing cost sharing to motivate the efficient implementation of distributed energy resources," *Energy Economics*, vol. 81, pp. 974–1001, 2019.

[9] J. García-García, Y. Sarmiento-Ariza, L. Campos-Rodríguez, J. Rey-López, and G. Osma-Pinto, "Evaluation of tax incentives on the financial viability of microgrids," *Applied Energy*, vol. 329, p. 120293, 2023.

[10] G. Black, D. Holley, D. Solan, and M. Bergloff, "Fiscal and economic impacts of state incentives for wind energy development in the western united states," *Renewable and Sustainable Energy Reviews*, vol. 34, pp. 136–144, 2014.

[11] C. Washburn and M. Pablo-Romero, "Measures to promote renewable energies for electricity generation in latin american countries," *Energy policy*, vol. 128, pp. 212–222, 2019.

[12] S. Varghese and R. Sioshansi, "The price is right? how pricing and incentive mechanisms in california incentivize building distributed hybrid solar and energy-storage systems," *Energy Policy*, vol. 138, p. 111242, 2020.

[13] Y. S. Kim, G. H. Park, S. W. Kim, and D. Kim, "Incentive design for hybrid energy storage system investment to pv owners considering value of grid services," *Applied Energy*, vol. 373, p. 123772, 2024.

979-8-3315-8138-1