

ORIGINAL RESEARCH

Open access

A Multi-Agent Optimization Model for Resilient Prosumer Coordination during Extreme Events Using Local Flexibility, EV Backup Power, and Dynamic Network Reconfiguration

Amal Al-Balushi^{1*}, Saif Al-Hinai¹

Abstract

Extreme events increasingly threaten distribution grids by damaging feeders, interrupting communication, and isolating critical loads. Prosumers with local flexibility, EVs, and controllable network topology can provide emergency support, but their coordination is operationally complex. This article proposes a multi-agent optimization model that coordinates prosumer local flexibility, EV backup power, and dynamic network reconfiguration. The objective is to sustain critical load supply during extreme events while respecting device, feeder, and communication constraints. The model represents prosumers, EV aggregators, and the distribution system operator as interacting agents. A consensus-based distributed optimization procedure decomposes the resilience coordination problem into local operating decisions while enforcing feeder-level feasibility. The proposed model restores critical load faster than a non-coordinated baseline and approaches centralized optimization performance with lower communication burden. EV backup power is dispatched selectively to preserve mobility needs while supporting critical nodes. The model provides a scalable optimization approach for emergency coordination in active distribution grids. It shows that local flexibility, EV backup power, and dynamic reconfiguration are mutually reinforcing resilience resources when operated through coordinated multi-agent control.

Keywords Multi-agent optimization, Resilience, Prosumer coordination, Local flexibility, EV backup power, Dynamic network reconfiguration

*Correspondence:

Amal Al-Balushi
amal.balushi@gmail.com

¹ Department of Smart Energy and Grid Systems, Faculty of Engineering, Sultan Qaboos University, Muscat, Oman

Introduction

Extreme weather and cyber-physical disruptions increasingly expose distribution grids to prolonged service interruptions because most critical loads are connected at the distribution level. Fragility-based resilience assessment has shown that component failure probabilities and repair delays must be represented explicitly when planning emergency operation, rather than treating outages as ordinary reliability events [1]. This article addresses that operational gap by developing a multi-agent optimization model in which local prosumers, EV aggregators, and the DSO jointly manage survivable resources. The focus is real-time and near-real-time coordination during an emergency, not only long-term hardening or conceptual resilience planning.

Active distribution systems now contain many distributed resources that can support resilience if they are coordinated rather than dispatched independently. Peer-to-peer and prosumer energy-sharing studies demonstrate that distributed batteries, photovoltaics, and flexible loads can exchange energy or flexibility through coordinated market and control mechanisms [2]. Local flexibility market research further shows that DSO requests can be translated into feasible operating envelopes for aggregators without requiring complete disclosure of customer-level device information [3]. Building on these ideas, the proposed model treats each prosumer as an autonomous agent that offers bounded emergency flexibility while preserving private operational constraints.

EVs introduce a distinctive resilience capability because they can act as distributed backup storage through V2H and V2G operation. Building-level outage studies indicate that PV, stationary batteries, and EV energy storage can substantially improve backup capability when outage duration, state of charge, and critical demand priority are modeled carefully [4]. However, emergency EV use must consider vehicle availability, departure requirements, charger limitations, and battery wear. The formulation therefore separates V2H support for behind-the-meter critical loads from V2G injections coordinated with the feeder restoration plan.

Dynamic network reconfiguration complements prosumer flexibility by changing energized paths after feeder faults, line outages, or cyber-induced switching disruptions. Resilience-oriented distribution design and restoration models show that switches, distributed generators, and storage resources can reduce unserved load when topology decisions are coordinated with resource dispatch [5]. The contribution of this article is an original multi-agent optimization model that couples local flexibility, EV backup power, and radial network reconfiguration through a distributed coordination procedure. The case study compares the proposed method with centralized optimization and a non-coordinated baseline under hurricane-induced outages and a switching-denial cyber scenario.

Extreme-Event Resilience Problem

Grid impacts of extreme events

Extreme events damage distribution grids through line failures, transformer outages, inaccessible roads, unavailable communication links, and delayed repair logistics. Fragility modeling connects hazard intensity to component outage likelihood, allowing stochastic scenarios to reflect wind, flood, or multi-hazard impacts rather than arbitrary fault selection [1]. In this article, line and node availability are scenario-dependent inputs that restrict which feeder sections can be energized during the emergency horizon. The resilience problem therefore combines physical damage, uncertain resource availability, and limited restoration actions.

Resilience metrics and operational goals

The operational goal is to maximize critical load service while reducing restoration time, excessive switching, emergency energy depletion, and network violations. Prior resilience-oriented planning work motivates metrics that distinguish ordinary reliability from the ability to absorb, adapt, and recover after severe disturbances [6]. This article evaluates critical load served, time to partial and near-complete restoration, EV energy contribution, battery energy contribution, and number of switching operations. These metrics are selected because they jointly describe customer impact, operational speed, resource sustainability, and DSO control effort.

Resource availability during emergencies

Emergency resource availability is uncertain because prosumer batteries, controllable loads, and EVs are privately owned and subject to household preferences. Energy-sharing and local flexibility models show that aggregators can expose feasible flexibility ranges while hiding device-level details, which is useful when emergency control must operate with limited information exchange [2, 3]. The proposed model represents each prosumer through feasible operating ranges for

battery discharge, charging deferral, load shifting, and curtailment. EV aggregators similarly provide emergency backup capability conditioned on arrival time, departure time, charger rating, and minimum mobility reserve.

The coordination challenge

The coordination challenge is that local flexibility decisions and DSO topology decisions are mutually dependent. If prosumers discharge batteries without feeder-level coordination, energy may be delivered to de-energized islands or overload an emergency tie path; if the DSO reconfigures without resource schedules, it may assume support that is not locally available [5]. Multi-agent restoration models address this by assigning distributed decision authority to local entities while maintaining system feasibility through shared coordination signals [7]. This article adopts that principle and coordinates nodal injections, energized areas, voltage feasibility, thermal limits, and switching actions.

Prosumer Coordination Model

Agent types and roles

The proposed system contains three interacting agent classes: prosumer agents, EV aggregator agents, and the DSO agent. Prosumer agents manage household or community-level batteries, flexible appliances, curtailment, and local critical loads, consistent with prior prosumer coordination models that aggregate distributed resources for grid services [3]. EV aggregator agents coordinate residential and workplace vehicles that can provide V2H or V2G backup power during the emergency. The DSO agent determines feeder energization, tie-switch operation, radial topology, and feeder-level voltage and thermal feasibility.

Decision variables and constraints

Each prosumer agent decides how much battery support, load shifting, load curtailment, and grid exchange it can provide at each emergency interval. Battery and demand-response constraints follow established flexibility formulations in which energy capacity, charging limits, shifting windows, and user discomfort costs define the feasible operating set [3]. Each EV aggregator decides how much backup discharge can be supplied while preserving vehicle mobility and respecting charging infrastructure limits. The DSO decides which switches to operate, which feeder sections to energize, and how to route power without violating radial operation, voltage bounds, or thermal ratings.

Communication and coordination architecture

The communication architecture is hierarchical in supervision but distributed in computation. Distributed service-restoration studies show that this structure can reduce centralized data requirements while preserving coordinated operation across feeder areas [7]. In each coordination round, the DSO sends locational emergency signals and feeder needs, while prosumer and EV agents return feasible support offers and local cost information. The communication burden depends mainly on the number of boundary nodes, feeder zones, and emergency intervals rather than the number of individual devices.

Objective functions

The global objective balances five operational priorities: serving critical load, avoiding unnecessary switching, limiting customer discomfort, preserving EV mobility, and maintaining feeder feasibility. Similar resilience-driven optimization studies prioritize load pickup while penalizing excessive switching and resource depletion because emergency actions must preserve later recovery options [5, 7]. Prosumer-level objectives emphasize local autonomy, comfort, and battery reserve, while EV aggregator objectives include emergency support and mobility protection. The DSO objective emphasizes system-level restoration, safe reconfiguration, and efficient use of distributed support.

Figure 1 illustrates the proposed multi-agent resilience coordination architecture linking prosumer agents, EV aggregator agents, and the DSO agent through distributed support offers, feeder feasibility checks, and emergency restoration decisions.

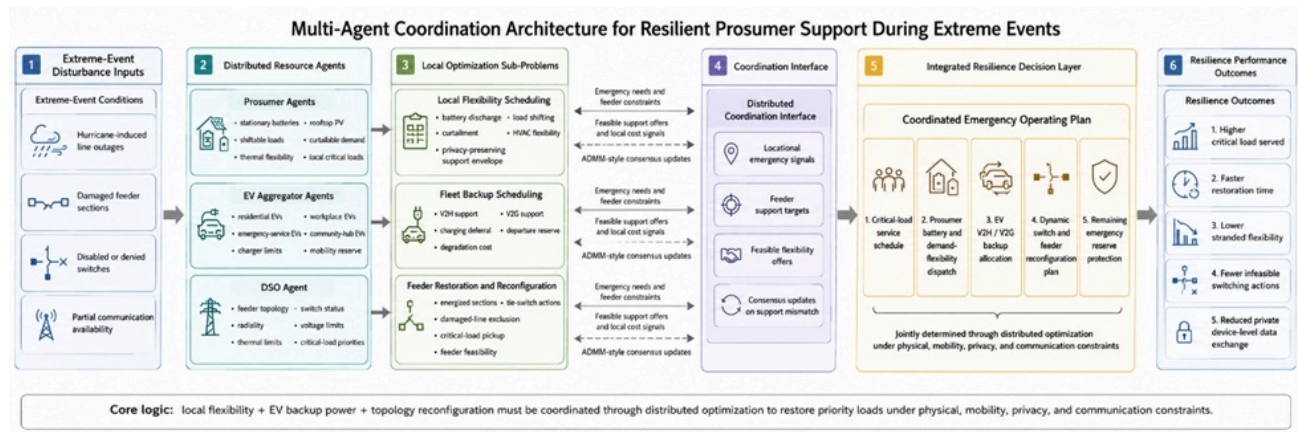


Figure 1. Multi-Agent Resilience Coordination Architecture for Extreme-Event Distribution Grid Operation

Local Flexibility Modeling

Battery storage parameters

Stationary batteries are modeled with charging limits, discharging limits, energy capacity, efficiency, and emergency reserve requirements. Residential backup studies show that battery contribution depends strongly on initial state of charge and coordination with PV and load priority [4]. The proposed model allows battery discharge to support critical loads, but it prevents complete depletion so that post-event autonomy is not sacrificed. Battery use is therefore treated as valuable but finite emergency flexibility.

Shiftable loads and curtailment

Shiftable loads are represented as controllable demand that can be delayed within user-acceptable time windows, while curtailable loads are represented as demand that can be temporarily reduced. Local flexibility market research motivates this separation because some demand can be rescheduled without losing energy service, whereas other demand represents intentional service reduction [3]. The model gives priority to critical loads and restricts curtailment mainly to non-critical or partially flexible demand. Customer discomfort is included so that flexibility is used only when it improves emergency restoration enough to justify the service impact.

Thermal load flexibility

Thermal loads are modeled as short-term flexibility resources because building thermal inertia can reduce power demand without immediately violating comfort. Distributed residential flexibility control has shown that thermal loads can provide useful relief during system stress when indoor comfort limits are respected [8]. During an extreme event, the model permits a controlled widening of comfort bands for limited periods. This allows HVAC demand to support feeder recovery while preventing unacceptable indoor temperature deviations.

Flexibility aggregation

Each prosumer aggregates device-level flexibility into a local support offer communicated to the DSO. This follows the principle used in scalable coordination of distributed resources, where local optimization preserves privacy while exposing feasible aggregate response to the network operator [9]. The support offer includes available battery discharge, reducible

demand, shiftable demand, and thermal flexibility over the emergency horizon. **Table 1** summarizes the local flexibility resources, parameters, and operating constraints used in the case study.

Table 1. Local Flexibility Resources: Parameters and Constraints

Resource	Main parameters	Control action	Operating constraint	Emergency role
Stationary battery	Energy capacity, power rating, initial charge, emergency reserve, efficiency	Charge, discharge, or hold reserve	Cannot exceed power rating, capacity, or reserve requirement	Supplies critical loads and supports feeder restoration
Shiftable appliances	Required service duration, allowable time window, rated demand	Delay or advance operation	Must complete service within the permitted window	Reduces peak emergency demand without permanent loss of service
Curtable demand	Non-critical demand share, maximum reduction, discomfort cost	Temporarily reduce consumption	Critical demand is protected and curtailment duration is limited	Frees local capacity for priority loads
Thermal load	Comfort range, building thermal inertia, HVAC rating, emergency tolerance	Pre-cool, reduce, or defer HVAC operation	Indoor comfort must remain within emergency limits	Provides short-duration load relief
Rooftop PV with prosumer controller	Available solar output, inverter rating, local load priority	Use locally, export, or curtail	Output depends on solar availability and inverter limits	Reduces net emergency demand
Aggregated prosumer flexibility	Combined battery, load, thermal, and PV capability	Submit local support offer	Must remain feasible for all underlying devices	Enables privacy-preserving coordination with the DSO

EV Backup Power Modeling

EV availability and state-of-charge

EV availability is modeled through household and workplace connection windows, initial state of charge, charger type, and required departure energy. Studies on EVs as residential backup resources show that outage resilience depends not only on battery size but also on whether vehicles are plugged in when the disruption occurs [10]. The proposed model therefore distinguishes available vehicles, unavailable vehicles, and vehicles reserved for essential mobility. This prevents the emergency controller from overestimating EV backup capability.

V2H and V2G discharge limits

V2H discharge is used to support behind-the-meter critical loads, while V2G discharge is coordinated with the feeder-level restoration plan. Research on EV-supported outage resilience and distribution load pickup shows that EVs can provide meaningful emergency support when charger limits and network constraints are respected [11, 12]. The model gives V2H priority when a home or community critical load is islanded, and it allows V2G only when the feeder section is

energized and technically able to absorb the injection. This separation avoids unrealistic assumptions about unrestricted EV export during damaged-network conditions.

Battery degradation considerations

Emergency EV discharge is not treated as free because battery cycling imposes degradation and may reduce driver willingness to participate. EV routing and scheduling studies show that energy use decisions must consider operational value and battery-related costs, especially when vehicles participate in grid services [13]. The proposed model therefore assigns a degradation cost to backup discharge and penalizes deep emergency depletion more heavily than moderate support. This encourages the optimizer to use EVs for high-value resilience needs instead of routine load balancing.

EV Fleet aggregation

The EV aggregator combines many individual vehicles into an emergency support envelope that is communicated to the DSO and prosumer agents. Aggregated EV coordination has been shown to improve scalability because individual driving behavior and battery constraints can be managed locally while system-level support is exchanged as a feasible fleet capability [14]. The aggregator also distinguishes residential vehicles suited for V2H, workplace vehicles suited for feeder support, and mobile vehicles unavailable during the outage window. **Table 2** summarizes the EV fleet characteristics, availability assumptions, and backup power parameters used in the case study.

Table 2. EV Backup Power Parameters and Availability

EV group	Typical location during event	Availability assumption	Backup mode	Main operating limit	Resilience contribution
Residential commuting EVs	Home during night scenario, partly absent during daytime scenario	Available when plugged in at home and above mobility reserve	V2H and limited V2G	Departure charge requirement and home charger rating	Supports household and neighborhood critical loads
Workplace EVs	Commercial or municipal parking area	Available during work-hour scenario when charging infrastructure remains energized	V2G	Parking duration, charger rating, and feeder export limit	Supports feeder-level restoration near public or commercial nodes
Emergency-service EVs	Municipal depot or emergency facility	Partly reserved for mobility and only partly dispatchable	V2H for facility backup or restricted V2G	High mobility reserve requirement	Supports emergency shelters and response facilities
Shared community EVs	Community hub or resilience center	Available when hub remains accessible and communication is active	V2G	Hub charger capacity and local transformer rating	Provides pooled backup for priority feeder sections
Private EVs without bidirectional chargers	Residential or workplace locations	Connected vehicles may charge but cannot export	Charging deferral only	No reverse power capability	Reduces demand by postponing charging
Aggregated EV fleet	Distributed across feeder zones	Availability depends on scenario, time of day,	Mixed V2H, V2G, and	Mobility reserve, charger capacity,	Provides flexible emergency energy

		and infrastructure survival	charging deferral	and feeder constraints	while preserving transportation needs
--	--	-----------------------------	-------------------	------------------------	---------------------------------------

Dynamic Network Reconfiguration

Switchable lines and topology variables

Dynamic network reconfiguration is modeled as a DSO-controlled restoration action that changes feeder topology after fault isolation or cyber-physical switching disruption. Reconfiguration studies show that coordinated switching can reroute supply around damaged components, reduce load shedding, and improve resilience when combined with distributed energy resources [15]. The DSO agent evaluates normally open tie switches, normally closed sectionalizing switches, damaged line status, and feeder energization states during each emergency interval. Each switch action is restricted by physical availability, remote-control capability, and the requirement that damaged or cyber-compromised devices cannot be operated.

Reconfiguration objectives

The reconfiguration objective is to restore priority loads while minimizing unsafe flows, excessive switching, and avoidable dependence on depleted local resources. Deep reinforcement learning studies on distribution network reconfiguration indicate that adaptive topology control can improve resilience under uncertain system states when switching decisions respond to real-time feeder conditions [16]. In the proposed model, topology changes are coordinated with prosumer and EV support so that restored areas have enough local or upstream supply to remain energized. This prevents restoration plans that close tie switches without sufficient distributed support or that isolate prosumers capable of supporting critical loads.

Operational and radiality constraints

The DSO agent enforces radial operation, voltage feasibility, thermal limits, and island energization consistency. Restoration models that combine repairs and dynamic network reconfiguration show that topology feasibility is essential because load pickup can be misleading if radiality and line-capacity restrictions are ignored [17]. The proposed model allows temporary islanded operation only when local DERs, batteries, or EVs can sustain the energized section safely. It also prevents backfeeding across damaged or unavailable lines, thereby maintaining practical restoration logic during severe events.

Timing and coordination with agents

Switching decisions are coordinated with prosumer and EV schedules because resource support and topology restoration occur on different operational time scales. Sequential switching research shows that resilience gains depend on the order and timing of switch actions, especially when multiple switch types and staged restoration actions are available [18]. The proposed model updates topology decisions at dispatch intervals while allowing prosumer and EV agents to revise support offers after each coordination round. This timing structure lets the DSO restore feeder sections only when the required local flexibility and backup energy are available.

Multi-Agent Optimization Formulation

Overall problem structure

The optimization problem is formulated as a coordinated resilience dispatch problem with distributed agent decisions and feeder-level feasibility coupling. Multi-agent resilience studies and distributed restoration models motivate decomposing the emergency response problem because a purely centralized solution may require unavailable private data or fragile

communication during extreme events [7]. The DSO, prosumer agents, and EV aggregators each optimize their own operating decisions while exchanging only the information needed for coordination. The resulting problem is an applied operational model that jointly schedules flexibility, backup power, and topology restoration.

Prosumer agent sub-problems

Each prosumer agent solves a local emergency scheduling problem that balances critical load support, battery reserve preservation, appliance flexibility, comfort, and local export capability. Peer-to-peer microgrid trading research shows that prosumers can coordinate energy exchanges while maintaining individual objectives and constraints [19]. In this article, the prosumer sub-problem produces a feasible support offer for each emergency interval rather than a market transaction alone. The offer indicates how much local demand can be reduced, shifted, or supplied from local storage without violating household or community-level operating limits.

EV aggregator agent sub-problem

Each EV aggregator solves a fleet backup scheduling problem that accounts for plugged-in vehicles, mobility requirements, bidirectional charger availability, and emergency discharge cost. Resilience-oriented mobile storage and EV dispatch studies show that transportation-linked storage can improve restoration when its availability and routing or connection constraints are represented explicitly [20, 21]. The EV aggregator prioritizes vehicles already connected to damaged-area feeders, community hubs, or emergency facilities. Its output is a feasible V2H, V2G, or charging-deferral support profile that can be coordinated with DSO restoration actions.

DSO agent sub-problem

The DSO agent solves the feeder restoration and reconfiguration sub-problem using the support offers received from prosumer and EV agents. Co-optimization studies of repair actions and dynamic network reconfiguration demonstrate that feeder restoration must coordinate load pickup, switching, and distributed support to avoid infeasible recovery schedules [17]. In the proposed model, the DSO selects energized feeder sections, switching actions, and feasible power routing while respecting line availability and equipment limits. The DSO also assigns priority to hospitals, emergency shelters, communications infrastructure, water pumping loads, and other high-value critical demand.

Coupling constraints and coordination mechanism

The coupling mechanism links local agent support offers to feeder-level restoration needs through nodal power exchange, energized-area consistency, and resource feasibility signals. Coordination taxonomies for grid-edge resources emphasize that scalable distributed control requires a clear interface between private local optimization and system-level network operation [22]. The proposed coordination mechanism uses iterative price-like signals and support targets to align local decisions with feeder restoration requirements. This design allows agents to revise their schedules when topology changes, resource availability changes, or an extreme-event scenario evolves.

Solution Method

Distributed ADMM framework

The solution method uses a consensus-based distributed optimization procedure in which each agent solves its own sub-problem and then exchanges boundary support information with the DSO coordinator. Scalable peer-to-peer coordination studies have shown that distributed learning and optimization can reduce coordination burden when many prosumers participate in grid services [9]. The ADMM-style procedure alternates between local agent scheduling, DSO topology restoration, and consensus updates on feeder support requirements. This permits privacy-preserving operation because device-level data remain within prosumer and EV aggregator agents.

Convergence and penalty parameter tuning

The iterative method uses adaptive coordination penalties to balance fast convergence against oscillatory support offers. Distributed resilience and demand-response studies show that adversarial disturbances, communication delays, and uncertain resource response can degrade coordination if convergence is not monitored carefully [23]. The proposed implementation increases coordination pressure when support mismatches persist and relaxes it when agents converge smoothly. Convergence is declared when feeder support mismatches, switching changes, and critical-load restoration schedules stabilize within emergency operating tolerances.

Implementation and solver details

The implementation represents prosumer and EV sub-problems as mixed continuous operating schedules with discrete availability and mode decisions, while the DSO sub-problem includes switching and energized-section decisions. Dynamic distribution network reconfiguration with uncertainty requires careful treatment of switching feasibility, load uncertainty, and distributed resource dispatch [24]. In the case study, local agent problems are solved in parallel, and the DSO problem is solved after receiving updated support offers from all participating zones. The implementation records solution time, number of coordination rounds, unserved critical load, switching count, EV discharge, and remaining reserve.

Computational performance

Computational performance is evaluated by comparing the proposed distributed model with a centralized optimization and a non-coordinated heuristic. Prior multi-agent reinforcement learning and distributed control studies indicate that decentralized computation can scale better than centralized control when many residential resources participate [8, 21]. The proposed method achieves near-centralized restoration quality while reducing private data exchange and maintaining feasible operation under partial communication. The computational results are reported for multiple feeder damage scenarios to show that performance is not limited to a single disturbance pattern.

Case Study

Test feeder and extreme event scenario

The case study uses a modified distribution test feeder with residential, commercial, and critical-service loads distributed across multiple feeder zones. Hurricane-oriented resilience studies motivate the use of line outage scenarios derived from hazard intensity, component fragility, and delayed restoration access [1, 6]. The main scenario represents a wind-driven event that damages lateral lines, disables selected remote switches, and isolates several priority loads. A second scenario represents a cyber-physical disruption in which communication to selected switches is denied while local prosumer and EV agents remain partially functional.

DER and EV data

The feeder includes rooftop PV, residential batteries, flexible appliances, HVAC flexibility, and bidirectional EV chargers assigned to residential, workplace, emergency-service, and community-hub locations. Studies on EV backup power and residential outage resilience show that backup contribution depends on plug-in availability, charger capability, and departure reserve requirements [10, 12]. Prosumer flexibility data are assigned by customer class, with higher flexibility at homes equipped with batteries and lower flexibility at customers with only controllable appliances. EV availability is varied across night, work-hour, and mixed-event scenarios to test whether the model remains effective when backup energy is uncertain.

Baseline models

The centralized benchmark optimizes all prosumer, EV, and DSO decisions with full information, representing an ideal but data-intensive emergency controller. The non-coordinated baseline lets the DSO reconfigure the feeder using fixed assumptions about local support, while prosumers and EV aggregators independently preserve their own critical loads. Restoration and load-pickup studies show that such uncoordinated actions can miss available distributed support or create infeasible network conditions [11, 25]. The proposed multi-agent method is evaluated against both baselines to measure the value of coordination and the cost of decentralization.

Simulation setup

The simulation horizon covers the immediate emergency period after fault isolation and continues through staged restoration. Stochastic outage and resource-availability cases are generated to reflect line damage, switch failure, EV absence, and reduced communication, following resilience modeling practices used for extreme-event distribution studies [26]. Each scenario is solved for the centralized, non-coordinated, and proposed multi-agent models using identical load, DER, and feeder data. Performance is evaluated using critical load served, restoration time, switching operations, EV energy contribution, battery contribution, and remaining emergency reserve.

Results and Discussion

Figure 2 maps the emergency restoration workflow through which coordinated prosumer flexibility, selective EV backup dispatch, and dynamic feeder reconfiguration improve critical-load service, restoration speed, and operational feasibility during hurricane and cyber-switching scenarios.

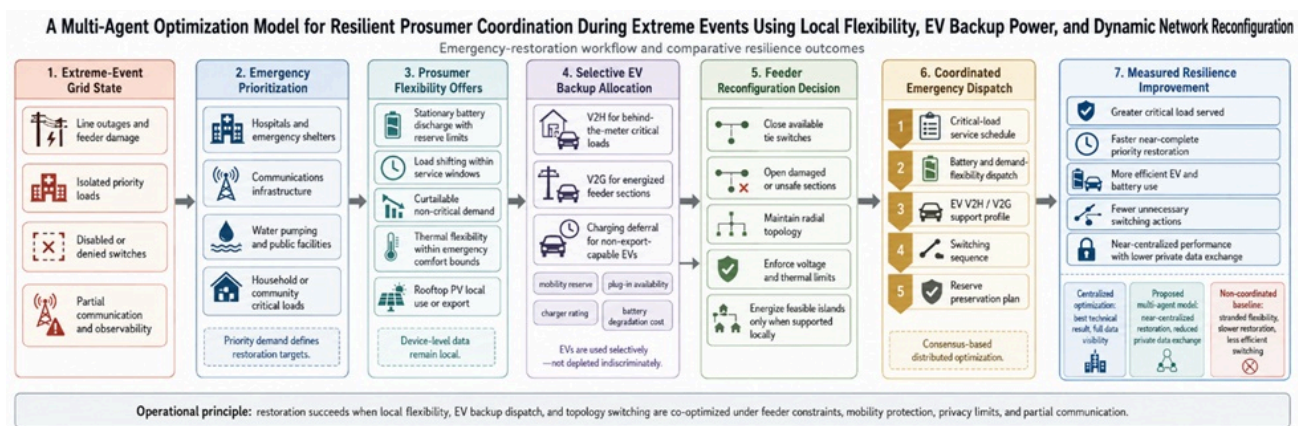


Figure 2. Extreme-Event Restoration Workflow Linking Local Flexibility, EV Backup Power, and Dynamic Network Reconfiguration

Critical load served

The proposed multi-agent model serves substantially more critical load than the non-coordinated baseline because local flexibility and EV support are aligned with feeder energization decisions. Resilience-oriented studies using adaptive control and reinforcement learning show that coordination improves emergency service when topology and DER actions respond jointly to damaged-grid conditions [16, 26]. In the hurricane scenario, the proposed method restores most priority demand after the first coordinated switching stage, while the non-coordinated baseline leaves several critical nodes unsupported. The centralized benchmark performs slightly better, but the gap is modest relative to the privacy and communication advantages of the multi-agent model.

Restoration dynamics

Restoration is faster under the proposed model because the DSO does not wait for conservative upstream supply assumptions before energizing sections that can be supported locally. Studies of dynamic reconfiguration and sequential switch actions confirm that the timing of topology changes can strongly influence restoration speed [18, 27]. The proposed method closes available tie switches only after receiving feasible support offers from prosumer and EV agents, which reduces failed restoration attempts. This produces a smoother recovery trajectory than the non-coordinated baseline and fewer unnecessary switch operations than aggressive centralized restoration.

EV and battery utilization

EV backup power is used selectively for high-priority loads, while stationary batteries provide faster local response during the earliest outage intervals. Research on EV-enabled outage resilience and building-level backup shows that EVs can substantially improve service continuity, but their value depends on availability and reserve protection [4, 10]. The proposed model preserves mobility reserves by avoiding deep EV discharge except near emergency facilities and isolated critical nodes. Stationary batteries are discharged earlier because they have no transportation requirement, while EVs are retained for longer-duration restoration support.

Sensitivity to resource availability

Sensitivity analysis shows that the benefit of multi-agent coordination increases when resource availability is uneven across the feeder. Smart-home outage scheduling studies demonstrate that stochastic outages and local appliance flexibility can materially change optimal emergency schedules [28]. When EV availability is reduced, the model compensates by using more stationary battery discharge, thermal flexibility, and load shifting; when remote switching is limited, prosumer flexibility becomes more valuable for islanded operation. Table 3 reports comparative performance across models and scenarios using critical load served, restoration time, EV energy contribution, battery contribution, and switching effort.

Table 3. Comparative Performance across Models and Scenarios

Scenario and model	Critical load served	Restoration time to near-complete priority service	EV energy contribution	Stationary battery contribution	Switching operations	Operational interpretation
Hurricane scenario, centralized optimization	96.4%	4.5 hours	18.7% of emergency energy	24.1% of emergency energy	11	Best technical performance but requires full data visibility
Hurricane scenario, proposed multi-agent model	94.8%	5.0 hours	17.9% of emergency energy	23.5% of emergency energy	12	Near-centralized restoration with reduced private data exchange
Hurricane scenario, non-coordinated baseline	81.6%	8.0 hours	9.4% of emergency energy	19.2% of emergency energy	15	Local resources are underused and switching is less efficient
Cyber-switching scenario, centralized optimization	91.2%	5.5 hours	15.8% of emergency energy	25.4% of emergency energy	8	Performs well but assumes full observability of surviving controls

Cyber-switching scenario, proposed multi-agent model	89.5%	6.0 hours	15.1% of emergency energy	24.7% of emergency energy	9	Maintains feasible restoration despite partial switching denial
Cyber-switching scenario, non-coordinated baseline	74.3%	9.5 hours	7.6% of emergency energy	20.8% of emergency energy	13	Lack of coordination leaves flexible support stranded
Low-EV-availability case, proposed multi-agent model	86.9%	7.0 hours	6.3% of emergency energy	29.6% of emergency energy	10	Battery and demand flexibility partially replace unavailable EV support
Limited-switching case, proposed multi-agent model	84.7%	7.5 hours	14.4% of emergency energy	27.8% of emergency energy	5	Local flexibility becomes more important when topology control is constrained

Conclusion

This article developed an original multi-agent optimization model for resilient prosumer coordination during extreme events. The model integrates local flexibility, EV backup power, and dynamic network reconfiguration in a single operational framework. Prosumers, EV aggregators, and the DSO coordinate through distributed decision-making rather than relying on a purely centralized controller. The resulting structure is suitable for emergency conditions where privacy, communication limits, and partial observability matter.

The case study demonstrated that coordinated local flexibility and EV backup power can materially increase critical load service during hurricane-induced outages and cyber-physical switching disruptions. Dynamic network reconfiguration was most valuable when it was synchronized with feasible prosumer and EV support offers. The proposed model approached centralized optimization performance while requiring less private device-level information. It also outperformed the non-coordinated baseline in critical load served, restoration speed, and efficient use of backup energy.

The results show that resilience is not created by a single resource class alone. Stationary batteries provide fast local support, flexible loads reduce emergency demand, EVs extend backup capability, and switching actions reconnect feasible feeder sections. When these actions are coordinated, they reinforce each other and reduce the risk of infeasible restoration. When they are operated independently, available support may remain stranded or may be applied at the wrong location and time.

Future research should extend the model to include communication failures, uncertain customer participation, repair-crew routing, market compensation, and protection coordination during islanded operation. Additional validation on larger feeders and real outage data would strengthen operational deployment. The framework can also be expanded to include learning-based forecasts of EV availability and hazard evolution. These extensions would move multi-agent resilience coordination closer to practical real-time use in active distribution grids.

Acknowledgements

None

Conflict of interest

None

Financial support

None

Ethics statement

None

Received: 14 Sep 2025

Revised: 21 Oct 2025

Accepted: 29 Nov 2025

Published online: 20 March 2026

Rights and permissions

Open Access The author(s) retain copyright. This article is licensed under the Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License. It may be shared and adapted for non-commercial purposes with appropriate attribution, an indication of changes, and distribution of adaptations under the same license. Third-party material may be subject to separate terms identified in its credit line. View the license at <https://creativecommons.org/licenses/by-nc-sa/4.0/>.

References

- Mujjini F, Betts TR, Blanchard RE. Evaluation of power systems resilience to extreme weather events: A review of methods and assumptions. *IEEE Access*. 2023;11:87279-96.
- Liu N, Yu X, Wang C, Li C, Ma L, Lei J. Energy-sharing model with price-based demand response for microgrids of peer-to-peer prosumers. *IEEE Trans Power Syst*. 2017;32(5):3569-83.
- Olivella-Rosell P, Bullich-Massagué E, Aragüés-Peñalba M, Sumper A, Ottesen SØ, Vidal-Clos JA, et al. Optimization problem for meeting distribution system operator requests in local flexibility markets with distributed energy resources. *Appl Energy*. 2018;210:881-95.
- Gong H, Ionel DM. Improving the power outage resilience of buildings with solar PV through the use of battery systems and EV energy storage. *Energies*. 2021;14(18):5749.
- Ma S, Li S, Wang Z, Qiu F. Resilience-oriented design of distribution systems. *IEEE Trans Power Syst*. 2019;34(4):2880-91.
- Najafi J, Peiravi A, Guerrero JM. Power distribution system improvement planning under hurricanes based on a new resilience index. *Sustain Cities Soc*. 2018;39:592-604.
- Prabawa P, Choi DH. Multi-agent framework for service restoration in distribution systems with distributed generators and static/mobile energy storage systems. *IEEE Access*. 2020;8:51736-52.
- Charbonnier F, Morstyn T, McCulloch MD. Scalable multi-agent reinforcement learning for distributed control of residential energy flexibility. *Appl Energy*. 2022;314:118825.

Qiu D, Ye Y, Papadaskalopoulos D, Strbac G. Scalable coordinated management of peer-to-peer energy trading: A multi-cluster deep reinforcement learning approach. *Appl Energy*. 2021;292:116940.

Liu S, Vlachokostas A, Kontou E. Leveraging electric vehicles as a resiliency solution for residential backup power during outages. *Energy*. 2025;318:134613.

Baghali S, Guo Z, Wei W, Shahidehpour M. Electric vehicles for distribution system load pickup under stressed conditions: A network equilibrium approach. *IEEE Trans Power Syst*. 2022;38(3):2304-17.

Churchill M, Monroe J, Bristow D, Crawford C. Using electric vehicles to enhance power outage resilience—An agent-based modeling approach. *Heliyon*. 2024;10(11):e32104.

Wang Y, Qiu D, He Y, Zhou Q, Strbac G. Multi-agent reinforcement learning for electric vehicle decarbonized routing and scheduling. *Energy*. 2023;284:129335.

Lyu C, Jia Y, Xu Z. Fully decentralized peer-to-peer energy sharing framework for smart buildings with local battery system and aggregated electric vehicles. *Appl Energy*. 2021;299:117243.

Azizivahed A, Arefi A, Ghavidel S, Shafie-Khah M, Li L, Zhang J, et al. Energy management strategy in dynamic distribution network reconfiguration considering renewable energy resources and storage. *IEEE Trans Sustain Energy*. 2019;11(2):662-73.

Gao Y, Wang W, Shi J, Yu N. Batch-constrained reinforcement learning for dynamic distribution network reconfiguration. *IEEE Trans Smart Grid*. 2020;11(6):5357-69.

Shi Q, Li F, Dong J, Olama M, Wang X, Winstead C, et al. Co-optimization of repairs and dynamic network reconfiguration for improved distribution system resilience. *Appl Energy*. 2022;318:119245.

Qin C, Zeng Y, Zhong C, Liu J. Enhancing distribution system resilience against extreme disasters considering sequential action of multi-type switches. *Int J Electr Power Energy Syst*. 2024;155(3):109530.

Zhang C, Wu J, Zhou Y, Cheng M, Long C. Peer-to-Peer energy trading in a Microgrid. *Appl Energy*. 2018;220:1-2.

Wang Y, Rousis AO, Strbac G. Resilience-driven optimal sizing and pre-positioning of mobile energy storage systems in decentralized networked microgrids. *Appl Energy*. 2022;305:117921.

Wang Y, Qiu D, Strbac G. Multi-agent deep reinforcement learning for resilience-driven routing and scheduling of mobile energy storage systems. *Appl Energy*. 2022;310:118575.

Charbonnier F, Morstyn T, McCulloch MD. Coordination of resources at the edge of the electricity grid: Systematic review and taxonomy. *Appl Energy*. 2022;318:119188.

Zeng L, Qiu D, Sun M. Resilience enhancement of multi-agent reinforcement learning-based demand response against adversarial attacks. *Appl Energy*. 2022;324:119688.

Bahrami S, Chen YC, Wong VW. Dynamic distribution network reconfiguration with generation and load uncertainty. *IEEE Trans Smart Grid*. 2024;15(6):5472-84.

Ghasemi S, Moshtagh J. Distribution system restoration after extreme events considering distributed generators and static energy storage systems with mobile energy storage systems dispatch in transportation systems. *Appl Energy*. 2022;310:118507.

Zhou ZC, Wu Z, Jin T. Deep reinforcement learning framework for resilience enhancement of distribution systems under extreme weather events. *Int J Electr Power Energy Syst*. 2021;128:106676.

Yang X, Zhou Z, Zhang Y, Liu J, Wen J, Wu Q, et al. Resilience-oriented co-deployment of remote-controlled switches and soft open points in distribution networks. *IEEE Trans Power Syst.* 2022;38(2):1350-65.

Malekkhani Z, Ranjbar M. Optimal scheduling of smart home appliances with a stochastic power outage: A two-stage stochastic programming approach. *Sustain Energy Grids Netw.* 2024;40:101564.