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Research Article

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Posted Date: September 21st, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10611679/v1>

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Additional Declarations: No competing interests reported.

Multi-objective graph partitioning-based two-stage planning of agriculture-PV-storage systems in rural distribution networks

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Abstract

This paper proposes a two-stage cooperative planning method for agriculture-photovoltaic-storage resources in rural distribution networks with high-penetration distributed photovoltaics (PV). In the first stage, the distribution network is partitioned into virtual power plants (VPPs) by a multi-objective graph partitioning model that jointly considers electrical distance, load similarity, geographical compactness, and voltage security. In the second stage, load devices inside each VPP are clustered by multi-feature K-means, and a capacity-operation co-optimization model is established to maximize life-cycle net present value while improving voltage quality and local PV consumption. After weighted normalization and standard linearization of the discrete planning decisions, the resulting optimization subproblems are solved by a branch-and-bound procedure. A case study on a rural distribution network in North China shows that the proposed scheme increases net present value by 87.7% and 20.2% compared with unpartitioned allocation and partitioned uniform allocation, respectively. It also raises the PV self-consumption rate to 90.2%, reduces the network loss rate to 4.1%, lowers voltage deviation by 51.0%, and decreases annual voltage-limit violations by 69.4%. The results demonstrate that coordinated partitioning, siting, sizing, and operation can improve economic performance, renewable-energy accommodation, and operational robustness.

Keywords: Rural distribution network; Virtual power plant; Agriculture-PV-storage system; Multi-objective graph partitioning; Capacity-operation co-optimization; Voltage quality

1 Introduction

Under the global energy transition and carbon-neutrality targets, rural distribution networks are becoming important carriers for distributed renewable generation. Agriculture-PV-storage integration can improve land-use efficiency and rural energy benefits by coordinating agricultural production, PV generation, and storage operation. Recent agrivoltaic studies show that land use, crop production, PV output, and system operation should be considered jointly for practical agriculture-PV deployment [1, 2, 3, 4]. However, high-penetration distributed PV may still cause voltage violations, reverse power flow, network losses, and temporal-spatial mismatch between generation and rural loads. Recent studies on rural-network hosting capacity, PV integration, and distributed energy resources indicate that voltage quality, uncertainty, storage siting, and operation should be coordinated at the system level [5, 6, 7, 8, 9, 10].

Existing studies can be grouped into three streams. Agrivoltaic research mainly focuses on feasibility assessment and project-level optimization [1, 2, 3, 4]. VPP studies have addressed aggregation, operation planning, market participation, and wind-solar-storage coordination [11, 12, 13, 14, 15, 16], but many assume predefined aggregation boundaries. Distribution-network planning and partitioning studies have considered source-load coordination, electrical distance, PV-storage allocation, community detection, and graph-based network division [9, 10, 17, 18, 19, 20]. Nevertheless, network partitioning, capacity allocation, and operation scheduling are still often optimized separately.

Three gaps can therefore be identified. First, rural energy-demand structures, such as irrigation, breeding, and residential loads, are not sufficiently represented. Second, the coupling among VPP partitioning, PV-storage siting, sizing, and operation is still weak. Third, a tractable planning framework is needed to connect macro-level network partitioning with micro-level resource allocation while keeping the engineering interpretation clear.

To address these gaps, this paper develops a two-stage cooperative planning model for agriculture-PV-storage systems based on multi-objective graph partitioning. The main contributions are: (1) a partition-then-optimize framework linking VPP partitioning with capacity-operation optimization; (2) a graph-partitioning model integrating electrical distance, load similarity, geographical compactness, and voltage security; and (3) a cluster-based PV-storage allocation model that considers economic performance, voltage quality, and PV accommodation inside each VPP.

2 Two-stage optimization planning model

To coordinate agriculture-PV-storage resources in rural distribution networks, a two-stage model is established. The first stage partitions the network into VPPs according to electrical topology and geographical information. The second stage clusters internal load devices and determines PV-storage capacity and activation decisions within each VPP.

2.1 Upper-level VPP partitioning objectives and constraints

2.1.1 VPP partitioning objective

The upper-level partitioning model divides the rural distribution network into VPPs that are geographically compact, electrically coherent, and reasonably balanced in scale. These VPPs provide regional planning units for subsequent distributed-resource allocation, as expressed in Eq. (1).

$$\min F = \alpha \sum_{k=1}^{K_{max}} [\beta \cdot \sum_{i=1}^{n_b} y_{i,k} \cdot \bar{d}_i + \gamma \cdot \sum_{i=1}^{n_b} y_{i,k} \cdot d_i^{source}] \cdot \sum_{i=1}^{n_b} y_{i,k} / \delta + \eta \cdot \sum_{k=1}^{K_{max}} z_k + \theta \sum_{k=1}^{K_{max}} \sum_{i=1}^{n_b} y_{i,k} \cdot \bar{d}_i \quad (1)$$

where $\alpha, \eta, \theta, \beta, \gamma, n_b, K_{max}, y_{i,k}, i, k, d_i, \bar{d}_i, source, n_k, \delta, z_k, k$ where the weighting, distance, assignment, scale, and activation variables follow the definitions in Table 1.

2.1.2 VPP partitioning constraints

The partitioning process must satisfy the following rules: each node is assigned to only one VPP; each VPP contains at most one grid-connection node; the number of nodes in each VPP remains within a reasonable range; and the total number of activated VPPs is bounded to balance operational flexibility and management complexity.

The following electrical operating constraints are further considered.

(1) Power-balance constraint

At each time period, the injected power of each VPP equals the sum of nodal loads inside the VPP, as shown in Eq. (2).

$$P_{inj}(t, 1, k, sea) = \sum_{i=1}^{n_b} y_{i,k} \cdot P_{load}(i, t, sea) \quad (2)$$

where $P_{inj}(t, 1, k, sea)$ is the injected power of the grid-connection node in VPP k at time t and season sea ; $P_{load}(i, t, sea)$ is the load power of node i at time t and season sea .

(2) Voltage-security constraint

To guarantee voltage quality, nodal voltages must remain within the allowable range. The simplified voltage-estimation model is given in Eqs. (3) and (4).

$$V_{i,t,k,sea} = V_0^2 - \lambda \cdot y_{i,k}, \forall i \in S \quad (3)$$

$$V_{min}^2 \leq V_{i,t,k,sea} \leq V_{max}^2, \forall i \in S \quad (4)$$

$V^{\wedge}OV_{min}V_{max}\lambda$ where the voltage limits and voltage-drop coefficient are defined in Table 1.

Table 1 Parameter settings of the phase-I VPP partitioning model

Symbol	Meaning	Value
alpha	Network-loss weight	0.5 [18]
beta	Internal-distance weight	0.4 [18]
gamma	Grid-connection distance weight	0.6 [18]
eta	VPP-number weight	0.3 [18]
theta	Geographical compactness weight	0.2 [18]
delta	VPP scale-normalization coefficient	10 [11]
Nmax	Maximum number of nodes in one VPP	5 [11]
Kmin	Minimum number of VPPs	3 [11]
Kmax	Maximum number of VPPs	15 [11]
lambda	Voltage-drop coefficient	0.05 [22]

2.2 Lower-level capacity allocation and investment optimization model

In the second stage, load devices inside each VPP are clustered to form refined agriculture-PV-storage allocation units. A multi-feature K-means method is adopted to integrate geographical, electrical, and economic characteristics.

(1) Feature-vector construction

For each load device, a five-dimensional feature vector is constructed as shown in Eq. (5).

$$X = [x_{pos}^{(1)}, x_{pos}^{(2)}, x_{cap}, x_{volt}, x_{sens}], x_{pos}^{(1)}, x_{pos}^{(2)} \in R \quad (5)$$

where X is the load-device feature vector, including geographical coordinates (x, y) , load capacity P_{load} , voltage margin V_{margin} , and network-loss sensitivity S_{loss} .

(2) Weighted feature distance

A weighted Euclidean distance is used to measure the similarity among devices and balance the importance of different features, as shown in Eq. (6).

$$D(i, j) = \sum_{m=1}^5 \omega_m \cdot (x_{i,m} - x_{j,m})^2 \quad (6)$$

where ω_g , ω_c , ω_v , and ω_s are the weights of geographical position, capacity, voltage-related features, and sensitivity-related features, respectively.

The geographical weight gives priority to spatially close devices and facilitates centralized management. The capacity weight reflects the effect of load size. The voltage-feature weight gives priority to devices with limited voltage margin, and the sensitivity weight highlights devices whose configuration can more effectively improve system performance.

(3) Clustering objective

The K-means objective minimizes the within-cluster sum of squared errors so that devices in the same cluster have similar characteristics, as shown in Eq. (7).

$$\min \sum_{k=1}^K \sum_{sc \in C_{sc}} \|X_i - \mu_{sc}\|^2 \quad (7)$$

where S_k is the number of subclusters in VPP k and μ_{sc} is the centroid of subcluster sc .

2.2.1 Optimization objectives for capacity allocation and investment

(1) Comprehensive objective function

The second-stage model adopts a multi-objective optimization framework that considers economic performance, voltage quality, and renewable-energy accommodation, as shown in Eq. (8).

$$\max F = \omega_{NPV} \cdot \frac{NPV}{N_{base}} + \omega_V \cdot \frac{J_{voltage}}{V_{base}} + \omega_U \cdot \frac{J_{utilization}}{U_{base}} \quad (8)$$

where ω_{NPV} , ω_V , and ω_U are objective weights, and f_{NPV}^{base} , f_V^{base} , and f_U^{base} are the corresponding normalization benchmarks.

(2) Economic objective

The economic objective maximizes net present value (NPV), as expressed in Eq. (9).

$$\max NPV = -C^{inv} + \sum_{y=1}^Y \frac{CF_y}{(1+r)^y} \quad (9)$$

where C^{inv} is the total investment cost; CF_y is the cash flow in year y ; r is the discount rate; and Y is the project lifetime.

$$C^{inv} = \sum_{k=1}^K \sum_{sc=1}^{S_k} (c_k^{pv} \cdot x_{k,sc}^{pv} + c_{k,sc}^{ess,p} \cdot P_{k,sc}^{ess} + c_{k,sc}^{ess,e} \cdot E_{k,sc}^{ess} + c_{k,sc}^{acc} \cdot z_{k,sc} + c_{k,sc}^{load} \cdot C_{k,sc}^{load}) \quad (10)$$

where the PV, storage, connection-cost, activation, and cluster-load variables are defined in Table 2.

(3) Voltage-quality objective

The voltage-quality objective penalizes voltage deviation and voltage-limit violations while rewarding the improvement of key-node voltage, as shown in Eq. (11).

$$\min J_{voltage} = \lambda_{dev} \cdot \sum_{i=1}^{n_i} \sum_{t=1}^T \sum_{s=1}^{S_k} |V_{i,t,s} - V_{ref}| + \lambda_{viol} \cdot \sum_{i=1}^{n_i} \sum_{t=1}^T \sum_{s=1}^{S_k} I(V_{i,t,s} \notin [V_{min}, V_{max}]) + \lambda_{imp} \cdot \sum_{k=1}^K \sum_{i \in C_k} \max(0, V_i^{after} - V_i^{before}) \quad (11)$$

where the voltage penalty/reward coefficients and before-after voltage variables are defined in Table 2.

(4) Renewable-energy accommodation objective

The renewable-energy accommodation objective penalizes PV curtailment and rewards higher accommodation rates and storage-assisted accommodation, as shown in Eq. (12).

$$\max J_{utilization} = -J_{curtailment} + J_{rate} + J_{storage} \quad (12)$$

where J_{curt} , J_{rate} , and $J_{storage}$ are the PV-curtailment penalty, accommodation-rate reward, and storage-assisted accommodation reward, respectively, as defined in Eqs. (13)-(15).

$$J_{curtailment} = \lambda_{curt} \cdot \sum_{k=1}^K \sum_{sc=1}^{S_k} \sum_{t=1}^T \sum_{s=1}^{n_s} PV_{curtailment}(k, sc, t, s) \quad (13)$$

where λ_{curt} is the PV-curtailment penalty coefficient and $P_{curt}(k, sc, t, s)$ is the curtailed PV energy of subcluster sc in VPP k under season s and time t .

$$J_{rate} = \lambda_{rate} \cdot \sum_{k=1}^K \sum_{t=1}^T \sum_{s=1}^{n_s} U_{pv}(k, t, s) \quad (14)$$

where λ_{rate} is the accommodation-rate reward coefficient and $U_{pv}(k, t, s)$ is the PV accommodation rate of VPP k .

$$J_{storage} = \lambda_{store} \cdot \sum_{k=1}^K \sum_{sc=1}^{S_k} \sum_{t=1}^T \sum_{s=1}^{n_s} P_{ch}(k, sc, t, s) \cdot I(P_{pv}^{avail}(t) > P_{th}) \quad (15)$$

where $\lambda_{storage}$ is the storage-assisted accommodation reward coefficient and $P_{ch}(k, sc, t, s)$ is the charging power of subcluster sc in VPP k .

2.2.2 Constraints for capacity allocation and investment optimization

(1) Subcluster constraints

Each VPP must activate at least one subcluster, and the total number of activated subclusters is limited by the investment scale, as shown in Eqs. (16) and (17).

$$\sum_{sc=1}^{S_k} z_{k,sc} \geq 1, \forall k \quad (16)$$

$$\sum_{k=1}^K \sum_{sc=1}^{S_k} z_{k,sc} \leq S_{max} \quad (17)$$

where S_{max} is the maximum number of activated subclusters.

(2) PV installation constraint

PV installed capacity is constrained by subcluster load capacity and activation state, as shown in Eq. (18).

$$x_{k,sc}^{pv} \leq \rho \cdot C_{k,sc}^{load} \cdot z_{k,sc} \quad (18)$$

where $P_{sc,k}^{PV}$ is the PV installed capacity of subcluster sc in VPP k and ρ is the PV capacity coefficient.

(3) Energy-storage installation constraint

Storage power and energy capacities must satisfy technical limits and duration requirements, as shown in Eqs. (19) and (20).

$$P_{k,sc}^{ess} \leq \min(P_{ess}^{max}, \sigma \cdot C_{k,sc}^{load}) \quad (19)$$

$$\tau_{min} \cdot P_{k,sc}^{ess} \leq E_{k,sc}^{ess} \leq \tau_{max} \cdot P_{k,sc}^{ess} \quad (20)$$

where $P_{sc,k}^{max}$ is the maximum storage power capacity, and τ_{min} and τ_{max} are the minimum and maximum storage durations, respectively.

(4) Investment-budget constraint

The total investment and the investment of each VPP must not exceed their budget limits, as shown in Eqs. (21) and (22).

$$\sum_{k=1}^K \sum_{sc=1}^{S_k} (c_k^{pv} x_{k,sc}^{pv} + c_{k,sc}^{ess,p} P_{k,sc}^{ess} + c_{k,sc}^{ess,e} E_{k,sc}^{ess}) \leq B_{total} \quad (21)$$

$$\sum_{sc=1}^{S_k} (c_k^{pv} x_{k,sc}^{pv} + c_{k,sc}^{ess,p} P_{k,sc}^{ess} + c_{k,sc}^{ess,e} E_{k,sc}^{ess}) \leq B_{vpp} \quad (22)$$

where B_{total} and B_{vpp} denote the total investment budget limit and the single-VPP investment budget limit, respectively.

(5) Power-balance constraint

The system power-balance constraint accounts for grid purchase, grid sale, VPP generation, and VPP load, as shown in Eq. (23).

$$\sum_{k,sc} (P_{pv} + P_{dis}) - \sum_{k,sc} (P_{load} + P_{ch}) = P_{sell} - P_{buy} \quad (23)$$

where P_{sell} and P_{buy} denote power sold to and purchased from the main grid, respectively.

(6) Energy-storage operation constraint

The state-of-charge dynamics and charge-discharge power limits of the storage system are imposed to guarantee safe operation, as shown in Eqs. (24) and (25).

$$SOC(t) = SOC(t-1) + \eta_{ch} P_{ch}(t) - P_{dis}(t) / \eta_{dis} \quad (24)$$

$$SOC_{min} \cdot E_{ess} \leq SOC(t) \leq SOC_{max} \cdot E_{ess} \quad (25)$$

where $P_{ch}(t)$ and $P_{dis}(t)$ are charging and discharging power, and SOC_{min} and SOC_{max} are the minimum and maximum state of charge.

(7) Voltage-quality constraint

Nodal voltages are constrained within the allowable range, and voltage deviation and voltage-limit violation are calculated by Eqs. (26)-(28).

$$V_{min}^{sys} \leq V_i(t) \leq V_{max}^{sys} \quad (26)$$

$$V_{dev}(i,t) \geq |V_i(t) - V_{ref}| \quad (27)$$

$$V_{viol}(i,t) \geq I(V_i(t) < V_{min}^{sys}) + I(V_i(t) > V_{max}^{sys}) \quad (28)$$

where V_{min}^{sys} and V_{max}^{sys} are the lower and upper system voltage limits in p.u.

(8) Renewable-energy accommodation constraint

PV accommodation rate and curtailment are calculated according to Eqs. (29) and (30).

$$PV_{curtailment}(k,sc,t) \geq P_{pv}^{available}(k,sc,t) - P_{pv}^{used}(k,sc,t) \quad (29)$$

$$U_{pv}(k, t) = \frac{\sum_{sc} P_{pv}^{used}(k, sc, t)}{\sum_{sc} P_{pv}^{available}(k, sc, t)} \quad (30)$$

where $P_{pv,available}(k, sc, t)$ and $P_{pv,used}(k, sc, t)$ denote available PV power and actually utilized PV power at time t . The second-stage model parameters are listed in Table 2.

Table 2 Parameter settings of the phase-II VPP capacity allocation and investment optimization model

Symbol	Meaning	Value
lambda_dev	Voltage-deviation penalty coefficient	100 yuan/p.u. [22]
lambda_viol	Voltage-violation penalty coefficient	1000 yuan/event [22]
lambda_imp	Key-node improvement reward coefficient	500 yuan/0.01 p.u. [22]
lambda_curt	PV-curtailment penalty coefficient	50 yuan/kWh [22]
lambda_rate	Accommodation-rate reward coefficient	20 yuan/% [23]
lambda_store	Storage-assisted accommodation reward coefficient	10 yuan/kW [23]
P_th	Available PV threshold	0.3 [23]
c_kpv	Unit PV cost	3710 yuan/kW [24]
c_ess,p	Storage power cost	500 yuan/kW [24]
c_acc	Connection cost coefficient	100 yuan/kW [24]
c_line	Line/access distance cost coefficient	50000 yuan/km [24]
Smax	Maximum number of activated subclusters	12 [22]
rho	PV capacity coefficient	1.5 [24]
sigma	Storage power coefficient	0.5 [24]
tau_min	Minimum storage duration	2 h [24]
tau_max	Maximum storage duration	6 h [24]

2.3 Solution method and procedure

The proposed method contains three steps. First, seasonal load and PV-output data are clustered into weighted typical scenarios. Second, the first-stage VPP partitioning objective is normalized and weighted, with the weights of electrical distance, load-characteristic similarity, and voltage quality set to 0.4, 0.3, and 0.3, respectively. Third, the weighted objectives and engineering constraints are transformed into tractable mixed-integer planning subproblems; binary assignment and activation variables are handled by branch-and-bound, and continuous operating variables are solved under the linearized constraints [21]. The first stage determines VPP boundaries, and the second stage determines PV-storage allocation and operation schedules.

The overall solution procedure is shown in Fig. 1.

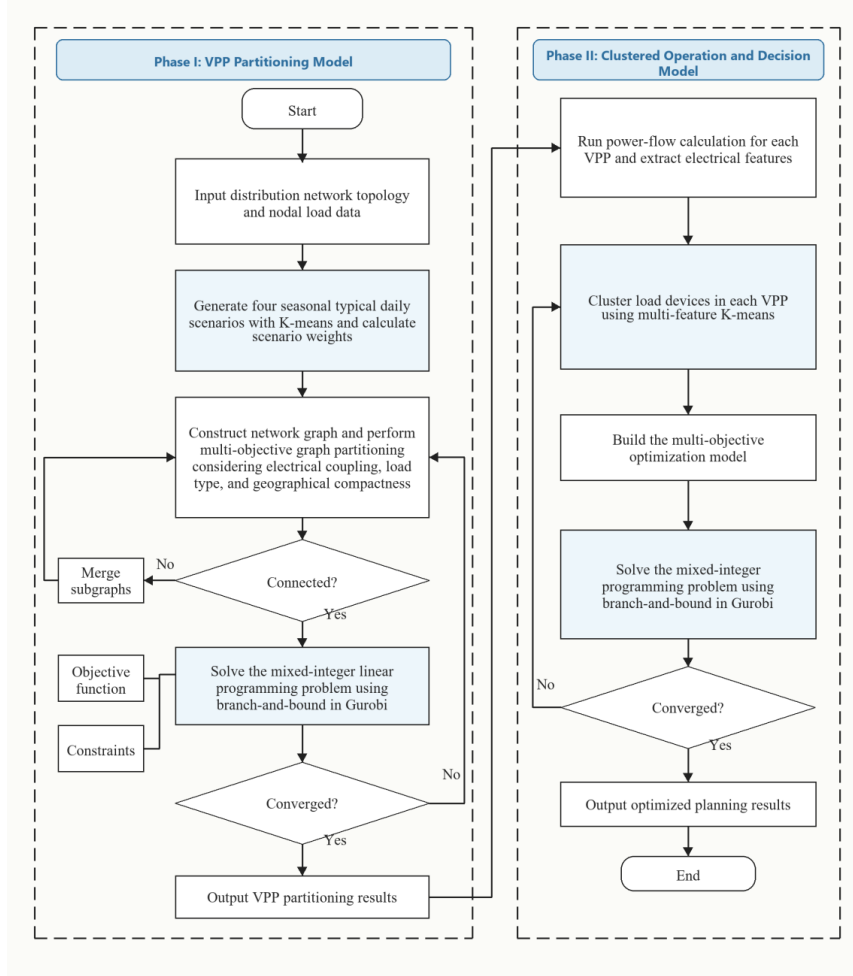


Fig. 1 Two-stage collaborative planning framework for PV-storage resources in rural distribution networks

3 Case study

3.1 Case data

To verify the effectiveness of the proposed two-stage agriculture-PV-storage cooperative planning model, a typical rural distribution network in North China is selected as the study system. The area contains three core load types: residential living, agricultural irrigation, and livestock breeding. The distribution network covers approximately 25 km² and contains 33 nodes. Annual meteorological data, load data, and network parameters are collected to construct the simulation case.

Figure 2 shows the network topology of the rural distribution network. The system has a radial structure with one power source and 32 load nodes. Branch connections consider both geographical distribution and electrical characteristics, forming a reasonable power-supply network.

Economic indicator (10 ⁴ yuan)	Group 1	Group 2	Group 3
Net present value	105.8	165.2	198.6

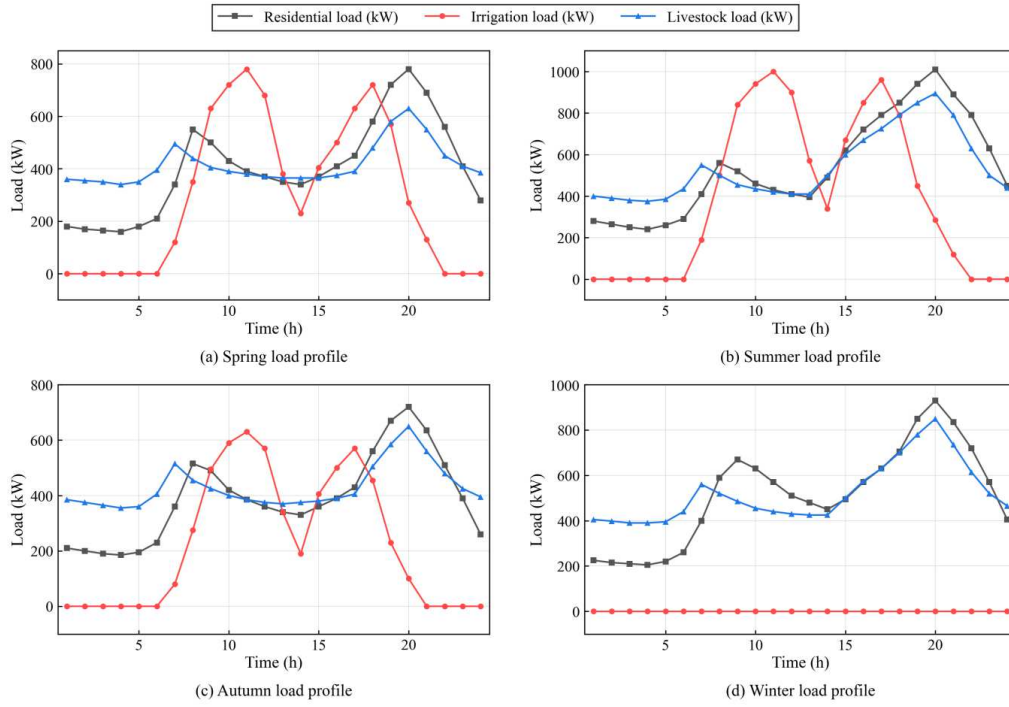


Fig. 3 Seasonal load profiles

Table 4 Technical comparison metrics

Technical indicator	Group 1	Group 2	Group 3
PV self-consumption rate (%)	68.5	86.3	90.2
PV curtailment rate (%)	30.2	12.5	9.3
Network loss rate (%)	6.8	4.8	4.1
Voltage deviation (p.u.)	0.051	0.032	0.025
Voltage-limit violations (events/year)	72	31	22
Annual carbon emission reduction (t CO ₂)	298	428	472

The technical results in Table 4 show that Group 3 performs best in all key indicators: the PV self-consumption rate is the highest (90.2%), while the curtailment rate (9.3%) and network loss rate (4.1%) are the lowest. Voltage deviation decreases to 0.025 p.u., annual voltage-limit violations decrease to 22 events, and annual carbon emission reduction reaches 472 t CO₂. These results verify the comprehensive advantages of the proposed cooperative planning model in renewable-energy accommodation, voltage-quality improvement, network-loss reduction, and environmental performance.

3.2.2 VPP partitioning and cluster results

Figure 4 shows the final result of the first-stage VPP partitioning. The original distribution network is divided into five relatively independent VPPs by the multi-objective graph partitioning algorithm, and each VPP has similar load characteristics and close electrical connections.

The partitioning result indicates that VPP 1 mainly contains residential loads in the town center. VPP 2 and VPP 3 mainly contain agricultural irrigation loads in the eastern and southern farmland areas. VPP 4 mainly contains livestock-breeding loads in the northwestern hilly area. VPP 5 is a mixed-load VPP that provides connection and balancing functions. This partitioning considers geographical distribution, load characteristics, and electrical distance, thereby providing a sound basis for second-stage optimization.

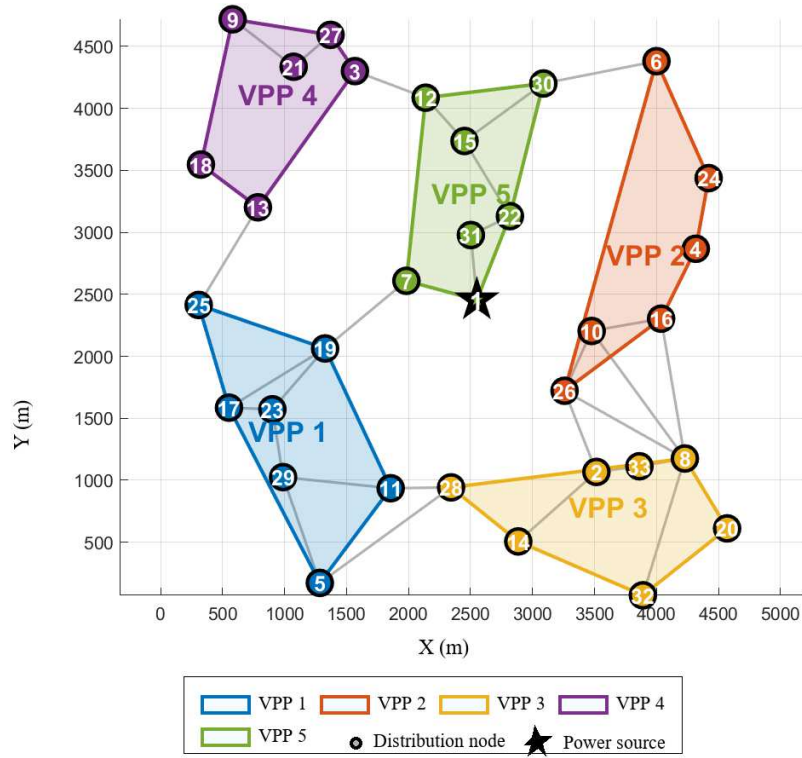


Fig. 4 VPP partitioning results

Figure 5 shows the clustering results inside the VPPs. Within each VPP, load devices are further clustered according to electrical and geographical features, forming more refined allocation units.

The second-stage clustering results form two to four subclusters inside each VPP. These subclusters are highly consistent in terms of load density, voltage level, and electrical distance. For example, in VPP 2, which is dominated by agricultural irrigation, the multi-feature K-means method divides the irrigation load into three subclusters: a high-efficiency irrigation area with high load density and regular electricity use, a traditional irrigation area with larger load fluctuation, and a supplementary irrigation area with lower load but higher voltage-quality requirements.

This fine-grained clustering provides four advantages. First, it supports precise resource allocation instead of average investment. Second, it enables differentiated operation strategies for residential, agricultural, and livestock loads. Third, it improves investment efficiency by activating key subclusters rather than investing uniformly across the whole network. Fourth, it improves scalability because new load nodes can be connected and configured according to the cluster structure.

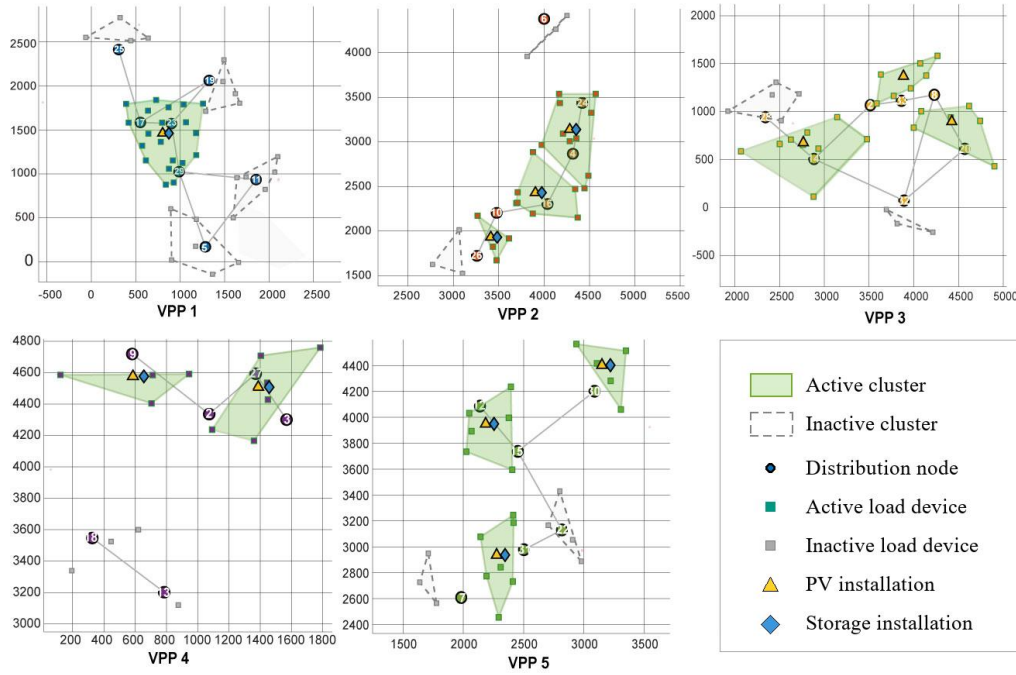


Fig. 5 Cluster activation and PV-storage siting results

3.3 Operation-result analysis

3.3.1 Power-balance analysis

Figure 6 compares the spring power balance of the three schemes. Compared with Groups 1 and 2, Group 3 schedules storage charging during low-load hours, reduces PV curtailment from 30.2% and 12.5% to 9.3%, and limits the evening purchased-power peak to about 300-400 kW. These results show that coordinated PV-storage configuration and operation improve power-balance smoothing, curtailment suppression, and peak purchased-power control.

3.3.2 Voltage-quality analysis

Figure 7 shows the average network voltage fluctuation on typical summer and winter days, revealing clear differences among the three schemes.

In summer, Group 1 experiences voltage-limit violations during high PV output at noon, with the maximum voltage reaching 1.068 p.u.; it also suffers from low voltage during the evening load peak, with the minimum voltage reaching 0.938 p.u. Group 2 alleviates these problems through partitioning, but the noon voltage of 1.045 p.u. remains close to the upper limit. Group 3 keeps the voltage within the safe range of 0.972-1.032 p.u. throughout the day by combining appropriate VPP partitioning, key-node storage configuration, and coordinated operation.

In winter, Group 1 has low-voltage problems during morning and evening load peaks, with the minimum voltage reaching 0.923 p.u. Group 2 improves the situation but remains close to the lower limit. Group 3 supports voltage through timely storage discharge and optimized scheduling, maintaining the voltage within 0.955-1.018 p.u. over the whole day.

Annual statistics show that Group 3 reduces voltage deviation by 51.0% and annual voltage-limit violations by 69.4% compared with Group 1, indicating a significant improvement in voltage quality.

To evaluate robustness against electricity-price fluctuation, a comparative Group 4 is introduced. Group 4 uses the same capacity configuration as Group 3 but prohibits energy mutual support among VPPs; all deficits and surpluses are balanced only through transactions with the main grid. Comparing Groups 3 and 4 isolates the contribution of coordinated VPP operation to economic robustness.

The grid-purchase price is selected as the sensitivity factor. Under the same capacity configuration, Group 3 has a sensitivity coefficient of 0.30, whereas Group 4 has a coefficient of 0.59. This indicates that inter-VPP coordinated operation buffers electricity-price shocks more effectively by reducing dependence on high-price grid purchases.

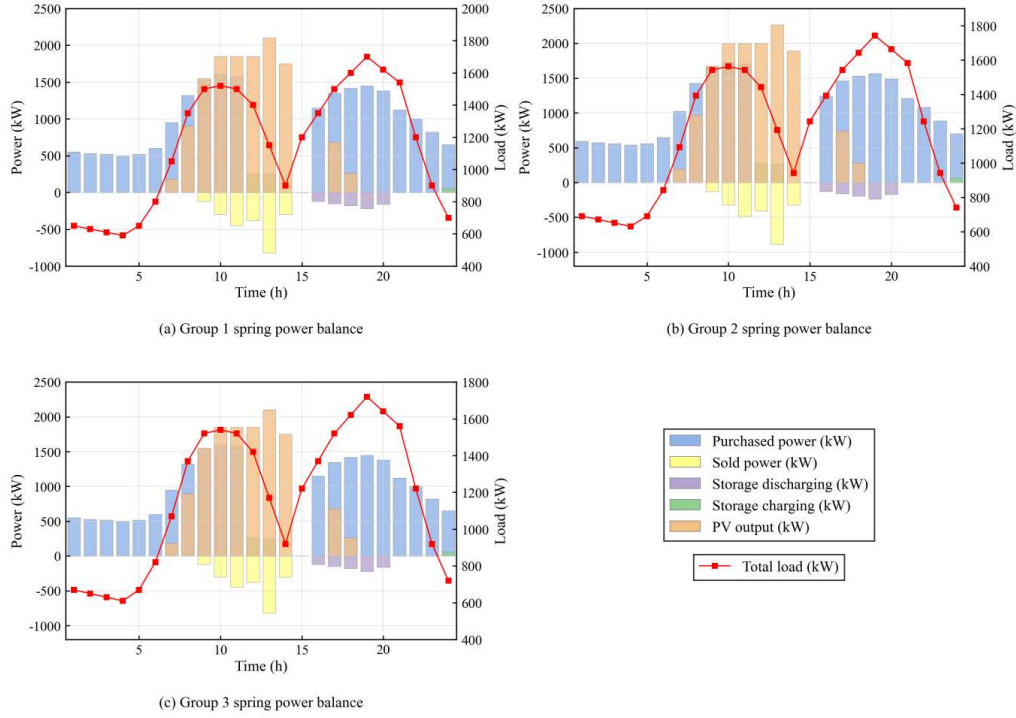


Fig. 6 Spring power balance comparison

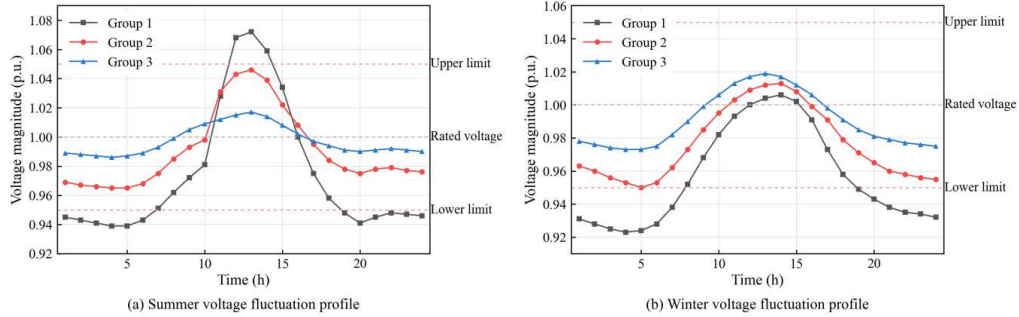


Fig. 7 Voltage fluctuation profiles

4 Conclusions

This paper proposes a two-stage agriculture-PV-storage cooperative planning model based on multi-objective graph partitioning for rural distribution networks with high-penetration renewable energy. In the first stage, the network is reasonably divided into multiple VPPs by integrating electrical, load, and geographical information. In the second stage, multi-feature clustering and cooperative optimization are used inside each VPP to determine PV-storage capacity and operation strategies.

The main conclusions are as follows.

(1) The proposed partition-then-optimize framework effectively reduces system complexity and realizes full-process coordination from macro-level structural partitioning to micro-level resource sizing, providing a systematic method for distribution-network planning with diversified distributed resources.

(2) The coordinated optimization significantly improves overall system performance. Compared with unpartitioned allocation and partitioned uniform allocation, the proposed method improves economic performance, PV self-consumption, voltage quality, and network-loss reduction, verifying the necessity

of integrated network-source-storage-load planning.

(3) The sensitivity analysis shows that inter-VPP coordinated operation can substantially reduce sensitivity to electricity-price fluctuation under the same capacity configuration, demonstrating the importance of optimized operation for investment resilience and system robustness.

The proposed model provides a decision-support tool for the low-carbon upgrading of rural distribution networks and offers a practical planning approach for distribution networks with high-penetration distributed renewable energy. Future work will consider source-load uncertainty and explore trading strategies for VPP participation in electricity markets.

Acknowledgements

The authors thank the anonymous reviewers and editors for their constructive comments.

Author contributions

Ruhang Xu: conceptualization, methodology, modelling, simulation, writing-original draft. Chuanbin Zhao: supervision, methodology, writing-review and editing. Yonghua Wang: data curation, validation, and engineering interpretation.

Funding

This work was supported by the State Grid Headquarters Science and Technology Project (5218A023000N).

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

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