



Research article

Small hydropower cluster partitioning based on multidimensional feature network model and community detection algorithm

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Abstract: The disorderly integration of small hydropower plants into distribution networks can easily lead to problems such as curtailed power generation, voltage overshooting, and difficulty in regulation. Therefore, it is crucial to study small hydropower clustering methods for regional coordinated control and optimal scheduling. Traditional methods often rely on geographic location or administrative divisions for clustering, but they struggle to simultaneously account for multidimensional characteristics such as electrical characteristics, operational characteristics, and spatial distribution of power plants, thus failing to meet the optimized regulation requirements of distribution networks. To this end, this paper introduces complex network analysis methods and proposes a small hydropower cluster partitioning method based on the multidimensional feature network model and the community detection algorithm. Hydropower stations are modeled as network nodes, different coupling dimensions are mapped into weighted edges, and the similarity network fusion (SNF) method is employed to achieve multidimensional feature fusion. Furthermore, a hydropower coordination index is defined to quantify cluster quality in multiple spatiotemporal scenarios. Clustering is then performed using the Louvain community detection algorithm. Small hydropower stations in the Meijiang River Basin, Zunyi, China, were selected as the case study. The results show that the proposed method can improve the physical interpretability of the partitioning results and provide an effective solution for the coordinated control and optimized regional scheduling of small hydropower stations.

Keywords: multidimensional characteristic network model; Louvain algorithm; partitioning of small

1. Introduction

Driven by the global transition toward low-carbon energy systems, small hydropower has become an important component of regional power systems due to its renewable nature and low emissions [1]. However, due to factors such as inadequate communication infrastructure, geographically dispersed locations, and complex river basin structures, the majority of small hydropower stations are still connected to the grid in a standalone mode, lacking effective coordinated dispatch mechanisms. This has led to frequent occurrences of issues such as wasted hydropower, local voltage fluctuations, and inefficient operational control [2]. To address these issues, there is an urgent need to establish a coordinated operation mechanism for small hydropower plants at the system level [3]. The accurate characterization of external bidding functions of virtual power plants can support efficient non-iterative market participation of aggregated distributed resources [4]. By considering the operational characteristics, spatial distribution, and grid connection characteristics of small hydropower plants, research should be conducted on the planning of coordinated clusters of small hydropower plants to enhance their controllability on the generation side and their ability to participate in the electricity market [5].

Existing studies have employed clustering algorithms to group distributed energy resources based on dimensions such as geographic location, spatial correlation, and source distribution characteristics [6,7]. The objective is to address the uncertainty associated with distributed energy resources. Such methods typically rely on the similarity of power plant attributes and use distance metrics to form groups, making them suitable for the initial aggregation of large-scale clusters. However, traditional clustering algorithms struggle to handle cross-dimensional features among multi-source data. In particular, they face challenges in uniformly modeling heterogeneous data such as geographic information, power output sequences, and electrical topologies, which limits their ability to identify collaborative clusters of power plants [8,9]. In addition, forecasting-oriented studies have been conducted for geographically distributed renewable stations to improve the perception of temporal output uncertainty under heterogeneous data conditions [10].

Complex network theory and community detection algorithms offer new approaches to address the aforementioned issues. By modeling distributed energy resources and load clusters as network structures and applying community partitioning methods, researchers have identified topological correlations and functional modules at the network level, thereby enabling the functional partitioning of power grid systems [11,12]. Existing research on complex networks has primarily focused on internal structural analysis of distribution grids, such as fault detection and identification [13], reactive power partitioning [14,15], and identification of critical nodes/edges and transmission sections [16]. In [17], a method that combines the k-means algorithm with evolutionary algorithms was proposed for power grid partitioning that integrates electrical distance with multi-attribute objectives. In [18], a reactive power transmission-weighted graph was constructed to evaluate inter-node relationships by comprehensively considering both electrical distance and reactive power flow weights. On the other hand, a functional clustering method based on electrical coupling strength by extending the weighted adjacency matrix and redefining the modularity function was proposed in [19]. In [20], metrics such as PV reactive power regulation capacity, internal coupling degree, and cross-subnetwork coupling degree were introduced, while taking electrical topology into account to achieve clustering that meets grid control requirements. Furthermore, security-region-based methods

have been explored to enhance the resilient operation of distributed energy systems under extreme events [21,22]. However, complex network analysis methods still have significant shortcomings in the context of small hydropower:

- 1) Due to their large numbers and dispersed distribution, small hydropower stations exhibit significant heterogeneity and dynamism, with their generation capacity and operational status influenced by multiple factors such as geographical location, hydrometeorological conditions, seasonal variations, grid topology, and power flow patterns [23]. Traditional single-feature modeling methods struggle to effectively capture the potential synergistic relationships between these stations.
- 2) In complex network modeling, traditional adjacency matrices take the form of binary 0–1 values, indicating only the presence or absence of connections; they are unable to capture physical properties such as the strength of electrical coupling. Furthermore, modeling methods for networks involving different types of nodes and edges remain underdeveloped, and there is a lack of research on the integration of multidimensional heterogeneous networks, making it difficult to fully reflect the complex coupling characteristics between hydropower stations.
- 3) Most current network partitioning algorithms evaluate the quality of partitioning results based on the modularity Q-function; however, as this method relies primarily on network structure to assess quality, it struggles to reflect the interdependencies between power stations in small-scale hydropower scenarios across electrical, operational, and geographical dimensions, thereby limiting its applicability.

Therefore, to enhance the practicality of small hydropower clustering, there is an urgent need to explore methods for constructing network models that integrate multidimensional features and to achieve high-quality identification and classification of distributed small hydropower plants. To this end, this paper proposes a method for small hydropower clustering based on a multidimensional feature network model and a community detection algorithm. Specifically, a network model for small hydropower stations that integrates multidimensional features and possesses dynamic evolution capabilities is first constructed. Building upon this, the hydropower coordination index $Q^{\text{hydro}}(t)$ is proposed, and clustering of small hydropower stations is achieved by combining this with an improved Louvain algorithm. Finally, simulation verification is conducted using nine typical small hydropower stations in the Meijiang River basin in Zunyi, China, as a case study.

2. Construction of the multidimensional feature network model for small hydropower

2.1. Fundamental principles and modeling process

As a typical complex network, the power system is characterized by a complex topological structure, heterogeneous node attributes, and dynamic operational states [24]. Constructing a complex network model can effectively reveal its internal structural patterns and coupling characteristics [25]. Therefore, in response to the challenges posed by the dispersed layout and complex coupling relationships of small hydropower stations, this paper proposes a method for constructing a network model of small hydropower stations that integrates multidimensional features and possesses dynamic evolution capabilities. The basic procedure is as follows:

- 1) Each hydropower station is modeled as a node in the network model, with different types of coupling relationships mapped as weighted edges between nodes, where the edge weight W_{ij} represents the coupling strength across various dimensions.

- 2) Based on the principles of electrical coupling, similar operational characteristics, and geographical proximity, three types of network edge weights are constructed: the electrical coupling edge weight $W_{ij}^{(elec)}$, the coordinated operation edge weight $W_{ij}^{(corr)}$, and the geographical distribution edge weight $W_{ij}^{(geo)}$. These weights are used to characterize the coupling relationships among hydropower stations from the electrical, operational, and spatial perspectives, respectively. The process for constructing a multidimensional feature network model for small hydropower stations is shown in Figure 1.
- 3) The similarity network fusion (SNF) method is employed to adaptively fuse the aforementioned multidimensional edge weights, forming a fused similarity matrix W_{fused} and thereby deriving a multidimensional feature network model for small hydropower stations.

Building on this, a hydropower coordination index $Q^{hydro}(t)$ is proposed to quantify the synergy between any two hydropower stations under different spatio-temporal scenarios. Combined with an improved Louvain algorithm, this enables the identification and classification of small hydropower clusters.

2.2. Electrical coupling network

To overcome the limitations of traditional topology-based modeling methods, which are unable to capture electrical coupling relationships within power systems, this paper introduces an electrical distance metric based on voltage-reactive power sensitivity during the construction of electrical coupling network models. This method is based on Newton-Raphson power flow analysis. By extracting the submatrix from the Jacobian matrix that describes the relationship between voltage and reactive power, it quantifies the voltage response sensitivity between small hydropower nodes, thereby quantifying the strength of electrical coupling between nodes.

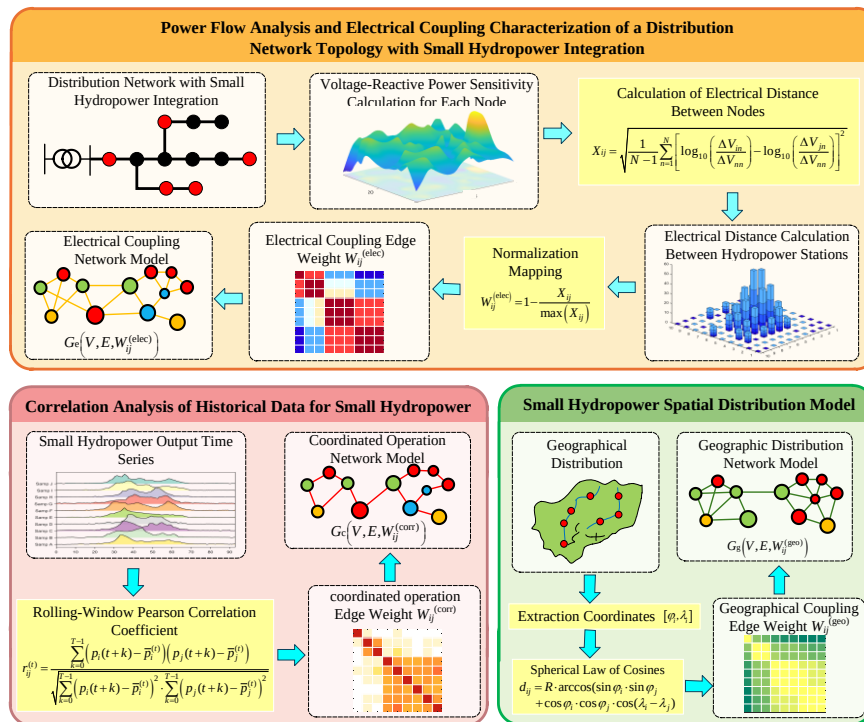


Figure 1. Construction process of the multidimensional feature network model for small hydropower stations.

The Jacobian matrix $\mathbf{J}$ in power flow analysis describes the partial derivative relationships between power and voltage magnitudes and phase angles, being expressed as follows:

$$\mathbf{J} = \begin{bmatrix} \partial P / \partial \theta & \partial P / \partial V \\ \partial Q / \partial \theta & \partial Q / \partial V \end{bmatrix} = \begin{bmatrix} \mathbf{J}_{11} & \mathbf{J}_{12} \\ \mathbf{J}_{21} & \mathbf{J}_{22} \end{bmatrix} \quad (1)$$

where P and Q denote the active and reactive power injection vectors, respectively; θ and V denote the bus voltage phase angle vector and voltage magnitude vector, respectively; ∂P , ∂Q , $\partial \theta$, and ∂V denote their corresponding incremental variations; and $\mathbf{J}_{11}$, $\mathbf{J}_{12}$, $\mathbf{J}_{21}$, and $\mathbf{J}_{22}$ denote the submatrices of the Jacobian matrix.

This paper focuses on the response of voltage to reactive power disturbances. The submatrix $\mathbf{J}_{22}$ is selected as the modeling basis, and its inverse is used to obtain the voltage-reactive power sensitivity S_{VQ} :

$$S_{VQ} = \partial V / \partial Q = \mathbf{J}_{22}^{-1} \quad (2)$$

where $\mathbf{J}_{22}^{-1}$ denotes the inverse of the Jacobian submatrix $\mathbf{J}_{22}$, representing the sensitivity relationship between voltage and reactive power.

In distributed energy cluster partitioning, the electrical distance between nodes is a key indicator for measuring their voltage control and power flow regulation capabilities. To characterize the electrical coupling relationship between nodes, the electrical distance factor K_{ij} is introduced, which is defined as the ratio of the voltage response at node j to its own response when a unit reactive power disturbance occurs at node i :

$$K_{ij} = \left| \lg \frac{S_{VQ,ji}}{S_{VQ,ij}} \right|, \quad i, j = 1, \dots, N \quad (3)$$

where $S_{VQ,ij}$ denotes the sensitivity of the voltage change at node j caused by a unit reactive power disturbance at node i ; $S_{VQ,ji}$ denotes the sensitivity of the voltage change at node j caused by its own disturbance; N denotes the total number of system nodes.

In the electrical coupling matrix constructed from K_{ij} , each node i corresponds to a row vector, which is used to describe its electrical coupling characteristics with other nodes:

$$\mathbf{K}_i = [K_{i1}, K_{i2}, \dots, K_{iN}] \quad (4)$$

Based on this, the electrical distance X_{ij} between node i and node j is defined as the Euclidean distance between the corresponding row vectors, which is used to measure the electrical connection tightness between small hydropower stations and other nodes in the power grid, that is:

$$X_{ij} = \|\mathbf{K}_i - \mathbf{K}_j\|_2 \quad (5)$$

Finally, to reflect this relationship in the network model, the electrical distance X_{ij} is mapped to the edge weight $W_{ij}^{(\text{elec})}$ of the electrical coupling network, which is used for constructing the network model from the perspective of electrical coupling, and the mathematical relationship is given as:

$$W_{ij}^{(\text{elec})} = 1 - \frac{X_{ij}}{\max(X_{ij})} \quad (6)$$

2.3. Coordinated operation network

To quantify the historical output behavior and coordinated operation capability among small hydropower units, this paper conducts correlation analysis based on historical operation data and constructs a coordinated operation network [26]. The Pearson correlation coefficient with a time sliding window is introduced to measure the dynamic correlation between power stations. For stations i and j , within a sliding window starting at time t with length T , the output correlation coefficient is defined as follows:

$$r_{ij}(t, T) = \frac{\sum_{k=0}^{T-1} (p_i(t+k) - \bar{p}_i^{(t)}) (p_j(t+k) - \bar{p}_j^{(t)})}{\sqrt{\sum_{k=0}^{T-1} (p_i(t+k) - \bar{p}_i^{(t)})^2 \cdot \sum_{k=0}^{T-1} (p_j(t+k) - \bar{p}_j^{(t)})^2}} \quad (7)$$

where $p_i(t+k)$ denotes the output of station i at time $t+k$, and $\bar{p}_i^{(t)}$ denotes its average output within the time window:

$$\bar{p}_i^{(t)} = \frac{1}{T} \sum_{k=0}^{T-1} p_i(t+k) \quad (8)$$

Based on this correlation metric, the edge weight $W_{ij}^{(\text{corr})}$ of the coordinated operation network can be constructed at each time t , and the mathematical relationship is given as:

$$W_{ij}^{(\text{corr})}(t, T) = |r_{ij}(t, T)| \quad (9)$$

2.4. Geographic distribution network

To achieve small hydropower cluster partitioning with strong spatial aggregation and high operational consistency, a geographic distribution network is constructed based on geographical distance to model the spatial distribution of small hydropower stations.

Let λ_i and φ_i denote the longitude and latitude of node i , respectively. The spherical law of cosines is adopted to calculate the geographical distance between any two nodes i and j , given as follows:

$$d_{ij} = R \cdot \arccos[\sin \varphi_i \cdot \sin \varphi_j + \cos \varphi_i \cdot \cos \varphi_j \cdot \cos(\Delta \lambda)] \quad (10)$$

where d_{ij} denotes the spherical distance between nodes i and j ; R denotes the Earth's radius, taken as 6371 km; and $\Delta \lambda = \lambda_i - \lambda_j$ denotes the longitude difference between the two nodes.

Furthermore, the geographical distance is mapped to the edge weight in the geographic distribution network model. The mapping relationship between the edge weight $W_{ij}^{(\text{geo})}$ and the distance d_{ij} is defined as:

$$W_{ij}^{(\text{geo})} = 1 - \frac{d_{ij}}{\max(d_{ij})} \quad (11)$$

where $\max(d_{ij})$ represents the maximum geographical distance between any two nodes in the studied network.

2.5. Multidimensional network fusion

Traditional feature fusion methods often struggle to effectively integrate multidimensional heterogeneous information while preserving the structural characteristics of each feature dimension. To address this issue, this paper introduces the SNF method to integrate the coupling relationships of small hydropower stations from different feature dimensions at the network level. The inputs of SNF are not the raw heterogeneous data themselves, but the three edge-weight matrices constructed. For each dimension, SNF first preserves the local neighborhood structure by constructing a local similarity matrix, and then iteratively updates the propagation matrix by incorporating information from the other dimensions. Through this cross-dimensional iterative propagation process, complementary similarity information can be gradually fused while the local structural characteristics of each dimension are retained [27]. The multidimensional network fusion process is as follows:

- 1) Each feature dimension is represented as an independent weighted network. The network models of small hydropower stations under different dimensions can be expressed as follows:

$$G^{(v)} = (V, E, W^{(v)}), \quad v = 1, \dots, M \quad (12)$$

where $V = \{V_1, V_2, \dots, V_n\}$ denotes the set of small hydropower station nodes; E denotes the set of edges with coupling relationships; $W^{(v)}$ denotes the network edge weight matrix under dimension v ; and M denotes the number of dimensions.

- 2) For the network edge weight matrix $W^{(v)}$ of each dimension, the local similarity matrix $S^{(v)}$ is constructed by retaining, so as to preserve the local neighborhood structure of each single-dimensional network and reduce the influence of weak connections.
- 3) The normalized propagation matrix $P^{(v)}$ of each dimension describes the similarity propagation process within the v -th network, which is calculated as:

$$P^{(v)} = (D^{(v)})^{-1} S^{(v)} \quad (13)$$

where $D^{(v)} = \text{diag}(\sum_j S_{ij}^{(v)})$ denotes the degree matrix, and $S_{ij}^{(v)}$ denotes the element value in the local similarity matrix $S^{(v)}$.

- 4) In each iteration, the propagation matrix of each dimension is updated to fuse information from other dimensions while retaining its own local structural characteristics, denoted as $P_{\text{new}}^{(v)}$:

$$P_{\text{new}}^{(v)} = S^{(v)} \cdot \left(\frac{1}{M-1} \sum_{u \neq v} P^{(u)} \right) \cdot (S^{(v)})^T \quad (14)$$

where $P^{(v)}$ denotes the current propagation matrix of the v -th dimension, and $\sum_{u \neq v} P^{(u)}$ denotes the information sources from all dimensions except the v -th dimension.

- 5) After multiple rounds of iteration, the results of all dimensions are fused to obtain the fused similarity matrix:

$$W_{\text{fused}} = \frac{1}{M} \sum_{v=1}^M P^{(v)} \quad (15)$$

The fused similarity matrix W_{fused} preserves local structural features while integrating complementary similarity information from different dimensions and can be used as the input model for the cluster partitioning algorithm.

2.6. Dynamic network model of small hydropower

In the preceding sections, network models of small hydropower stations were constructed separately from the electrical, operational, and geographical dimensions, and multidimensional feature fusion was achieved through SNF, thereby completing the static modeling of the multidimensional network of small hydropower. However, in actual operation, the output level, voltage response, and coupling relationships of small hydropower systems are affected by factors such as seasonal variation, water resource dispatch, and load changes, exhibiting dynamic time-varying characteristics. Traditional static network models are therefore difficult to reflect their dynamic processes.

As a possible extension of the above static multidimensional network method, a dynamic modeling strategy is further introduced to describe the time-varying operating characteristics of small hydropower systems. In this method, the continuous temporal evolution process is discretized into a series of time snapshots $\{G^{(v)}(t_1), G^{(v)}(t_2), \dots, G^{(v)}(t_z)\}$. On each snapshot graph, the multidimensional feature network model is independently constructed, and the community structure is identified, so as to characterize the operating characteristics and dynamic cluster variation of small hydropower at z time instants over the full-time horizon. The implementation steps are as follows:

- 1) The dataset is divided into a series of time slices according to the variation cycle of the operation data, with each time slice corresponding to a static snapshot graph.
- 2) On each time slice, a dynamic multidimensional feature network model of small hydropower is constructed as:

$$G^{(v)}(t) = (V, E, W_{\text{fused}}^{(t)}) \quad (16)$$

where $W_{\text{fused}}^{(t)}$ denotes the fused similarity matrix at different time instants t .

The dynamic network model of small hydropower can provide a modeling foundation for full-time-horizon characteristic analysis and dynamic cluster partitioning of small hydropower systems. Based on the constructed snapshot graph sequence and combined with dynamic community detection algorithms, the variation trend of community structures over time can be further explored, thereby realizing time-varying partitioning of small hydropower clusters.

3. Cluster partitioning method

3.1. Hydropower coordination index

The modularity Q can measure the difference in connection density within and between communities and effectively evaluate the significance of community structure [28]. To measure the quality of small hydropower cluster partitioning, this paper defines the hydropower coordination index $Q^{\text{hydro}}(t)$ on each time snapshot graph based on the fused similarity matrix W_{fused} , which is used to quantify the deviation of the coordination capability among hydropower stations within a cluster relative to a random network.

$$Q^{\text{hydro}}(t) = \frac{1}{2\mu^{(t)}} \sum_{i,j} \left[W_{\text{fused},ij}^{(t)} - \frac{s_i^{(t)} s_j^{(t)}}{2\mu^{(t)}} \right] \delta(c_i, c_j) \quad (17)$$

where $W_{\text{fused},ij}^{(t)}$ denotes the comprehensive similarity relationship between nodes i and j at time t ; $s_i^{(t)}$ denotes the degree of node i ; $\mu^{(t)}$ denotes the total network edge weight; and $\delta(c_i, c_j)$ denotes the

community indicator function, which equals 1 when nodes i and j are assigned to the same cluster, and 0 otherwise.

3.2. Cluster partitioning algorithm

The Louvain algorithm is a community detection method based on modularity optimization. Its core idea is as follows: after traversing all neighboring communities, each network node chooses to join the community that yields the maximum modularity gain; when the overall modularity reaches a local optimum, each community is regarded as a new node to reconstruct the network, and this process is repeated until the gain converges.

Accordingly, this paper takes the hydropower coordination index $Q^{\text{hydro}}(t)$ as a new objective function and transforms the small hydropower cluster partitioning problem into a community detection problem with the objective of maximizing the hydropower coordination index. The procedure of the improved Louvain algorithm based on $Q^{\text{hydro}}(t)$ is as follows:

- 1) Initialization stage: Each small hydropower station is regarded as an independent community to construct the initial partition, and the hydropower coordination index $Q^{\text{hydro}}(t)$ under the current partition is taken as the initial coordination index.
- 2) Local coordination index gain search: For each node i , an attempt is made to move it to the community C_j to which a neighboring node belongs, and the corresponding coordination degree increment is calculated as:

$$\Delta Q^{\text{hydro}} = Q_{\text{new}}^{\text{hydro}} - Q_{\text{old}}^{\text{hydro}} \quad (18)$$

If $\Delta Q^{\text{hydro}} > 0$, node i is moved into community C_j so as to improve the overall hydropower coordination degree.

- 3) Community aggregation and new network construction: According to the current community partitioning result, each community is treated as a meta-node to generate a new network. In the new network, the edge weight between meta-nodes is the accumulated value of all corresponding edge weights between communities in the original network. Then, Step 2 is repeated on the new graph to continuously optimize the partition structure.
- 4) Convergence determination: The algorithm terminates when no node movement can further increase the modularity between two consecutive iterations. The current community partition is then regarded as the final clustering result.

3.3. Dynamic cluster partitioning extension

The above Louvain-based cluster partitioning method is mainly applied to a single snapshot network. The sequence of snapshot networks can be further formulated as a temporal multilayer network for dynamic community detection. To describe the temporal continuity of the same hydropower station across adjacent time snapshots, an interlayer coupling parameter ω is introduced. The temporal multilayer modularity matrix B_{multi} can be constructed as:

$$B_{\text{multi}} = \begin{bmatrix} B^{(t_1)} & \omega I & \cdots & 0 \\ \omega I & B^{(t_2)} & \cdots & 0 \\ \vdots & \vdots & \ddots & \omega I \\ 0 & 0 & \omega I & B^{(t_n)} \end{bmatrix} \quad (19)$$

where $\mathbf{I}$ is the identity matrix, and ω represents the interlayer coupling strength between the same station in adjacent time layers. The diagonal submatrix $B^{(t)}$ denotes the intralayer modularity matrix of the snapshot network at time t . When ω is set to 0, the community detection results of different snapshots are independent; when ω increases, the community affiliation of the same station tends to remain more continuous over time.

For each time snapshot t , the fused similarity matrix $W_{\text{fused}}^{(t)}$ is first obtained using the SNF-based multidimensional feature fusion method, and the element $B_{ij}^{(t)}$ of $B^{(t)}$ is calculated as follows:

$$B_{ij}^{(t)} = W_{\text{fused},ij}^{(t)} - \frac{s_i^{(t)} s_j^{(t)}}{2\mu^{(t)}} \quad (20)$$

The temporal multilayer modularity matrix B_{multi} can be optimized using the generalized Louvain framework described in [29,30] to obtain dynamic cluster partitioning results. The generalized Louvain algorithm follows the same basic optimization idea as the Louvain algorithm used in this paper. Therefore, as this subsection mainly serves as an extension discussion, the detailed algorithmic procedure is not repeated. In this way, the proposed static method can be extended to dynamic cluster evolution analysis under time-varying operating conditions.

3.4. Evaluation indices

Community detection algorithms belong to unsupervised learning algorithms, and the quality of their partitioning results cannot be judged by a single standard. To objectively evaluate the effectiveness of the partitioning results, three-dimensional evaluation indices are proposed, namely the cluster electrical coupling index ρ_e , the cluster coordination index ρ_c , and the cluster geographical aggregation index ρ_g , which are used to verify the quality of the partitioning results. All three are based on the same mathematical framework, that is, the average value of the attribute over all pairs of station nodes within each cluster is calculated. The general calculation formula is as follows:

$$\rho_\theta = \frac{1}{\sum_{k=1}^{N_C} |E_k|} \sum_{k=1}^{N_C} \sum_{(i,j) \in E_k} \theta_{ij}, \theta \in \{x_{ij}, r_{ij}, d_{ij}\} \quad (21)$$

where N_C denotes the number of clusters; E_k denotes the set of all node pairs within the k -th cluster; $|E_k|$ denotes the number of node pairs in the k -th cluster; θ_{ij} denotes the attribute value corresponding to nodes i and j ; x_{ij} denotes the electrical coupling strength between stations i and j ; r_{ij} denotes the historical output correlation coefficient between stations i and j ; and d_{ij} denotes the geographical distance between stations i and j .

- 1) When $\theta_{ij} = x_{ij}$, the index is the cluster electrical coupling index ρ_e , which reflects the electrical coupling strength among stations within the cluster. The stronger the voltage and reactive power coupling between stations, the better the regulation capability and coordination potential.
- 2) When $\theta_{ij} = r_{ij}$, the index is the cluster coordination index ρ_c , which measures the coordination among stations within each cluster during historical operation. Clusters with high coordination have stronger synchronous response capability and dispatch feasibility in coordinated operation.
- 3) When $\theta_{ij} = d_{ij}$, the index is the cluster geographical aggregation index ρ_g , which measures the geographical distribution distance among stations within the cluster. When the spatial locations of stations are concentrated, they tend to have similar resource distribution conditions and higher

regulation feasibility.

However, measuring only the average distance within a cluster through ρ_g is insufficient to comprehensively reflect the boundary clarity and spatial separation effect of cluster partitioning. Therefore, the silhouette coefficient (SC) is introduced as an evaluation index to measure the clustering quality of the clusters in the geographical spatial dimension. The calculation formula is as follows:

$$S = \frac{1}{N} \sum_{i=1}^N \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \quad (22)$$

where $a(i)$ denotes the average distance between station i and other stations within its own cluster; $b(i)$ denotes the average distance between station i and stations in the nearest neighboring cluster; and N denotes the total number of stations.

4. Case study analysis

4.1. Scenario setting

This paper selected nine small hydropower stations in the Meijiang River Basin, Zunyi, China, as the research objects. In this region, small hydropower stations have long operated independently, resulting in low dispatch coordination efficiency and frequent occurrences of water spillage and energy curtailment. To verify the effectiveness of the proposed method, a multidimensional feature network model was constructed and a simulation analysis was carried out. The case study scenario is shown in Figure 2.

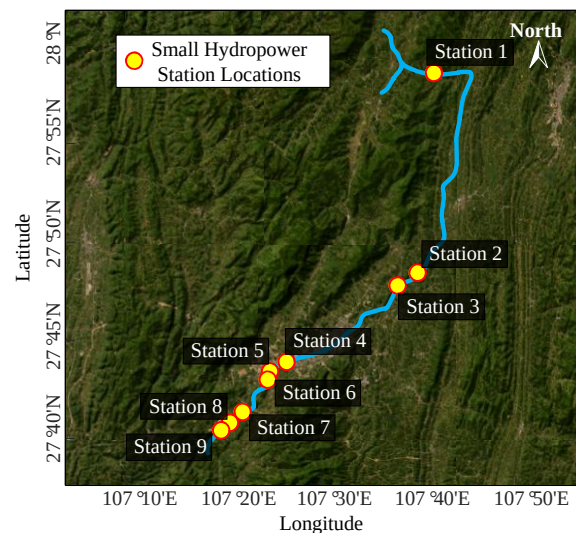


Figure 2. Case study scenario of small hydropower stations.

The simulation was carried out on the MATLAB R2019b platform, and the distribution network case adopted the modified IEEE 33-bus system shown in Figure 3. The system voltage level was 12.66 kV, and the base capacity was 10 MVA. The system included 33 buses and 32 branches, consisting of 1 slack bus, 23 conventional load buses, and 9 hydropower buses, with a total active load of approximately 3.715 MW and a total reactive load of approximately 2.3 MVar.

On this basis, simulation analysis was conducted for multidimensional feature network

modeling, reactive power partitioning of the distribution network, and small hydropower cluster partitioning.

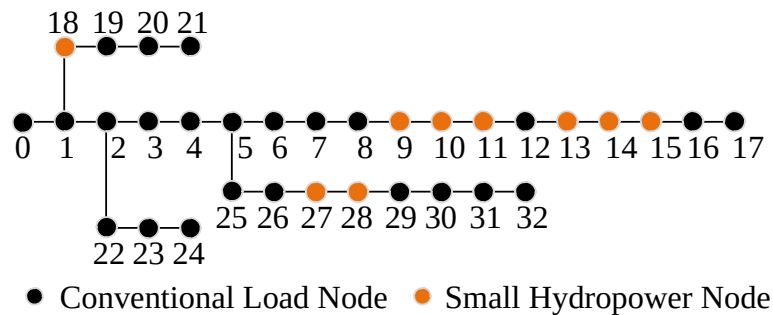


Figure 3. Modified IEEE 33-bus system.

4.2. Reactive power partitioning of the distribution network

The Louvain algorithm was adopted for community partitioning, and a comparative experiment was conducted with the partitioning results based on the traditional topological adjacency matrix to verify the effectiveness of the proposed electrical coupling network model. The experimental procedure is as follows: as shown in Figure 1, power flow analysis is performed on the distribution network with integrated small hydropower, the voltage-reactive power sensitivity is obtained, the electrical distance is calculated, and the electrical coupling edge weights are generated to construct the electrical coupling network model. Then, the improved Louvain algorithm is applied to complete the reactive power partitioning of the distribution network.

The partitioning result based on the electrical coupling network model is shown in Figure 4. There are no isolated nodes in the result, and the cluster structure is consistent with the electrical connections, with a modularity Q of 0.1597. Two small hydropower clusters with distinct electrical coupling characteristics are formed, where Cluster 1 includes nodes 0–7 and nodes 18–32, and Cluster 2 includes nodes 8–17.

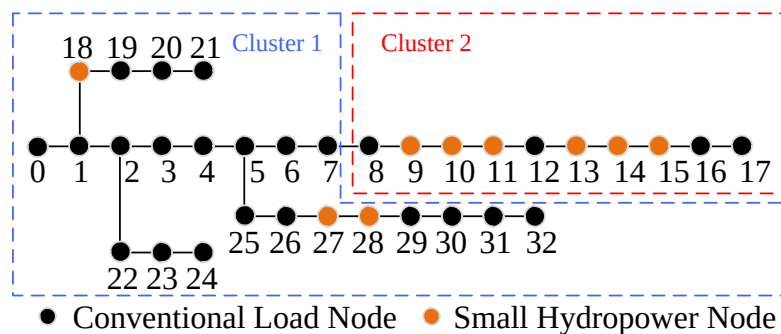


Figure 4. Reactive power partitioning of the distribution network considering electrical coupling.

For comparison, the partitioning procedure based on the traditional topological adjacency matrix model was carried out on the modified IEEE 33-bus system. In this method, the distribution network is directly represented by a binary adjacency matrix according to the physical connection relationships among nodes, and the Louvain algorithm is then applied to obtain the partitioning result. The partitioning result based on the traditional topological adjacency matrix model is shown in Figure 5, where the network is divided into seven clusters. Although this result is consistent with the

topological structure characteristics, the partitioning process does not consider the electrical coupling characteristics between nodes and therefore cannot reflect the interaction requirements of voltage and reactive power response.

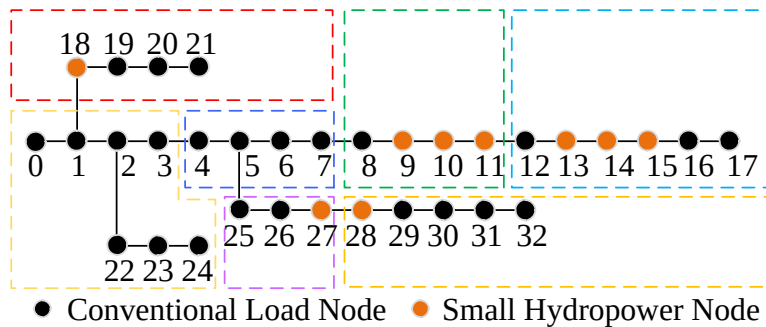


Figure 5. Distribution network partitioning considering topological adjacency.

Furthermore, the electrical distances among the nine small hydropower stations were extracted to model the electrical coupling relationships among the stations, as shown in Figure 6. In the figure, the horizontal and vertical coordinates represent the station indices, and the height and color of the bars jointly reflect the magnitude of the electrical distance. A larger value indicates weaker electrical coupling between the two stations. It is evident that the electrical distance between Station 1 and Stations 2–3 is relatively small, indicating a close coupling relationship; the distance between Station 1 and Stations 4–6 increases slightly; and the electrical distance between Station 1 and Stations 7–9 is the largest, indicating the weakest electrical coupling. If Stations 2–3, 4–6, and 7–9 are partitioned into three clusters, the electrical distances within each cluster are generally small, showing strong electrical functional modularity.

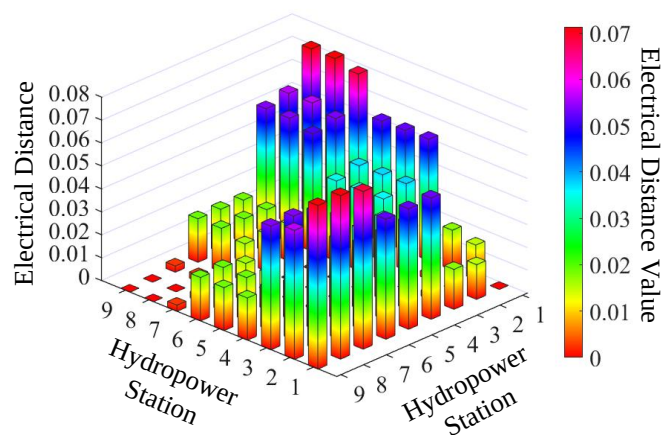


Figure 6. Electrical distances between the nodes of nine hydropower stations.

4.3. Small hydropower cluster partitioning results

To verify the effectiveness of the multidimensional feature network modeling method and the cluster partitioning algorithm for small hydropower, four comparative experimental scenarios were designed based on the geographical coordinates, output data of nine typical small hydropower stations in the Meijiang River Basin, Zunyi, China, and the electrical parameters of the modified IEEE 33-bus system. The characteristics of cluster partitioning under different feature dimensions

and multidimensional feature fusion were analyzed. Among them, Scenario 1, Scenario 2, and Scenario 3 compare and illustrate the characteristics and significance of cluster partitioning results from different feature perspectives, while Scenario 4 is used to demonstrate the effectiveness of the SNF-based multidimensional feature network model. The comparative experimental scenarios are set as follows:

- 1) Scenario 1: The geographic distribution network is constructed based on geographical coordinates, and cluster partitioning is performed according to spatial distribution.
- 2) Scenario 2: The coordinated operation network is constructed based on historical output data, and cluster partitioning is performed according to operational behavior.
- 3) Scenario 3: The electrical coupling network is constructed based on electrical distance, and cluster partitioning is performed according to voltage-reactive power response capability.
- 4) Scenario 4: The multidimensional feature network model is constructed using the multidimensional feature fusion method, and cluster partitioning is performed based on comprehensive similarity.

The partitioning results under different scenarios were quantitatively compared using evaluation metrics including $Q^{\text{hydro}}(t)$, SC , ρ_g , ρ_c , and ρ_e .

Parameter settings: For scenarios 1–3, the geographical distribution matrix $\mathbf{W}^{(\text{geo})}$, the coordinated operation matrix, $\mathbf{W}^{(\text{corr})}$, and the electrical coupling matrix $\mathbf{W}^{(\text{elec})}$ were used as the input matrices of the algorithm. In Scenario 4, multidimensional feature fusion was performed using the SNF method described in Eqs. (12)–(15). Specifically, the SNF inputs were $\mathbf{W}^{(\text{geo})}$, $\mathbf{W}^{(\text{corr})}$, and $\mathbf{W}^{(\text{elec})}$. The local similarity matrix $S^{(v)}$ was constructed by retaining the ε nearest neighbors of each node, where $\varepsilon = 2$, and the number of SNF iterations was set to 1. During each fusion iteration, the propagation matrix of each feature layer was updated using the average information from the other feature layers. The fused similarity matrix W_{fused} was then obtained by averaging the updated matrices, followed by symmetrization and normalization to $[0,1]$. Before community detection, the diagonal elements of W_{fused} were set to zero, and edges with weights lower than a predefined threshold were removed. The algorithm terminates when the community partition no longer changes between two successive iterations.

Figure 7 presents the coupling characteristics among small hydropower stations under different feature perspectives and the cluster partitioning results based on the improved Louvain algorithm. In Figure 7(d)–(f), the relatively strong coupling relationships are highlighted. The cluster partitioning results under each feature perspective exhibit the following characteristics:

As shown in Figure 7(a), the geographic distribution network characterizes the positional proximity among power stations. The coupling values between Station 1 and Stations 2 and 3 are relatively high, indicating that the three stations are geographically close. Among them, the coupling value between Stations 2 and 3 is close to 1, indicating that they are basically located at the same position. In contrast, the coupling values between Station 1 and Stations 4–9 are lower than 0.2, especially those with Stations 7–9, which are close to 0, indicating a long geographical distance. As shown in Figure 7(b), the coordinated operation network reflects the correlation of historical output states among power stations. The coupling values between Station 1 and the other stations are all lower than 0.5, indicating weak historical output correlation; the local coupling value between Stations 2 and 3 is higher than 0.72, indicating strong historical output correlation; and the average coupling values among Stations 4–9 are higher than 0.67, indicating that the historical operating states of these local stations have good consistency. As shown in Figure 7(c), the electrical coupling network model reflects the voltage-reactive power response relationships among power stations and,

overall, exhibits two highly coupled regions, namely Stations 1–3 and Stations 4–9, where the local electrical coupling values within both regions exceed 0.7. Among them, Stations 4–6 and Stations 7–9 further form two locally coupled subregions, with coupling values close to 1, indicating good voltage-reactive power response capability.

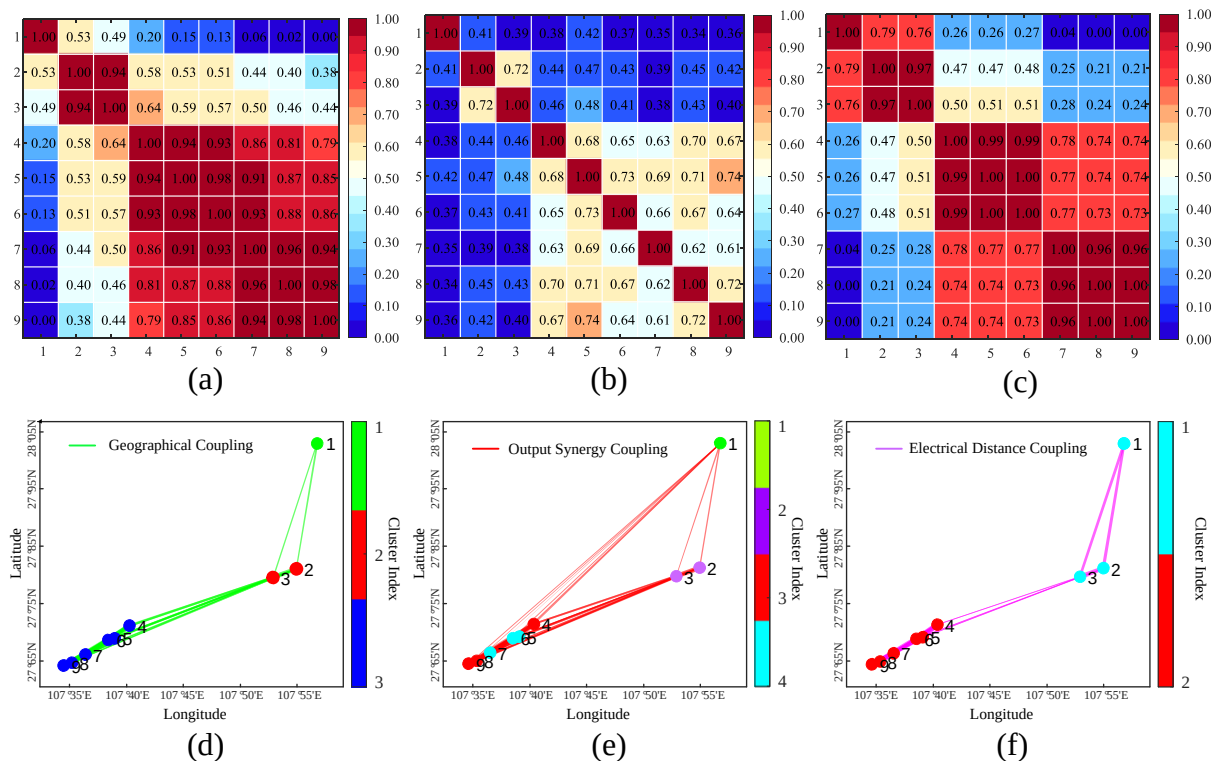


Figure 7. Coupling relationship of hydropower stations from different perspectives.

On this basis, the cluster partitioning performance of different single-dimensional feature methods was further analyzed to verify the identification capability of the network models. Figures 7(d)–(f) show the hydropower station cluster partitioning results obtained by the improved Louvain algorithm based on the above three types of network models, which can reflect the characteristics and limitations of the partitioning results under different feature dimensions:

When only the geographical spatial distribution is considered, the partitioning is mainly based on the geographical location relationships among the power stations, and the nine stations are divided into three clusters, as shown in Figure 7(d). The clusters exhibit obvious spatial aggregation. However, this method does not consider the operational behavior or electrical attributes of the stations and, therefore, cannot satisfy the requirements of coordinated dispatch and electrical control.

When only the operational behavior characteristics are considered, partitioning is mainly based on the correlation among the historical outputs of the power stations, and the nine stations are divided into four clusters, as shown in Figure 7(e). Some stations that are far apart in space are still assigned to the same cluster due to their high dynamic correlation. This method has good modeling capability for the operational behavior of the stations.

When only the voltage-reactive power response capability is considered, the partitioning is based on the electrical distance among hydropower stations, and the nine stations are divided into two clusters. The partitioning result is consistent with the reactive power control partitioning of the distribution network, indicating that the network model based on electrical distance has the ability to map the reactive power regulation capability of the distribution system.

Based on the above comparative analysis, Scenario 4 can reflect the overall relationships among hydropower stations from multiple dimensions, including electrical, operational, and geographical perspectives, as shown in Figure 8.

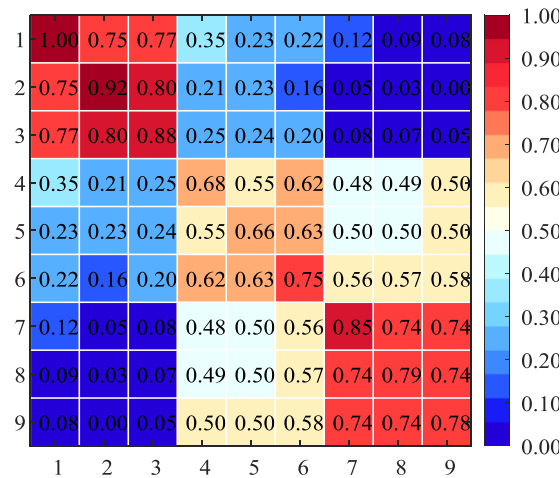


Figure 8. Coupling relationship under SNF multidimensional feature fusion.

Multidimensional feature fusion was performed based on the SNF method to achieve complementarity of local similarity information. The local coupling relationships among Stations 1–3 are enhanced, with the average local similarity exceeding 0.85, thereby forming a highly coupled local region. Stations 4–9 exhibit clear boundary characteristics, among which the average local similarity of Stations 7–9 exceeds 0.77.

Figure 9 shows the small hydropower cluster partitioning result under the multidimensional feature network model, and the result is consistent with that in Figure 7(f), where only the electrical coupling characteristics are considered.

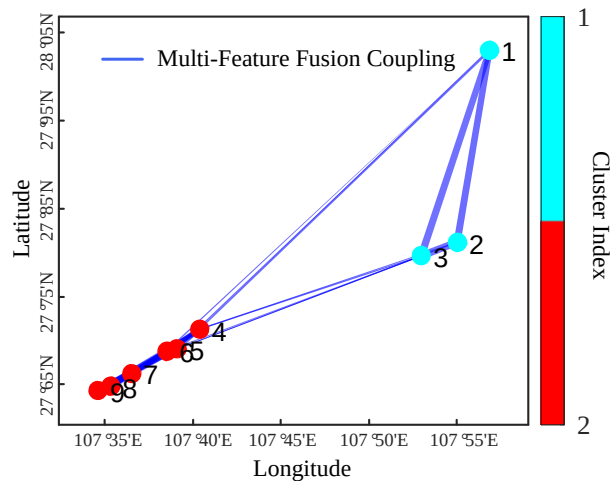


Figure 9. Partition results of small hydropower clusters under multidimensional feature fusion.

It should be noted that although the cluster partitioning results are the same, the multidimensional feature network model incorporates the coupling relationships of the stations in the electrical, operational, and spatial distribution dimensions during the partitioning process. The physical meaning of the weighted edges between station nodes is therefore changed, enabling a more comprehensive reflection of the multidimensional complex coupling relationships.

To verify the applicability and differences of different feature perspectives and

multidimensional feature fusion in small hydropower cluster partitioning, a comprehensive quantitative evaluation of the partitioning performance was carried out from multiple dimensions. The partitioning results under each scenario are shown in Table 1.

Table 1. Cluster partitioning result indicators in different scenarios.

Scenario	Cluster	Q^{hydro}	ρ_g	ρ_c	ρ_e	SC
Scenario 1	3	0.1218	3.9066	0.6675	0.0106	0.8326
Scenario 2	4	0.2164	3.7226	0.6986	0.0103	0.3678
Scenario 3	2	0.2762	5.6636	0.6467	0.0113	0.7068
Scenario 4	2	0.2847	5.6636	0.6467	0.0113	0.7068

The cluster partitioning results under different scenarios show significant differences in the evaluation indices, with the following characteristics:

- 1) Scenario 1 divides the stations into three clusters and achieves the highest SC of 0.8326, indicating clear cluster boundaries and strong spatial aggregation. However, since operational and electrical characteristics are not considered, the internal coordination capability and electrical regulation capability of the partitioning result are relatively weak.
- 2) Scenario 2 divides the stations into four clusters and achieves the highest ρ_c of 0.6986, indicating strong similarity in operational patterns within each cluster, which is favorable for coordinated dispatch. However, the spatial distribution is relatively dispersed, and the structural boundaries are unclear, with an SC of only 0.3678, indicating problems of spatial dispersion and structural ambiguity.
- 3) Scenario 3 divides the stations into two clusters and achieves the best ρ_e of 0.0113, indicating good voltage-reactive power response capability within the clusters and a foundation for reactive power regulation. However, the geographical aggregation index ρ_g reaches 5.6636, indicating that there are stations with relatively long distances within the same cluster, and that the spatial distribution is not sufficiently compact.
- 4) Scenario 4 divides the stations into two clusters, with the same partitioning result as Scenario 3. However, compared with Scenario 3, Q^{hydro} is further improved to 0.2847, which is the highest among the four scenarios.

In summary, the multidimensional feature network model of small hydropower constructed based on the SNF method not only achieves the best performance in Q^{hydro} but also takes into account the complex coupling relationships among different dimensions, including geographical, electrical, and operational characteristics, during the partitioning process.

5. Conclusions

This paper proposes a multidimensional feature-fused small hydropower network modeling method with dynamic evolution capability and combines it with an improved Louvain algorithm to achieve refined cluster partitioning of small hydropower systems. The proposed method is validated and analyzed using small hydropower stations in the Meijiang River Basin, Zunyi, China, as a case study. The main conclusions are as follows:

- 1) A multidimensional dynamic network model integrating electrical characteristics, operational characteristics, and geographical distribution information is constructed based on complex

network theory, which can effectively map the multidimensional coupling relationships of distributed small hydropower under different spatiotemporal scenarios. The model has strong physical interpretability and adaptability.

- 2) The hydropower coordination index $Q^{\text{hydro}}(t)$ is proposed to evaluate the quality of small hydropower cluster partitioning, and refined partitioning is achieved in combination with the improved Louvain algorithm. The experimental results show that the method based on the multidimensional feature network model achieves the best performance in identifying coordination capability, with the Q^{hydro} value improved to 0.2847, outperforming traditional single-dimensional partitioning methods. The proposed method provides a solution for accurate cluster identification in small hydropower systems.

Author contributions

Meiqi Yuan: Conceptualization, Methodology, Writing – original draft, Formal analysis; Jun Cai: Methodology, Formal analysis, supervision, writing – review & editing; Xinyu Luo: Formal analysis, Visualization, Writing – review & editing; Ying Lu: Data curation, Validation, Project administration, Writing – review & editing; Tinghao Ren: Visualization, Validation, Writing – review & editing. All authors have read and agreed to the published version of the manuscript.

Use of Generative-AI tools declaration

The authors declare they have not used Artificial Intelligence tools in the creation of this article.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

References

1. Qiu J, Zhao J, Wen F, Zhao J, Gao C, Zhou Y, et al. (2023) Challenges and Pathways of Low-Carbon Oriented Energy Transition and Power System Planning Strategy: A Review. *IEEE Trans Netw Sci Eng* 11: 5396–5416. <https://doi.org/10.1109/TNSE.2023.3344729>
2. Koç C (2022) A study on solutions and problems of hydroelectric power plants in the operation. *Sustainable Water Resour. Manage* 8: 90. <https://doi.org/10.1007/s40899-022-00677-2>
3. Wang Z, Fang G, Wen X, Tan Q, Zhang P, Liu Z (2023) Coordinated operation of conventional hydropower plants as hybrid pumped storage hydropower with wind and photovoltaic plants. *Energy Convers Manage* 277: 116654. <https://doi.org/10.1016/j.enconman.2022.116654>
4. Song Y, Wang J, Wang Y (2025) Non-Iterative Market Participation of Virtual Power Plants via Bidding Function Representation. *J Mod Power Syst Clean Energy*, 1–12.
5. Liu J, Hu H, Yu SS, Trinh H (2023) Virtual Power Plant with Renewable Energy Sources and

- Energy Storage Systems for Sustainable Power Grid-Formation, Control Techniques and Demand Response. *Energies* 16: 3705. <https://doi.org/10.3390/en16093705>
6. Sun J, Xu J, Ke D, Liao S, Ling Z (2023) Cluster partition for distributed energy resources in Regional Integrated Energy System. *Energy Rep* 9: 613–619. <https://doi.org/10.1016/j.egy.2023.04.312>
 7. Resch B, Sagl G, Törnros T, Bachmaier A, Eggers JB, Herkel S, et al. (2014) GIS-Based Planning and Modeling for Renewable Energy: Challenges and Future Research Avenues. *ISPRS Int J Geo-Inf* 3: 662–692. <https://doi.org/10.3390/ijgi3020662>
 8. Ruan G, Qiu D, Sivaranjani S, Awad ASA, Strbac G (2024) Data-driven energy management of virtual power plants: a review. *Adv Appl Energy* 14: 100170. <https://doi.org/10.1016/j.adapen.2024.100170>
 9. Zhang R, Hredzak B (2021) Distributed Dynamic Clustering Algorithm for Formation of Heterogeneous Virtual Power Plants Based on Power Requirements. *IEEE Trans Smart Grid* 12: 192–204. <https://doi.org/10.1109/TSG.2020.3020163>
 10. Song Y, Li T, Geng Y, Wu C, Wang Y, Wang J (2026) Explanation-enhanced federated fine-tuning of large language models for photovoltaic power forecasting. *IEEE T Sustain Energy*, 1–14. <https://doi.org/10.1109/TSTE.2026.3655809>
 11. Mao M, Wu Z, Xu D, Xu J, Hu Q (2024) Community-detection-based Approaches for Distribution Network Partition. *CSEE J Power Energy Syst* 10: 1965–1976.
 12. Zhang J, Zhang Y, Wang G, Li F, Xie J (2025) Vulnerability and resilience assessments of power grid based on community partition. *IEEE T Netw Sci Eng* 12: 3131–3144. <https://doi.org/10.1109/TNSE.2025.3556836>
 13. Ngo QH, Nguyen BLH, Zhang J, Schoder K, Ginn H, Vu T (2025) Deep graph neural network for fault detection and identification in distribution systems. *Electr Power Syst Res* 247: 111721. <https://doi.org/10.1016/j.epsr.2025.111721>
 14. Hasanvand S, Sobhani H, Khooban MH (2025) Distribution network clustering for reactive power planning and distributed voltage control. *IET Gener Transm Distrib* 19: e70002. <https://doi.org/10.1049/gtd2.70002>
 15. Meng L, Yang X, Zhu J, Wang X, Meng X (2024) Network partition and distributed voltage coordination control strategy of active distribution network system considering photovoltaic uncertainty. *Appl Energy* 362: 122846. <https://doi.org/10.1016/j.apenergy.2024.122846>
 16. Li Y, Ge Y, Xu T, Zhu M, He Z (2024) Controllability evaluation of complex networks in cyber–physical power systems via critical nodes and edges. *Int J Electr Power Energy Syst* 155: 109625. <https://doi.org/10.1016/j.ijepes.2023.109625>
 17. Cotilla-Sanchez E, Hines PD, Barrows C, Blumsack S, Patel M (2013) Multi-Attribute Partitioning of Power Networks Based on Electrical Distance. *IEEE Trans Power Syst* 28: 4979–4987. <https://doi.org/10.1109/TPWRS.2013.2263886>
 18. Wang X, Xue F, Lu S, Jiang L, Bompard E, Masera M (2022) Understanding communities from a new functional perspective in power grids. *IEEE Syst J* 16: 3072–3083. <https://doi.org/10.1109/JSYST.2022.3151388>
 19. Zhao C, Zhao J, Wu C, Wang X, Xue F, Lu S (2019) Power Grid Partitioning Based on Functional Community Structure. *IEEE Access* 7: 152624–152634. <https://doi.org/10.1109/ACCESS.2019.2948606>
 20. Cheng Z, Wang L, Zeng S, Su C, Zhang R, Zhou W (2024) Partition-global dual-layer collaborative voltage control strategy for active distribution network with high proportion of renewable energy. *IEEE Access* 12: 22546–22556.

<https://doi.org/10.1109/ACCESS.2024.3364543>

21. Song Y, Wang J, Zhang T, He G, Wang Y (2025) Characterizing spatiotemporal-coupled resilience of power systems via a security region-based method. *CSEE J Power Energy Syst*, 1–12.
22. Song Y, Gu J, Mao H, Deng G, Wang J (2026) Proactive scheduling of resilient networked microgrids via data-efficient security region learning. *Energy AI* 24: 100720. <https://doi.org/10.1016/j.egyai.2026.100720>
23. Wen X, Gao X, Su L, Fan Q, Peng W (2017) Analysis of influencing factors and characteristics of small hydropower generation. *2017 9th International Conference on Modelling, Identification and Control (ICMIC)*, 658–662. <https://doi.org/10.1109/ICMIC.2017.8321537>
24. Li Z, Liu J, Wu K (2018) A multiobjective evolutionary algorithm based on structural and attribute similarities for community detection in attributed networks. *IEEE Trans Cybern* 48: 1963–1976. <https://doi.org/10.1109/TCYB.2017.2720180>
25. Saleh M, Esa Y, Mohamed A (2023) Applications of Complex Network Analysis in Electric Power Systems. *Energies* 11: 1381. <https://doi.org/10.3390/en11061381>
26. Teklebrhan N, Seres I, Farkas I (2023) Energetic complementarity solar PV and wind power based on satellite data. *Eur J Energy Res* 3: 7–12. <https://doi.org/10.24018/ejenergy.2023.3.4.97>
27. Wang B, Mezlini AM, Demir F, Fiume M, Tu Z, Brudno M, et al. (2014) Similarity network fusion for aggregating data types on a genomic scale. *Nat Methods* 11: 333–337. <https://doi.org/10.1038/nmeth.2810>
28. Newman MEJ (2004) Fast algorithm for detecting community structure in networks. *Phys Rev E* 69: 66133. <https://doi.org/10.1103/PhysRevE.69.066133>
29. Mucha PJ, Richardson T, Macon K, Porter MA, Onnela JP (2010) Community structure in time-dependent, multiscale, and multiplex networks. *science* 328: 876–878. <https://doi.org/10.1126/science.1184819>
30. Bazzi M, Porter MA, Williams S, McDonald M, Fenn DJ, Howison SD (2016) Community detection in temporal multilayer networks, with an application to correlation networks. *Multiscale Model Simul* 14: 1–41. <https://doi.org/10.1137/15M1009615>



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