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The search method for key transmission sections based on an improved spectral clustering algorithm

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With the increased complexity of power systems stemming from the connection of high-proportion renewable energy sources, coupled with the escalating volatility and uncertainty, the key transmission sections that serve as indicators of the power grid's security status are also subject to frequent changes, posing challenges to grid monitoring. The search method for key transmission sections based on an improved spectral clustering algorithm is proposed in this paper. A branch weight model, considering the impact of node voltage and power flow factors, is initially established to comprehensively reflect the electrical connectivity between nodes. Subsequently, a weighted graph model is constructed based on spectral graph theory, and an improved spectral clustering algorithm is employed to partition the power grid. Finally, a safety risk indicator is utilized to identify whether the partitioned sections are key transmission sections. Results from case studies on the IEEE39-node system and actual power grid examples demonstrate that the proposed method accurately and effectively searches for all key transmission sections of the system and identifies their security risks. The application in real power grid scenarios validates its ability to screen out some previously unrecognized key transmission sections.

KEYWORDS

renewable energy, power grid partitioning, key transmission section, spectral clustering, normalized cut, security risk index

1 Introduction

In the backdrop of substantial integration of intermittent renewable energy sources such as wind and solar, combined with the rapid expansion of electric vehicle charging stations into the power grid, the power system experiences augmented volatility and uncertainty (Cheng et al., 2022). During occurrences of severe weather events that lead to transmission line outages, a widespread transfer of power flow takes place, a significant redistribution of power flow ensues, potentially triggering a series of cascading system incidents (Wang et al., 2021; Hui et al., 2023). Key Transmission Sections (KTS) have emerged as critical safety features of the power grid, revealing susceptible areas. Monitoring and analyzing KTS can significantly enhance the stability and operational efficiency of power systems (Wang et al., 2019). Conventional methodologies rely on the expertise of power grid dispatch professionals for the identification of KTS. However, in light of the escalating intricacies of the power grid, this manual selection approach proves inadequate to meet the heightened requisites of the contemporary intelligent power grid. Consequently, researching an expeditious KTS search method and conducting an thorough analysis of safety stability assumes paramount significance.

Currently, methods for searching KTS can be categorized into two main types: those based on the analysis of power flow transfer relationships and those depending on power grid partitioning. Methods centered around power flow transfer relationships commonly start from a particular overloaded branch and utilize parameters such as power flow transfer distribution factors or clustering indicators to identify line cut sets that exhibit strong electrical associations with the overloaded line. Zio and Golea. (2012) approached from the perspective of power grid security, searching for a set of lines closely associated with overloaded lines as transmission sections. Yu et al. (2023) proposed a transmission section search method based on graph theory and PMU data. It obtains transmission sections by searching the first k path with the minimum weight and ultimately filters KTS by calculating the safety margin of the sections. Lv et al. (2018) studied the impact of multiple faults on security and stability characteristics of power grid and weak transmission sections, and proposed a KTS identification method considering multiple preconceived faults. The K value setting in the shortest path method is relatively subjective, and the range of searching for the shortest path in the entire network is too large, resulting in a waste of search resources. Hu et al. (2023) employed the transient safety assessment method of feature selection, but it needs to screen a high-accuracy power flow feature set and the expression ability of the model needs to be enhanced. Diao et al. (2023) utilized a deep learning model to predict KTS, which has strong expressive ability (Bo et al., 2024), but cannot discover new KTS.

The methodologies for power grid partitioning are grounded in common attributes shared among network nodes, such as electrical distance, power voltage, or energy sensitivity (Samudrala et al., 2020). These approaches segment the power grid into several zones, classifying sections within high-safety risk areas as KTS (He and Fang, 2017). The methods for grid partitioning can be categorized into two types: one is the method of disconnecting lines to split the grid. Luo et al. (2014) utilized the Gervan-Newman (GN) algorithm to find tie lines with high transmission betweenness, and removed these tie lines to partition the power grid. Nonetheless, the search for lines within the partitions was neglected. Wang et al. (2022) utilized the fuzzy C-means clustering algorithm to explore lines with similar power composition to those broken, thus forming the initial transmission section. Additionally, a composite factor criterion was introduced to identify KTS. However, the clustering results are greatly affected by the initial clustering center.

Another partitioning method is the node clustering partitioning method, which clusters nodes or lines with the same properties into a group of transmission sections. Hou et al. (2014) proposed a fast search and identification method for weak transmission section searching based on automatic subnetwork combination. Zhao et al. (2017) proposed a network partitioning method based on community detection algorithm, which divides the distribution network into multiple communities. Xue and Duan (2019) introduced an online search method for identifying typical transmission sections with consideration for geographical attributes. The method employs a cut-set search algorithm based on matrix operations of graph theory and utilizes safety margin criteria to screen typical transmission sections within the power grid. For the numerous transmission sections resulting from partitions, Liang et al. (2022) employed N-1 and N-2 fault verification to identify sections at risk of exceeding limits as KTS. Wu et al. (2023) utilized comprehensive indicators based on the line outage distribution factor and line load rate to determine KTS. The aforementioned methodology transforms the process of grid partitioning into a graph partitioning process. During the construction of the branch weight matrix, it may lack the incorporation of multivariate characteristics in the data (Bai et al., 2021), such as line parameters, geographical location, system operating status, etc., thereby posing challenges in ensuring the accuracy of the partitioning. Deficiencies in conducting KTS searches for internal sections within the sub-partitions may lead to the problem of overlooked or missed KTS.

In view of the above problems, a method for searching KTS based on an improved spectral clustering algorithm is proposed in this paper. The approach conceptualizes the power system as a weighted graph model, with branch weights determined by considering the influences of voltage stability and power flow characteristics. The power grid is partitioned using the improved normalized cut spectral clustering algorithm. To tackle the challenge of numerous transmission sections emerging between partitions, making it difficult to ascertain their criticality, a safety risk indicator is devised and employed as a screening criterion. This method fully exploits the advantages of spectral clustering algorithms in terms of their low computational complexity and reduced solution difficulty, while concurrently circumventing the issue of potential omissions caused by the lack of internal section searches within partitions, thereby achieving a significant enhancement in accuracy.

2 Power grid partitioning method based on spectral clustering

The spectral clustering algorithm has gained increasing attention in the realm of electrical engineering due to its solid theoretical foundation and commendable clustering efficacy (Saxena et al., 2017). Derived from the theory of spectral graph partitioning, this algorithm transforms data clustering challenges into graph cutting problems, providing a fresh perspective for addressing power grid partitioning. This study utilizes the spectral clustering algorithm to partition the power grid. Initially, the electrical power system is abstracted into a weighted graph, with due consideration given to both voltage and power flow factors in branch weighting. Subsequently, by constructing the weight matrix and Laplacian matrix of the graph, the power grid is divided into multiple partitions based on the normalized cut criterion.

2.1 Construct branch weight model

The application of spectral clustering for power grid partitioning fundamentally hinges upon the utilization of eigenvalues and eigenvectors derived from the Laplacian matrix. A pivotal stage in this process involves the formulation of a weight matrix for the graph's branches, wherein different weight models wield a direct influence on the partitioning method's effectiveness. Typically, these

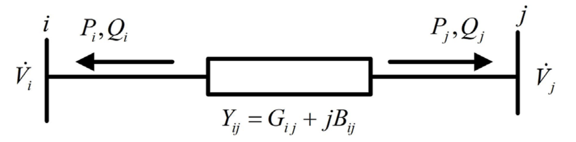

FIGURE 1
Simplified branch mode.

models consider similar characteristics among network nodes, like electrical distance, node voltage, branch power flow, etc. However, prevalent methods mostly consider the above-mentioned single factors when assigning branch weights, and cannot comprehensively reflect multiple factors, making it difficult to ensure the rationality and accuracy of the partitioning outcome (Li et al., 2023). This study proposes a novel weight model that amalgamates considerations of both node voltage levels and branch power flow dynamics, providing a comprehensive reflection of electrical interconnectedness. The simplified branch model is shown in Figure 1.

In the diagram, $Y_{ij} = G_{ij} + jB_{ij}$ is the branch admittance; $\dot{V}_i = V_i \angle \theta_i$ and $\dot{V}_j = V_j \angle \theta_j$ are the voltages at the ends of the branch. The injected power at node i on the branch side is given by:

$$\begin{cases} P_i = V_i V_j \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij} \right) + V_i^2 G_{ij} \\ Q_i = V_i V_j \left(G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij} \right) - V_i^2 B_{ij} \end{cases} \tag{1}$$

where, θ_{ij} is the phase angle difference; The partial derivative of reactive power Q_i and voltage amplitude V_j is:

$$\frac{\partial Q_i}{\partial V_j} = V_i \left(G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij} \right) \tag{2}$$

In the above equation, due to the significantly higher reactance than resistance in high-voltage transmission lines, that is, $B_{ij} \gg G_{ij}$. The voltage phase angle difference θ_{ij} between the ends of the branch is usually small, and $\sin\theta_{ij}$ close to 0, so $G_{ij}\sin\theta_{ij}$ can be ignored. The branch's susceptance parameter B_{ij} serves as a direct indicator of the electrical distance between two nodes, while $|\theta_{ij}|$ is linked to the load ratio of the line, exhibiting an increase as the load ratio expands. From this, it can be inferred that the partial derivative $\partial Q_i / \partial V_j$ is directly proportional to the node voltage V_i and the susceptance B_{ij} of the line, and inversely proportional to the voltage phase angle $|\theta_{ij}|$. That is, when the node voltage is smaller, the electrical distance between nodes is larger, and the load ratio is greater, the partial derivative becomes smaller.

In spectral clustering algorithms, it is required that all branch weights be positive values. To avoid the possibility of a negative value for $\partial Q_i / \partial V_j$ due to a smaller reactance of the intermediate winding in the equivalent circuit of a three-winding transformer, the absolute value of $\partial Q_i / \partial V_j$ is taken (Zhao and Yu, 2008). At the two ends of the same branch, the partial derivative values $\partial Q_i / \partial V_j$ and $\partial Q_j / \partial V_i$ can be obtained, and their deviation is minimal when the power grid is operating normally. Therefore, the branch weight is determined by taking the average of these two values:

$$w_U = \frac{1}{2} \left(\left| \frac{\partial Q_i}{\partial V_j} \right| + \left| \frac{\partial Q_j}{\partial V_i} \right| \right) \tag{3}$$

The KTS in the power grid refers to a collection of transmission lines connecting two partitions. These lines are characterized by high active power flow values at steady-state. Considering the network losses, for any branch $i - j$, the weight based on active power flow factor is given by:

$$w_P = \frac{|P_i| + |P_j|}{2} \tag{4}$$

From the preceding discussion, it is clear that node voltage and branch power flow are pivotal factors influencing branch weighting. The branch weights in this study are designated as:

$$w_{ij} = \frac{w_U}{w_P} = \left(\left| \frac{\partial Q_i}{\partial V_j} \right| + \left| \frac{\partial Q_j}{\partial V_i} \right| \right) / \left(|P_i| + |P_j| \right) \tag{5}$$

The equation indicates that as the voltage at node increases, the branch power flow decreases, resulting in a higher branch weight and signifying a close connection between the two nodes. Therefore, two closely interconnected nodes are typically assigned to the same partition. Conversely, as the power flow in the branch increases, the weight of the branch decreases, indicating weaker connectivity between the two nodes, and they are partitioned into different regions. Hence, this branch weight model provides a comprehensive representation of factors including node electrical distance, active power flow value in the branch, and load conditions. Consequently, it facilitates the spectral clustering algorithm in partitioning nodes with similar features into the same region.

2.2 Construct a weighted graph based on spectral graph theory

The power system can be conceptualized as a graph with weighted branches. Leveraging spectral graph theory, a weighted graph comprising n nodes and m edges can be expressed as:

$$\boldsymbol{G} = (\boldsymbol{V}, \boldsymbol{E}, \boldsymbol{W}) \tag{6}$$

where, $\boldsymbol{V}$ is the set of nodes; $\boldsymbol{E}$ is the set of branches; $\boldsymbol{W}$ is the weight matrix, where the matrix elements are defined as:

$$W_{ij} = \begin{cases} w_{ij} & (i,j) \in E \\ 0 & (i,j) \notin E \end{cases} \tag{7}$$

where, w_{ij} is the weight of branch $i - j$. The connection relationship between nodes can be represented by a degree matrix, where non-diagonal elements are zero, and diagonal elements are the sum of the row elements of the weight matrix. The Laplacian matrix of the constructed graph is:

$$\boldsymbol{L} = \boldsymbol{D} - \boldsymbol{W} \tag{8}$$

2.3 Power grid partitioning method based on normalized cut criteria

In the realm of spectral clustering for power grid partitioning, the efficacy of graph cutting criteria exerts a significant bearing

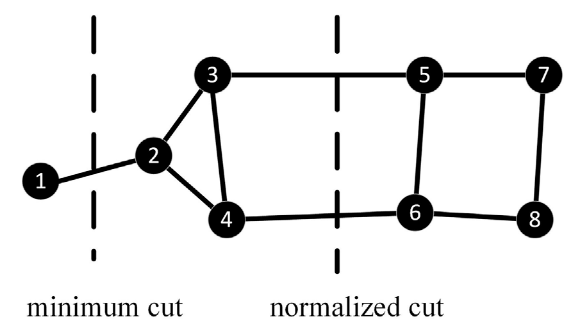

FIGURE 2
The comparison between the minimum cut and normalized cut criteria.

on the partitioning outcomes. Various graph cutting criteria, including but not limited to minimum cut, ratio cut, normalized cut, and minimum-maximum cut, can be utilized by optimizing the corresponding objective functions through minimization or maximization, thereby yielding optimal clustering results (Jia et al., 2014). Some scholars have observed that the minimum cut criterion might lead to unbalanced partitions (Von Luxburg, 2007). To address this concern, Shi and Malik proposed the normalized cut criterion, aiming to mitigate significant differences in the size of vertex sets between subgraphs (Shi and Malik, 2000). The comparison between the minimum cut and normalized cut criteria is illustrated in Figure 2.

The normalized cut criterion serves the dual purpose of assessing the internal closeness of nodes within subgraphs and evaluating the inter-subgraph connection looseness. Furthermore, it ensures equitable subgraph sizes, effectively averting the possibility of skewed partitions. The objective function for the normalized cut criterion, dividing the graph into subgraphs A and B, is expressed as follows:

$$\mathrm{Ncut}Ncut(A,B) = \frac{\mathrm{Cut}(A,B)}{\mathrm{vol}(A)} + \frac{\mathrm{Cut}(A,B)}{\mathrm{vol}(B)} \tag{9}$$

where, $\mathrm{Cut}(A,B)$ is the total sum of weights of all branches connecting subgraphs A and B; $\mathrm{vol}(A)$ is the sum of weights of all branches within subgraph A; $\mathrm{vol}(B)$ is the sum of weights of all branches within subgraph B. Minimizing the function $\mathrm{Ncut}(A,B)$, referred to as the normalized cut criterion, is tantamount to optimizing the objective function for the most favorable partitioning of node data. When employing the normalized cut criterion for power grid partitioning, it takes into account not only the external connections between partitions but also the internal connections within each partition, resulting in a balanced partitioning effect.

The optimal solution to the graph partitioning criterion presents an NP-hard challenge, yielding $2^{\mathrm{n}-1}$ potential outcomes for a graph comprising n nodes. For this problem, Donath and Hoffman proposed a solution method based on the eigenvector of the adjacency matrix, while Fiedler demonstrated the intimate correlation between graph bisection and the second eigenvector of the Laplacian matrix, advocating for the utilization of this eigenvector in graph partitioning (Fabjawska, 2012). The optimization problem of the normalized cut criterion can then be transformed into an eigenvalue problem as follows:

$$\boldsymbol{L}\boldsymbol{y} = \lambda \boldsymbol{D}\boldsymbol{y} \tag{10}$$

Transforming the problem into solving the normalized form of the Laplacian matrix:

$$\boldsymbol{L}' = \boldsymbol{D}^{1/2}(\boldsymbol{D} - \boldsymbol{A})\boldsymbol{D}^{1/2} \tag{11}$$

$$\boldsymbol{Z} = \boldsymbol{D}^{1/2}\boldsymbol{Y} \tag{12}$$

$$\boldsymbol{L}'\boldsymbol{Z} = \lambda \boldsymbol{Z} \tag{13}$$

Solving the equation for Fiedler's eigenvector, denoted as $\boldsymbol{V}_F$, corresponding to the second smallest eigenvalue of matrix $\boldsymbol{L}'$, enables the derivation of the graph's partitioning indicator vector based on the Fiedler eigenvector. Let $n \times 1$ order vector be:

$$\boldsymbol{K} = \boldsymbol{V}_F + \rho \tag{14}$$

As the variable ρ spans from negative infinity to positive infinity, the elements of vector $\boldsymbol{K}$ undergo n sign changes, yielding $n-1$

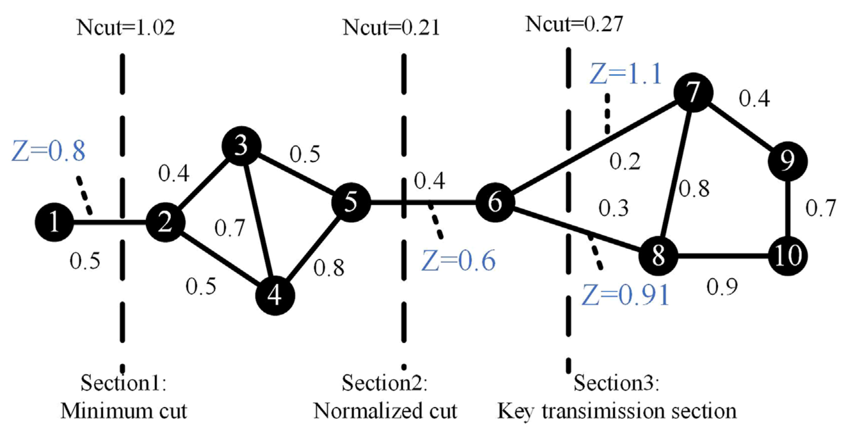

FIGURE 3
The simple 10-bus system and its transmission sections.

distinct segmentation indicator vectors $\boldsymbol{X} = (x_1, x_2, \ldots, x_n)^T$. The process entails calculating $n-1$ normalized cut objective function values based on partitioning indicator vectors. Among these, the partition that corresponds to the indicator vector which minimizes the objective function is identified as the optimal partition.

3 Search method for KTS

3.1 The KTS identification method based on power grid partitioning

Grid partitioning facilitates the identification of KTS. In the case of practical large-scale power grids, power experts typically divide the grid into several sub-areas based on geographic or administrative regions, forming multiple partitioned section. When a partition section or a combination of multiple partitioned sections can divide the system into independent subsystems, several important transmission lines that are closely connected between these partitions constitute a transmission section (Liu et al., 2017). However, after the power grid is divided, a large number of transmission sections will be formed, and it is difficult to monitor all transmission sections. KTS that have a greater impact on the stability of the power system are usually selected as the focus of safety analysis and monitoring. Currently, there is no strict definition for KTS, leading to different identification methods. To facilitate the identification of KTS and distinguish them from non-KTS, this study defines KTS as follows:

1) The active power flow of the section's lines is high, and the flow direction is consistent;
2) The transmission lines forming the section are closely connected, with the outage distribution factor between lines;
3) The section's line loading rate is high, and there are overloaded lines in the section under N-1 failure;
4) The system is divided into several mutually independent and connected subsystems once all lines in the transmission sections are disconnected.

The study employs a spectral clustering algorithm based on normalized cut for power grid partitioning, where the cut sets between partitions are identified as KTS. Throughout the power grid partitioning process, the algorithm strives to cluster similar node data into the same partition, ensuring that nodes within a given partition are closely connected, while nodes in different partitions exhibit weaker connections.

3.2 Defects in methods for identifying KTS through power grid partitioning

The KTS identification method based on power grid partitioning exhibits limitations as it tends to overlook internal searches within partitions during the KTS search process, potentially resulting in the omission of relevant KTS. In section 2.3 of this study, the selection of KTS relies on the minimum value of the normalized cut's objective function corresponding to a partition section. However, the omission of further identification for the remaining $n-2$ objective values related to transmission sections may lead to misidentifications or exclusions of KTS. To illustrate this, the drawbacks of the partition method based on the normalized cut are discussed using the simple 10-bus system and its transmission sections depicted in Figure 3 as an illustrative example.

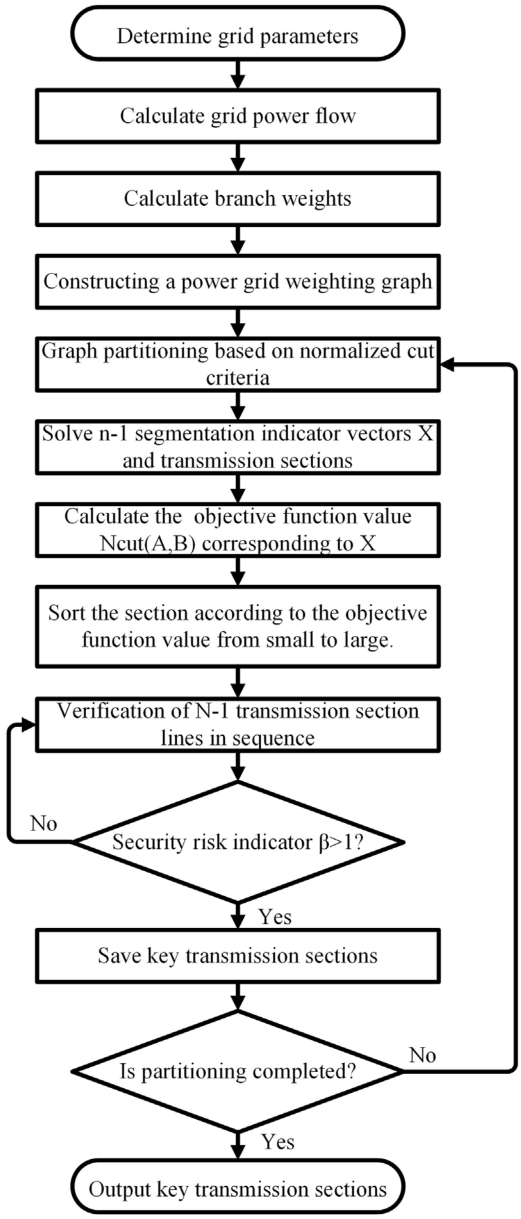

FIGURE 4
The workflow for searching KTS.

In Figure 3, the numerical values assigned to the branches represent their respective weights, denoted as Ncut for the normalized cut objective function value, and Z for the load ratio of the lines. Section 1 is the minimum cut, with the largest objective function value and a skew-cut issue. Section 2, a normalized cut, boasts the smallest objective function value, resulting in a more balanced partitioned subgraph, albeit without overloaded lines. Although the objective function value of section 3 is larger than the objective function value of section 2, the lines in section 3 are

TABLE 1 The results of the comparison between the two methods.

Method	KTS	Component lines	Security risk index	N-1 over-limit line
Reference (Wang et al., 2020)	RKTS 1	6-11,13-14	1.39	l_{6-11}^{13-14}, l_{13-14}^{6-11}
	RKTS 2	10-11,10-13	1.09	l_{10-13}^{10-11}, l_{10-11}^{10-13}
	RKTS 3	2-25,26-27	1.01	l_{2-25}^{26-27}
	RKTS 4	5-6,6-7,13-14	0.91	Non
	RKTS 5	16-21,16-24 or 16-24,21-22	0.68or1.05	non or l_{16-24}^{21-22}
This paper	SKTS 1	6-11,13-14	1.39	l_{6-11}^{13-14}, l_{13-14}^{6-11}
	SKTS 2	10-11,10-13	1.09	l_{10-13}^{10-11}, l_{10-11}^{10-13}
	SKTS 3	2-25,26-27	1.01	l_{2-25}^{26-27}
	SKTS 4	16-21,23-24	1.15	l_{23-24}^{16-21}, l_{16-21}^{23-24}
	SKTS 5	6-11,4-14,16-17	1.06	l_{4-14}^{6-11}, l_{6-11}^{4-14}
	SKTS 6	1-2,2-3,26-27	1.07	l_{2-3}^{26-27}

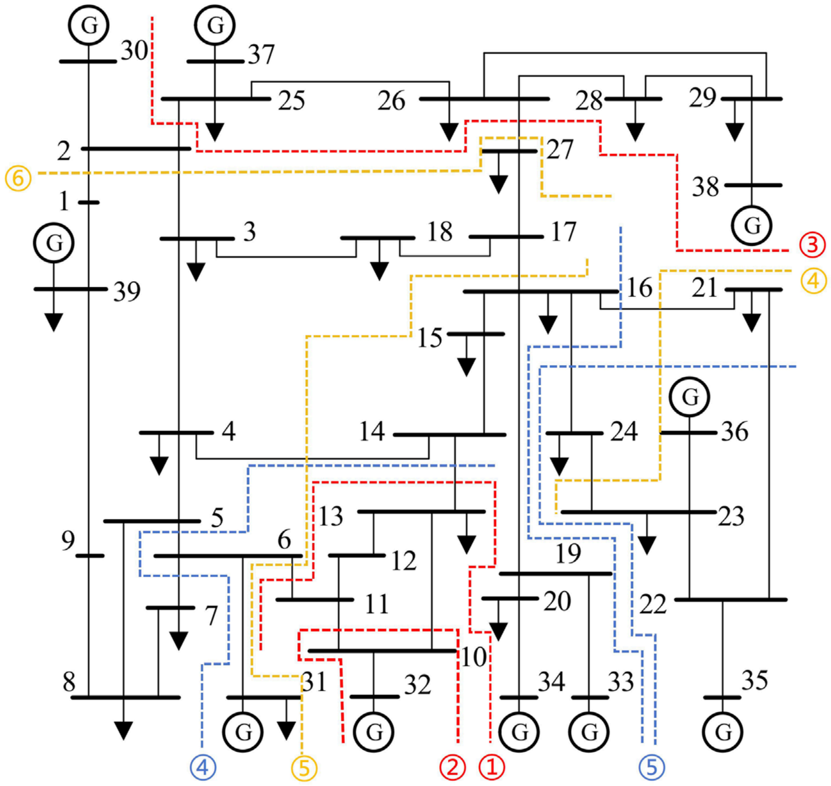

FIGURE 5
Distribution of KTS obtained by the two methods.

subject to heavy load operation and load over-limit. According to the definition of KTS, it is obvious that section 3 is the real KTS. Upon the above analysis, the identification method for KTS based on the normalized cut exhibits the following shortcomings:

1) The assessment of section criticality relies solely on the magnitude of normalized cut objective function values, and the accuracy of partitioning depends excessively on the settings of branch weights.

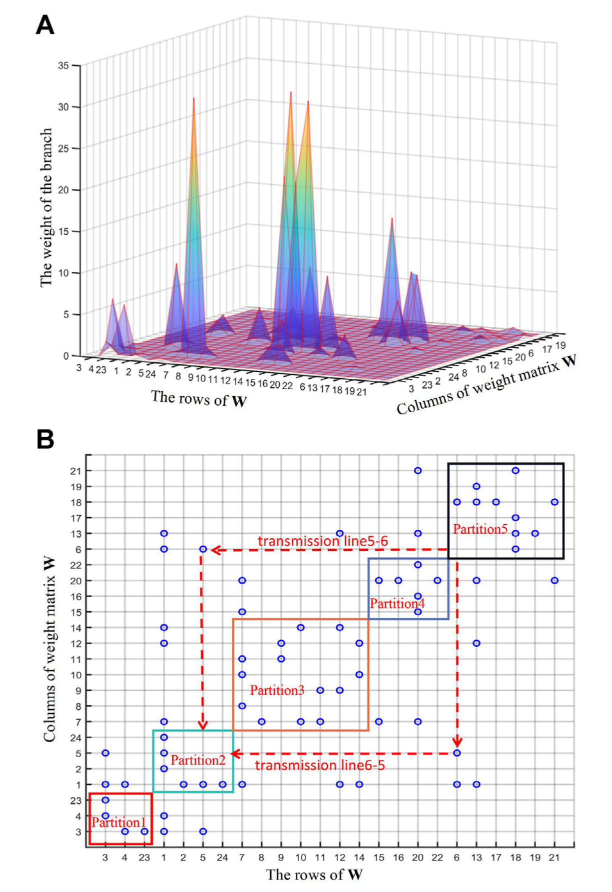

FIGURE 6
Three-dimensional diagram and its top view of the sorted weight matrix. **(A)** The weight of branches. **(B)** Node partitioning and its transmission lines.

2) The exploration of KTS is not incorporated within the partitioning process.
3) There is a lack of specific criteria for distinguishing between KTS and non-critical transmission sections.

3.3 The KTS search method based on security risk indicator

In order to systematically search KTS and avoid the issue of omission, this paper improves the spectral clustering algorithm based on the normalized cut. It introduces a safety risk indicator for evaluating the criticality of transmission sections and employs this indicator to identify KTS during the partitioning process. When an N-1 fault occurs on a transmission section, the over-limit value of the transmission line is:

$$\gamma = \frac{P_l + \alpha_{k\to l} P_k}{P_l} - 1, l \in S, k \in S \tag{15}$$

where, S is the set of transmission section lines; P_l and P_{l-max} are the active power flow and transmission limits of the line l; P_k is the active power flow of the line k; $\alpha_{k\to l}$ is the outage distribution factor when the power flow transfers to line l after line k is disconnected.

The defining characteristics of KTS, as per its definition, involve a high line load rate and a small safety margin. When the lines of KTS experience an N-1 fault, the remaining lines in KTS exceed their flow limits, denoted as $\gamma > 0$. To highlight the ascending correlation between the line overload values of the transmission section and safety risk more vividly, this study opts for the natural exponent e as the base and utilizes over-limit value γ as the exponent, thereby formulating the safety risk index for the transmission section as:

$$\beta = \max\left\{\exp\left(\frac{P_l + \alpha_{k\to l} P_k}{P_{l-max}} - 1\right)\right\}, l \in S, k \in S \tag{16}$$

It can be seen from the above formula that the over-limit value and the safety risk increase exponentially. If the transmission section surpasses the limit value and the safety risk index exceeds 1, it is identified as KTS. Hence, this safety risk index serves as an evaluative criterion for distinguishing between KTS and non-critical transmission sections.

The procedural aspects of the spectral clustering algorithm based on normalized cut are improved in this paper, with security risk indicators being utilized to conduct KTS searches within the partition. As indicated in Section 2.3, during the partitioning of an n-node system, the search for KTS within the partitions is overlooked, implying that identification is not conducted for the remaining $n-2$ transmission sections. The algorithmic procedure outlined in the preceding text is refined in this study. Initially, the $n-1$ transmission sections undergo sorting in ascending order based on their normalized cut target values. Subsequently, a sequential N-1 safety verification is executed on the lines within each transmission section, resulting in the derivation of the outage distribution factor $\alpha_{k\to l}$ and the safety risk indicator β. The selection of a transmission section as a KTS is made when the safety risk indicator meets criterion $\beta > 1$.

3.4 The KTS search process

This paper presents a KTS search methodology based on an enhanced spectral clustering algorithm. The approach initially computes the power flow and branch weights of the power grid according to its operational scenarios, leading to the construction of a weighted graph for the power grid. Subsequently, a recursive spectral clustering algorithm is applied to partition the power grid, and the criticality of the partitioned sections is assessed through safety risk indicators. The partitioning process is iteratively conducted until no KTS is identified in any partition. The procedural framework for the KTS search is illustrated in Figure 4.

4 Case studies

This paper selects the IEEE 39-node system and the actual power grid 23-node system to verify the effectiveness of the proposed method.

4.1 IEEE 39-bus system example

Based on the parameters of the IEEE 39-bus system, a comparison was conducted between the Search Key Transmission

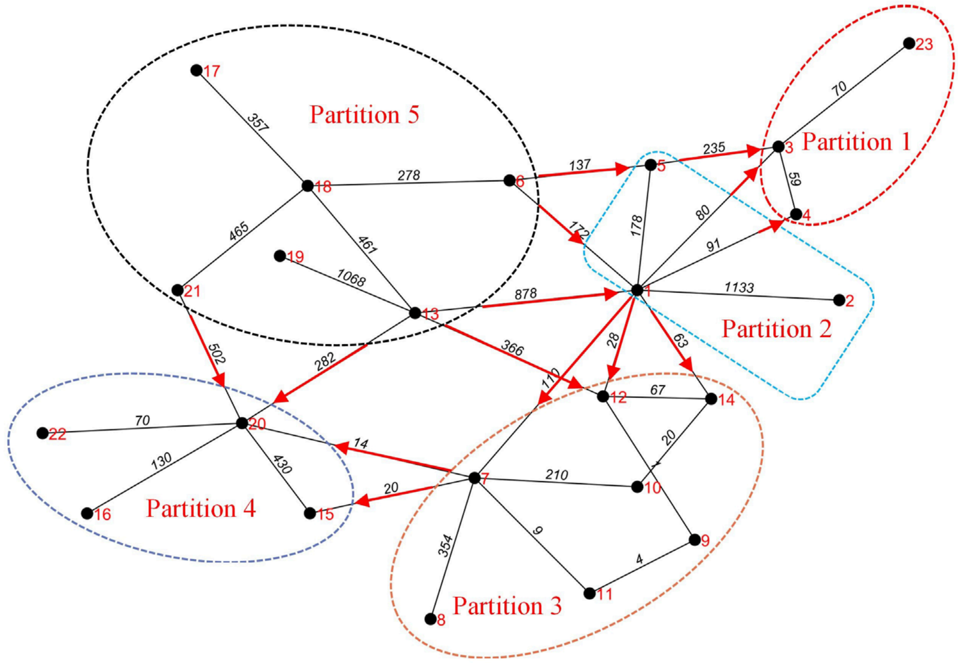

FIGURE 7
The partition results of the 23-bus system.

TABLE 2 The search results for partitioned sections.

Partitioned section	Location	Component lines	Line power(MW)	Load rate	Security risk indicators
1	Partition 2,5	1-6,1-13,5-6	171,878,136	0.90,0.50,0.47	1.11
2	Partition 1,2	1-3,1-4,3-5	80,90,371	0.65,0.40,0.85	1.01
3	Partition 4,5	20-21,13-20	501,288	0.38,0.21	0.61
4	Partition 2,3,5	1-13,12-13	878,396	0.30,0.27	0.46
5	Partition 2,3	1-7,1-12,1-14	110,28,62	0.08,0.06,0.06	0.4
6	Partition 3,4	7-20,7-15	14,20	0.01,0.03	0.3

Section (SKTS) recognized by the method proposed in this paper and the Reference Key Transmission Section (RKTS) identified in reference (Wang et al., 2020). The results of the comparison between the two methods are presented in Table 1, where the superscript of l denotes the disconnected line, and the subscript indicates the overloaded line.

From Table 1, it can be discerned that the method presented in this paper identifies 6 SKTS, compared to 5 RKTS in reference (Wang et al., 2020). Notably, SKTS1, SKTS2, and SKTS3 align perfectly with RKTS1, RKTS2, and RKTS3. Upon conducting a comparative analysis of safety risk indicators, it is evident that all SKTS exhibit safety risk indices greater than 1, accompanied by transmission lines exceeding their limits under N-1 fault scenarios. Conversely, the safety risk indicators for RKTS 4 (16–21, 16–24) and RKTS 5 (16–21, 16–24) are less than 1, with no over-limit lines, thereby excluding them as KTS. The distribution of KTS identified by both methodologies is depicted in Figure 5, wherein red dotted lines denote identical KTS shared by both methods, and yellow dotted lines and blue dotted lines respectively illustrate the additional SKTS and RKTS.

A comparative analysis of the criticality between SKTS 4 (16–21,23–24) and RKTS 5 (16–24,21–22) was carried out. As displayed in Figure 5, both transmission sections consist of four branches connecting nodes 16, 21, 22, 23, and 24, embodying an instance of an optimal cut problem within the graph. The active power flows across these four branches are: $P_{16-21} = 330$, $P_{23-24} = 354$, $P_{16-24} = 43$, $P_{21-22} = 604$. It is evident that the SKTS 4 has larger active power flows and a higher safety risk value.

Through the above discussion and analysis, it can be concluded that the KTS identified by the proposed method have larger power

TABLE 3 The comparison between SKTS searched in multiple scenarios and MKTS.

Monitoring KTS	Component lines	Search KTS	Component lines	Probability	Comparative Results
MKTS 1	1-6,13-18	SKTS 1	1-6,5-6,13-18	15.30%	cover
MKTS 2	5-6,13-18				
MKTS 3	1-6,5-6				
MKTS 4	1-3,1-4,3-5	SKTS 2	1-3,1-4,3-5	11%	same
MKTS 5	1-6,20-21	SKTS 3	1-6,5-6,20-21	0.7%	cover
MKTS 6	5-6,20-21				
MKTS 7	1-6,1-13	SKTS 4	1-6,1-13,5-6	0.5%	cover
MKTS 8	5-6,1-13				
		SKTS 5	1-5,1-6,1-13	9.1%	new search

flows and higher safety risks, which align with the established definition of KTS. Moreover, the proposed method incorporates a safety risk indicator into the algorithmic process to filter KTS and non-critical transmission sections, ensuring result accuracy while minimizing the potential for false positives and false negatives selections.

4.2 The actual electrical grid example

In order to verify the effectiveness of this method in actual power grids, this paper selects an actual power grid in a city in Guangdong, China, which contains a high proportion of new energy, as a calculation example. The power stations and lines of the power grid with voltage levels above 220 kV are simplified into a system of 23 bus and 34 lines. The power nodes include 1 pumped hydro storage, 2 thermal power units and 3 large-scale wind and solar farms. The total installed capacity of the power supply is 7300 MW, and the proportion of new energy installed capacity is 49%.

4.2.1 KTS in summer load peak scenario

In actual power grid operations, electrical experts commonly select representative operational scenarios to identify KTS. Therefore, this study initially identified KTS in the actual power grid in the scenario of the summer peak load. The proposed method effectively segmented the power grid into five partitions, after which the nodes were rearranged based on their partition sequence, culminating in a sorted weighted matrix. Three-dimensional diagram and its corresponding top-down view of the sorted weight matrix are shown in Figure 6.

As can be seen in Figure 6, the element distribution chart of the weighted matrix, sorted according to the partition results, clearly illustrates the connections between nodes and the connections between different partitions. In Figure 6A, the vertical axis represents the weight of branches between two nodes, where higher weight indicates a closer connection between the nodes, increasing the likelihood of both nodes being assigned to the same partition. In Figure 6B, dots represent branches between two nodes. The five rectangles indicate the 5 partitions, each containing nodes and branches. High branch weights inside the rectangle indicate strong connections between nodes, leading to their assignment to the same partition. Low branch weights outside the box suggest weaker connections, making them inter-partition transmission lines. For example, the transmission line between partition 5 and partition 2 identified as five to six, with a considerably low weight, representing a weak link connecting the two partitions. The partition results of the 23-bus system under typical operating conditions in the summer peak load scenario are illustrated in Figure 7.

Based on the above partitioning results, the partitioned section is obtained in the scenario of the summer peak load, that is, the collection of transmission lines between partitions. The search results for partitioned sections are shown in Table 2.

From Table 2, it is evident that a total of 6 partitioned sections were identified in the scenario of the summer peak load. Among them, partitioned section 1 and partitioned section 2 have higher power flow and load rate, and the safety risk index value is greater than 1, which means they are KTS.

4.2.2 KTS in multiple scenarios

There are 8 Monitoring Key Transmission Sections (MKTS) identified by experts in the actual power grid, but the SKTS in the scenario of the summer peak load is only 2. Therefore, the KTS obtained in one scenario cannot cover all MKTS. To address this, this paper employs Monte Carlo sampling to generate 1,000 scenarios based on the historical power output and load demand data of the actual power grid, producing a scenario set that encompasses all extreme conditions (Bao et al., 2021). KTS are searched in every scenario, and their occurrence probabilities are calculated. The comparison between SKTS searched in multiple scenarios and MKTS is shown in Table 3.

As can be seen from Table 3, a total of 5 SKTS were identified in multiple scenarios, among which SKTS 2 is the same as MKTS

4, and SKTS 5 is a new searched section. SKTS 1, SKTS 2, and SKTS 4 merge multiple MKTS respectively, reducing the number of MKTS, thereby decreasing the overall number of MKTS while enhancing monitoring efficiency. For example, SKTS 1 combines the monitoring of MKTS 1, MKTS 2, and MKTS 3. In order to verify its rationality, N-1 verification is performed on the three lines 1–6, 5–6, 13–18. The breaking distribution factors are all greater than 0.2 and there are line overruns. This shows that the three lines of SKTS 1 are closely connected, that is, when one line is broken, the power flow quickly transfers to the other two lines. However, MKTS 1, MKTS 2, and MKTS 3 only monitor two of these lines, resulting in a case of missing monitored lines. Therefore, the approach presented in this paper is more accurate and efficient.

Through searching and analyzing KTS in 1,000 scenarios, the results show that the maximum probability of SKTS 1 occurrence is 15.3%, while the minimum probability for SKTS 4 is 0.5%. Among them, the newly searched SKTS 5 has a probability of occurrence at 9.1%, indicating a higher risk of section overload. Therefore, SKTS 5 should be included in the monitored sections.

5 Conclusion

This paper studies the KTS search method of power systems and proposes a KTS search method based on improved spectral clustering algorithm. The advantages of this method include: 1) An improved normalized cut spectral clustering algorithm is adopted for partitioning the power grid, which features a lower computational complexity and is suitable for large-scale power networks; 2) Consideration of both node voltage and active power flow when constructing branch weights, providing a comprehensive reflection of the tight connections between nodes and thus improving the accuracy of the model; 3) Search the internal sections of the partition during the partitioning process to avoid missing KTS; 4) Establishing a safety risk indicator for identifying KTS in cases where numerous partitioned sections are formed. The proposed method has been validated through practical applications in power system engineering. It can not only accurately and efficiently search for KTS currently monitored in operational control, but also filters out KTS with high risk that operational experts may have overlooked. This contributes to risk mitigation and enhances monitoring efficiency for operational dispatch personnel.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

JL: Formal Analysis, Methodology, Writing–original draft. ML: Conceptualization, Funding acquisition, Resources, Supervision, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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