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Intelligent Sectorization Method for Lighting Networks Based on Clustering Algorithm

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Abstract: *In order to balance energy saving and safety requirements, the intelligent lighting system divides the streetlight network into multiple sectors so that only the streetlights in the corresponding sector are activated when traffic elements such as pedestrians and vehicles pass by, thereby achieving traffic element-based sectorized lighting control. This strategy requires the manual pre-configuration of neighbor relationships among streetlights so that when a traffic element passes a streetlight, only the other streetlights within its sector are activated. However, in complex and large-scale roadway lighting networks, manually configuring neighbor relationships for a vast number of streetlights is extremely tedious and prone to errors. To address this issue, a method for modeling the streetlight network as a social network and performing sectorization through clustering algorithms is proposed. In this method, traffic element events detected by streetlights and network advertising are used to construct a probabilistic graph of neighbor relationships, and the ACO-CUG algorithm is employed to mine the neighbor relationships among streetlight nodes, with the clustering result thus obtained regarded as the sectorization of the streetlight network. Experimental results on a simulation dataset demonstrate that the proposed method can effectively partition streetlights in different areas, thereby achieving intelligent sectorization of the streetlight network.*

Keywords: *Intelligent Streetlights, Sectorization, Probabilistic Graph, Clustering*

1. Introduction

Traffic element adaptive lighting is an effective method for energy-saving illumination, based on the fundamental principle that high brightness of streetlights is unnecessary when traffic elements are not in their vicinity. Consequently, a mechanism has been proposed to partition the lighting network into multiple sectors so that only the streetlights within a specific sector are activated when traffic elements pass, rather than activating all streetlights [1]. This sectorized lighting system is capable of automatically dimming the streetlights in a sector after the traffic elements leave, thereby balancing energy efficiency and safety requirements.

However, for complex and intricately interwoven roadway networks, the traditional relay-based advertising mechanism may result in imprecise information transmission, as the advertising affects all nodes within the communication range rather than being confined to those nodes located within the sector where the traffic element is present. In order to achieve precise lighting control, streetlight nodes must accurately determine their neighbor relationships, that is, whether they are situated within the same sector. In large-scale lighting networks, relying on GPS or communication-based positioning techniques to ascertain these neighbor relationships may become unreliable due to the crisscross arrangement of roads, while manually configuring such relationships can be both tedious and error-prone, thereby limiting the scalability and reliability of the system.

To resolve these challenges, a systematic method is proposed that models the streetlight network as a social network and employs clustering algorithms to mine the neighbor relationships of the streetlights, thereby partitioning the sectors. Communities in social networks are sets of nodes characterized by tight internal connections and relatively sparse external connections [2]. Graph structures, as a modeling tool, are widely used to depict and analyze large-scale data networks. However, the uncertainty inherent in graph data is an issue that cannot be overlooked, as it may arise from factors such as measurement noise and inaccurate information sources [3, 4]. Probabilistic graph models provide a means of modeling natural phenomena with uncertain interactions by assigning an existence probability to each edge. In the field of probabilistic graph data mining, clustering is a commonly used technique, whose primary objective is to group similar nodes in the graph into clusters while assigning dissimilar nodes to different clusters [5].

The lighting system designed in this article is composed of multiple streetlight nodes equipped with millimeter-wave radar sensors and Bluetooth Low Energy (BLE) modules. Among these, the millimeter-wave radar sensor is employed to detect nearby traffic elements. When a traffic element approaches a node, a message is advertised by that node. As the traffic element moves, further advertising are triggered by subsequent nodes upon detection of the traffic element. A series of records generated by traffic element detection events and network advertising is periodically uploaded to a gateway for mining the neighbor relationships among streetlight nodes. Considering the uneven distribution of nodes, unstable communications, and advertising storms, the relationships between nodes are uncertain. Therefore, probabilistic graphs are used to model the streetlight network. To mine the neighbor relationships among nodes, a probabilistic graph clustering algorithm based on Ant Colony Optimization (ACO) [6] is adopted in this article. This algorithm is built upon the conventional ACO-based clustering algorithm [7], extending it into the domain of probabilistic graphs.

In summary, the main contributions of this article are as follows:

1) A modeling method is proposed that does not rely on the geographical location information of streetlight nodes but, instead, models the streetlight network as a social network represented by a probabilistic graph based on traffic element detection events and network advertisements.

2) By applying a probabilistic graph clustering method, the neighbor relationships among streetlight nodes are mined on the basis of the social network modeling, thereby achieving intelligent sectorization of the streetlight network.

3) Simulation datasets have been generated for various scenarios, and extensive experiments on the proposed sectorization method have verified its effectiveness.

The remainder of this article is organized as follows: Section 2 provides an overview of the literature related to this work. Section 3 details the proposed method, including the social network modeling approach and the clustering algorithm. Section 4 presents the detailed experimental results, and Section 5 concludes the work.

2. Related Work

2.1. Traffic Element Adaptive Lighting

In recent years, with the maturation of information and communication technologies, an increasing number of studies have introduced wireless modules into lighting systems. This approach has not only enabled more precise and adaptive lighting management but also further reduced energy consumption while ensuring safety [8, 9]. The switching of streetlights should be automatically adjusted according to the movement of objects to further decrease energy consumption [10]. Mobile lighting strategies provide necessary illumination solely around traffic elements by tracking them [11]. This mobile-object-centric control method minimizes energy consumption by monitoring the dynamics of traffic elements.

Some intelligent lighting systems have achieved traffic element adaptive lighting control through sectorization. In the system proposed in [12], when two nodes in a region consecutively detect pedestrians, the illumination levels of all nodes increase, even if some nodes have not yet detected pedestrians. In [13], multiple streetlights are arranged in a junction area to form a streetlight island. When the sensor at the junction detects a traffic element, the control unit turns on all streetlights and maintains the illumination for a fixed period. In [1], the entire highway is divided into multiple sectors, and when a vehicle approaches an anchor node, all streetlights in the corresponding sector, as well as some streetlights in the next sector, are activated. In [14], a zonal control strategy is employed during nighttime, where half of the streetlights are illuminated at regular intervals, and the other half are pre-activated based on the position of the traffic element. As mentioned earlier, the sectorization method requires determining the neighbor relationships among nodes, which is the starting point of the work presented in this article.

2.2. Probabilistic Graph Clustering

As one of the core tasks in data mining and machine learning, clustering analysis has been extensively

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studied for over half a century. Nevertheless, research on clustering in probabilistic graphs remains relatively scarce, and this field is rapidly expanding. Some algorithms have extended traditional deterministic graph clustering techniques to probabilistic graph clustering. For example, [15] proposed the pKwikCluster algorithm, which randomly selects a node at each step and considers this node along with all its neighbors having a probability greater than 0.5 as a cluster, continuing this process until all nodes are traversed. In [16], the USCAN algorithm was introduced, incorporating the concept of reliable structural similarity and efficiently computing similarity probabilities between nodes using a dynamic programming algorithm. In [17], traditional k-median and k-center algorithms [18] were improved by employing possible world sampling to provide approximate solutions. In [19], a density-based clustering algorithm was proposed, utilizing graph density and neighborhood information for clustering.

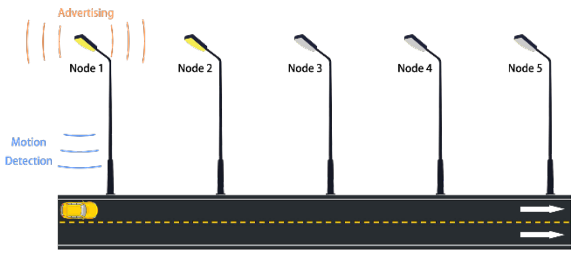
In probabilistic graph clustering algorithms, the works of [20], [21] and [6] have integrated clustering with evolutionary algorithms. [20] proposed a clustering method based on a multi-population genetic algorithm, called EA-CPG. This algorithm converts a probabilistic graph into multiple deterministic graphs using different thresholds and generates multiple initial populations accordingly. During the genetic evolution process, EA-CPG adjusts the clustering results using the pKwikCluster algorithm. [21] improved upon EA-CPG and proposed the EEA-CPG algorithm, which employs a higher-order random walk model to evaluate node similarity and incorporates a local search algorithm. [6] introduced an Ant Colony Optimization (ACO) based clustering method called ACO-CUG, which utilizes the improved k-means algorithm FDCC [22] to initialize the pheromone matrix, providing a well-optimized initial solution. Given the complexity of large-scale road lighting networks, this article adopts the ACO-CUG algorithm to cluster the probabilistic graph, achieving intelligent sectorization of the streetlight network.

3. Sectorization Method

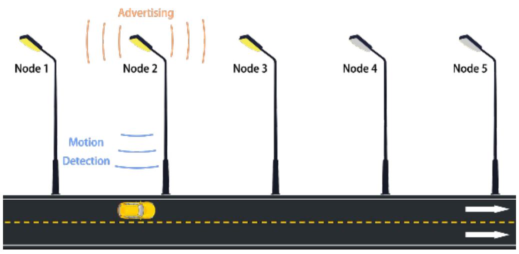
3.1. Social Network Modeling Approach

The lighting system designed in this article consists of multiple streetlight nodes, each equipped with a BLE module. Through these modules, streetlight nodes can communicate with each other, forming a self-organizing BLE mesh network. In addition to the streetlight nodes, the system includes a gateway node responsible for collecting and processing data from the streetlight nodes. Besides the BLE module, each streetlight node is also integrated with a millimeter-wave radar sensor, which can detect passing traffic elements in real time.

Streetlight nodes follow a specific operational process. As shown in Figure 1(a), when Streetlight Node 1 detects an approaching traffic element, it advertises a message through the BLE mesh network. The time-to-live (TTL) of this message is set to 1 to ensure that only nearby nodes receive it. Upon receiving the message, Node 2 temporarily stores the sender's MAC address, denoted as MAC_1, in its local memory. When the traffic element continues moving and approaches Node 2, this node also broadcasts a message, as illustrated in Figure 1(b). Additionally, Node 2 associates the data from both events and creates a temporary record in the form of $\{MAC_1, MAC_2, n_{1,2}\}$, where $n_{1,2} = 1$. This record indicates that a traffic element has sequentially passed through Node 1 and Node 2 exactly once, suggesting that these two nodes might be neighbors. As the traffic element continues to move, the streetlight nodes continuously update these cached records based on the aforementioned operations. Collectively, these records form a relational network that maps the potential neighbor relationships between nodes.



(a) Node 1 detects a traffic element.



(b) Node 2 detects a traffic element.

Figure 1: Nodes detect a traffic element.

The lighting system features a periodic data reporting mechanism. At fixed intervals of T_c, the gateway node requests all streetlight nodes to sequentially report all cached records they have maintained during the past T_c period. These records are then centrally processed to construct a count matrix C. In matrix C, the element c_{ij} represents the occurrence count of the event where a traffic element sequentially passes through Node i and Node j.For instance, if Node j reports a cached record in the form of $\{MAC_i, MAC_j, n_{i,j}\}$, then $c_{ij} = n_{i,j}$. By applying a normalization process to matrix C, each element c_{ij} is converted into a probability value p_{ij}. This transformation considers the maximum value within each row to ensure the reasonableness and comparability of the probability values. Through this processing, the count matrix C is converted into an adjacency matrix P. Based on the adjacency matrix P, the gateway node is able to construct a complete probabilistic graph.

3.2. Clustering Algorithm

To mine the neighbor relationships among streetlight nodes, this article adopts the ACO-CUG algorithm [6]. This algorithm is based on ACO and obtains clustering results by continuously adjusting the pheromone matrix and dynamically updating the ant colony. Notably, the ACO-CUG algorithm innovatively applies the FDCC method to initialize the pheromone matrix, providing a high-quality initial solution for the iterative process of the algorithm. The workflow of the ACO-CUG algorithm will be briefly outlined next.

The specific process of the ACO-CUG algorithm is as follows: In the initial stage, for the given probabilistic graph, six different thresholds are independently applied to generate six subgraphs. For each subgraph, the higher-order random walk similarity between all nodes is calculated. Then, the FDCC method is used to select multiple cluster centers and initialize the pheromone matrix accordingly. During each iteration, an ant colony is generated based on the current pheromone matrix, and local search operations are performed on the colony. The corresponding objective function value is computed, and the pheromone matrix is updated based on the best-performing ants. The algorithm continues to generate new ants until the objective function converges or the preset stopping criteria are met. After iteration terminates, the globally optimal ant is determined based on the objective function value, and the corresponding solution is taken as the final clustering result.

One of the significant advantages of the ACO-CUG algorithm over other probabilistic graph clustering algorithms is its use of the FDCC method to initialize the pheromone matrix. The FDCC method determines K initial cluster center groups through multiple rounds of selection. In the first round, the first cluster center is selected randomly. For the subsequent $K-1$ cluster centers, nodes with the lowest higher-order random walk similarity to the already selected cluster centers are chosen as new centers. This ensures that each new cluster center is as far as possible from the previously selected cluster centers. In the second round of selection, the process continues following the same principle, and so on, until all rounds of cluster center selection are completed. After multiple rounds of selection, each cluster center is most similar to the previously selected centers within its own cluster, while being maximally dissimilar to the centers in other clusters. Compared to the traditional k-means algorithm, where cluster centers are randomly selected, the FDCC method is able to more evenly select nodes from different areas of the probabilistic graph as initial cluster centers. This characteristic is particularly beneficial for the sectorization of the streetlight network.

4. Experiments and Results

In this section, the experimental evaluation of the proposed algorithm and the analysis of its results are described in detail. To verify the effectiveness of the proposed method, a series of simulation datasets were designed and generated for the experiments. These datasets vary in complexity and scale, allowing for a comprehensive test of the algorithm's adaptability. In the following sections, the datasets used in the experiments and the evaluation metrics are introduced, followed by an analysis of the experimental results to demonstrate the performance of the proposed method across different datasets.

4.1. Datasets

To evaluate the effectiveness of the proposed method, custom simulation datasets were used. As mentioned earlier, these datasets are derived from traffic element detection events and network advertising in the streetlight network. Considering the complexity of the dataset generation process and the unavailability of such data from existing public sources, a series of datasets were designed and generated for this study. The following are the detailed steps for generating the datasets:

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1) **Node Distribution Graph Design**: This study first obtains publicly available regional maps from the internet, which serve as the foundational road network framework. Then, nodes are placed reasonably along the roads to simulate the actual streetlight layout. Once the nodes are placed, a complete node distribution graph G^N is obtained.

2) **Sector Division**: Based on the real map data, special nodes such as intersections, corners, and building entrances/exits are marked in G^N. After marking the special nodes, logical partitions are made for the remaining nodes with these special nodes as endpoints, forming the ideal streetlight sector divisions (i.e., the ground truth). Once the division is completed, a node distribution graph G^L with sector information is obtained.

3) **Virtual Object Movement**: To simulate the movement of pedestrians and vehicles, an algorithm is used to randomly deploy multiple virtual objects in G^N and move them at different speeds. The movement process of these objects is recorded in detail, including the nodes they pass through and the times they arrive at each node. After the movement is completed, the nodes are sorted according to the time sequence, thus obtaining the sequence of nodes where traffic elements were detected.

4) **BLE Mesh Networking Simulation**: In MATLAB, BLE nodes are deployed according to the node distribution graph G^N generated in step 1, and advertising messages are sent in the sequence of nodes as per the sequence generated in step 2. All advertising messages have the destination address set to FFFF, and the TTL is set to 1. The nodes that receive the advertising temporarily store the MAC address of the advertiser and update the cache record during the next advertising. As described in Section 3.1, after the simulation is complete, a series of cache records are obtained.

5) **Generating the Probability Graph**: The cache records are processed according to the method described in Section 3.1 to generate the probability graph G^P. G^L and G^P together form the dataset.

In the experiment, a total of three regional maps were selected as the base road network framework, including a park, a city commercial area and a city residential area, as shown in Figures 2-4. These maps vary in scale, road characteristics, and other aspects, allowing for a comprehensive assessment of the proposed method's adaptability to different traffic conditions.

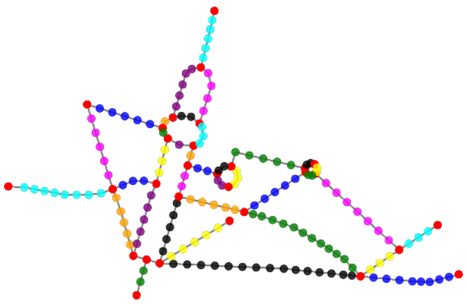

Figure 2: Node distribution graph of the park.

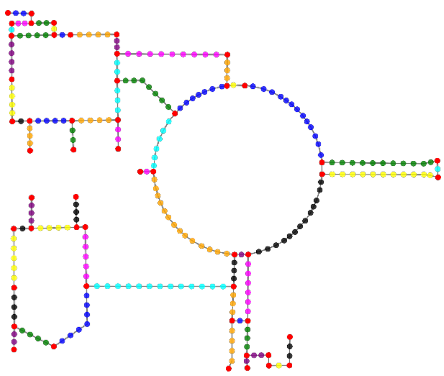

Figure 3: Node distribution graph of the city commercial area.

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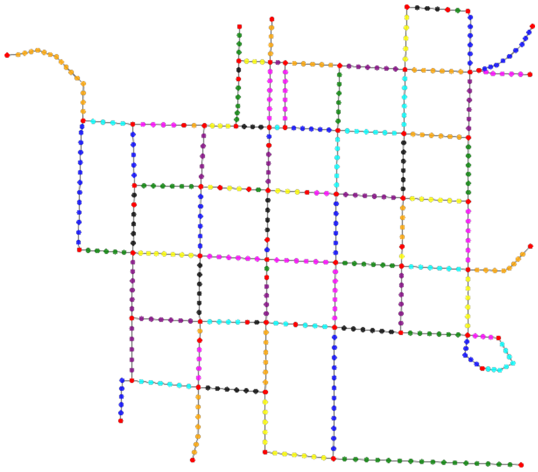

Figure 4: Node distribution graph of the city residential area.

As shown in the figures, different colors have been assigned to the nodes to intuitively identify and distinguish the different sectors. Red represents special nodes, such as junctions, corners, and building entrances. Apart from the special nodes, other nodes in the figures are colored according to the sector to which they belong. Connected nodes of the same color indicate that they belong to the same sector, while nodes of different colors and unconnected same-color nodes belong to different sectors. These sectors will serve as the ground truth for validating the performance of the proposed method.

4.2. Evaluation Metrics

This study uses Normalized Mutual Information (NMI) [23], a widely used metric in the field of community detection, to evaluate the performance of the proposed method. NMI is a measure of similarity between two community divisions, proposed by Danon et al. Given two different community divisions, A and B, the formula for calculating NMI is as follows:

$$NMI = -\frac{2\sum_{i=1}^{c_A}\sum_{j=1}^{c_B} M_{ij}\log\left(\frac{M_{ij}n}{M_{i.}M_{.j}}\right)}{\sum_{i=1}^{c_A} M_{i.}\log\left(\frac{M_{i.}}{n}\right)+\sum_{j=1}^{c_B} M_{.j}\log\left(\frac{M_{.j}}{n}\right)} \tag{1}$$

In the formula, n is the total number of nodes in the network. M_{ij} is the element of the confusion matrix M, representing the number of nodes that are in community i of partition A and community j of partition B. c_A and c_B represent the number of communities in partitions A and B, respectively. $M_{i.}$ is the sum of the elements in the i^{th} row of the confusion matrix, and $M_{.j}$ is the sum of the elements in the j^{th} column.

4.3. Experimental Results

In this section, the clustering results of the ACO-CUG algorithm on three simulation datasets and their NMI scores are presented. The sector division of the streetlight network is visualized, as shown in Figures 5-7. In these figures, nodes of the same color represent those within the same cluster, while the gray lines represent the edges of the probability graph.

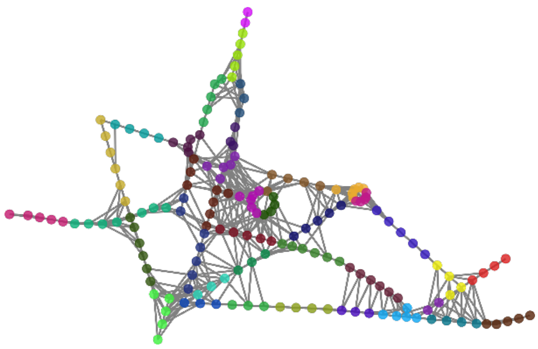

Figure 5: Clustering results of the park.

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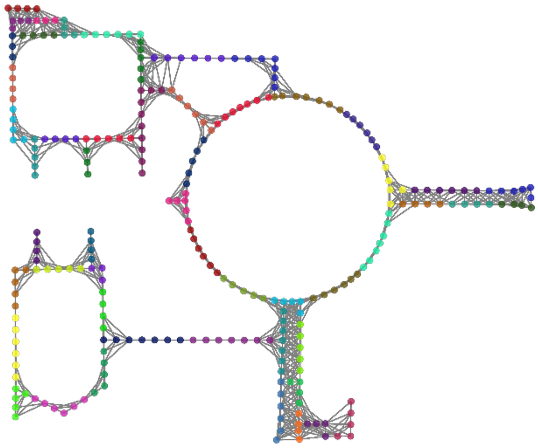

Figure 6: Clustering results of the city commercial area.

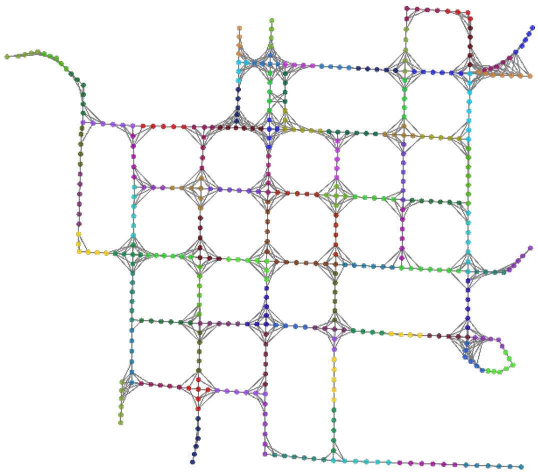

Figure 7: Clustering results of the city residential area.

Figure 5 shows the clustering results for the park, with an NMI score of 0.885. The characteristics of this dataset include a dense node distribution and several small circular road structures, which can easily cause interference between non-neighboring nodes, increasing the difficulty of clustering. From the clustering results and the score, it can be seen that despite the interference, the algorithm still accurately identifies the nodes in different areas and reasonably assigns them to different clusters.

Figure 6 shows the clustering results for the city commercial area, with an NMI score of 0.901. The dataset has the feature of having many parallel roads that are close together, which can cause interference in clustering. From the clustering results, it is clear that the algorithm effectively distinguishes between closely spaced parallel roads and does not assign them to the same cluster. This is beneficial for the sectorization of streetlight networks, as turning on the lighting for a nearby parallel road while traffic is on one road does not significantly contribute to safety and is not energy-efficient.

Figure 7 shows the clustering results for the city residential area, with an NMI score of 0.932. The dataset has the characteristic of relatively consistent road segment lengths and evenly distributed nodes. From the results, it can be seen that the boundaries between clusters are clear, and the number of nodes within each sector is relatively uniform.

Through the clustering results and analysis of the three datasets above, it can be seen that the proposed sectorization method achieves good results across different types of datasets. Whether dealing with areas with densely distributed nodes, closely spaced parallel roads, or small circular road structures, the clustering algorithm is able to uncover the neighbor relationships of the streetlight nodes and realize intelligent sectorization of the streetlight network.

5. Conclusion

To address the cumbersome issue of manually setting neighbor relationships between nodes in

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lighting networks, this paper proposes a method of modeling the lighting network as a social network and using a probabilistic graph model to represent this network. This method does not require the geographic location information of streetlight nodes, but dynamically adjusts the structure of the social network based on the actual flow of traffic elements, thus enabling it to adapt to different regions and traffic environments. On this basis, the paper applies a probabilistic graph clustering algorithm to mine the neighbor relationships of streetlight nodes. The advantage of this algorithm lies in the use of the FDCC method to initialize the pheromone matrix, and achieve better clustering results by iteratively adjusting the pheromone matrix and the ant colony. The proposed method has been tested on multiple simulation datasets. The experimental results show that the method can effectively perform sectorization of the streetlight network, providing strong support for adaptive lighting control in intelligent streetlight systems.

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