Received October 8, 2021, accepted October 26, 2021, date of publication October 29, 2021, date of current version November 8, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3124213

Signal Control Period Division Method Based on Locally Linear Embedding and Particle Swarm Optimization Combined With K-Means Clustering

XIUJUAN TIAN, CHUNYAN LIANG, TIANJUN FENG, AND CHUN CHEN
School of Transportation Science and Engineering, Jilin Jianzhu University, Changchun, Jilin 130118, China

Corresponding author: Xiujuan Tian (jidatianxj@126.com)

This work was supported by the Science and Technology Projects of Education Department of Jilin Province under Grant JJKH20200285KJ and Grant JJKH20210270KJ.

ABSTRACT In order to optimize the existing signal control period division method and improve signal control effect, a new period division method based on Locally Linear Embedding and Particle Swarm Optimization combined with K-means clustering (LLE-PSO-K) algorithm is proposed in this paper. Firstly, traffic flow characteristics of signal-controlled intersections are fully considered, and a multi-dimensional flow matrix is constructed based on the phase traffic flow. In order to reduce the computational complexity of the model and improve the operating efficiency of the method, manifold learning Locally Linear Embedding (LLE) algorithm is brought in to reduce the dimension of the multidimensional phase flow matrix. Then, the dimensionality reduction matrix is used as input data, and signal control period is divided by using Particle Swarm Optimization combined with K-means clustering (PSO-K) algorithm. Finally, an actual intersection in a city is selected to verify the performance of the proposed method. For comparative analysis, control periods are divided based on the phase traffic flow data with 15min, 30min and 1h interval respectively. Results show that for different time intervals, the division of the proposed method is better than other methods, of which the invalid control periods are less. Besides, the optimal clustering number can be obtained, which proves the effectiveness of the new proposed method.

INDEX TERMS Traffic engineering, signal control, control period division, PSO-K clustering, LLE dimension reduction.

I. INTRODUCTION

Considering the control effect and implementation cost comprehensively, time-of-day (TOD) control is still the mainstream intersection signal control method adopted in most cities [1]. The existing study shows that the TOD control period division scheme highly matching with traffic flow characteristic can effectively reduce vehicle delay and improve road capacity.

TOD multi-period control belongs to off-line signal timing mode, which is less dependent on traffic information collection and has better reliability. The basic idea is to divide 24h into several control periods based on the changing characteristics of traffic flow at the intersection. The traffic flow in the same period is basically unchanged, so the signal control scheme is the same. The signal control schemes in different control periods are different. Besides, signal control scheme is automatically switched by the signal machine. Therefore, scientific and reasonable control period division is the premise and basis for effective implementation of TOD control schemes.

The current TOD periods are still mainly divided by artificial experience classification method. The main idea is that the collected intersection traffic flow is drawn into a flow time curve. And the engineers divide control periods according to their subjective judgment. Consequently, the results are usually very subjective and one-sided. So the objective rationality needs to be improved. Moreover,

The associate editor coordinating the review of this manuscript and approving it for publication was Yanli Xu.

it is difficult to adapt to the random and sudden traffic demands.

In order to make up for the deficiency of traditional empirical division methods, a lot of relevant theoretical division methods have been researched. Since the core idea of TOD multi-period control is that similar traffic demand adopts the same control strategy, which is similar to that of clustering analysis. Therefore, clustering algorithm can be used to divide control period.

Based on the concept of system state, Hauser and Scherer [2] discussed the possibility that Hierarchical Cluster Analysis (HCA) could be used for control period division. On the basis of the intersection traffic flow and time occupancy rate, Smith *et al.* [3] used K-means algorithm to divide control periods. And the classification regression tree method was used to evaluate the division results. In order to solve the period conflict problem of hierarchical clustering algorithm, Park *et al.* [4]–[6] introduced heuristic algorithms such as Genetic Algorithm (GA) to automatically divide the signal control periods and optimized the optimal time switching points of TOD control scheme. However, the result was easy to fall into local optimal.

In order to make up for the above deficiencies, Wang *et al.* [7] optimized the control period division method by using K-means algorithm. But the clustering number needed to be specified in advance. Based on 15min traffic flow data of intersections, Ratrout [8] combined the subtractive algorithm with K-means algorithm to study the control period division method. And Synchro software was employed to verify the model. Based on the above researches, Guo and Zhang [9] studied the optimal switching time of coordinated semi-actuated TOD control scheme based on data acquisition. But the number of schemes still needed to be specified in advance.

Taking intersection delay as the evaluation index, Yang and Yang [10] compared Kohenen clustering algorithm with K-means algorithm based on the historical traffic flow data of the intersection. The research found that K-means algorithm performed well, but the clustering number and the initial clustering center should be given in advance. And the result was easy to fall into local optimal. On the basis of traffic data repair, Yao *et al.* [11] used the hybrid clustering algorithm to determine the number of multi-period control points and the optimal switching time. Firstly, K-means algorithm was used to conduct initial clustering of historical traffic data. And then cubic group criterion was introduced as the termination condition. Finally, system clustering was used to analyze and divide the data in details. The algorithm took time sequence into consideration and performed well. Liu *et al.* [12] proposed a period division method based on signal cycle on the basis of the traffic volume change characteristics in different directions. The method provided a theoretical basis for multi-period signal timing. Zhao *et al.* [13] improved Ng-Jordan-Weiss (NJW) algorithm of the spectral clustering algorithm and divided the control periods, and the effect was good. Yu *et al.* [14] improved Fuzzy C-Means (FCM) clustering algorithm and simulated annealing genetic algorithm was employed to optimize the initial clustering center and select the clustering number automatically. Then a new traffic signal control period division method was proposed.

A series of achievements have been made in the method of single factor period division, but it still could not meet the increasing traffic demand. Therefore, a lot of multi-factor control period division methods have been researched gradually.

Taking traffic flow and signal cycle as data input, Lee *et al.* [15] divided the coordinated control periods of multiple intersections, and traffic cost was taken as the evaluation index of the algorithm. The proposed method fully considered traffic cost in the switching transition stage of different control schemes. Based on real-time traffic data, Guo and Zhang [16] took the abrupt change time of traffic flow as the main factor, traffic delay and average speed as the evaluation index, and a multi-factor period division method was proposed. Intersection traffic flow, signal control cycle, phase offset were the basic data of cluster analysis, which performed well. By using recursive ordered clustering algorithm, Li *et al.* [17] studied signal control period division method. To reduce the time complexity of traditional ordered clustering, a dynamic recursive strategy was introduced. And the optimal segmentation number and optimal scheme could be obtained through identifying the mutation point of the minimum loss value under different segmentation numbers.

Taking traffic flow and traffic flow direction as main basis, Wang and Chen [18] established a two-dimensional model of flow and vector in polar coordinates. And CUSUM algorithm was employed for clustering. Then a new control period division method was proposed which took the difference of diverging amount into account in the case of similar total flow. Xu *et al.* [19] constructed a three-dimensional vector based on the total traffic flow, total flow direction, and the time frequency of the conflict point with the downstream at the intersection. And the distances between adjacent vectors were recursively combined to determine control period division points. Results showed that compared with traditional single-factor period division method which only considered the total traffic volume, the new proposed method could effectively reduce average vehicle delay and had a certain engineering implementation effect. However, the method had some certain limitations.

Based on the trajectory data of probe vehicles, Wan *et al.* [20] proposed a time-of-day breakpoints identification method for isolated intersection. To overcome the limitations of long sampling intervals and low market penetration rates, multiple sampling days were aggregated. Moreover, bisecting K-means algorithm was employed to identify TOD breakpoints. Ma *et al.* [21] put forward a time-of-day breakpoints optimization through recursive time series partitioning. The TOD breakpoints optimization problem was formulated as a time series data partitioning problem. Then elbow method was used to determine appropriate partitions number. Finally, the proposed method was evaluated by real data. Based on clustering and image segmentation, Shen *et al.* [22] proposed a new traffic time division method. A new concept-transportation overlap rate was put forward for the clustering of daily traffic flow patterns. Then the fast and robust fuzzy C-means clustering (FRFCM) method was used to divide the time-of-day breakpoints.

Summarizing the existing researches, it is not difficult to find that most of the existing control period division methods belong to single-factor methods, which are only based on one kind of data. It cannot accurately reflect actual traffic state and the change of traffic flow direction at the intersection. Besides, it is easy to cause mismatch between control period division results and actual traffic flow characteristics. Although multi-factor control period division method makes up for the deficiency of the single-factor division method, it is easy to cause division results to be too trivial and affect the control efficiency due to the numerous influencing factors and the complicated calculation. Especially with the growing maturity of big data theory and technology, more and more traffic flow information can be collected. However, some models are established based on specific collection environments or specific data. As a consequence, the exclusivity of some models is becoming more and more obvious. Therefore, the multi-factor period division method needs to be further optimized.

Based on existing studies, a new control period division method is proposed which fully takes traffic flow characteristics at intersections into consideration in this paper. Firstly, a multi-dimensional traffic flow matrix is constructed based on the phase traffic flow at the intersection. In order to reduce the complexity of the algorithm, LLE dimension reduction algorithm is applied to reduce the dimension of the multi-dimensional traffic matrix. And a two-dimensional dimension reduction matrix can be obtained. Secondly, the dimensionality reduction matrix is taken as input data, and PSO-K clustering algorithm is used for data clustering. Then control period division model can be established. Finally, the performance of the proposed method is verified and compared. Results show that the method in this paper can obtain the optimal number of clusters, and the results are more consistent with the actual traffic flow characteristics. Moreover, the invalid periods are less. Therefore, the effectiveness of the new proposed method can be verified.

II. CONTROL PERIOD DIVISION BASED ON LLE-PSO-K ALGORITHM

In order to ensure the rationality of signal period division and reduce the algorithm complexity, a control period division model is built based on LLE-PSO-K algorithm. In this paper, the matrix composed of phase traffic flow data is defined as phase traffic flow matrix.

Firstly, the phase traffic flow data matrix of the intersection $Q = (q_1, q_2, \cdots, q_m)$ is constructed. m is the phase number and q_i is traffic volume of the ith phase at the intersection. LLE algorithm is employed to reduce the dimension of matrix Q. Then, the dimensionality reduction matrix obtained by LLE algorithm is used as input data, and control period is divided by PSO-K algorithm.

A. TRAFFIC DATA DIMENSION REDUCTION BASED ON LLE ALGORITHM

Locally Linear Embedding (LLE) algorithm belongs to the classical manifold learning algorithm and is a nonlinear dimension reduction algorithm. The low-dimensional manifold of the local linear form of any dimension can be learned and the calculation process can be reduced to the eigenvalue calculation of the sparse matrix. Hyperplane can be constructed through local linearization, and then high-dimensional data can be mapped to low-dimensional space. The local linear structure of data can be kept unchanged [23], and the computational complexity of the algorithm is relatively small.

The basic idea of LLE algorithm is that the manifold can be approximately equivalent to the Euclidean space locally. So that the reconstruction weight of each neighborhood in the low-dimensional space can be kept unchanged. Under the condition that the embedded mapping is local linear, minimize the reconstruction error. Finally, the problem is formalized into eigenvalue decomposition problem, and the data with reduced dimension can maintain the original manifold structure.

Assume that a given sample of high-dimensional traffic data is denoted by $Q = [q_1, q_2, \cdots, q_m] \in R^{n\times m}$. Data dimensionality is reduced by LLE algorithm and the steps are as follows.

Step 1. Determine the neighborhood. Similar to KNN algorithm, the k nearest neighbors of each traffic sample data are determined by Euclidean distance d_{ij} as formula (1).

$$d_{ij} = \left[\sum_{k=1}^{D} \left|q_{ik} - q_{jk}\right|^2\right]^{1/2} \tag{1}$$

Step 2. Weight matrix W is calculated to reconstruct the weight for the neighborhood of the sample q_i and the local reconstruction weight matrix is constructed. The linear relationship between each sample q_i and its nearest neighbors is sought, and the mean square error is taken as a loss function and minimized as formula (2).

$$J(w) = \min \varepsilon(W) = \sum_{i=1}^{m} \left\| q_i - \sum_{j\in S(i)} w_{ji} q_j \right\|^2, \quad \sum_{j\in S(i)} w_{ji} = 1 \tag{2}$$

where $S(i)$ represents the k nearest neighbors set of sample q_i. w_{ji} is the weight coefficient, representing the weight between sample q_i and q_j. If q_j is not a neighbor of q_i, w_{ji} is equal to 0.

Step 3. Calculate the dimensionality reduction matrix $Y = [y_1, y_2, \cdots, y_m] \in R^{d\times m}$. Using the weight matrix W obtained by Step 2, keep the weight w_{ji} unchanged and minimize loss function $J(Y)$. The loss function and constraint conditions are as follows:

$$J(Y) = \sum_{i=1}^{m} \left\| y_i - \sum_{j=1}^{m} w_{ji} y_j \right\|^2, \quad \sum_{i=1}^{m} y_i = 0;$$
$$\frac{1}{m}\sum_{i=1}^{m} y_i y_i^T = I \tag{3}$$

where I is the n-dimensional identity matrix. The above equation is further solved and formula (4) can be obtained.

$$J(Y) = tr\left(YMY^T\right) \tag{4}$$
$$M = (I - W)(I - W)^T \tag{5}$$

where M denotes the eigenvector of the equivalent sparse matrix of data set y. Therefore, solving matrix Y can be equivalent to finding the eigenvectors of the matrix M, whose eigenvalues are the low-dimensional matrix of the final output of the algorithm.

B. CONTROL PERIOD DIVISION BASED ON PSO-K CLUSTERING ALGORITHM

Clustering analysis is an unsupervised classification method, which divides the given samples into several categories according to certain rules. The samples divided into the same category have a high degree of similarity, and the samples of different categories have great differences. It is not hard to find that the principle of multi-period is similar to the idea of clustering analysis. In addition, there is a certain correlation between traffic data. Therefore, clustering analysis method can be used to divide signal control periods.

1) PSO-K ALGORITHM INTRODUCTION

Particle Swarm Optimization (PSO) is a population intelligent algorithm with good adaptability and robustness. The principle of PSO algorithm is simple. The fewer empirical parameters are required and local optimum can be achieved, with high convergence precision. As it is well known that clustering can be understood as a complex optimization problem. Therefore, PSO algorithm can be used for clustering analysis. Moreover, studies have shown that the clustering effect of PSO algorithm is better than traditional methods [24], [25].

K-means algorithm is a partition-based clustering algorithm, which has been widely used. But it is susceptible to the selection of initial clustering center and tends to converge to local extreme value. However, K-means algorithm based on Particle Swarm Optimization (PSO-K) is an optimization algorithm which uses the idea of PSO to solve clustering problems. Moreover, PSO-K algorithm overcomes the defects of K-means algorithm to a certain extent [26].

The basic principle of PSO-K algorithm is as follows:

Assume that the given sample set is $X = \{x_1, x_2, \ldots, x_n\}$, where $x_i\,(i = 1, 2, \ldots, n)$ represents the members of the sample set X and n is sample number. Divide it into k categories, and division result is expressed by $C = \{C_1, C_2, \ldots, C_k\}$. $C_j\,(j = 1, 2, \ldots, k)$ is the jth division category. Then the following formulas exist: $X = \bigcup_{j=1}^{k} C_j$, $C_j \neq \emptyset\,(j = 1, 2, \ldots, k)$ and $C_i \cap C_j \neq \emptyset\,(i, j = 1, 2, \ldots, k;\, i \neq j)$.

The dispersion between the clustering center and the sample set can be calculated by formula (6).

$$z_{rj} = \frac{1}{n_j} \sum_{x_i \in C_j} x_i \tag{6}$$

where z_{rj} is clustering center position of the $r(1 \leq r \leq N)$th particle in the $j\,(1 \leq j \leq k)$th category. N is the number of particles. n_j represents the sample data amount in class j.

The clustering criterion function $f(Z_r)$ is the sum of distances between each sample and the corresponding clustering center z_{rj}, namely, the particle fitness function, which can be calculated by formula (7).

$$f(Z_r) = \sum_{j=1}^{k} \sum_{x_i \in C_j} d\left(x_i, z_{rj}\right) \tag{7}$$
$$d\left(x_i, z_{rj}\right) = \left\| x_i - z_{rj} \right\| \tag{8}$$

where $d\left(x_i, z_{rj}\right)$ is the distance between the ith sample data and the corresponding clustering center z_{rj}. Euclidean space distance is adopted and calculated by formula (8).

The particle velocity and position are updated by the following formula:

$$V_r^{t+1} = wV_r^t + c_1 r_1 \left(P_r^t - Z_r^t\right) + c_2 r_2 \left(P_g^t - Z_r^t\right) \tag{9}$$
$$Z_r^{t+1} = Z_r^t + V_r^{t+1} \tag{10}$$

where the position of the rth particle is denoted by Z_r, which represents a potential solution. The velocity of the particle is denoted by V_r. P_r is the best position of the rth particle so far. P_g is the best position of all particles so far searched. t is the number of algorithm iterations. c_1 and c_2 are learning factors, also known as acceleration factors, which represent the statistical acceleration weights that push each particle to positions P_r and P_g. w is the inertia weight factor. r_1 and r_2 are uniformly distributed random numbers with values between [0, 1], which are used to increase population diversity and search randomness.

After clustering centers are determined, clustering division is carried out by the nearest neighbor rule. It means that each data is first divided into the category nearest to it.

2) CONTROL PERIOD DIVISION BASED ON PSO-K ALGORITHM

The dimensionality reduction data obtained by LLE algorithm is taken as the input of the model, and PSO-K clustering algorithm is used to divide control periods. The specific steps are as follows:

Step1. Conduct dimensionless processing as formula (11) for the dimensionality reduction data reduced by LLE algorithm.

$$y_{ij} = {}^{y_{ij}}\!/_{\max\{y_i\}} \tag{11}$$

Step2. Initialization of population. Set the population size N, clustering number k, and maximum iteration times $t_{\max}$. Initial clustering centers are generated randomly, that is, the particle distribution is randomly generated. Assign value to each particle to generate particle velocity randomly. Each particle is assigned a value and particle velocity is randomly generated.

Step3. Divide particles according to the principle of minimum distance, and calculate the fitness value of each particle according to formula (7) and formula (8). And update the individual extremum.

Step 4. Obtain the global extreme value and global extreme position according to the individual extreme value of each particle.

Step 5. Compare the fitness value of each particle with the fitness value of the best position P_r experienced. If it is better, update the particle position P_r.

Step 6. Compare the fitness value of each particle with the fitness value of the best position P_g of the population. If it is better, update position P_g.

Step 7. Update particle velocity and position according to formula (9) and formula (10), and make them within a limited range. The weight w can be calculated by formula (12).

$$w = w_{\min} + (w_{\max} - w_{\min}) \left[1 - \left(\frac{F_i - F_s}{F_b - F_s} \right)^3 \right]^5 \tag{12}$$

where F_s denotes the fitness value of the current worst particle. F_b is the fitness value of the current best particle. $w_{\max}$ is the initial value of inertia weight and $w_{\min}$ is the final value of inertia weight.

Step 8. After each update iteration, re-calculate clustering centers using K-means algorithm as formula (6) and update.

Step 9. Determine whether the termination condition is met. If so, the algorithm will be finished and the optimal k clustering centers and clustering results will be output. Otherwise, return to Step 3 and algorithm continue.

The termination condition of the algorithm can be that the maximum number of iterations is achieved, the best fitness value hardly changes within the iterations, clustering centers change little or clustering results do not change any more.

3) CLUSTERING RESULTS EVALUATION

Silhouette Coefficient function [27] was selected in this paper to evaluate the results of control period division. Silhouette Coefficient is a method proposed by Rousseuw *et al.* [27] to evaluate the clustering effect. It takes cohesion and separation into account, and can be used to evaluate the performance of different algorithms.

For sample i, silhouette coefficient is defined as follows:

$$S(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \tag{13}$$

where $a(i)$ represents the average distance between sample i and other sample in the same category C_i, usually using Euclidean distance. The smaller the value is, the more the sample i should be classified into this category. Therefore, $a(i)$ is also called intra-class dissimilarity or dissimilarity of sample i. The mean of $a(i)$ of all samples in category C_i is called the class dissimilarity. $b(i)$ represents the minimum value of the difference degree between sample i and other categories, that is, the formula $b(i) = \min\{b_{i1}, b_{i2}, \ldots, b_{ik}\}$ exists. Where b_{ij} is the average distance between sample i and all other samples in category C_j. b_{ij} is also called the dissimilarity between sample i and category C_j, and $b(i)$ is also called the dissimilarity between categories and sample i.

The value of $S(i)$ is between $[-1, 1]$. And the closer the value is to 1, the clustering of sample i is more reasonable and more inclined to belong to the current category. The closer the value is to -1, the more the sample i should be classified into other categories. The value close to 0 indicates that sample i is on the boundary of the two categories.

The mean value $\overline{S(i)}$ of all samples $S(i)$ is called the silhouette coefficient of clustering results, to measure the rationality and validity of clustering results.

III. MODEL VERIFICATION

In order to verify the effectiveness of the method proposed in this paper, an intersection in a city is selected for model verification analysis. The intersection consists of four entrance lanes. Traffic flow in east-west entrance lanes includes left-turn traffic flow, straight traffic flow and right-turn traffic flow. And there are four lanes at both east and west entrances. There is only straight traffic flow in the north entrance, of which there is only one lane. And there are two lanes in the south entrance for the running of left-turn traffic flow, straight traffic flow and right-turn traffic flow. The geometric characteristics and channelization of the intersection is shown in Fig. 1. Each entrance lane at the intersection is equipped with a traffic flow detector to collect traffic flow information.

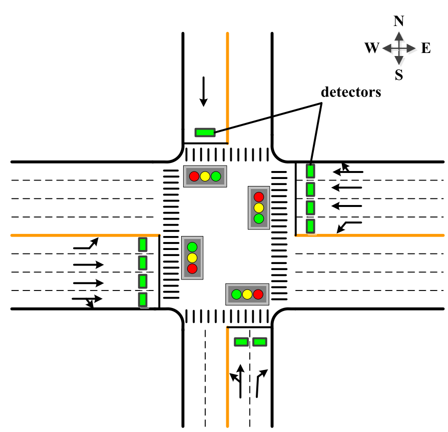

FIGURE 1. Intersection geometry information.

The intersection is a signal-controlled intersection and three-phase signal control scheme is adopted, shown as Fig. 2. As shown in Fig. 2, the phase of eastbound and westbound straight traffic is the first phase, denoted by Phase A. The phase of eastbound and westbound left-turn traffic is the second phase, denoted by Phase B. And the phase of southbound and northbound straight traffic and left-turn traffic is the third phase, denoted by Phase C.

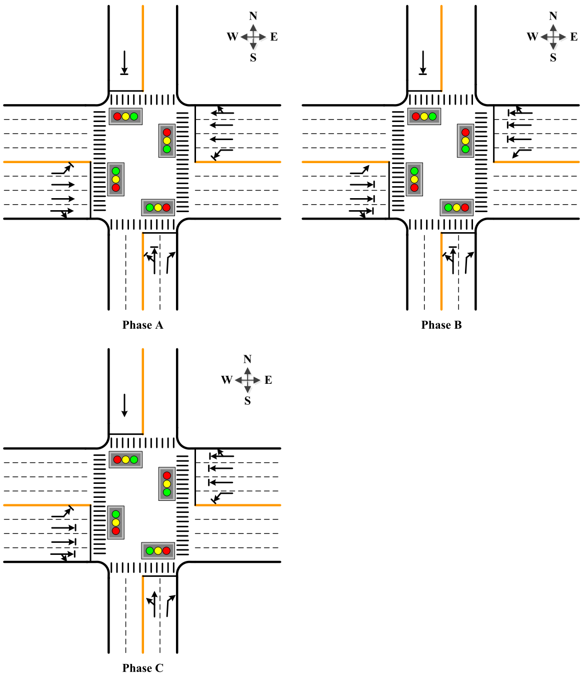

FIGURE 2. Intersection signal control phase scheme.

A. DIMENSION REDUCTION PROCESSING OF TRAFFIC FLOW

Firstly, data preprocessing was carried out on the intersection traffic flow for 24 hours. Data were obtained from the SCATS control system, and the particle size of the acquisition time was 5min.

Phase traffic flow could be obtained by adding the traffic flow data of each lane in the same phase. Then, at intervals of 15min, 30min and 1h, traffic flow data of Phase A, B and C at the selected intersection were counted and processed to construct a multidimensional traffic flow matrix which was denoted by $Q = (q_A, q_B, q_C)$. q_A, q_B, q_C denoted traffic volume of Phase A, Phase B and Phase C, respectively. Then LLE algorithm was used to reduce the dimension of the phase flow matrix at the intersection. Here D = 2, that was, the three dimensional phase flow matrix was transformed into a two dimensional flow matrix.

Based on the existing researches, it is not hard to found that when the value of k is small, the algorithm cannot map the multi-dimensional traffic data to the low-dimensional space well. Because when the number of nearby neighbors is too few, the topology structure of the data cannot be well reflected. However, if the value of k is too large, the data will overlap. It means that too many nearby neighbors cannot reflect the manifold information of the data. When the value of k is appropriate, different data can be well separated and maintain at suitable relative distances. Therefore, the appropriate value of k should be chosen. After trial calculation, the optimal k values are 14, 10 and 10 for 15min, 30min and 1h phase traffic flow, respectively.

The three-dimensional diagram of 15min phase traffic flow at the intersection is shown in Fig. 3, where X axis is the 15min traffic flow at the intersection of Phase A, Y axis is the 15min traffic flow of Phase B, and Z axis is the 15min traffic flow of Phase C. The 15min flow diagram after dimension reduction by LLE algorithm is shown in Fig. 4, where $k = 14$.

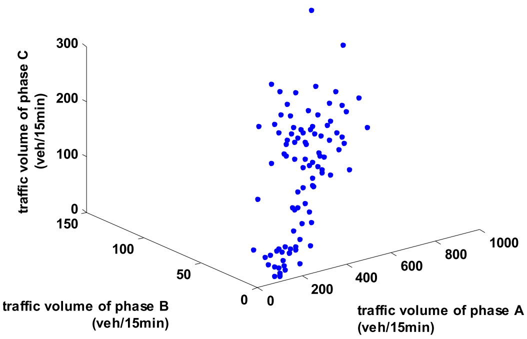

FIGURE 3. 15min phase traffic flow distribution.

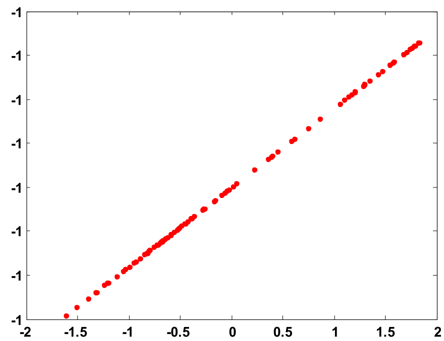

FIGURE 4. 15min phase traffic flow dimension reduction diagram.

The three-dimensional diagram of 30min phase traffic flow at the intersection is shown in Fig. 5. In Fig. 5, X axis is the 30min traffic flow of Phase A, Y axis is the 30min traffic flow of Phase B, and Z axis is the 30min traffic flow of Phase C. The 30min traffic flow diagram after dimension reduction through LLE algorithm is shown in Fig. 6, where $k = 10$.

The three-dimensional diagram of 1h phase traffic flow at the intersection is shown in Fig. 7. In Fig. 7, X axis is the 1h traffic flow of Phase A, Y axis is the 1h traffic flow of Phase B, and Z axis is the 1h traffic flow of Phase C. The 1h traffic flow diagram after dimension reduction by LLE algorithm is shown in Fig. 8, where $k = 10$.

B. PERIOD DIVISION RESULTS ANALYSIS

According to relevant studies, the value of category n of control period was set as 3 to 8. Using MATLAB software, PSO-K algorithm and LLE-PSO-K algorithm were

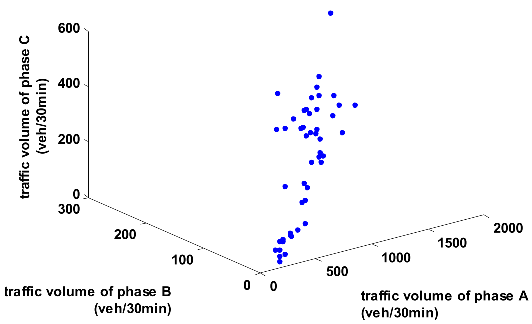

FIGURE 5. 30min phase traffic flow distribution.

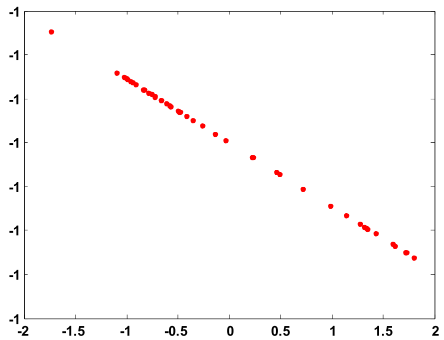

FIGURE 6. 30min phase traffic flow dimension reduction diagram.

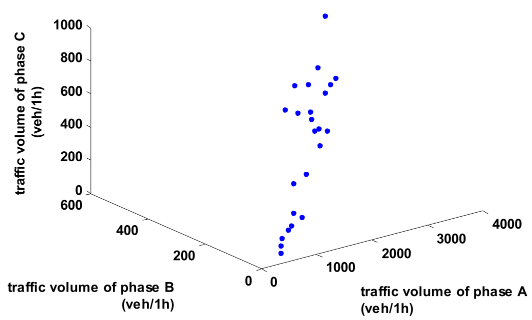

FIGURE 7. 1h phase traffic flow distribution.

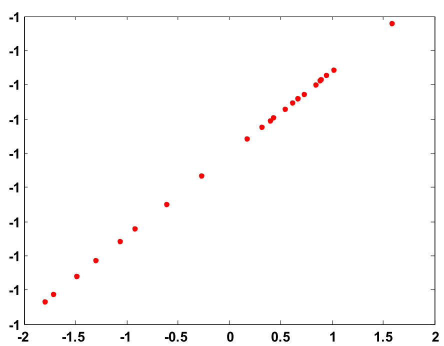

FIGURE 8. 1h phase traffic flow dimension reduction diagram.

used to divide the signal control periods respectively. The average value of Silhouette function $\overline{Si}$ would be used as the basis for selecting the optimal clustering number n. Relevant parameters were set as follows: population size of particle swarm was set to $N = 100$. And acceleration factors were set as $c_1 = c_2 = 2$. Besides, the maximum iteration number was set as $t_{\max} = 100$. Weights were set as $w_{\max} = 0.9$ and $w_{\min} = 0.3$. Particle movement speed range was set as $[-0.05, 0.05]$. Particle swarm position range was set as $[0.02, 1]$.

1) CONTROL PERIOD DIVISION RESULTS ANALYSIS OF TWO ALGORITHMS

PSO-K and LLE-PSO-K algorithm were used to divide the 15min phase traffic flow, 30min phase traffic flow and 1h phase traffic flow, respectively. And then the control period division results of the two algorithms were analyzed and compared.

Firstly, PSO-K algorithm and LLE-PSO-K algorithm were used to divide the control period of 15min phase traffic flow. Si values corresponding to different clustering number n of two algorithms are shown in Fig. 9.

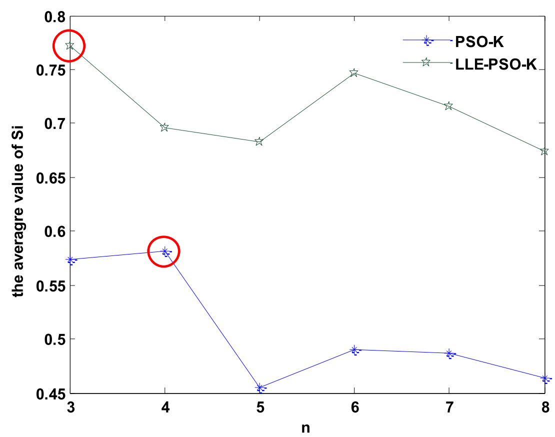

FIGURE 9. $\overline{Si}$ values of 15min phase traffic flow control period division based on PSO-K algorithm and LLE-PSO-K algorithm.

As shown in Fig. 9, the $\overline{Si}$ value based on PSO-K algorithm is 0.581 when $n = 4$, reaching the maximum value. Therefore, for the 15min phase traffic flow, the optimum number of control periods based on PSO-K algorithm is 4.

Besides, it can be concluded that the $\overline{Si}$ value based on LLE-PSO-K algorithm is 0.772, reaching the maximum value when $n = 3$. It means that for the phase traffic flow period of 15min, the optimum number of control periods based on LLE-PSO-K algorithm is 3.

By comparing the $\overline{Si}$ values of the two algorithms, it is not hard to find that LLE-PSO-K algorithm has the larger value. It means that the control period division results of 15min phase traffic flow based on LLE-PSO-K algorithm are obviously better than that of PSO-K algorithm.

To further evaluate the control period division results of the two algorithms, Si distribution diagrams of different categories for the optimal clustering numbers is drawn based on two algorithms. The Si distribution of different categories based on PSO-K algorithm is shown in Fig. 10. And the

Si distribution of different categories based on LLE-PSO-K algorithm is shown in Fig. 11.

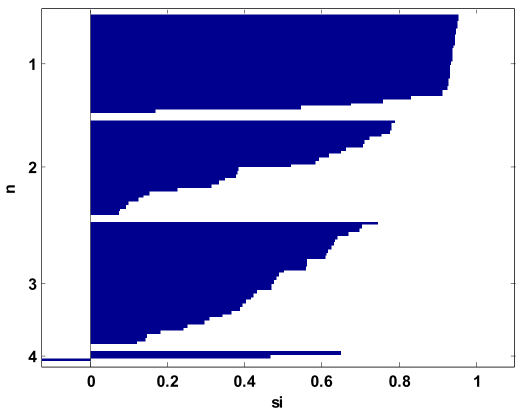

FIGURE 10. ***Si*** **distribution of 15min phase flow control period division based on PSO-K algorithm ($n = 4$).**

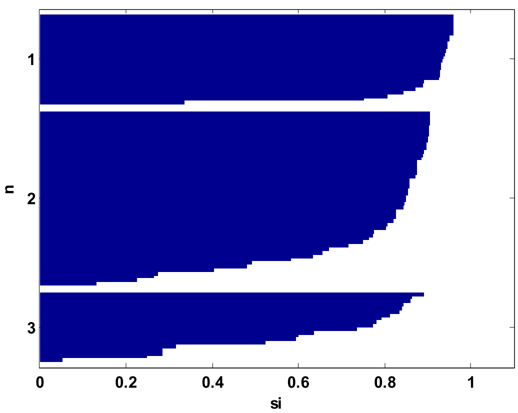

FIGURE 11. ***Si*** **distribution of 15min phase traffic flow control period division based on LLE-PSO-K algorithm ($n = 3$).**

It can be seen from Fig. 10 that some *Si* values based on PSO-K algorithm are less than 0, which indicates that there is a deviation in the division result. In other words, the time points of which the *Si* values are less than 0 are more suitable to be classified into other categories. Even so, for 15min phase traffic flow control period division based on PSO-K algorithm, when $n = 4$, the distribution of *Si* values of various categories is still relatively good. Therefore, it is regarded as the optimal division result.

It can be concluded from Fig. 11 that the *Si* values based on LLE-PSO-K algorithm are all greater than 0, which indicates that the division result is better. Therefore, it is regarded as the optimal division result. To sum up, the control period division obtained by LLE-PSO-K algorithm is better than PSO-K algorithm.

According to the results of control period division, the period division diagrams for two algorithms can be drawn. The control period diagram of 15min phase traffic flow based on PSO-K algorithm are shown in Fig. 12. And the control period diagram of 15min phase traffic flow based on LLE-PSO-K algorithm are shown in Fig. 13. The y-axis of Fig. 12 and Fig. 13 denotes the control period categories. It is also equivalent to different signal control schemes.

It can be seen from Fig. 12 that the control periods of 15min based on PSO-K algorithm has a total of 24 breaking points, representing that the signal control schemes need to be switched 24 times. As shown in Fig. 13, the control periods of 15min based on LLE-PSO-K algorithm has a total of 12 breaking points, representing that the signal control schemes need to be switched 12 times. The switching times of signal control period obtained by LLE-PSO-K algorithm are obviously less than that of PSO-K algorithm, which has less influence on the signal control effect. Therefore, LLE-PSO-K algorithm is better than PSO-K algorithm in control period division of 15min phase traffic flow.

Secondly, PSO-K algorithm and LLE-PSO-K algorithm were used to divide the control period of 30min phase traffic flow. *Si* values corresponding to different clustering n of two algorithms are shown in Fig. 14.

It can be seen from Fig. 14, the $\overline{Si}$ value based on PSO-K algorithm is 0.685 when $n = 4$, reaching the maximum value. Therefore, for the phase traffic flow period of 30min, the optimum number of control periods based on PSO-K algorithm is 4.

Moreover, it can be concluded that the $\overline{Si}$ value based on LLE-PSO-K algorithm is 0.832, reaching the maximum value when $n = 3$. It means that for the phase traffic flow period of 30min, the optimum number of control periods based on LLE-PSO-K algorithm is 3.

By comparison, the $\overline{Si}$ value of LLE-PSO-K algorithm is larger than that of PSO-K algorithm. It means that the control period division results of 30min phase traffic flow based on LLE-PSO-K algorithm are obviously better than that of PSO-K algorithm.

The *Si* distribution of different categories based on PSO-K algorithm of 30min phase traffic flow is shown in Fig. 15. And the *Si* distribution of different categories based on LLE-PSO-K algorithm is shown in Fig. 16.

As shown in Fig. 15 and Fig. 16, the *Si* values distribution of various categories is relatively good, of which the values are all larger than 0. Therefore, the division results can be regarded as the optimal division results.

According to the division results, control period division diagrams are drawn. The 30min phase traffic flow control period diagrams based on PSO-K algorithm and LLE-PSO-K algorithm are shown in Fig. 17 and Fig. 18, respectively.

It can be seen from Fig. 17 that the control periods of 30min based on PSO-K algorithm has a total of 8 breaking points, representing that the signal control schemes need to be switched 8 times. As shown in Fig. 18, the control periods of 30min based on LLE-PSO-K algorithm has a total of 4 breaking points, representing that the signal control schemes need to be switched 4 times. Therefore, LLE-PSO-K algorithm is better than PSO-K algorithm in control period division of 30min phase traffic flow.

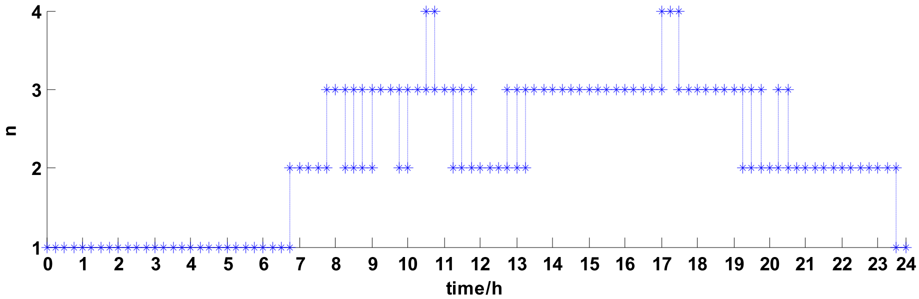

FIGURE 12. **Phase traffic flow control periods of 15min divided by PSO-K algorithm ($n = 4$).**

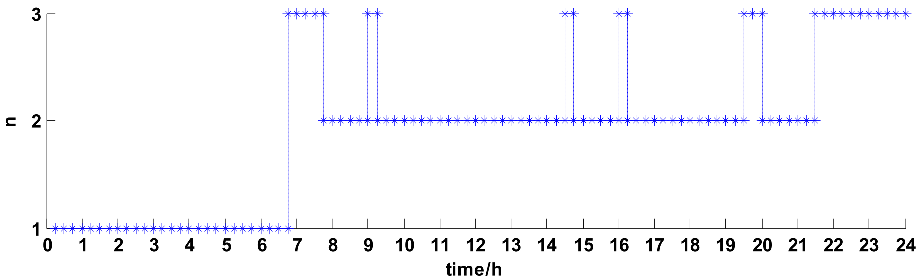

FIGURE 13. **Phase traffic flow control periods of 15min divided by LLE-PSO-K algorithm ($n = 3$).**

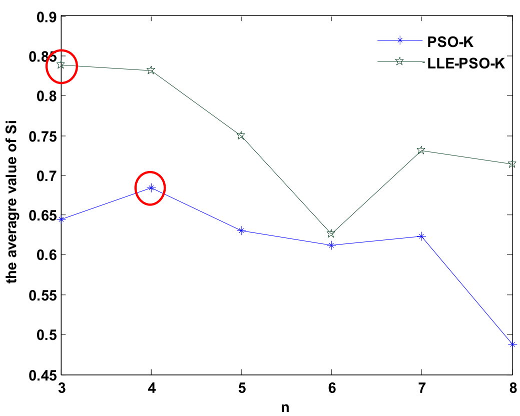

FIGURE 14. **$\overline{Si}$ value of 30min phase traffic flow control period division based on PSO-K algorithm and LLE-PSO-K algorithm.**

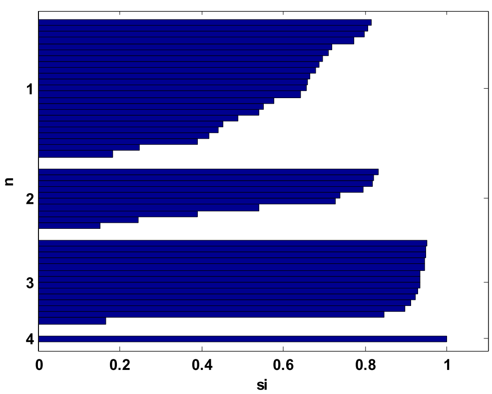

FIGURE 15. **Si distribution of 30min phase traffic flow control period division based on PSO-K algorithm ($n = 4$).**

At the end, PSO-K algorithm and LLE-PSO-K algorithm were used to divide the control period of 1h phase traffic flow. Si values corresponding to different clustering n of two algorithms are shown in Fig. 19.

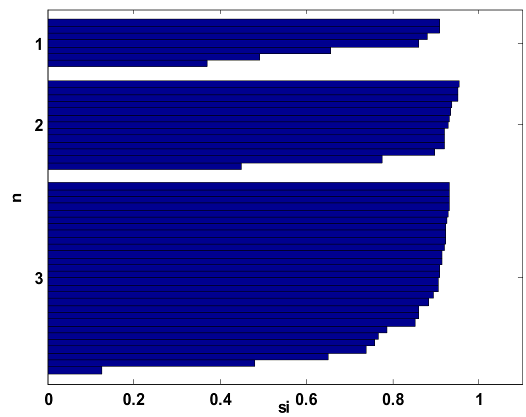

FIGURE 16. **Si distribution of 30min phase traffic flow control period division based on LLE-PSO-K algorithm ($n = 3$).**

It can be seen from Fig. 19, the $\overline{Si}$ value based on PSO-K algorithm is 0.661 when $n = 5$, reaching the maximum value. Therefore, for the 1h phase traffic flow period, the optimum number of control periods based on PSO-K algorithm is 5.

Moreover, it can be concluded that the $\overline{Si}$ value based on LLE-PSO-K algorithm is 0.772, reaching the maximum value when $n = 4$. It means that for the phase traffic flow period of 30min, the optimum number of control periods based on LLE-PSO-K algorithm is 4.

By comparison, the $\overline{Si}$ value of LLE-PSO-K algorithm is larger than that of PSO-K algorithm. It means that the control period division results of 1h phase traffic flow based on LLE-PSO-K algorithm are obviously better than that of PSO-K algorithm.

The Si distribution of different categories based on PSO-K algorithm of 1h phase traffic flow is shown in Fig. 20. And the

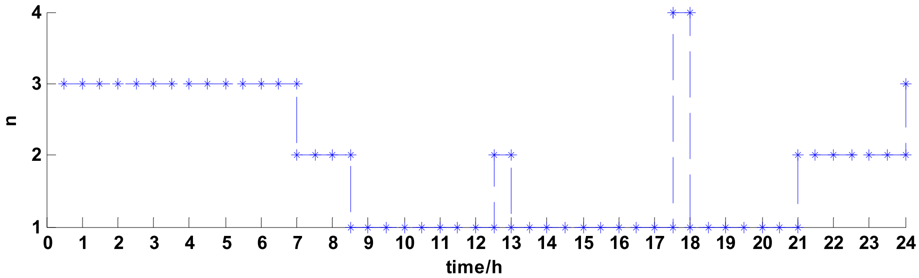

FIGURE 17. Phase traffic flow control periods of 30min divided by PSO-K algorithm ($n = 4$).

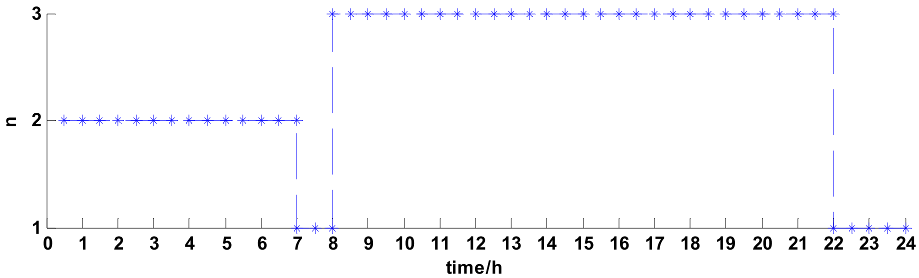

FIGURE 18. Phase traffic flow control periods of 30min divided by LLE-PSO-K algorithm ($n = 3$).

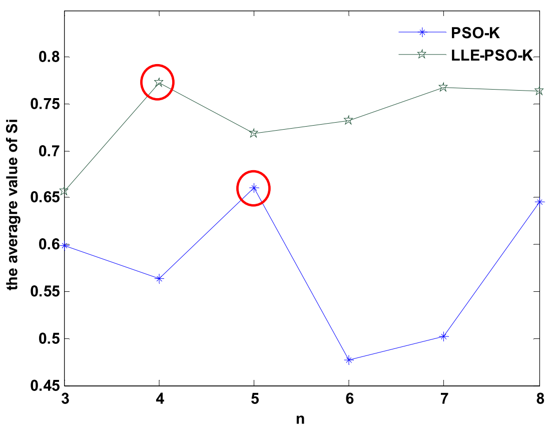

FIGURE 19. $\overline{Si}$ value of 1h phase traffic flow control period division based on PSO-K algorithm and LLE-PSO-K algorithm.

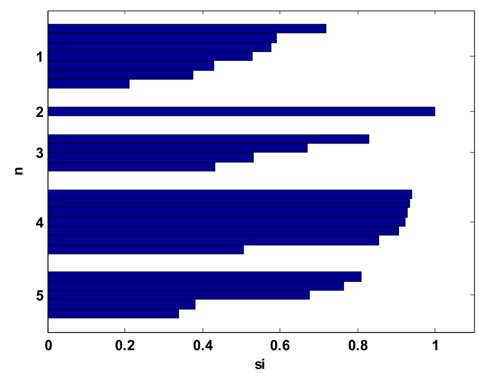

FIGURE 20. *Si* distribution of 1h phase traffic flow control period division based on PSO-K algorithm ($n = 5$).

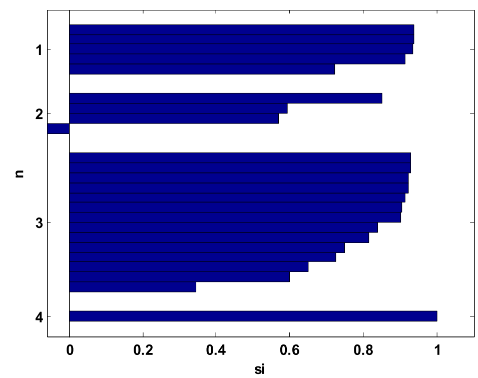

FIGURE 21. *Si* distribution of 1h phase traffic flow control period division based on LLE-PSO-K algorithm ($n = 4$).

Si distribution of different categories based on LLE-PSO-K algorithm is shown in Fig. 21.

It can be seen from Fig. 20, when $n = 5$, *Si* value of each class based on PSO-K algorithm is relatively good. Therefore, it can be taken as the final division result.

Furthermore, it can be found that form Fig. 21, when $n = 4$, *Si* value of each class based on LLE-PSO-K algorithm is good. Therefore, it can be taken as the final division result.

According to the division results, period division diagrams are drawn based on PSO-K algorithm and LLE-PSO-K algorithm, as shown in Fig. 22 and Fig. 23, respectively.

It can be seen from Fig. 22 that the control periods of 1h based on PSO-K algorithm has a total of 9 breaking points, representing that the signal control schemes need to be switched 9 times. As shown in Fig. 23, the control periods of 1h based on LLE-PSO-K algorithm has a total of 6 breaking points, representing that the signal control schemes need to be switched 6 times. Therefore, LLE-PSO-K algorithm is better than PSO-K algorithm in control period division of 1h phase traffic flow.

In conclusion, through the above analysis, it can be concluded that the results of control period division

TABLE 1. Control period division results comparison of different algorithms.

Time interval	Methods	n	$\overline{Si}$	Period division results
15min	PSO-K	4	0.581	Category 1：23：30-6：45 Category 2：6：45-7：45；8：15-8：30；8：45-9：00；9：45-10：00；11：15-11：30；11：45-12：45；13：00-13：15；19：15-19：30；19：45-20：15；20：30-23：30 Category 3：7：45-8：15；8：30-8：45；9：00-9：45；10：00-10：30；11：30-11：45；11：45-12：00；12：45-13：00；13：15-17：00；17：30-19：15；19：30-19：45；20：15-20：30； Category 4：10：30-10：45；17：00-17：30；
	LLE-PSO-K	3	0.772	Category 1：0：00-6：30 Category 2：7：30-8：45；9：00-14：15；14：30-15：45；16：00-19：15；19：45-21：15 Category 3：6：30-7：30；8：45-9：00；14：15-14：30；15：45-16：00；19：15-19：45；21：15-24：00
30min	PSO-K	4	0.685	Category 1：8：00-12：00；12：30-17：00；17：30-20：30； Category 2：6：30-8：00；12：00-12：30；20：30-23：30 Category 3：23：30-6：30 Category 4：17：00-17：30；
	LLE-PSO-K	3	0.832	Category 1：6：30-7：30；21：30-24：00 Category 2：0：00-6：30； Category 3：7：30-21：30
1h	PSO-K	5	0.661	Category 1：9：00-14：00；19：00-21：00； Category 2：17：00-18：00； Category 3：7：00-8：00；21：00-24：00 Category 4：00：00-7：00； Category 5：8：00-9：00；14：00-17：00；18：00-19：00；
	LLE-PSO-K	4	0.772	Category 1：1：00-6：00； Category 2：22：00-1：00；6：00-7：00 Category 3：7：00-17：00；18：00-22：00； Category 4：17：00-18：00；

based on LLE-PSO-K algorithm are significantly better than that based on PSO-K algorithm with different time intervals.

2) PERIOD RESULTS EVALUATION AND ANALYSIS

In order to compare the division results in details, the two algorithms were evaluated and analyzed according to the control period diagrams.

Taking 15min, 30min and 1h as time intervals respectively, the control period division results of the two algorithms were compared. And the effectiveness of the algorithms was evaluated by comparing the values of $\overline{Si}$ under the corresponding clustering number n. Table 1 shows the corresponding period division results based on PSO-K algorithm and LLE-PSO-K algorithm.

As can be seen from Table 1, both algorithms can determine the optimal clustering number n, and the values of $\overline{Si}$ obtained by LLE-PSO-K algorithm is significantly larger than that of PSO-K algorithm in different time intervals. It indicates that LLE-PSO-K algorithm can better divide control periods with similar traffic flow characteristics into the same category, compared with PSO-K algorithm.

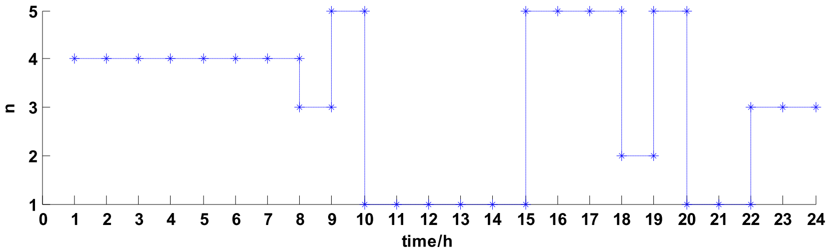

FIGURE 22. Phase traffic flow control periods of 1h divided by PSO-K algorithm ($n = 5$).

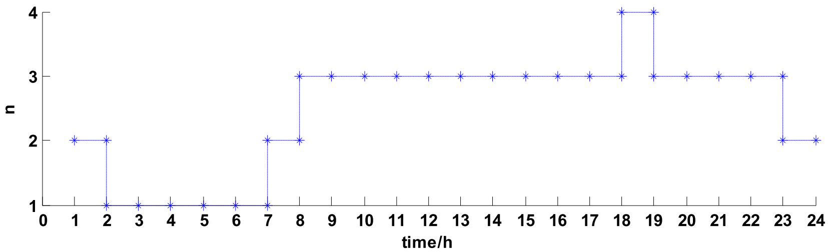

FIGURE 23. Phase traffic flow control periods of 1h divided by LLE-PSO-K algorithm ($n = 4$).

Previous studies have shown that different signal timing schemes need a certain transition time (usually 15-20min) [11], [28] when switching. During the transition, traffic flow is unstable and cannot truly reflect the control effect. In addition, too many TOD periods will lead to frequent switching of signal control schemes, and signal control performance will decline. So the switching of signal control schemes should not be too frequent. Therefore, the control period less than 30min is regarded as no practical value, which is defined as invalid control period in this paper.

It is not difficult to find that, for 15min phase traffic flow data, the divided control periods and invalid control periods (period length less than 30min) are more. Especially for PSO-K algorithm, the invalid control periods are much more than that of LLE-PSO-K algorithm. Due to the large number of invalid periods, the signal control scheme is easily switched frequently, which will directly affect signal control effect. Therefore, the phase traffic flow of 15min is not suitable as the input data of control period division. For 30min and 1h phase traffic flow data, the number of invalid control periods based on PSO-K algorithm and LLE-PSO-K algorithm is 0. Therefore, the phase traffic flow of 30min and 1h can be considered suitable for control period division. Because the phase switch has little influence on the control effect.

In conclusion, the results of control period division based on LLE-PSO-K algorithm are obviously better than that of PSO-K algorithm. As a consequence, the effectiveness of the new proposed algorithm can be proved.

IV. CONCLUSIONS

In order to optimize the existing signal control period division methods and improve signal control effect, a new control period division method based on LLE-PSO-K algorithm was put forward in this paper.

Firstly, based on the phase traffic flow, the traffic flow characteristics of signal-controlled intersections were fully considered to construct a multi-dimensional traffic flow matrix. Then, manifold learning LLE algorithm was introduced to reduce the dimension of the multidimensional phase traffic flow matrix. Besides, PSO-K clustering algorithm was employed to divided periods with the dimensionality reduction matrix as input data. Finally, an actual intersection in a city was chosen to verify the performance of the proposed method. In order to better verify the effect of the method, the phase traffic flow of 15min, 30min and 1h were respectively analyzed. Results showed that for different time intervals, the two methods could get the best clustering numbers, which made up for the shortage of some existing methods which needed to specify clustering number in advance. In addition, the average silhouette coefficient values obtained by LLE-PSO-K method in this paper were all larger than those obtained by PSO-K method. It indicated that the results of control period division obtained by the new proposed method were more consistent with the actual traffic flow characteristics, with high objectivity and rationality. In addition, the number of invalid control periods was less. In conclusion, the effectiveness of the proposed method was proved.

Due to the limitations of experimental conditions and traffic data, the method proposed in this paper is only built based on phase flow data. Therefore, it is advisable to take other traffic characteristic parameters into account in the future research. Moreover, the further research will be carried out with more field data collection efforts.

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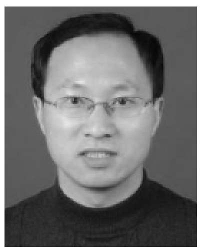
XIUJUAN TIAN was born in Nong'an, Changchun, Jilin, China, in 1990. She received the Ph.D. degree in traffic information engineering and control from Jilin University, Changchun, China, in 2018.

Since 2018, she has been a Lecturer with the School of Transportation Science and Engineering, Jilin Jianzhu University. She is the author of 17 articles. Her research interests include traffic control and intelligent transportation systems.

CHUNYAN LIANG was born in Changchun, Jilin, China, in 1978. She received the Ph.D. degree in traffic information engineering and control from Jilin University, Changchun, China, in 2007.

From 2005 to 2011, she was a Lecturer with the School of Transportation Science and Engineering, Jilin Jianzhu University. Since 2011, she has been an Associate Professor. She has participated in two national projects, six provincial projects, three horizontal projects, and 21 scientific research papers. Her research interests include traffic control, residents travel mode, and traffic channelization.

Dr. Liang has won one Third Prize for Teaching Achievement at the University Level, two awards for Excellence in Instructing Students to participate in the National Transportation Technology Competition for College Students, and one Third Prize and one Second Prize in the Lecturing Competition at the University Level.



TIANJUN FENG was born in 1978. He received the Ph.D. degree in traffic information engineering and control from Jilin University, Changchun, China, in 2016.

From 2008 to 2014, he was a Lecturer with the School of Transportation Science and Engineering, Jilin Jianzhu University. Since 2014, he has been an Associate Professor. He was a Visiting Scholar of the University of Nevada, Las Vegas, USA. He is an Evaluation Expert of the doctoral/master dissertation of with the Degree Center of the Ministry of Education. He is a Science and Technology Expert of Changchun. He is the author of two science and technology projects of the "13th Five-Year Plan" of the Department of Education, one doctoral Research Start-Up Fund, one Science and Technology Project of the Department of Education, and seven horizontal projects. He has participated in three National Natural Science Foundation projects and four provincial and ministerial-level projects. His research interests include traffic management and traffic safety.

Dr. Feng is a member of the Editorial Board of the *International Journal of Transportation Engineering and Technology*.

CHUN CHEN was born in Datong, Shanxi, China, in 1984. He received the master's degree, in 2010. From 2010 to 2020, he was a Designer at the Design Institute. Since 2020, he has been an Associate Professor with the School of Transportation Science and Engineering, Jilin Jianzhu University, Changchun, China. He is the author of more than ten design projects and three articles.