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Optimize Grouping and Path of Pylon Inspection in Power System

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ABSTRACT In order to ensure the normal operation of the power system, it is an essential concern for optimizing inspection path based on limited human and material resources. Despite a wide body of literatures for path planning, however, a framework to optimize grouping and inspection path with minimum number of inspection teams is still lacking. Given the target transmission lines and constrained work hours for each inspector, we study the theoretical solution of the minimum number of inspection teams for task assignment. Furthermore, we develop an improved k-means algorithm, and combine with heuristic intelligent algorithms, such as ant colony algorithm and simulated annealing algorithm, we put forward a universal framework for optimizing grouping and inspection path with minimum number of inspection teams. By applying our framework to both synthetic transmission line and the real transmission lines in Jinhua city, the results verify the theoretical solution of the minimum number of inspection teams. In addition, experimental results demonstrate that our framework can provide quasi-optimal inspection paths and balance work hours for each team. By comparison of the results with different algorithms, we find that the simulated annealing algorithm works the best. Our work paves a new way to solve the vehicle routing problem, travelling salesman problem and some other related problems.

INDEX TERMS Network science, inspection of transmission lines, optimize grouping and path, balancing work hours.

I. INTRODUCTION

Transmission line is the backbone of power grid, where the safe and reliable operation is crucial to national economic development and social livelihood. For example, subtle perturbations could cause huge losses in the power system [1], [2]. Due to the long-term exposure of the transmission line to the harsh environment of nature, it bears not only the internal pressure of normal mechanical and electric load, but also the damage of external environment such as lightning strike, strong wind, earthquake, bird damage. Hence, routine inspection of transmission lines is a basic and important work to ensure reliable power supply [3]. At present, the inspection of the transmission line is mainly based on the experience, and then assign a few vehicles and inspection teams to inspect the transmission lines and pylons one by one, resulting in some inspection teams working overtime while others getting off work for a long time. In other words, the work hours of each inspection team are very uneven. Therefore, it is of great significance to provide an effective approach for the optimal grouping and path planning for pylon inspection with the minimum number of inspection teams.

For the task of inspecting transmission lines and pylons, the inspectors must travel to the target pylons before inspecting. Thus, the total spending time for inspection contains both travel time and inspection time. As some transmission lines span mountains, rivers and other complex landforms,

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to efficiently inspect the transmission lines, unmanned aerial vehicles (UAVs) have been used instead of human in recent years [3]–[8]. UAVs have the characteristics of flexible operation, good expansibility and adaptability to various harsh environments. For example, UAVs can adaptively find the optimal flight path to avoid collision and take photos for diagnosis. However, UAVs are always limited by the control range and endurance of remote control, which results in that they cannot conduct for ultra-long distance and inspect for a long time. Meanwhile, it needs controllers to manually control the UAVs. As the inspection task can be completed by UAVs, in this paper, we investigate the spending time about the optimal path by setting the inspection time as a constant.

Optimal inspection path planning refers to the shortest distance or time of inspecting all the target pylons and transmission lines starting from a certain location, under the condition that each pylon can be visited only once and the inspector(s) must return to the origin. It belongs to the classic travelling salesman problem (TSP) or vehicle routing problem (VRP) in combinatorial optimization, and it is NP-hard [9], [10]. There were many research methods for optimal path planning [11], such as integer programming [12], dynamic programming [13], branch and bound algorithm [14], [15]. However, one disadvantage of exact algorithms is that the computational complexity is too high, which leads to inapplicability to the large-scale data. To deal with this situation, many heuristic intelligent algorithms have been proposed, for example, genetic algorithm [16], [17], bee colony algorithm [18], ant colony algorithm [19], simulated annealing algorithm [20], [21], and particle swarm algorithm [22]. These heuristic intelligent algorithms have their own advantages and disadvantages based on various constraint conditions. Thus, better optimization results may be achieved by hybrid algorithms [23]–[25]. The survey of methods on TSP and VRP can be found in literatures [26]–[28]. In order to cope with different tasks, multi-objective optimization algorithms have been developed, such as a heuristic hybrid multi-objective evolutionary algorithm with local search [29]. To further reduce the running time of the computer, it is effective to divide the task into multiple sets or clusters, and then independently optimize the path for each set [30]–[37].

Because the large workload for one single inspection team, it is more common to assign multiple inspection teams to complete the task. The problem of optimal inspection path with multiple inspection teams can be transformed into the multiple travelling salesman problem (MTSP), which is a generalization of the TSP. Instead of only one inspection team, each inspection team must inspect at least one pylon, and all inspection teams start from the same location and return to the starting point. The constraint conditions are that each pylon can be visited only once and the total distance or spending time is the minimum. The problem is also NP-hard [38]. The above algorithms or improved hybrid algorithm can also be used to solve the MTSP [11], [17], [39]–[45]. For example, with the help of k-means clustering, the path planning is carried out for each cluster [46]–[48]. Nevertheless, due to the imbalance workload, recently, the problem associated with balancing the workload for MTSP has attracted increasing attention, such as minimizing the maximum journey or balancing the number of destinations of travel agents [49]–[51]. Comparing with balancing the journey or the number of travel destinations, it is fairer to balance the work time. Although Lee *et al.* investigated the balance of the travel time, the travel time among each pair of destinations is linear with the distance [52]. Vandermeulen *et al.* studied the MTSP with balanced time by translating the task assignment problem into the minimum Hamiltonian partition problem [53]. Despite this innovative work, a better way to quantify the time cost is to use real data instead of simulated data or the cost reflected by other types [54]. What's more, before assigning task to each team, the optimal inspection path should take both travel time and inspection time into consideration.

Our goal is to minimize work hours and balance the work hours of each inspection team with the minimum number of inspection teams. The main contributions of our work are as follows:

- As work hours of workday for individual is limited, we study the theoretical solution of the minimum number of inspection teams for fulfilling the inspection task. The theoretical solution is verified by both synthetic and real transmission lines.
- To balance the work hours of inspection teams, we propose an improved k-means algorithm. The algorithm is very different from k-means algorithm except for the first step of initialization, in which the time among each pair of pylons can't be quantified by centroid. The core of our algorithm is to move one pylon from the inspection team with the maximal spending time to the inspection team with the minimal spending time.
- Combine the proposed algorithm with greedy algorithm, ant colony algorithm and simulated annealing algorithm, we put forward a framework for optimizing grouping and inspection paths with the minimum number of inspection teams.
- Different from others work, we study the inspection path planning with real transmission lines. Making full use of the longitudes and latitudes of pylons on transmission line No. 5876 (line-5876 for short) and No. 5803 (line-5803 for short) in Jinhua City, Zhejiang Province of China, we excavate the travel time between each pair of pylons with the help of the API interface of Baidu Map and web crawler. To a great extent, the crawled travel times from office to pylons agree well with the real ones. What's more, we successfully obtain the quasi-optimal inspection paths under the balanced workload for each inspection team by our framework.

The rest of the paper will proceed as follows. In section II, we describe our model. In section III, we explore the theoretical solution of the minimum number of inspection teams, and propose the improved k-means algorithm for balancing the workload of each inspection team. It is the key of the general framework for optimizing grouping and path planning. In section IV, the experimental analysis about grouping and path planning on both synthetic and real transmission lines under our framework are shown. Finally, we conclude and discuss this paper in Section V.

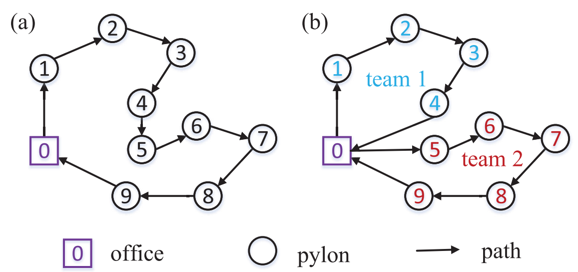

FIGURE 1. (Color online) One simple example of model of optimal grouping and path planning. (a) The optimal inspection path for single inspection team to fulfill the task. The working time is $t_{tra} + 9t_{ins}$. (b) The optimal inspection paths for two inspection teams with balanced work hours. The spending times are t^1_{spe} and t^2_{spe} for the two teams, respectively. $t_{diff} = |t^1_{spe} - t^2_{spe}|$, where $|\cdot|$ is the absolute value of $\cdot$.

II. SYSTEM MODEL

The office (depot) and target pylons can be constructed as a complete graph G = (V, E, T), where node set V $= \{v_0, v_1, \ldots, v_N\}$ is consist of the office (depot) v_0 and N target pylons, see Fig 1. The edge set E $= \{e_{v_iv_j} = (v_i, v_j)|v_i, v_j \in$ V$, i \neq j\}$ denotes the edges among each pair of nodes. T $\in \mathbb{R}^{(N+1)\times(N+1)}$ is the travel time matrix, where the entry $t_{v_iv_j}$ in T stands for the travel time starting from v_i to v_j, thus the matrix may be not symmetric. In order to analyze our problem, we further define the following variables:

t_{tra}, the travel time for a single inspection team to visit all the pylons and return to the office.

t_{ins}, the inspection time of each pylon and the transmission line connected to the pylon, which can be completed by UAVs and can be set to a constant. Thus, the spending time for a single inspection team to complete the task is $t_{tra} + t_{ins}N$.

t_{max}, the maximum work hours for workday. Generally, t_{max} is 8 hours or 28800 seconds.

t^r_{spe}, the spending time of r-th inspection team, which includes both travel time and inspection time on the pylon set. Here $r = 1, 2, \ldots, k$ and k is the number of inspection teams. So the spending time for each inspection team should satisfy $t^r_{spe} \le t_{max}$.

t_{diff}, the maximum difference of the spending time among inspection teams, which can be expressed as $\max\{t^{r_1}_{spe}\} - \min\{t^{r_2}_{spe}\}$ with $r_1, r_2 = 1, 2, \ldots, k$.

The objective is to minimize the total work hours and balance the work hours of each inspection team, see Fig. 1, which can be expressed by

$$\min Z = \sum_{i=0}^{N}\sum_{j=0}^{N} t_{v_iv_j} x_{v_iv_j}, \tag{1}$$

$$\text{Subject to} \sum_{j=1}^{N} x_{v_0v_j} = k \tag{2}$$

$$\sum_{i=1}^{N} x_{v_iv_0} = k \tag{3}$$

$$\sum_{i=0, i\neq j}^{N} x_{v_iv_j} = 1, \quad \forall j = 1, 2, \ldots, N \tag{4}$$

$$\sum_{j=0, i\neq j}^{N} x_{v_iv_j} = 1, \quad \forall i = 1, 2, \ldots, N \tag{5}$$

$$u_{v_i} - u_{v_j} + p x_{v_iv_j} \le p - 1, \quad \forall i, j = 1, 2, \ldots, N,\ i \neq j \tag{6}$$

$$1 \le u_{v_i} \le p, \quad \forall i = 1, 2, \ldots, N \tag{7}$$

$$t^r_{spe} \le t_{max}, \quad \forall r = 1, 2, \ldots, k \tag{8}$$

$$t_{diff} \le \delta \tag{9}$$

where

$$x_{v_iv_j} = \begin{cases} 1, & \text{if the pylon } v_i \text{ precedes pylon } v_j \text{ on a travel} \\ 0, & \text{others} \end{cases}$$

for $v_i, v_j \in V$ and u_{v_i} = visiting rank of pylon v_i in order, $\forall i = 1, 2, \ldots, N$, and $2 \le p \le N + 1 - k$ denotes the maximum number of pylons that can be inspected by any inspection team. The term δ is a threshold to show fairness. For example, let us set δ to one quarter, which means the maximum difference of work hours among all inspection teams is less than one quarter.

Constraints (2) and (3) ensure that exactly k inspection teams depart from and return to the office(depot). Constraint sets (4) and (5) are the assignment constraints requiring that each pylon should be preceded by and precedes exactly one another pylon. Constraint sets (6) and (7) are the Miller-Tucker-Zemlin subtour elimination constraints [12]. Constraints (8) and (9) are weak and are also our optimization objectives.

Note that the optimization objective or weak constraint (9) is from the perspective of balancing work hours, also called as minmax. The objective (1) is to minimize the total spending time, also called as minsum. However, there is a contradictory between the two objectives [55], [56]. For the challenging problem, we first use ant colony algorithm (antcol) and simulated annealing algorithm (SA) to optimize the inspection path and calculate the spending time when assigning a single inspection team to complete the task. Then we provide a theoretical solution for the minimum number of inspection teams. At last, we explore the quasi-optimal paths with balanced workload for inspection team by the improved clustering algorithm.

In order to compare with antcol and SA, we also present a greedy algorithm. The greedy algorithm is described as follows: Assumed the current visited pylon is v_i, and the pylon set containing all the pylons that has been visited is defined as V_c, the next pylon v_j that will be selected to visit should satisfy the condition $\min_{v_j \in V \setminus V_c} t_{v_i v_j}$. Here $V \setminus V_c$ is the pylon set in V but not in V_c.

III. THEORETICAL ANALYSIS

In this section, we will give the framework for optimizing grouping and path planning with the minimum number of inspection teams.

A. THE THEORETICAL SOLUTION OF MINIMUM NUMBER OF INSPECTION TEAMS

Theorem 1: The minimum number of inspection teams k is the integer from Eq. (10)

$$k \in \{\frac{t_{tra} + t_{ins}N - t_{ave}}{t_{max} - t_{ave}} - 1, \frac{t_{tra} + t_{ins}N - t_{ave}}{t_{max} - t_{ave}}, \frac{t_{tra} + t_{ins}N - t_{ave}}{t_{max} - t_{ave}} + 1\}, \tag{10}$$

and satisfies Eq. (11) at the same time

$$k \geq (t_{tra} + t_{ins}N)/t_{max}. \tag{11}$$

The condition for the equality in Eq. (11) is that $(t_{tra} + t_{ins}N)/t_{max} = 1$. Here t_{tra} is the travel time of the optimal path for a single inspection team and $t_{ave} = \frac{\sum_{v_i \in V}(t_{v_0 v_i} + t_{v_i v_0})}{N}$ is the average round-trip time from the office to each pylon.

Proof: Let's define that the minimum number of inspection teams is k, ignoring the round-trip time of $k-1$ inspection teams, we have

$$k \geq (t_{tra} + t_{ins}N)/t_{max},$$

where the numerator $t_{tra} + t_{ins}N$ is the spending time for a single inspection team to complete the task. Therefore, the condition that the equal sign is established is $(t_{tra} + t_{ins}N)/t_{max} = 1$.

For the round-trip time of k inspection teams, we approximately use the average round-trip time $t_{ave} = \frac{\sum_{v_i \in V}(t_{v_0 v_i} + t_{v_i v_0})}{N}$ from the office to all pylons to replace. Thus, the total spending time for all teams is $t_{tra} + N \times t_{ins} + (k-1) \times t_{ave}$, where the term $k-1$ instead of k is because that there is one round-trip time in t_{tra}. Therefore, the minimum number of inspection team should satisfy

$$\frac{t_{tra} + t_{ins}N - t_{ave}}{t_{max} - t_{ave}} \leq k.$$

Then k is the smallest integer and not less than $\frac{t_{tra} + t_{ins}N - t_{ave}}{t_{max} - t_{ave}}$. Because the total spending time of multiple inspection teams must be larger than that of a single inspection team to complete the task, and the round-trip time here is an estimated value, so the conditions for the minimum k should be relaxed, which yields

$$k \in \{\frac{t_{tra} + t_{ins}N - t_{ave}}{t_{max} - t_{ave}} - 1, \frac{t_{tra} + t_{ins}N - t_{ave}}{t_{max} - t_{ave}}, \frac{t_{tra} + t_{ins}N - t_{ave}}{t_{max} - t_{ave}} + 1\}.$$

In conclusion, the minimum k can be obtained by combining Eq. (10) with Eq. (11).

B. THE ALGORITHM FOR OPTIMIZING GROUPING AND PATH WITH k INSPECTION TEAMS

The last section presents the theoretical solution for the minimum number of inspection teams, here we will give a clustering algorithm to partition the target pylons to balance the work hours. As the number of inspection teams is known, so k-means algorithm can be used to offer an excellent classification [57]. But the original k-means algorithm can't cope with the balance situation. Although some literatures studied the balanced k-means algorithms, their attentions were on balancing the size or some other constraints [58]–[62]. One challenging problem is that it is different between time and space, leading to infeasibility for us to use the average travel time in each group as the new centroid of its group. In order to deal with this problem, here we will present the improved k-means clustering algorithm to optimize grouping to balance the work hours, and show the quasi-optimal path by combining greedy algorithm, antcol and SA, respectively. The algorithm is as follows:

1) Initialization. There are k empty sets and the total spending time $\sum_{r=1}^{k} t_{spe}^{r}$ is infinity. The maximum iterations is N_{ite}^{max}.

2) The initial classification. Select k pylons from the pylon set $V \setminus v_0$ by random, and assign the other pylons to one of the k sets like the first step of k-means algorithm. For example, for the unassigned pylon v_i, we assign it to the pylon set v_j if $t_{v_i v_j}$ is the minimum among the k pylons.

3) Computing the total spending time $\sum_{r=1}^{k} t_{spe}^{r}$ and optimizing inspection paths of each inspection team by greedy algorithm, antcol and SA, respectively.

4) If the maximum difference of the spending time of the inspection teams t_{diff} is not more than a certain value, for example one quarter (900s), and the spending time of each team is not more than a certain value, say $\max\{t_{spe}^{r}\} \leq$ 28800s, and the total spending time $\sum_{r=1}^{k} t_{spe}^{r}$ is smaller than that of the last iteration. Then we replace the optimization result of the last iteration by the current one, and go to step 7.

5) Otherwise, if one of the two weak constraints is satisfied, and the total spending time $\sum_{r=1}^{k} t_{spe}^{r}$ is smaller than that of the last iteration. Then the last optimization result is replaced by the current one, and go to step 7.

6) If step 5 is not satisfied. If the current $\sum_{r=1}^{k} t_{spe}^{r}$ is smaller than that of the last classification, at the same time, the standard deviation of t_{spe}^{r} is smaller than that of the last classification, then the last optimization result is replaced by the current one.

7) Move one pylon from the pylon set with the maximum spending time to the pylon set with the minimum spending time, by random. Repeat the steps 3-6. *This step is the key for balancing the work hours.*

8) If the maximum iterations N_{ite}^{max} is satisfied, the current grouping and inspection path is the final optimization result.

We also show the flow chart of the algorithm in Fig. 2.

In this paper, the maximum iterations N_{ite}^{max} is set to 1000. For antcol, the iterations N_{ite}^{antcol} and the number of

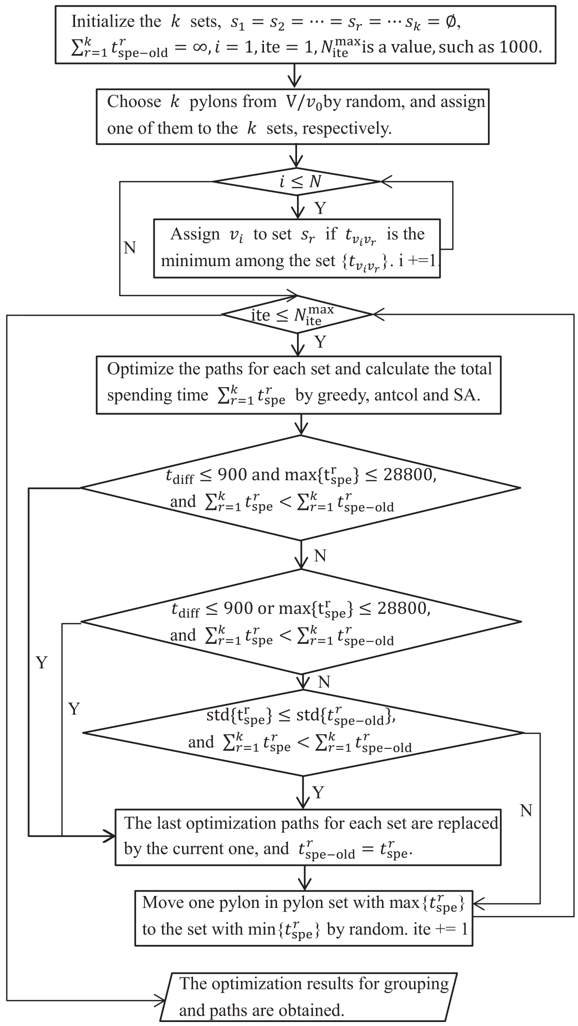

FIGURE 2. The algorithm flow chart.

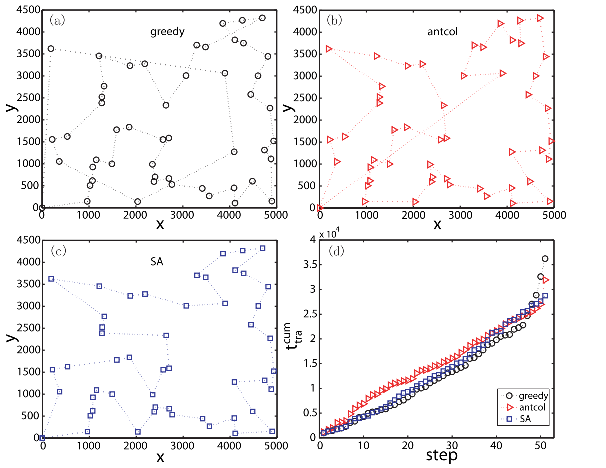

FIGURE 3. (Color online) (a-c) The quasi-optimal path planning results for the three algorithms. Here the coordinate (0, 0) is the starting point, namely, the office. (d) The cumulative travel time $t_{\text{tra}}^{\text{cum}}$ (s) for the quasi-optimal inspection paths of each step for the three algorithms. The number of pylons N is 50 and the coordinates of the pylons are randomly scattered in the range [100m, 5000m], the velocity is set to 1m/s.

ants N_{ant} are set to 50 and $N/3$, respectively. For SA, the iterations $N_{\text{ite}}^{\text{SA}}$ is set to 1000, and the range of temperature is from 1 to 100 with 1 as the temperature increment. Thus, the computation complexity for the worst case is $O((N-k)k + N_{\text{ite}}^{\max} N(N-1)/2)$, $O((N-k)k + N^2 N_{\text{antcol}} N_{\text{ite}}^{\text{antcol}} N_{\text{ite}}^{\max})$ and $O((N-k)k + N N_t^{\text{SA}} N_{\text{ite}}^{\text{SA}} N_{\text{ite}}^{\max})$ for greedy algorithm, antcol and SA, respectively. Here $O((N-k)k)$ is the computation complexity for step 2 in the algorithm, and N_t^{SA} is the number of different temperature in SA.

IV. EXPERIMENTAL ANALYSIS

In this section, we will apply our framework of optimal grouping and path planning to synthetic and real transmission lines.

A. RESULTS OF SYNTHETIC TRANSMISSION LINE

1) SINGLE INSPECTION TEAM OF SYNTHETIC TRANSMISSION LINE

Assumed that the target pylons are uniformly distributed in a two-dimensional plane in the range from 100 meters to 5000 meters, and the office is at coordinate $(x = 0, y = 0)$. Without loss of generality, let's define the velocity as a constant, say 1m/s, which indicates that the Euclidean distance among each pair of nodes, taking v_i and v_j for instance, quantifies the corresponding travel time $t_{v_i v_j}$. Figure 3 (a-c) show the optimization result of inspection paths under greedy algorithm, antcol, and SA, respectively. As the inspection time of each pylon and the corresponding transmission line connected to the pylon, t_{ins}, is assumed to be equal, in Fig. 3 (d), we present the cumulative travel times $t_{\text{tra}}^{\text{cum}}$ of each inspection step on quasi-optimal inspection paths with the three algorithms. We can see that the greedy algorithm performs well at the beginning, but SA takes the shortest time in the end, followed by antcol. Besides, from Fig. 3 (a-c), we can find that the path for greedy algorithm is a bit confused, while the one of SA is regular and orderly. The travel times t_{tra} of visiting all the pylons by the three algorithms are 34798s, 32512s and 31839s, respectively. Assumed that t_{ins} is 600s, then the total spending times for this task is 64798s, 62512s and 61839s, respectively. Normally, the work time for each person is about 28800s one day, so it is necessary to assign this task to multiple inspection teams.

2) OPTIMIZE GROUPING AND PATH PLANNING OF SYNTHETIC TRANSMISSION LINE

Here we study the grouping and path planning of the last example with our framework. Because of the symmetry of the matrix T in this example, the average travel time t_{ave} from office to each pylon is $\frac{2\sum_{v_i \in V} t_{v_0 v_i}}{N} = 7768.12\text{s}$. With Eq. (10), the minimum number of inspection teams is one of the values in $\{2, 3, 4\}$. With Eq. (11), the minimum number of inspection teams satisfies $k > 2$ for all the three algorithms. Therefore, the optimal value of k is 3 or 4 by combining Eqs. (10) with (11).

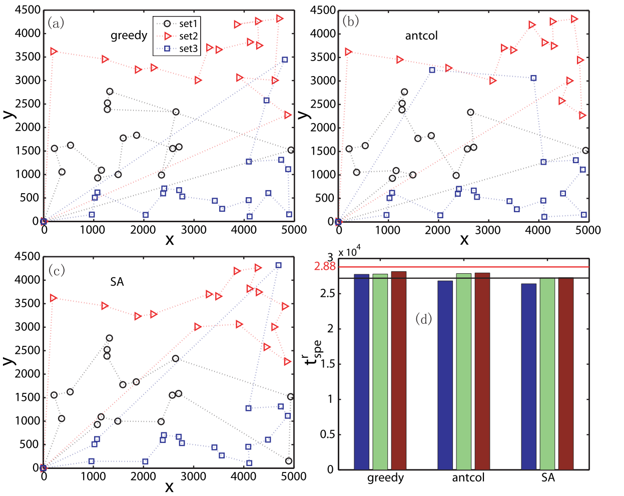

FIGURE 4. (Color online) (a-c) The quasi-optimal inspection paths and (d) the total spending times t_{spe}^{r} for each inspection team under the three algorithms. The coordination (0, 0) stands for the office, and the value of k is 3. The difference of the maximum and minimum spending time for inspection teams satisfies $t_{diff} \leq 900$s. The red line is the upper bound of the spending time for each inspection team, and the black line is only used for comparison.

The quasi-optimal inspection paths and the total spending times for each team by the three algorithms are shown in Fig. 4. We find that when k equals to 3, the total spending time for each inspection team does not exceed 28800s, and the workload of each team is well balanced. From Fig. 4 (d), it can be seen that SA performs the best, and antcol is the second, and greedy algorithm is the worst. The spending time of the three algorithms (greedy, antcol, SA) for each team are {27748s, 27790s, 28145s}, {26824s, 27866s, 27951s} and {26407s, 27243s, 27272s}, respectively. It takes more 2760s for greedy algorithm comparing with SA, and more 1719s for antcol comparing with SA.

B. RESULTS OF REAL TRANSMISSION LINES

In this section, we test our framework to real transmission lines. Nevertheless, the incomplete data prevents us from using the framework immediately. Thus, one key of this section is to mining the necessary data.

1) ANALYSIS OF REAL DATA

The real data contains the following details:

(i) Longitudes and latitudes of all pylons and office in Jinhua City, Zhejiang Province.

(ii) Longitudes and latitudes of drop off points of each pylon.

(iii) The driving times $t_{v_0 v_i}^{\mathrm{d}}$ from the office to drop off points of each pylon.

The optimal path should start from the office, after inspecting all the target pylons and transmission lines, and finally return to the origin, as shown in Fig. 5. Therefore, apart from the driving times from office to the drop-off points of pylons, we need the following data:

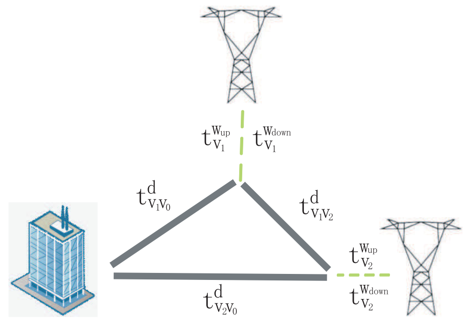

FIGURE 5. (Color online) A schematic diagram of one office and two pylons. The term $t_{v_0 v_i}^{\mathrm{d}}$ is the driving time from v_i to v_j. $t_{v_i}^{\mathrm{Wup}}$ stands for the walking time from the drop-off point to the pylon v_i. $t_{v_i}^{\mathrm{Wdown}}$ represents the walking time from v_i to the picking up point of the next destination.

(i) The walking time $t_{v_i}^{\mathrm{Wup}}$ from the drop-off point to the pylon v_i.

(ii) The walking time $t_{v_i}^{\mathrm{Wdown}}$ from the pylon v_i to the picking up point of the next destination.

(iii) The driving time $t_{v_0 v_i}^{\mathrm{d}}$ among each pair of pylons.

The $t_{v_i}^{\mathrm{Wup}}$ and $t_{v_i}^{\mathrm{Wdown}}$ may be different, which can be obtained by mobile devices when going to inspect the pylons, but it is impractical to collect the driving times $t_{v_0 v_i}^{\mathrm{d}}$ by driving along the paths for each pair of pylons. However, we have an alternative method. Given the longitudes and latitudes of all pylons and office, we use the API interface of Baidu Map and web crawler to excavate $t_{v_i}^{\mathrm{Wup}}$, $t_{v_i}^{\mathrm{Wdown}}$ and $t_{v_0 v_i}^{\mathrm{d}}$. Thus we can obtain travel times $t_{v_0 v_i}^{\mathrm{d}} + t_{v_i}^{\mathrm{Wup}}$ from the office to each pylon and travel times between each pair of pylons $t_{v_i}^{\mathrm{Wdown}} + t_{v_0 v_i}^{\mathrm{d}} + t_{v_i}^{\mathrm{Wup}}$, so the travel time matrix T is available.

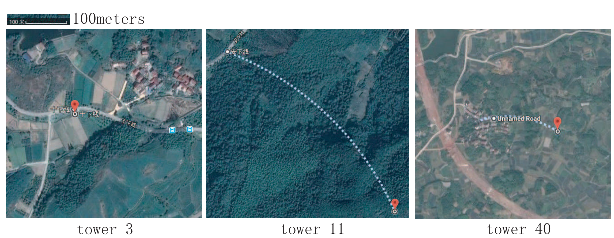

FIGURE 6. (Color online) Maps of the paths from the drop-off points to the pylons with three different sites in the line-5876.

To test our method, in this paper two transmission lines, the line-5876 and line-5803, are selected by random. Note that some pylons are on the road that vehicle can reach directly, so the walking time is 0s. For example, pylon 3 on the line-5876 in Fig. 6. Besides, there is another case that the pylon is on a mountain, such that it takes long time for walking even though the straight distance is short. For example, pylon 11 on the line-5876 in Fig. 6, there are no routes outlined on the map. The straight distance from the drop-off point to pylon 11 is only about 600m, however, it takes 2300s for walking. Pylon 40 on the line-5876 is a normal case. The distance of the path is 179m, and it takes 153s for walking.

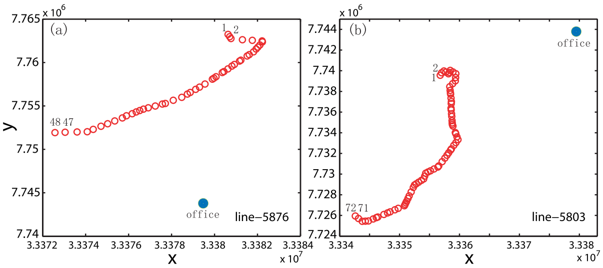

FIGURE 7. **(Color online) The coordinates of the transmission lines, the line-5876 and line-5803. Only the first two pylons and the last two pylons, as well as the location of office, are marked.**

Figure 7 shows the projection of the longitudes and latitudes of all pylons on the two transmission lines into x and y coordinates. The x and y coordinates here are the result from Miller cylindrical projection [63]. For example, the longitude and latitude of the office is (119.705681, 29.133654) and the projected coordinate is (x = 33379472m, y = 7743785m).

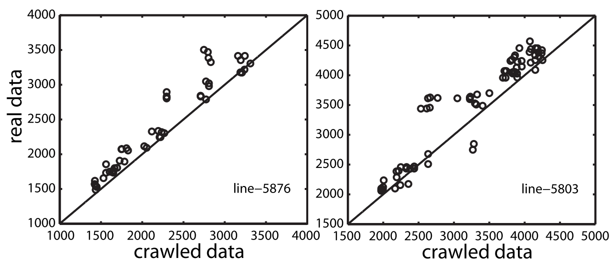

FIGURE 8. **Comparison of real driving time $t_d^{v_0 v_i}$ and the one from crawled data for two transmission lines.**

As we only have the real driving time $t_d^{v_0 v_i}$ from the office to the drop-off point of each pylon, we should explore the reliability of the crawled data from our method. From Fig. 8, we can find that the real data is some larger than the crawled data, and the difference is about 198.5s and 236.7s on the average for the two transmission lines, respectively. To a great extend, the crawled data are coincided with the real data. Therefore, we can approximately use the crawled data to replace the lack of real data, and then use the framework to show the optimization result of grouping and path planning.

2) SINGLE INSPECTION TEAM FOR REAL TRANSMISSION LINES

Firstly, we analyze the case that the task is assigned to a single inspection team. In Fig. 7, we can see that the pylons are close to each other, so it is not convenient to present the inspection trajectory as Fig. 3. Here we present it in an alternative way, as shown in Fig. 9, which contains the results of quasi-optimal path and the cumulative travel times $t_{\mathrm{tra}}^{\mathrm{cum}}$ of each inspection step under three algorithms for the line-5876 and line-5803. The results in Fig. 9 indicate that the SA algorithm is the best, and the greedy algorithm is the worst, which is similar to the result of Fig. 3.

In Fig. 10, we further study the fluctuation of the travel time for the three algorithms. It can be found that SA has the best

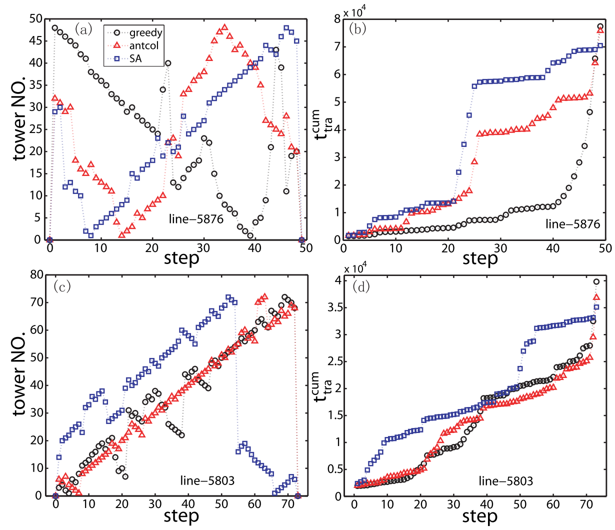

FIGURE 9. **(Color online) (a, c) Quasi-optimal inspection paths under the three algorithms. (b, d) The cumulative travel times $t_{\mathrm{tra}}^{\mathrm{cum}}$ of each inspection step under the three algorithms. (a, b) The results for the line-5876. (c, d) The results for the line-5803.**

performance and little fluctuation. The antcol has a greater fluctuation and the greedy algorithm works the worst.

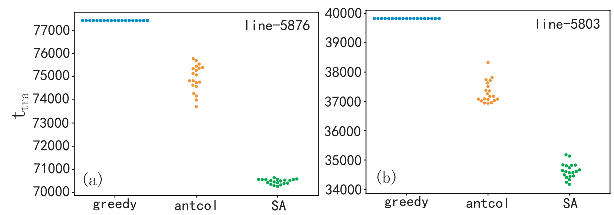

FIGURE 10. **(Color online) The total travel time of the two power transmission lines under the three algorithms with 20 independent simulations.**

3) OPTIMIZE GROUPING AND PATH PLANNING OF REAL TRANSMISSION LINES

In this section, we verify the theory of minimum number of inspection teams and give the optimization result of grouping and path planning for the two transmission lines. For the line-5876, the average of travel time t_{tra} for the three methods is 77419s, 74926.25s and 70475.7s, respectively, as shown in Fig. 10. The average travel time t_{ave} from the office to each pylon is 5668.64s and N is 48. From Eq. (10), the optimal value of k is in the set {3, 4, 5}. By using Eq. (11), we have $(t_{\mathrm{tra}} + 600N)/28800 > 3$. Thus, the optimal value is 4 or 5. For the line-5803, the travel time t_{tra} for the three methods is 39828s, 37313.5s and 34626.65s, respectively. The value of t_{ave} is 6712.8s and N is 72. Combining Eq. (10) with Eq. (11), the optimal k is in the set {3, 4, 5}.

Figure 11 shows that when k equals to 4, the spending time t_{spe}^{r} for each team is about 30000s, which exceeds the upper bound 28800s. When k is 5, t_{spe}^{r} for each team is about 25000s. Thus, the optimal k is 5. For the line-5803, it is found that when k equals to 3, t_{spe}^{r} for each team is about 35000s,

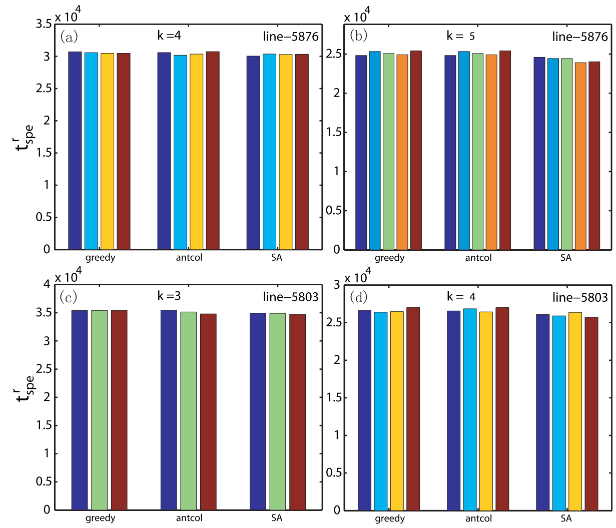

FIGURE 11. (Color online) (a, b) The spending times t^r_{spe} of each team under the three algorithms when the number of inspection teams is 4 and 5 for the line-5876, respectively. (c, d) The spending times t^r_{spe} of each team under the three algorithms when the number of inspection teams is 3 and 4 for the line-5803, respectively. Here the inspection time t_{ins} for each pylon and the corresponding transmission line is 600s.

which is far more than 28800s. When k equals to 4, t^r_{spe} for each team is about from 25500s to 27500s, and it satisfies all the constraint conditions. When k equals to 5, t^r_{spe} for each team is about 24000s, resulting in wasting human resources, so the optimization result of the line-5803 for $k = 5$ is not presented in the paper. Thus, for the line-5803, the optimal number of inspection teams is 4. Furthermore, we find that the workload of inspection teams are well balanced, and SA has the best performance. An interesting result is that the spending time for antcol and greedy algorithm is nearly the same.

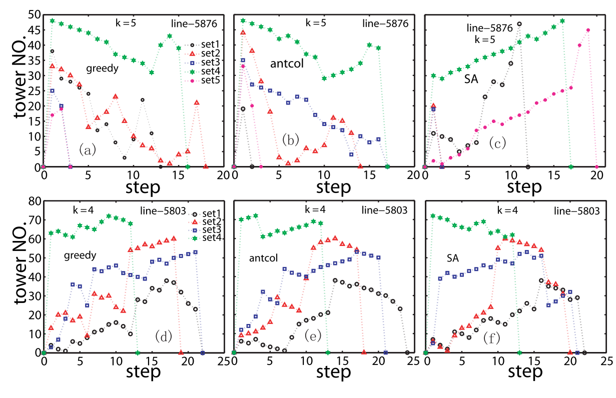

FIGURE 12. (Color online) The quasi-optimal inspection paths of each inspection team for the two transmission lines under the three algorithms. (a-c) Greedy, antcol and SA algorithms for the line-5876. (d-f) Greedy, antcol and SA algorithms for the line-5803.

In Fig. 12, we show the optimization result of inspection paths for each team under the three algorithms, respectively. It can be seen that, for the line-5876, there are two inspection teams only visit one or two pylons. The reason is that pylon 19 and 20 are on the mountain, and the straight distance from the drop-off point to pylon 19 or 20 is about 1200m. On the map there aren't any roads to the pylons, and it takes about 9300 seconds for walking, which is similar to the case of pylon 11 in Fig. 6. However, for the line-5803, the number of pylons in each team is relatively balanced, which is between 13 and 24.

Finally, we study the time consuming for convergence to the quasi-optimal result under the three algorithms. From Fig. 13, we can find that the greedy algorithm is the fastest, and the running time is about 0.05s. SA is the slowest, but it only needs several hundred seconds. For this optimal problem, we can also solve it with the help of Google OR-Tools or Concorde TSP solver. In conclusion, it is efficient of our framework for optimal grouping and path planning with the minimum number of inspection teams.

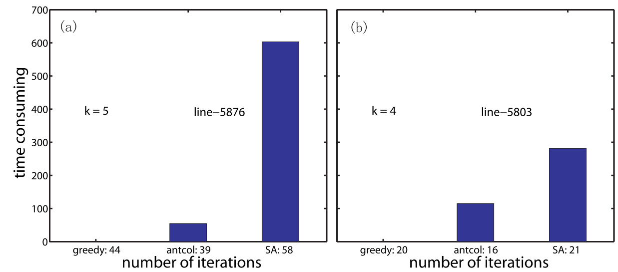

FIGURE 13. (Color online) The running time (seconds) of the three algorithms which is implemented by Python program language and running on a 3.6 GHz workstation with 8GB of RAM, Intel(R) Core(TM) i7-7700 CPU. The number of inspection teams is 5 and 4 for the line-5876 and line-5803, respectively. The horizontal ordinate represents the iteration times of convergence to the optimal result.

V. CONCLUSION

Task assignment and optimal path has practical applications. However, with constrained work hours, there are few researches on the optimal inspection path for the following objectives: (i) The minimum number of inspection teams. (ii) Balancing the work hours of inspection teams. (iii) The minimum work hours. In this paper, we have proposed a general framework for optimizing grouping and path planning with the minimum number of inspection teams, by taking into account both travel time and inspection time. The framework is composed of an improved k-means algorithm and intelligence algorithms. At first, we analyze the case of synthetic transmission line. Furthermore, we explore two real power transmission lines in Jinhua, one city in Zhejiang province, China. With the longitudes and latitudes of pylons and the drop-off points of pylons, the travel time is obtained by the API interface of Baidu Map and web crawler. The results on both synthetic and real transmission lines have suggested that the minimum number of inspection teams is agreed well with our theory. Besides, the work hours are well balanced. In addition, comparing with greedy algorithm and ant colony algorithm, the simulated annealing algorithm performs the best.

In this paper, we estimated the minimum number of inspection teams based on the average round-trip time. Except for some optimal methods we mentioned, there are several general approaches can be used to optimize the number of vehicles, which can be referred for optimizing the number of inspection teams [64], such as greedy algorithm [65], integer programming [66], lagrangian Relaxation Method [67]. We assume that inspection time t_{ins} of each pylon and the corresponding transmission line is the same, which can be replaced by heterogeneous inspection time. This paper proposed a general framework for the optimal grouping and path planning. For step 3 in our algorithm for optimizing path, some other approaches can also be introduced, such as hybrid algorithms [68], [69] and neural network algorithm [70], which may present a better performance. Besides, the question about how to balance the workload and minimize the consumption of vehicle fuel to reduce environmental pollution is worthy of further exploration.

CONTRIBUTORS

Zhao-Long Hu devised the research project. Zhao-Long Hu and Jia-Hui Li performed numerical simulations. All authors analysed the results. Zhao-Long Hu and Chang-Bing Tang wrote the article. All authors gave final approval for publication.

COMPETING INTERESTS

We declare we have no competing interests.

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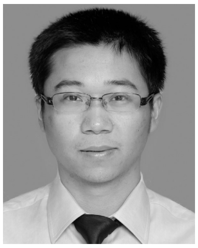

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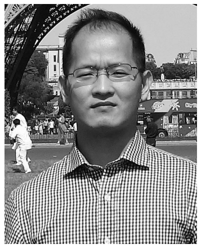

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