Energy Consumption-Driven UAV Dock Deployment Planning for Power Inspection

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Abstract:

As an important energy in modern society, the stable operation of electricity is the guarantee of social and economic operation, and the loss caused by the damage of power facilities is immeasurable, so the regular monitoring of power facilities is indispensable. UAVs, with flexible flight mode, have played an important role in power inspection. With the development of UAV docks, UAV inspection has entered a new stage. However, due to the fixed location of the docks and limited coverage, how to achieve the optimal deployment of the docks with the lowest cost and full coverage of power facilities through reasonable deployment is one of the important issues that need to be solved at this stage of dock construction. To solve this problem, this paper proposes an energy-driven adaptive optimization method for dock location by combining geospatial analysis with UAV performance index. The experiment results show that our method can achieve an efficient, reasonable and feasible optimal location for UAV dock deployment.

1. Introduction

In the past decade, global electricity demand has been persistently growing, boosting rapid development of clean energy sources such as wind, solar, and tidal power worldwide. The "2023 Electricity Market Report" released by International Energy Agency declares that global electricity demand increases with an annual growth rate of 3% from 2023 to 2025 (International Energy Agency, 2023). In terms of longer transmission lines and more complex environments, periodically manual inspections for transmission lines are labor-intensive and costly, time-consuming, and fraught with considerable danger. Unmanned aerial vehicles (UAVs), serving as low-altitude platforms capable of mounting various sensors, have been widely used for defect detection and operation assessment of transmission pylons with its flexible flight mode and efficient data acquisition capability (Luo et al., 2023). However, the limited battery capacity and communication range of UAVs reduce the inspection coverage, especially when equipped with various sensors (Li et al., 2023). To address the issue, UAV dock are established along transmission lines which alleviates the short endurance and poor adaptability to harsh environments of UAVs (Hassan et al., 2022; Huang and Savkin, 2020; Liu et al., 2019; Zhang et al., 2023). Due to the fixed location and limited coverage of UAV docks, how to achieve full coverage of power facilities and optimal configuration of airports with the lowest cost through reasonable deployment of UAVs is one of the important issues that need to be solved at this stage of airport construction.

However, the deployment of UAV docks in the field of electric power inspection is at outset. Liu et al (2019) realized UAV-dock optimization deployment by simply clustering inspection facilities in space, which is mainly aimed at the inspection situation of a small number of devices. Inspired by the site selection problem of communication facilities(ElSayed et al., 2022; Jin et al., 2022; Qin et al., 2022; Ribeiro et al., 2022; Zhang et al., 2021). Dai et al. (2023) focus on the cost of construction, maintenance, and inspection of docks, and thus define the site selection issue as a p-median problem with the lowest cost with principled constraints to achieve multi-objective optimization of the lowest cost site selection. Mai et al. (2023) propose a quantitative analysis decision method which use an improved simulated annealing algorithm to build a minimum total cost model, achieving optimal deployment of UAV docks.

Different from the facility deployment problem in the traditional two-dimensional network, the deployment of UAV docks is in the three-dimensional space, which needs to consider the capacity constraint, energy consumption, connectivity and other characteristics of the UAV, as well as external factors such as the distribution of power facilities and environmental conditions. Current research on UAV dock site selection only focuses on cost studies while ignoring the impact of various factors such as UAV performance and terrain conditions on electric power inspection, which can hardly be utilized in practice. Therefore, it is a great challenge that UAV docks are optimally deployed to comprehensively cover the power facilities that need to be inspected and simultaneously make the construction cost-effective. In response to this issue, this paper comprehensively considers the energy consumption, environmental conditions, economic costs and other conditions. We propose a UAV energy consumption-driven adaptive optimization method for dock site selection. First, based on the DSM and land-use data of the operation area, the candidate area of the dock is generated by geospatial calculation and analysis method. Then, a mathematical model of UAV inspection energy consumption is constructed by considering various environmental factors in the operation area and the performance of UAV. Meanwhile, according to the location of power facilities, the locations of the docks are generated by adaptive clustering, and the cost function is constructed. Finally, the cost function is optimized to achieve an efficient, rational, and feasible optimal site selection of UAV docks.

The remainder of this paper is organized as follows. In Section 2, the steps of the proposed method are elaborated in detail. In Section 3, experiments were undertaken to evaluate the performance of the proposed method, after which conclusion is drawn at the end of this paper.

2. Method

To achieve optimal dock layout, the method proposed in this paper mainly includes four key steps: First, candidate areas for the docks are generated using geospatial computational analysis methods based on Digital Surface Models (DSM) and land use data. Then, a UAV inspection energy consumption model is constructed according to the performance of the UAVs. And an energy-driven adaptive clustering algorithm is adopted to generate preliminary dock locations. Finally, optimization is used to generate reasonable dock deployment positions.

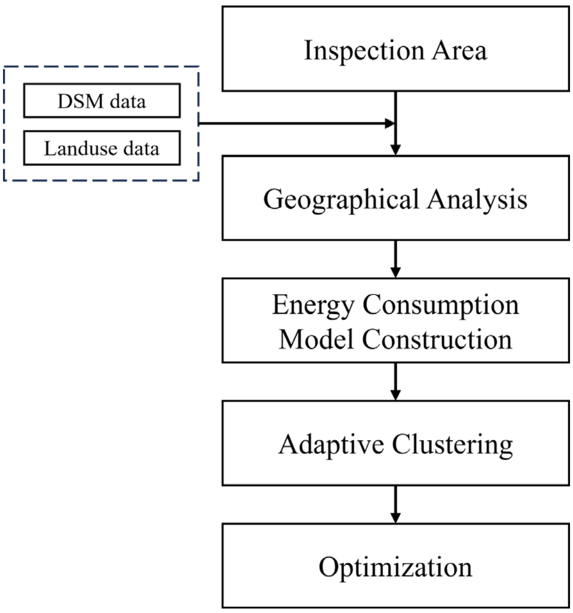

Figure 1. The workflow of the proposed method.

2.1 Extraction of Candidate Areas for UAV Docks

With the continuous development of Geographic Information System (GIS) technology, it has become an important decision-support tool in factor evaluation, and is widely used in site selection research.

The main principles for UAV dock deployment planning include ensuring the location is open and free from signal interference, with flat terrain, and distant from buildings and rivers. Based on these principles, utilizing data such as the locations of electrical equipment, Digital Surface Models (DSM), and land use/land cover (LULC) data and employing geospatial computational analysis methods, we can preliminarily obtain candidate areas that meet all the construction requirements. In addition to these requirements, it is also necessary to consider the radius of the UAV endurance coverage. In this study, the coordination of multiple UAV docks is not considered. For each dock, it is only responsible for the inspection target within its coverage radius.

The steps of the extraction of candidate areas for UAV docks are shown as follows, and as illustrated in Fig.2:

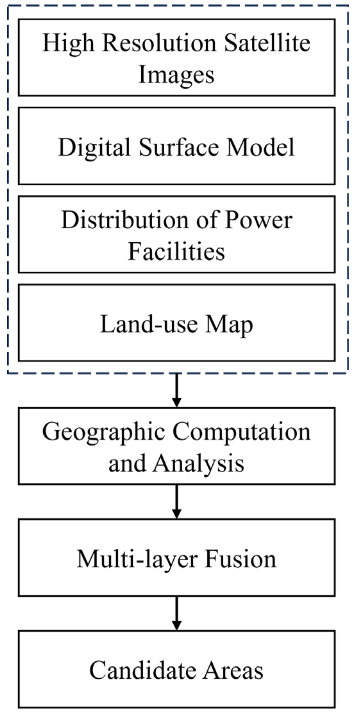

Figure 2. The workflow of the extraction of candidate areas.

(1) Geographic computation and analysis

Slope calculation: Slope is one of the most important geographical parameters in GIS, which is widely used to describe surface structure and analysis topographic data. In this paper, the slope of the inspection area is calculated using DSM data, and a certain threshold is set according to expert experience. The area with a slope greater than the threshold is regarded as an unsuitable area and assigned a value.

According to the raster characteristics of DSM data, many slope calculation methods based on 3×3 moving Windows have been proposed by predecessors, and the third-order inverse distance squared weight difference algorithm has been widely used(Liu et al., 2004).

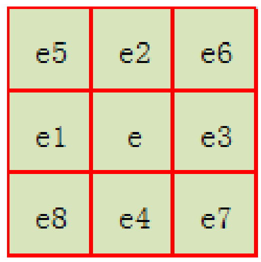

Figure 3. 3×3 template window.

The center of each window is an elevation point. The slope of the center point e in Fig.2 is evaluated by Eq.1. And The slope map of the inspection area is shown in the Fig.4.

$$\begin{cases} Slope = \tan\sqrt{Slope_{we}^2 + Slope_{sn}^2} \\ Slope_{we} = \dfrac{(e_8 + 2e_1 + e_5) - (e_7 + 2e_3 + e_6)}{8 \times Cellsize} \\ Slope_{sn} = \dfrac{(e_7 + 2e_4 + e_8) - (e_6 + 2e_2 + e_5)}{8 \times Cellsize} \end{cases} \tag{1}$$

where, Slope is the slope, $Slope_{we}$ is the slope in the X direction, and $Slope_{sn}$ is the slope in the Y direction. $Cellsize$ indicates the length of the mesh.

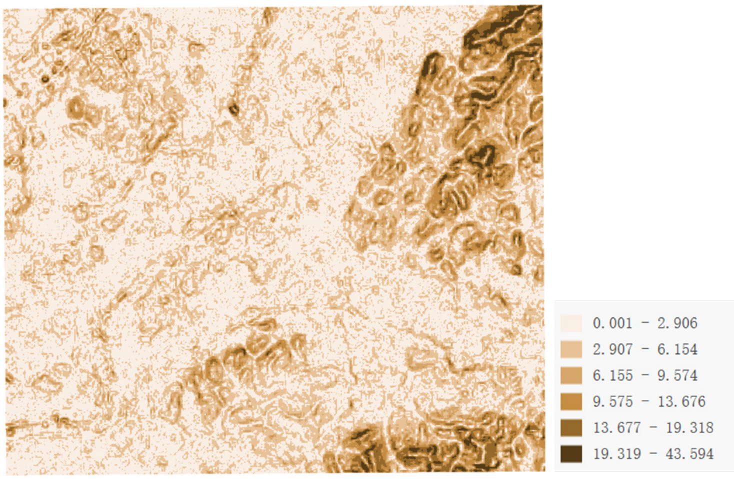

Figure 4. Slope Map.

Buffer generation: According to the radius of the UAV endurance coverage, buffer analysis is carried out based on the location distribution information of power facilities. Regions that are not in the buffer are treated as unsuitable regions and assigned a value.

At the same time, the land-use map is used to generate buffer zones for buildings, forest, rivers and other areas, and the buffer areas are regarded as unsuitable areas and assigned values.

(2) Multi-layer Fusion
In order to obtain comprehensive evaluation results, weights are set for the above layers according to their importance, and different layers are superimposed to achieve the extraction of candidate regions.

2.2 UAV Energy Consumption Model Construction

The optimal UAV dock deployment is to achieve the goal of minimizing the coverage cost under the premise of full coverage. To model the UAV dock site selection, we define the set of UAV dock as N and the equipment to be inspected as P. Based on the definitions above, the constraints in this problem can be described as follows:

$$\sum_{n\subseteq N} Y_{n,p} = 1, \forall p \in P; \tag{2}$$

$$\sum_{n\subseteq N}\sum_{p\subseteq P} t_{n,p} + \sum_{p\subseteq P} t_p \le \sum_{n\subseteq N} E \le T; \tag{3}$$

where the Eq.2 indicates that each equipment must be inspected by exactly one UAV. and Eq. 3 ensures that the inspection tasks must be completed within the required time, and the inspection capabilities of the established bases should meet the needs of the inspection tasks. $t_{n,p}$ represents the required time for a UAV to reach equipment and t_p indicates the inspection time for the equipment p. E represents the continuous operational endurance of a UAV in a single day, which is influenced by charging duration and daily effective working hours. Thereinto, e is defined as the single endurance duration of UAVs, T as the maintenance-required completion time for inspection tasks.

In this section, we transform the optimal deployment of UAV dock into a problem of optimization of inspection energy consumption. On the basis of the above constraints, the inspection cost function is constructed and further expressed as Eq.4:

$$C_e = \sum_{p\subseteq P} t_{n,p} + \sum_{p\subseteq P} t_p \, (n \in N) \tag{4}$$

Where $t_{n,p}$ represents the required time for a UAV to reach equipment and t_p indicates the inspection time for the equipment p

2.3 Energy Consumption-Driven Adaptive Clustering

In contrast to the site selection for UAV-based communication facilities, the site selection of UAV docks is more complex and cannot be simply defined as a set covering problem (SCP). Although the traditional optimization methods can cover the whole region, they lead to inefficient inspection and hardly ensure the operational safety of the power system. In addition to achieving all-sided coverage with the minimum number of base stations, it is crucial to take into account the trade-offs among multiple optimization objectives in actual application scenarios. For power facilities inspections with UAVs, the most significant factor is the energy consumption of the UAVs which directly impacts the efficiency of inspection work. Therefore, based on the constructed energy consumption model, we proposed an adaptive clustering algorithm to determine the candidate locations of UAV docks. The workflow is shown in Fig.5.

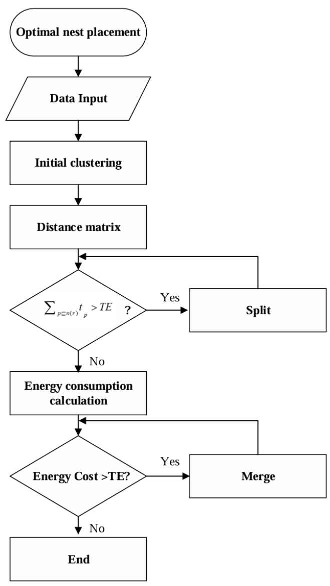

Figure 5. The workflow of the optimization algorithm.

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The input data consists of a distribution map of electrical equipment. The initialization of clustering is performed by using the maximum coverage radius r of the UAV as the clustering radius to cluster the electrical equipment data. After obtaining the cluster centers, which serve as the initial positions for the UAV docks, a distance matrix is calculated in conjunction with the distribution data of the electrical equipment. This matrix includes the distances between electrical equipment as well as the distances between the electrical equipment and the UAV.

2.4 Optimization

As discussed in the previous section, we can achieve the optimal UAV dock deployment by minimizing the energy consumption C_e. The UAV energy consumption model has a large number of parameters and high complexity, so this is essentially a nonconvex optimization problem in a high-dimensional space. The Monte Carlo method, also known as the statistical simulation method, has strong adaptability of performing approximate numerical calculations by taking random samples from a probabilistic model. However, the Monte Carlo method requires the sample to be independent, which is a relatively strict condition. The improved Markov Chain Monte Carlo (MCMC) algorithm (Andrieu et al., 2003) is suitable for the case that the probability density function is complex and can’t be sampled directly. It approximates a complex combinatorial problem to be approximated as a much simpler problem through statistical sampling, and is widely used in non-convex optimization problems for its good performance. Simply put, MCMC is a strategy for generating samples and exploring the state space using a Markov chain mechanism, which in turn achieves the simulation of the target distribution.

The convergence of a non-periodic Markov chain is of great importance for the MCMC algorithm. Regardless of the initial distribution probability, the Markov chain always converges to obtain a stationary distribution, which satisfies the detailed balance condition, as shown in Eq. 13.

$$\pi(i)P(i,j)=\pi(j)P(j,i) \tag{5}$$

where P is the status transition matrix of the Markov chain, and the probability distribution $\pi(x)$ is the stationary distribution of the matrix P.

However, in general, it is difficult to obtain the matrix corresponding to the stationary distribution from the detailed balance condition, as the transition matrix may not satisfy the detailed balance condition. Therefore, MCMC sampling introduces the parameter of acceptance rate to induce and satisfy the detailed balance condition.

$$\pi(i)Q(i,j)\alpha(i,j)=\pi(j)Q(j,i)\alpha(j,i) \tag{6}$$

$\alpha(j,i)$ satisfies the following two conditions:

$$\begin{cases}\alpha(i,j)=\pi(j)Q(j,i)\\ \alpha(j,i)=\pi(i)Q(i,j)\end{cases} \tag{7}$$

From this, we can obtain the target matrix by multiplying any Markov chain status transition matrix by $\alpha(j,i)$:

$$P(i,j)=\alpha(i,j)Q(i,j) \tag{8}$$

However, for complex problems, the traditional MCMC has the limitation that its sampling efficiency decreases sharply when the acceptance rate is small. The proposed Metropolis-Hastings algorithms solve this problem, and the MH algorithm achieves the efficiency improvement by improving the acceptance rate as shown in Eq. 9.

$$\alpha(i,j)=\min\{\frac{\pi(j)Q(j,i)}{\pi(i)Q(i,j)},1\} \tag{9}$$

In this paper, we achieve the optimal UAV dock deployment by minimizing the energy consumption. Based on the MH algorithm, we can perform global optimization from the detailed balance distribution of Markov chains. To achieve this, we employ the Simulated Annealing algorithm, which allows us to explore the search space effectively and avoid getting trapped in local optima.

$$\hat{x}=\arg\max_{x^{(i)};i=1,\dots,N} p(x^{(i)}) \tag{10}$$

Due to random sampling, there are few samples from the target region, and computational resources are wasted on exploring areas of no interest. So a Simulated annealing (SA) strategy is used in this paper for global optimization.

Simulated annealing improves efficiency based on the MH algorithm by constructing a non-simultaneous Markov chain.

$$p_i(x)\propto p^{1/T_i}(x) \tag{11}$$

where T represents a decreasing temperature series and $\lim_{i\to\infty} T_i=0$. Under the weak regularity assumption of $p(x)$, $p^{1/T}(x)$ is a probability density concentrated in the set of global maxima of $p(x)$. Also when T tends to 0, the target distribution $p(x)$ tends to be globally optimal.

Most convergence results of simulated annealing show that for a given T, the flush Markov transition kernel mixes fast enough, then the sequence T is guaranteed to converge to the global maximal set of $p(x)$. The detailed procedure of the simulated annealing algorithm is shown as follows:

Algorithm: Simulated Annealing Algorithm

//**Input:** T_0(initial temperature)
T_f(*end temperature of cooling process*)
α(the cooling rate), N(*iteration number*)
// **Initialization:** $i=0, T_i=T_0, x_0$ (original state)
do
    Obtain x_{i+1} via Metropolis Sampling Algorithm (input x_i ; and T_i).
        $k=0, s_0=x_i$
        do
            Construct s_m from s_k
            Calculate $E(s_m), \Delta E=E(s_m)-E(s_k)$
            if $\Delta E<0$
                $s_{k+1}=s_m$
            else
                if $random(0,1)<e^{\frac{\Delta E}{T_i}}$
                    $s_{k+1}=s_m$
                else
                    $s_{k+1}=s_k$
            $k=k+1$
        while $k<L_T$
        $x_{i+1}=s_{k+1}$
    $T_{i+1}=\alpha T_i$
    $i=i+1$
while $T_i>T_f$ **or** $i\geq N$
//**Output:** x_{i+1}

3. Experiment

3.1 Data Description

The experimental data used in this paper includes 153 High-Voltage pylons located in in Yangjiang City, Guang Dong

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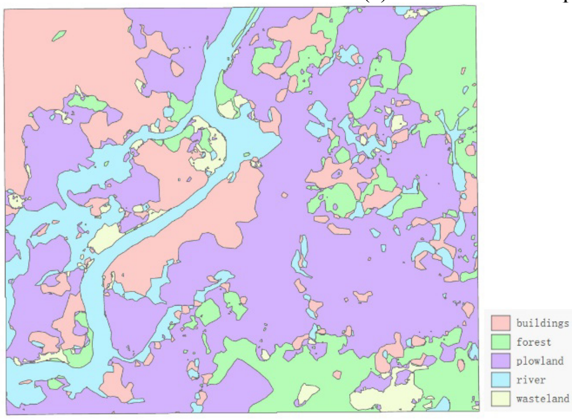
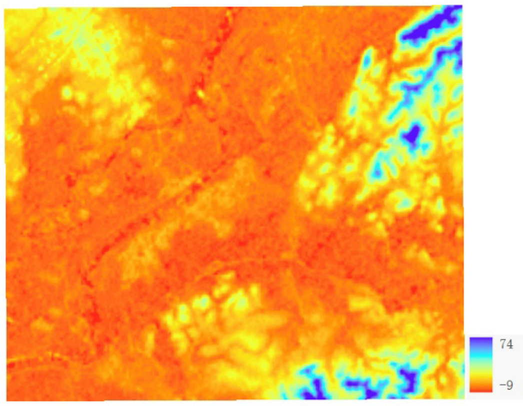
Province, China, with an area of 32km^2, which include multiple transmission lines forming a closed loop (See red points in Fig.6(a)). The background satellite image is acquired from Google Earth with a resolution of 0.5m. Meanwhile. we take the global map of LULC in 2022 derived from ESA Sentinel-2 imagery at 10m resolution from ESRI as a source data (In Fig.6(b)). And the ALOS World 3D 30m (AW3D30). that is a global DSM with a horizontal resolution of 30m (In Fig.6(c)), is used in our experiment.

(a). Overview of the pylon distribution.





(b) LULC data in 2022 (c) DSM data

Figure 6 The experimental data in this work

3.2 Experiment Results

Based on the method proposed in this paper, we achieve the optimal location of the UAV dock in the study area. The verification shows that the dock placement can realize efficient and reasonable inspection of the covered area.

The deployment sites of the 3 UAV docks obtained by the algorithm locate at 112°4'42"E 21°54'39"N, 112°5'53"E 21°54'28"N, 112°5'42"E 21°53'24"N, respectively, which cover all the 153 transmission power pylons in this region. As shown in Fig. 7, the dock 1 serves the pylons represented by blue points, the dock 2 serves the pylons represented by red points, the dock 3 serves the pylons represented by green points.

4. Conclusion

In this paper, we comprehensively consider the energy consumption, environmental conditions, economic costs and other conditions. We propose a UAV energy consumption-driven adaptive optimization method for dock site selection. First, the candidate area of the dock is generated by geospatial calculation and analysis method. Then, a mathematical model of UAV inspection energy consumption is constructed. Meanwhile, according to the location of power facilities, the locations of the docks are generated by adaptive clustering, and the cost function is constructed. Finally, the cost function is optimized to achieve site selection of UAV docks. The experiment results show that our method can achieve an efficient, reasonable and feasible optimal location for UAV dock deployment.

In future work, we will add more variables that affect the deployment of the UAV docks in the energy consumption model, to make the model more suitable to the actual situation and improve the practicability of our method.

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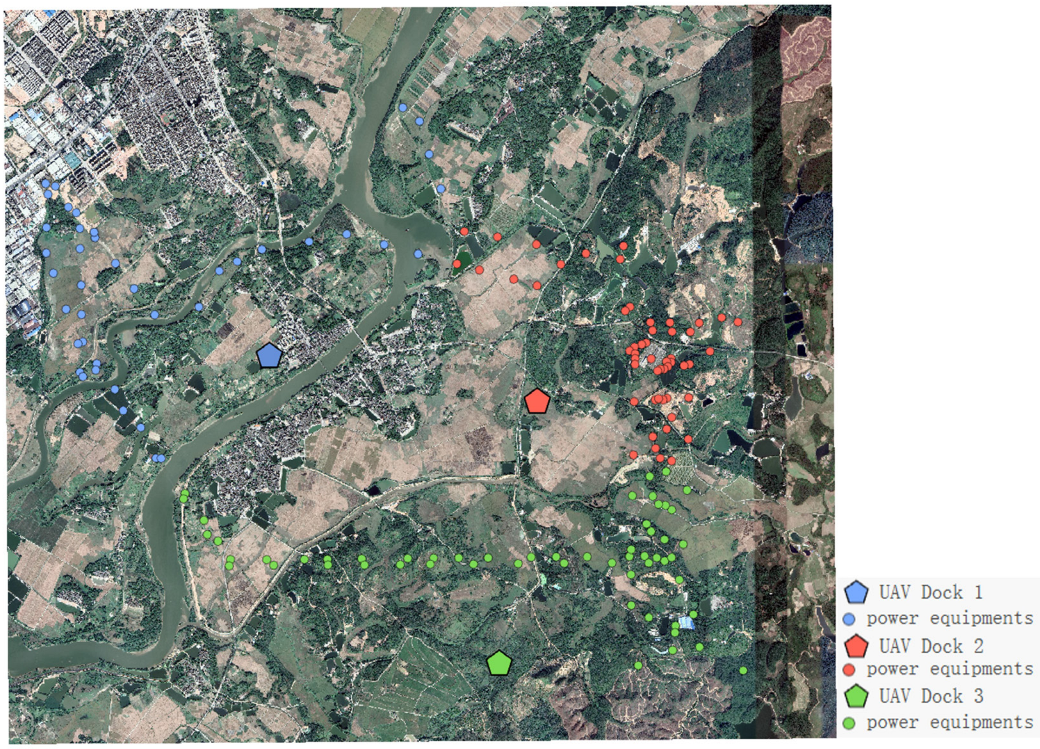

Figure 7. The qualitative result of dock deployment planning.

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