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Network Coverage Improvement during Natural Disaster using Self-Organizing Maps

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***Abstract*—This paper presents an emergency response management system to tackle the problem of the absence of network connectivity during the time of a natural disaster. Network connectivity is often enabled by the base stations on the ground. However, during the time of the disaster, the connectivity is disrupted due to the base station being damaged. During such scenarios, the Unmanned Aerial Vehicles (UAV) based stations could help in partially providing the network connectivity and help in the rescue operations. But, the UAVs need to be quickly deployed and placed at a suitable location based on the population coverage and base stations being impacted due to the disruptions. In this paper, we propose the Self Organizing Map (SOM) based optimal UAV deployment to enhance the network coverage, and increase the percentage of people having network access. In contrast to other Artificial Intelligence-based approaches, like Deep Neural Networks, our method does not require to be heavily trained using train and the test dataset.**

***Index Terms*—Emergency Response Management Systems (ERMs), Unmanned Aerial Vehicles (UAVs), Self-Organizing Maps(SOMs), Emergency Communication, Communication Retrieval, and strategic UAV deployment.**

I. Introduction

Emergency response to incidents such as natural disasters is an important challenge that has concerns for the governing bodies as well as the scientist. It is not a secret that a faster and more appropriate reaction to a natural disaster has the potential to save lives, prevent disruptions, and make an efficient recovery from the disaster. To manage the emergency response, a proactive and efficient response system is necessitated to forecast the allocation of resources, dispatch, mitigation, and recovery [1]. One specific problem during any natural calamity is that the area is affected by network connectivity as many base stations might have been destroyed. This worsens the situation and affects rescue operations as network connectivity is the most important for it.

To enable network connectivity, the deployment of UAVs, serving as the base stations, is feasible as the conventional base stations might be disrupted. (Figure2a) presents one such scenario where communication is lost because of the damage to some of the base stations. This poses an additional burden on the working base stations as they are overloaded. Often, the working base stations cannot meet the requirement as they are not spatially located near a region. In such cases, the multi-rover UAVs (Figure2b) or fixed-wing UAVs (2c) can deployed over the impacted region to restore the communication network. With the help of UAVs, the connection is established with working cell towers to form a network where information can be communicated with cells on wheels, first responders, and victims. The faster and more efficient establishment of this network plays important role in effective rescue operations.

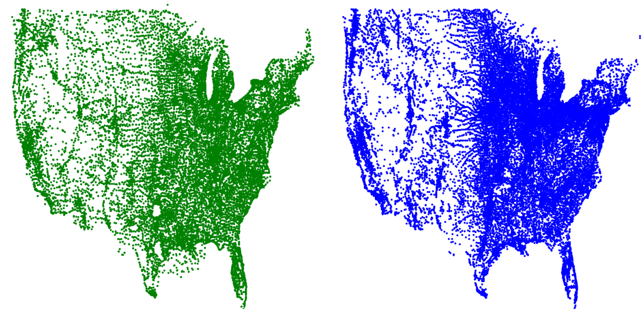
Although the network connectivity could be imparted using aerial vehicles, it needs to be determined where they should be located to increase the area of coverage as well as the percentage of the people having network connectivity. (Figure 1b) and (1a) shows the distribution of the US cellular coverage network and the population coverage. As shown in the figures ((1a) and (1b)), the distribution of the population and the cellular coverage is correlated and correspondingly the UAV deployment also needs to consider the distribution of the population.

To address the problem of the dynamic UAV deployment for providing network connectivity during a natural disaster, we propose a Self Organizing Map (SOM) based technique [2]. The advantage of the SOM over the other AI-based technique is that it is less compute-intensive and does not require an intensive training process. The paper uses intelligence-based SOMs to provide self-organization capabilities to a set of UAVs. When the deployment of the UAVs is requested or population pattern changes while being deployed, SOM enables autonomous UAVs to dynamically adjust the array. The advantage of using SOM is thus the algorithm can dynamically adjust its behavior based on the variation in the patterns of the dataset. Further, as the pattern changes, for example, due to the heavy movement of the population during the disaster, the outcome changes accordingly, i.e. the deployment is self-adjustable. The objective of the SOM-based deployment is to improve the area covered by the network connectivity and the number of people having access to the network. The major contributions of this work are:

- The paper proposes a SOM-based algorithm for UAVs deployment after a disaster.

- The proposed method adapts the position of UAVs dynamically with abrupt changes in population density or tower failure.
- The paper performs the real data analysis with the US City population and mobile tower location.

The rest of this paper is organized as follows: Section II presents the literature review related to this topic. Section III provides brief information about the background studies. Section IV presents the system model used to perform analysis. Section V provided the detailed methodology adopted to solve the problem. Section VI evaluates the results and section VII concludes this paper.



(a) US cellular coverage (b) US population map

Fig. 1. Cellular coverage and population density map of USA. The data is taken from [11]

II. Related Work

Numerous applications have been made available as a result of the widespread use of unmanned aerial vehicles (UAVs) in urban areas and the contribution that these vehicles have made to the development of vehicular ad hoc networks (VANETs) on the ground.

To react immediately to emergencies, emergency communication networks are built to address communication failures caused by a disaster. Mobile ad hoc networks (MANETs) or vehicle ad hoc networks (VANETs) create a movable wireless network for emergency ad hoc networks which are adopted from the Mobile IoT concept using mobile computing to control communications (Ke, Li, Tang, Pan, and Wang, 2018) [3]. Mobile devices, and vehicles become telecommunication nodes in MANETs and VANETs, and communication is established with these carriers.

In reality, UAVs have found widespread application in traffic monitoring, search and rescue operations, VANETs connection expansion, and urban surveillance. The literature on applications and effects of UAVs on environment is discussed by Mualla et al.,2019 [4] with aim to extend the usage of UAVs in various domains. This survey detailed research areas of interest in usage of UAVs stating that Urban planning and it is mostly used for surveillance of fields, any disaster management or patrolling the border. The other important discussion regarding the factors that are affecting the usage of UAVs like making the UAV autonomous,Explaining the UAV Behavior, Ensuring Security and Authentication, Increasing the flight duration, Proposing and Evaluating UAV regulations.

In urban surveillance (Semsch et al., 2009) [5], Multiple UAVs creating an aerial sub-network are used to conduct urban surveillance, which covers a large urban area and detect any ground incidents. UAVS stays connected ground nodes and come together to relay the information about the incident. In (Li et al., 2017) [6], authors designed a communication system that can be used during disaster management with the help of UAVs to locate victims' smartphones and connect them with servers. the three main components required for this rescue system are a smartphone with SOS reporting functionality, mobile stations, and servers to collect user data for analysis. Nevertheless, the optimum utilization of UAVs is not done during the victim search or in the process of road navigation. And the other application of using UAVs to detect a person with the help of electronic devices based on GPS location is presented in Lodeiro-Santiago et al. (2020) [7]. The ubiquitous accessibility of smartphones is an issue.

To improve disaster response and reduce the death rate from disasters, work on a 3D modeling system using UAVs by Verykokou et al. (2018) [8] demonstrated how UAVs can help detect victims. This paper discusses in detail the open-source software that can help in the reconstruction in 3D of the disaster scene. It helps in attending to the scenes. Another usage of UAVs in the rescue operation to monitor and detect accidents is presented in this paper [9]. information like detection of accidents, exact locations, and traffic density is shared among UAVs to plot the quickest path to the rescue location. Project by [10] calculates the optimum energy consumption and hence assures the optimum UAV flight path so that emergency response can be given to disaster sites.

In contrast to the above works, this paper considers the deployment of UAVs under the scenario of the varying population density. Our approaches uses Self-Organizing- Map that quickly finds the location of the UAVs and based on the varying population density it can be easily re-run so that the positions of the UAVs are self-adjusted.

III. Background

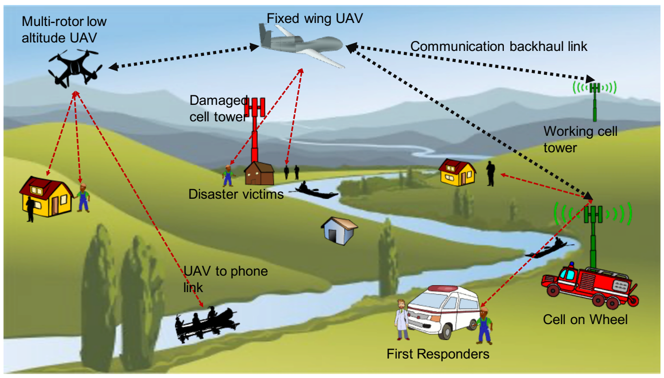
A. Emergency Response Management System

When a disaster happens, saving people's lives is the most important thing to do. The Worldwide Search and Rescue Advisory Group (INSARAG) establishes an international SAR procedure and methodology and publishes guidelines requiring teams to undertake SAR. Search and Rescue (SAR) efforts must be done rapidly and efficiently in the first 72 hours following a tragedy [12]. An incident commander coordinates all team operations and assigns activities to a team leader. In a Search and Rescue (SAR) mission, there are typically four main steps involved:

B. Unmanned Aerial Vehicle Deployment

The major impact of the disaster is that the terrestrial cell towers also get impacted. Hence, it is important that communication be established in such cases to ensure that the relief work does not get impacted and can continue with business as usual. The disaster response team needs to transport the necessary equipment quickly. However, because of the roadblocks, it is possible that the crew may not be able to reach the which could impact the relief effort. There are many existent solutions available that can aid during a disaster situation. They are Cells on Wheels (COWs) that can provide communication. However, the problem with COW is that during earthquakes and floods, In such scenarios, the aerial base station acts as a substitute to ensure continuity of operations as they can be efficiently deployed.

IV. System Model



(a) Disaster response network with UAV

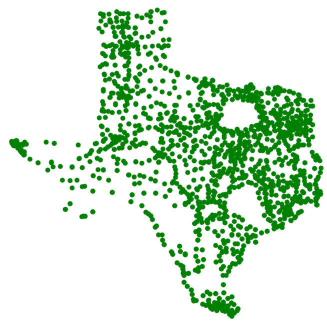
(b) Multi-rotor UAV

(c) Fixed-wing UAV

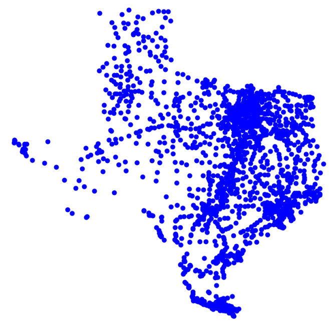
Fig. 2. Enhancing Disaster Response Operations with Un-manned Aerial Vehicles (UAVs): A Network Approach [13]

The system model is depicted in the Figure 2a and Figure 3. We consider the state of the Texas for analysis purpose. As shown in the Figure 3 , if some base stations are disrupted due to disaster then people will not have a network coverage and it will affect the rescue operations. It will also impact the working operations of the first responders in the area. During this scenario, temporary base stations can be employed that include - 1). Multi-rotor low altitude UAV and 2) fixed wing UAVs. These base stations establish the UAV to the phone link and assist the disaster victims and the first responders. The UAVs can also communicate between themselves to organize in in a suitable manner and coordinate with the working base stations.

The given system consists of UAVs initially stored in multiple locations or stations. The station also has the command center that manages and controls the deployment of the UAVs. The information about the population map of the area and base station locations are stored in the command center. If the disaster like scenario occurs, it analyzes the working and disrupted base stations and accordingly deploys the UAVs to the suitable location. The problem here is that, due to disaster the population pattern will vary abruptly and will not be the usual population distribution as many people may move out of the area. So, it is difficult to find the optimal locations of UAV deployment due to changing population scenarios. Also, during such time the population distribution varies dynamically in a short interval of time. In this paper, the objective is to maximize the area and population having network coverage in the scenario of rapidly changing population. Our assumption is that the command center knows the dynamics of the population during such scenarios. This is a realistic assumption, as this information can be easily collected using the real-time GPS data [11].



(a) Texas cellular coverage



(b) Texas population map

Fig. 3. Cellular and Population Coverage in Texas

To solve the problem of UAV deployment under the scenario of dynamically changing population, we use an Artificial Intelligence-based algorithm Self-Organizing Maps (SOMs) [14]. SOM is used to find the best location to deploy UAVs. SOMs reduces the dimensions of data and leans to classify without the requirement of training and test data. Thus, it reduces the burden on using hundreds of rows and columns and the data is processed into a simpler map known as a self-organizing map. The final weights returned by the algorithm as output indicate the location of UAVs allocation.

The objective of the SOM is to calculate of coordinates for UAV deployment in the incident area. SOM determines the location of the coordinates and the UAVs can travel from landing station location to destination the incident location. The aim is to maximize the area coverage and population having network coverage while some base stations are not working. We adapt the SOM to fit in our problem of the UAV deployment. The subsequent section explains how SOM can be used for the UAV deployment to achieve the objectives as mentioned above.

V. Methodology

We describe the methodology that the command center adopts to meet the objectives of the UAV deployment. The

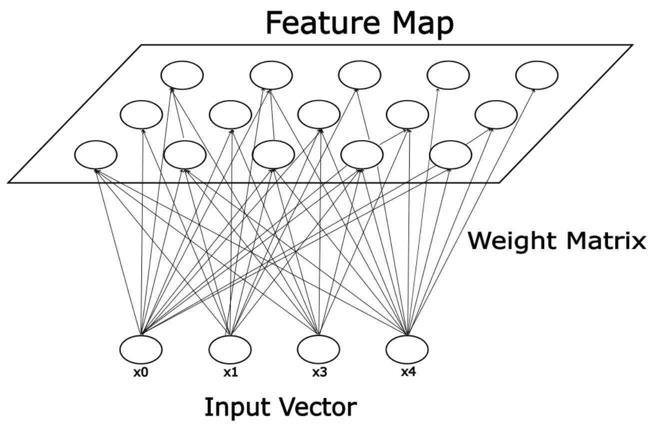


Fig. 4. Self Organizing Map architecture

base stations are present at the location $b_{i,j}$, where i, and j are the spatial coordinates. The coverage radius of a bases stations is assumed as R_b. A UAV is represented by a variable ζ_j, where $j \in \{1, 2, ...N\}$ such that there are a total N number of UAVs. Initially, the UAVs are located at the landing stations l_k, where $k \in \{1, 2, ...L\}$, and L are the total number of landing stations. Once an event occurs then a fraction of the base station will not work. The not working base stations are represented by the variable $b'_{i,j}$. The population density at coordinates $\{i, j\}$ is represented as $p_{i,j}$. The UAVs have the radius coverage of r_u. Based on the population density, the UAVs are allocated the optimal location using the SOM algorithm.

A. Self Organizing Maps (SOM)

Self-Organizing Map (SOM), an unsupervised ML algorithm is typically a class of Neural Networks but differs in that it uses competitive learning rather than optimization techniques such as gradient descent, and Adam optimization. The architecture of the SOM is presented in figure 4. Typically SOM contains two layers - 1) Input layer and Competition layers. The sample data i.e. input are connected to the neurons in the competition layers through weights. Normally, the number of neurons is less than the number of input samples. The output of the neurons is the representation of the input sample's low-dimensional discretized representation. As a result, its input is a high-dimensional space, and it converts it to a low-dimensional representation. Thus, they are mainly used for dimension reduction problems [15]. However, in this paper, we use SOM for the deployment problem rather than the dimensional reduction problem by extracting the weights.

For this problem, we chose SOM having N processing elements in a 2D space. Each element of the SOM receives input population density represented by values $\{x_1, x_2, ...x_n\}$. SOM has processing units that are called neurons. The connection between the input and the processing element has weights $w_{l,m}$ that represent the possible location of the deployed UAVs. Initially, the weights of the SOM are initialized randomly. Subsequently, we develop the SOM model by selecting random inputs in iterative steps i.e. population density at a location and finding the distance between N-dimensional space position and weights linked with the neurons in the competition layer. Thus, we get the Best Matching Neuron (BMU) according to the equation 1.

$$|x_i - m_c| = min_i d|x - m_i| \tag{1}$$

The next process is the weight updating process. In the weight-updating process, the winning neuron is moved closer to the input observation. In addition, the BMU's neighbors are also treated similarly. The process relocates the BMU and its neighbors to a location close to the input observation. The weight updating process is performed according to the following equation.

$$m_i(t + 1) = m_i(t) + \alpha(t).h_{ci}(t)[x_i - m_i(t)] \tag{2}$$

where x_i is the randomly drawn sample data, h_{ci} is the neighbourhood function. The neighborhood function is centered in the winning neuron c. $\alpha(t)$ is the learning rate of each iteration. The neighborhood function is an iteration-dependent shrinking function. Thus with each iteration, the neighborhood area decreases. Also, the influence of the movement is dependent upon the distance between the winning neuron and its neighborhood. The more the distance, the less the movement.

VI. Evaluation Results

This section presents the implementation details and the evaluation results.

A. Implementation

This section examines the usage of SOM to find a location to deploy UAVS and then comparing the locations of UAVs with three distinct regions of Texas. We implemented SOM with a primary focus on Texas in the United States from the data with cellular towers and population information shown in Figure 3.The training data is from city locations; the initial positions of UAVs are provided, and SOM calculates the distributed UAVs.

The first approach we take is to use SOM on training data and create initial graphs with locations. And then finalise any constants (radius range) and specifications (looping many times to observe how graphs change OR the initial UAVs are fixed on three different parts of Texas).

The next step in the implementation process is to calculate metrics such as the area under the UAVs-covering circles and the ratio of people in the region. To generalise the operation of UAVS, we randomly selected stations at different percentages and applied SOM to locations not covered by cellular stations. As we know, each location's population distribution cannot be the same. In this study, we divided Texas into regions and used SOM to study the allocation of positions to increase rescue operations in each region.

TABLE I. Statistics of SOM algorithm in region 1

Percentage of working base stations	**50%**	**30%**	**10%**
Total area under the circle when have UAVs:	9884.05	7083.20	4171.34
Total area under the circle when missing UAVs:	8443.56	5666.38	2124.49
Ratio of included population when have UAVs:	0.94	0.86	0.81
Ratio of included population when missing UAVs:	0.70	0.37	0.12

B. Results

This section presents the evaluation results for the SOM-based deployment of the network resources. We perform the analysis for the various cases. In particular, we evaluate our results for different percentage of working bases stations and the the different regions of the Texas. We perform our analysis for four different regions in the state of the Texas.

C. UAV deployment

Figure 5 presents the pictorial view of pre and post-deployment in the Panhandle region of Texas. The population distribution is represented using the blue dots. The green dots are the location of the cellular base stations. The figure presents three scenarios where the number of working base stations is varied from 10%, 30%, and 50%. Initially, the UAVs are located in a few locations (black triangles). Once the SOM algorithm is executed, the UAVs are deployed in locations represented by the red dots such that they cover more area as well as the population.

Figure 6 presents a similar scenario but for different regions of Texas. We consider North East Texas, South Texas, and the Gulf coast near Houston. Here, we considered that 30% of the cellular regions are working. From the figure, it can be said that UAVs are deployed according to population distribution and cellular coverage area.

D. Analysis for different regions

Tables I-IV show the analysis of four regions in terms of network coverage before and after deployment, as well as the population covered. The results demonstrate that both the total area and population covered by network coverage increased after deployment, regardless of the number of working base stations. This is true for various numbers of working base stations. For example, in Texas region 2, if 30% of the base stations are working then after the deployment, an additional 30% of the area is covered.

VII. Conclusions

In this paper, we proposed a SOM-based approach in emergency rescue operations to restore the communication network. The advantages of using UAVs when compared to other ad-hoc vehicles make it easier to deploy, faster gathering of information, and achieve greater coverage of an area. We presented how swarm intelligence is used to deploy UAVs for the efficient deployment of UAVs. We used Self-organizing maps to solve the multi-drone allocation problem and have analyzed two metrics - area covered and the ratio of the population included in the region. Furthermore, we have compared these metrics with and without the deployment of the UAVs. The results show that the use of UAVs could potentially improve rescue operations with increased coverage of area and number of people included from the location.

Based on the promising results of our proposed SOM-based approach in emergency rescue operations, these are the scopes for future research. First, additional studies could investigate the optimal number of UAVs needed to achieve maximum coverage and population inclusion in a given area. Furthermore, more research could be conducted to explore the potential benefits of incorporating multiple types of UAVs with varying capabilities in emergency response missions. Additionally, future work could investigate the feasibility of implementing our approach in real-world emergency scenarios and further evaluate the effectiveness of the proposed technique in such situations. Finally, the potential ethical and legal implications of utilizing UAVs in emergency response missions should be examined in greater depth in future research.

TABLE II. Statistics of SOM algorithm in region 2

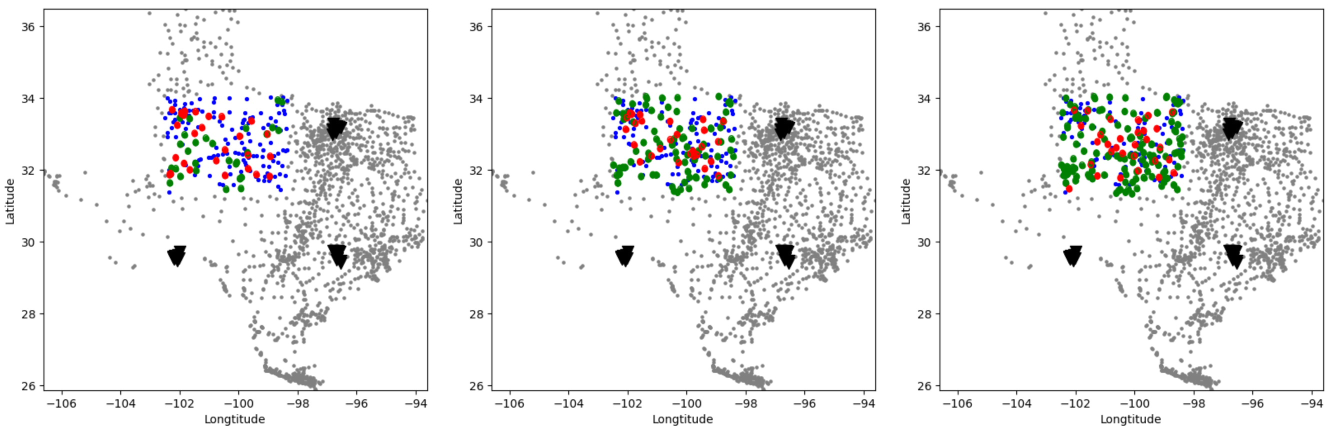
Percentage of working base stations	**50%**	**30%**	**10%**
Total area under the circle when have UAVs:	6740.46	5123.27	3265.41
Total area under the circle when missing UAVs:	5446.08	3537.35	1262.06
Ratio of included population when have UAVs:	0.93	0.84	0.71
Ratio of included population when missing UAVs:	0.49	0.34	0.24

TABLE III. Statistics of SOM algorithm in region 3

Percentage of working base stations	**50%**	**30%**	**10%**
Total area under the circle when have UAVs:	8091.05	6619.32	3623.80
Total area under the circle when missing UAVs:	6612.90	4641.56	1851.34
Ratio of included population when have UAVs:	0.94	0.93	0.82
Ratio of included population when missing UAVs:	0.74	0.82	0.05

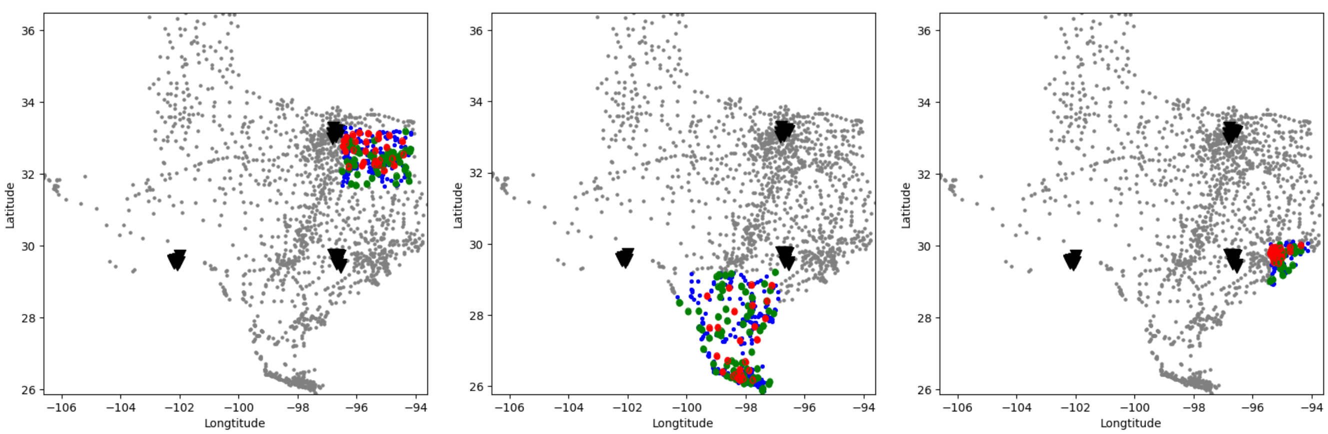
TABLE IV. Statistics of SOM algorithm in region 4

Percentage of working base stations	**50%**	**30%**	**10%**
Total area under the circle when have UAVs:	2080.86	1770.76	1445.03
Total area under the circle when missing UAVs:	1581.13	952.53	378.70
Ratio of included population when have UAVs:	0.96	0.95	0.94
Ratio of included population when missing UAVs:	0.13	0.08	0.03



(a) 10% cellular working (b) 30% cellular working (c) 50% cellular working

Fig. 5. Deployment of UAVs in region 1 (Panhandle region of Texas).



(a) 30% cellular working (b) 30% cellular working (c) 30% cellular working

Fig. 6. Deployment of UAVs in region 2 (North East Texas), 3 (South Texas), and 4 (Gulf coast near Houston).

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