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Research Article

Clustering approach with self-organizing maps for unmanned aerial vehicle response to post-earthquake fires: An application for Istanbul

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ABSTRACT

Earthquakes are hazardous natural disasters, and they may cause severe damage and losses where they occur. In addition to their devastating effects, they may trigger following disasters like tsunamis and fires. Post-earthquake fires are known as the most dangerous secondary disasters and generally cause much more damage than the damage caused by the earthquake itself. The difficulty in determining and responding to ignition sources, the lack of equipment and workforce, and obstacles like collapsed buildings that block the ways to reach fires may cause catastrophic disasters after an earthquake. In recent years, Unmanned Aerial Vehicle technologies (UAVs) have shown promising performance in post-disaster response operations. Parallel to technological improvements, they have been used for many purposes, like fire-fighting, victim location detection, base station support, and material distribution in disaster areas. To manage a possible response and improve the performance of UAVs in post-earthquake fire areas, it is crucial to be prepared in advance. This study proposes an artificial neural network-based clustering approach for unmanned aerial vehicle use in post-earthquake fire areas. After conducting a detailed literature review covering post-earthquake fires, usage of UAVs in disasters, and some aspects of Self Organizing Maps, the methodology used for clustering the neighborhoods regarding their post-earthquake fire risk similarities is introduced. A real-life application is carried out to identify and cluster the regions and provide preliminary information to the decision-makers on possible interventions. Neighborhoods of Tuzla district, one of the riskiest districts in terms of post-earthquake fires in Istanbul, are clustered with Self-Organizing Maps (SOM). In a possible post-earthquake fire disaster, the Tuzla district can be divided into three areas, and UAVs can be organized more efficiently and quickly based on this cluster information. The results of this real-life application can guide decision-makers by showing which regions have similarities for UAV response in possible post-earthquake fires and where they can be intervened together. The authorities can benefit from the findings of this study while preparing disaster plans, intervention actions, and post-disaster humanitarian activities.

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INTRODUCTION

An unmanned aerial vehicle (UAV) is an autonomous or remote-controlled aircraft without a driver. One of the significant advantages of UAVs is that they can be used in hard-to-reach areas for various purposes [1]. The use of UAVs in daily life, which was primarily preferred in military operations in the past years, has also become widespread over time, and they have begun to be preferred in different areas, such as entertainment [2], logistics delivery [3], security [4] and agriculture [5]. UAVs are also frequently used for post-disaster due diligence, resource planning, information gathering, and similar disaster-related operations. Reaching areas that are difficult to access in post-disaster operations, where resources are limited and time planning is critical, provides advantages in many respects. UAVs are a convenient option for delivering the necessary materials, information, and services for humanitarian aid in a short time [6].

Disaster management consists of four main stages: risk identification, preparedness, response, and post-disaster recovery. The UAVs have different applications at every step [7]. In the disaster risk identification and preparation phase, reconnaissance flights are carried out with the help of UAVs. There are attempts to predetermine risk factors and take precautions before a disaster occurs. The use of UAVs is quite common in pre-disaster operations, such as determining the risk of tsunami or flooding by monitoring the movements of the water with reconnaissance flights over the oceans [8] or early detection of fires by controlling forest breakouts [9]. Although using UAVs in disaster response operations is not as common as in other fields due to some limitations, it improves parallel to technological developments. For instance, Alshbatat [10] developed a four-propeller UAV by integrating fire extinguishers to intervene in fires that started in high-rise buildings. They are also frequently used for search and rescue operations in the affected areas. Mishra et al. [11] introduced an approach to identify victims or people seeking help from post-disaster images using UAV and image processing methods. By doing so, they could direct rescue efforts by detecting through various body movements whether the people in the picture need emergency help. Another benefit of UAVs in disaster areas is that they can detect damaged areas by providing photos or information. The remotely collected images can be used to command UAVs of damaged regions, provide essential information to the authorities on the actions to be taken, and help make faster decisions [12].

When focused on UAV applications specific to earthquakes and fires, many studies are found in the literature. While earthquake applications generally focus on damage detection and search and rescue after an earthquake, those on fire are mainly in the form of fire detection and early warning systems with the help of sensors and cameras [13]. For example, Diyana et al. [14] proposed a UAV-integrated artificial intelligence approach for the early detection of forest fires. Simulations and image detection applications have revealed essential findings for early warning systems. A similar approach is based on the Internet of Things and Cloud-based UAVs proposed by Kinaneva et al. [14] for monitoring urban fires. Unlike the previous studies, they integrated a detection rate with image processing in their research, which showed 98% better fire detection performance than traditional methods. Fire extinguisher balls are a promising solution, and they have been studied extensively in the literature on UAVs and firefighting methods. The balls made from special materials are filled with chemical substances that work as firefighters. When the ball comes into contact with the fire, the chemical reaction starts, and after a while, the ball explodes and extinguishes the flames. Aydin et al. [15] proposed a system that integrates a group of UAVs with fire extinguisher balls and an early detection system network. In their developed algorithm, the proposed system starts with detecting the fire in an area with the help of UAVs and defines the location. Then, the autonomous UAV carrying the fire extinguisher ball goes to the scene and intervenes in the fire by dropping the ball to the most appropriate point. Another similar approach for using extinguisher balls is proposed by Swapna et al. [16]. They integrated hardware and software systems to detect fires and drop the ball in the correct location. Their applications have shown promising results in terms of efficiency and practicality.

The literature research findings show that the use of UAVs in natural disasters profoundly contributes to managing the processes and improving the ability to respond. UAV-integrated approaches are promising not only for detection and risk analysis but also for active firefighting operations. Considering the earthquakes and post-earthquake fires, which are the subject of this study, it has been seen that UAVs are frequently included in the early warning, damage detection, and search and rescue stages for both natural disaster types. We believe presenting a real-life clustering application using a particular artificial network model will support further studies and give authorities a preliminary idea for disaster response operations with UAVs. The findings of this study reveal valuable insights into which parameters impact post-earthquake fire risks-based clustering, how the neighborhoods should be clustered, and in a possible disaster situation, which ones can be considered together for intervention. The rest of the paper is organized into four sections. The methodology part covers and discusses the steps of the particular clustering algorithm Self Organizing Maps (SOM). Then, a real-life clustering application based on the similarity of post-earthquake fire risks of neighborhoods of the Tuzla district is conducted. The findings of the application are presented in the conclusion, and then a discussion is given in the final section.

MATERIALS AND METHODS

This study uses a particular artificial neural network, Self-Organizing Maps (SOM), to cluster the neighborhoods considering their post-earthquake fire risks for a potential UAV intervention. There are many methods for separating a data set into clusters, such as k-means clustering or hierarchical clustering. The common purpose of all methods is to show maximum similarity for elements in the same cluster and minimum similarity for elements in different groups, maximizing the homogeneity. Also, there are plenty of learning algorithms in the literature, such as Multi-Layer Perceptron (MLP), Self-Organizing Maps (SOM), and Deep Belief Networks (DBN). Each of them is convenient for different datasets and has various features. For instance, MLP is a well-known supervised learning algorithm that is proper for solving optimization problems since it adjusts the weights in each step. On the other hand, SOM is an unsupervised learning algorithm without hidden layers and presents the outputs as a visual map. Unlike the classical clustering approaches in statistics, SOM can perform the functions of the k-means and the multidimensional sampling method together. In other words, it is an approach that performs visual mapping and divides the elements of the data set into clusters [17]. Furthermore, it can effectively cluster high-dimensional data. When we look at the statistical methods, the difficulty in clustering data with unknown or little-known relationships is eliminated with SOM, which means data sets that do not have a linear relationship can also be clustered. In addition, unlike the traditional clustering methods, the number of clusters in the SOM approach does not need to be determined in advance since the network determines the most appropriate clusters by grouping the elements according to their similarities. Because of all these advantages, SOM was preferred for clustering neighborhoods in this study.

SOM networks, also known as Kohonen SOM networks, were developed by Teuvo Kohonen [18] in 1982. They are identified with a feed-forward single-layer artificial neural network (ANN) and are an unsupervised learning algorithm. The data used for training these networks do not contain dependent variables, which causes them to be preferred, especially in solving problems related to clustering. Although they are advantageous in clustering, evaluating the resulting clusters with expert judgment is necessary for checking the accuracy [19]. SOMs are single-layer networks that do not contain hidden layers and consist of input and output layers. The number of neurons in the input layer determines the number of variables of the problem under consideration, and each input neuron is connected to neurons in the output layer. An output layer is a two-dimensional plane, and the arrangement of neurons here is significant. Neurons can be arranged as linear, quadrangular, or hexagonal, essential in topological neighborhoods. Although the hexagonal structure is generally preferred, the arrangement has no definite rules, just like the number of neurons in the output layer. It is necessary to determine the most appropriate number and sequence of neurons by trial and error. SOM networks work according to the principle of winning, and as a result, the winning neuron takes one and the losing neuron 0. Since presenting an input value to the network will change the winning neuron in the output layer and the neighborhood around it, the network is constantly updated [20]. Figure 1 illustrates an exemplary SOM network with four inputs.

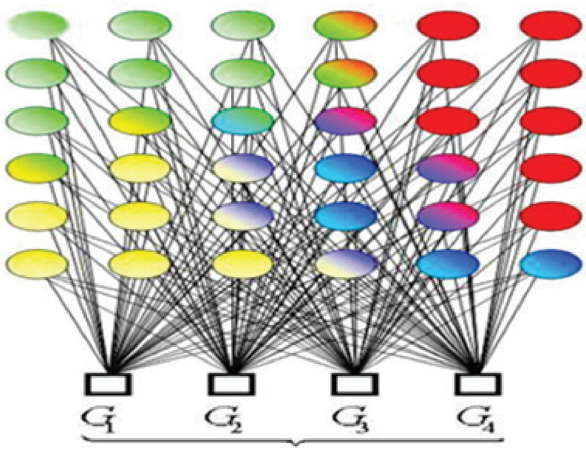

Figure 1. SOM network example [21].

Learning in SOM networks takes place according to a principle called "competitive learning," in which adjacent neurons have relative weight values. According to the input values presented to the network, the winning neuron and its neighborhood are determined and positioned according to the input value [22].In the next step, the same process is repeated with new input to the network, and a new winning neuron is detected. The neuron in the centre of the grid indicates the winning neuron, and the neurons adjacent to this neuron are from the neighborhood. The next step is taken by updating the weight values of this group during learning. The learning principle of SOM networks is given below in stages [17,21].

Step 1: The weight vector A of each node in the output layer is generated with random numbers in the range [0-1].

Step 2: An input vector G randomly selected from the training dataset is applied to the input of the SOM grid structure.

Step 3: Equation (1) calculates how similar the weight vector A of each node in the output layer is to the input vector G, that is, the Euclidean distance between vectors A and G.

$$Distance = \sqrt{\sum_{i=0}^{n}(G - A_i)^2} \tag{1}$$

At the end of the calculation, the node with the minimum distance is marked as the best matching unit (BMU).

Step 4: The weight vectors A of all nodes in the $\sigma(t)$ diameter neighborhood area of the BMU determined in the previous step must be simulated to the input vector G. For this, the neighborhood area of the BMU must be calculated. Neighborhood area changes over time. The neighborhood diameter $\sigma(t)$ is a time-dependent variable and decreases exponentially. The equation of time-dependent variation is shown by Equation (2).

$$\sigma(t) = \sigma_0 e^{\frac{-t}{\lambda}} \quad (2)$$

Here, the σ_0 is a fixed value and can be accepted as half of the longest side of the map and λ is the time constant.

Step 5: The weight vectors A of all nodes in the neighborhood area of the BMU are simulated to the input vector G with the help of Equation (3).

$$A(t+1) = A(t) + E(t)L(t)(G(t) - A(t)) \quad (3)$$

In this equation, $L(t)$ is the adaptation coefficient; it decreases exponentially with time and is calculated in Equation (4).

$$L(t) = L_0 e^{\frac{-t}{\lambda}} \quad , t=1,2,3\ldots \quad (4)$$

$E(t)$ in Equation (3) is the effect coefficient that changes depending on the distance of the node to the BMU and is calculated as follows in Equation (5).

$$E(t) = e^{\frac{-Distance^2}{2\sigma^2(t)}} \quad , t=1,2,3\ldots \quad (5)$$

As can be seen from the given equations, the variation of each node on the weight vector A varies depending on the node's distance from the BMU and time. The change is significant at nodes close to the BMU and smaller at nodes farther away. This situation is determined depending on the effect coefficient $E(t)$. In addition, while the adaptation coefficient $L(t)$ is high at the beginning, it decreases over time. With this principle, the vectors related to each other come together on the two-dimensional map from the first steps, and the map is completed with more precise adjustments over time.

Step 6: Going back to the second step, all operations are repeated N times.

In the next section, the application has been conducted using a code written with the help of MATLAB Neural Network Tool is presented.

Application

In this study, UAVs are investigated to strengthen the ability to respond to fires that may start after an earthquake. A clustering application is carried out with the SOM method for the areas to be covered by the UAV command centers and the regions with similar characteristics that can be intervened together. Tuzla district, located on the Anatolian side of Istanbul, is chosen as the application area. Gulum et al. [23] ranked the districts in the Anatolian Side of Istanbul according to their post-earthquake fire risk levels in their study. Since the Tuzla district was selected as one of the three riskiest districts in that study, it was chosen as

Figure 2. Tuzla district neighbourhood map.

the application area. The Tuzla district's neighborhoods are clustered for a possible UAV intervention activity to present a pre-determined plan and ideas to stakeholders and decision-makers. Tuzla is the district bordering the Anatolian side of Istanbul. While Pendik district is located in the north and west, Kocaeli (Gebze) is in the east. The district, which borders the Marmara Sea, consists of 18 neighborhoods. The positions of the neighborhoods are shown in Figure 2.

All data used in the application are taken from the Istanbul Possible Earthquake Loss Estimates Booklet report, published in 2019 by the Istanbul Metropolitan Municipality Earthquake and Soil Investigation Directorate [24]. Seven variables were selected to cluster the Tuzla district neighborhoods for the determined purpose. The clustering code was modified in a format suitable for the Neural Network Toolbox in the MATLAB program. The most appropriate structure was determined by trial and error, and clusters were obtained by running the code structure with the most suitable features. The critical point here is that the clusters defined are subject to expert evaluation. As explained earlier, one of the most critical steps of the clustering process is to test the accuracy of the results. The results obtained in this study were consulted with an expert group of scholars from disaster management seismology and a manager from a post-disaster operation center in Turkey. After this, the neighborhood clusters were formed according to the post-earthquake fire risks by making arrangements in line with the comments received.

Variables and Data Sets for Clustering

Seven variables were determined for the clustering of neighborhoods. These variables have been chosen to be variables that are likely to affect the fire risk after an earthquake. These parameters may be important in a fire disaster after an earthquake that will require the use of UAVs. Descriptions of the selected parameters and explanations for their intended use are given below [23,25].

Latitude (C1): Latitude information was chosen as a variable to include neighborhoods and their location in the clustering process.

Longitude (C2): For a reason similar to the latitude variable, longitude is selected as a parameter along with latitude to represent the area where the neighborhood coincides with the location.

The Number of Heavily Damaged Buildings (C3): The expected number of heavy and heavily damaged buildings in each neighborhood is included in the clustering as a variable since it will be effective in the fire risk after the earthquake. Considering that many fire risks may arise due to electricity, natural gas, or overturning in heavily damaged buildings, it is essential to include this parameter.

Expected Number of Death and Seriously Injured People (C4): The number of the expected loss of life or seriously injured people in neighborhoods was accepted as an indicator of earthquake sensitivity and was chosen as a variable. This parameter is also indirectly effective since fires after earthquakes will occur more in earthquake-risk areas. Performing search and rescue or surveillance flights with UAVs, primarily in regions with high mortality rates, will help effective disaster management.

Road Closure Status (C5): The advantages of using UAVs, especially in hard-to-reach areas, were mentioned in the previous sections. In this respect, it is also essential to determine the neighborhoods with many closed roads. The road closure status is shown in the study with four degrees, 0, 1, 2, and 3, depending on the density situation in the road closure maps in the Possible Earthquake Loss Estimates booklets.

The Number of Expected Damages in the Natural Gas System (C6): Fire risks caused by natural gas sources are calculated as the second most crucial main criterion [23]. For this reason, choosing the expected number of natural gas failures in each neighborhood would be necessary, as the possible losses explained in the report above were included in the study as a variable.

Number of Households in Need of Shelter (C7): One of the most critical needs that may arise after a disaster is the need for shelter. The number of households expected to need shelter in a region may indirectly indicate the disaster-affected status of that region. In this study, the number of homes expected to need shelter in each neighborhood was chosen as a variable to understand the neighborhood's disaster-affected status level of importance in the intervention with UAVs.

Table 2 shows the data of Tuzla district neighborhoods according to the seven determined variables.

Different trials were made to cluster 18 neighborhoods of the Tuzla district with SOM, and the most suitable structure for the problem was determined considering the homogeneity of the clusters. Table 3 shows the structures created with different variables. Since the most prominent clusters were observed in #12, the network was chosen to consist of 7x7 neurons.

Table 2. Data set for Tuzla district neighborhoods

Neighborhoods	C1	C2	C3	C4	C5	C6	C7
Akfirat	40,9276	29,4164	12	0	1	0	142
Anadolu	40,9066	29,3671	4	0	1	0	43
Askeri Bolge	40,8536	29,3222	0	0	1	0	0
Aydinli	40,8741	29,3334	217	34	2	2	3467
Aydintepe	40,8536	29,2983	49	18	2	1	1119
Cami	40,8174	29,3138	99	17	2	1	729
Evliyacelebi	40,8383	29,2995	84	12	2	1	931
Fatih	40,9274	29,3425	6	0	1	0	43
Icmeler	40,8492	29,3049	57	13	2	0	725
Istasyon	40,8292	29,3222	144	48	2	1	1930
Mescit	40,8983	29,3454	33	2	1	1	371
Mimar Sinan	40,841	29,3629	276	100	3	1	3143
Orhanli	40,897	29,3608	84	2	1	0	157
Orta	40,9002	29,3799	27	0	1	0	429
Postane	40,8176	29,2861	239	27	2	2	1878
Sifa	40,8324	29,3573	341	131	3	2	4163
Tepeoren	40,9096	29,3896	57	0	1	1	332
Yayla	40,8361	29,3092	88	31	2	1	1815

Table 3. SOM architecture trials for Tuzla

# no	Train Function	Topology	Distance Function	Learning Function	Dimension 1	Dimension 2	İteration	Initial Neighborhood
1	trainbu	hextop	dist	learnsomb	7	7	200	3
2	trainbu	hextop	linkdist	learnsomb	7	7	200	3
3	trainbu	hextop	boxdist	learnsomb	7	7	200	3
4	trainbu	gridtop	dist	learnsomb	7	7	200	3
5	trainbu	hextop	linkdist	learnsomb	6	6	200	3
6	trainbu	hextop	boxdist	learnsomb	6	6	500	3
7	trainbu	hextop	dist	learnsomb	6	6	500	3
8	trainbu	gridtop	linkdist	learnsomb	6	6	500	3
9	trainbu	hextop	boxdist	learnsomb	8	8	500	4
10	trainbu	hextop	boxdist	learnsomb	8	8	1000	4
11	trainbu	hextop	dist	learnsomb	7	7	1000	4
12	trainbu	hextop	dist	learnsomb	5	5	1000	3
13	trainbu	hextop	linkdist	learnsomb	5	5	1000	3
14	trainbu	hextop	boxdist	learnsomb	8	8	1000	3
15	trainbu	hextop	dist	learnsomb	8	8	500	3

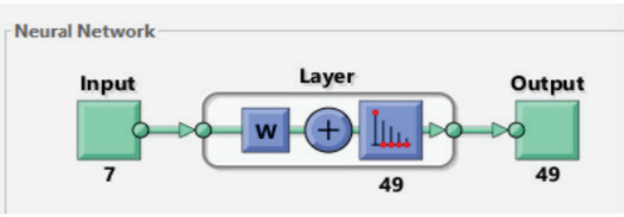

Figure 3. SOM network structure established for the Tuzla district.

This structure with hextop topology formed more distinct clusters at the end of 1000 iterations compared to others. Since the training function, “trainbu,” works best with SOM, it was preferred, and the “boxdist” distance, which gave the best result from three different distance functions, was used. The network was structured according to these rules, as shown in Figure 3.

RESULTS AND DISCUSSION

After running 1000 iterations of this network, 18 neighborhoods scattered to neurons and formed clusters. A suitable topological structure for the Tuzla district was determined to be a hexagon. The topology and neighborhood connections are shown in Figure 4.

After completing the iterations, 18 districts were distributed to 49 neurons, and thus clusters were obtained. This distribution was relatively homogeneous; as a result, 3 clusters emerged. These clusters are from the sample shots and neighborhood weights graphs in Figure 5.

As can be noticed visually from Figure 5, there were 2 clusters, while 2 neighborhoods were clustered in a separate place, and one neighbourhood remained independent. There is a backlog at the bottom left of the sample shots graph. In this context, it is possible to form 3 main clusters by keeping the neighborhoods clustered in the same cell. In

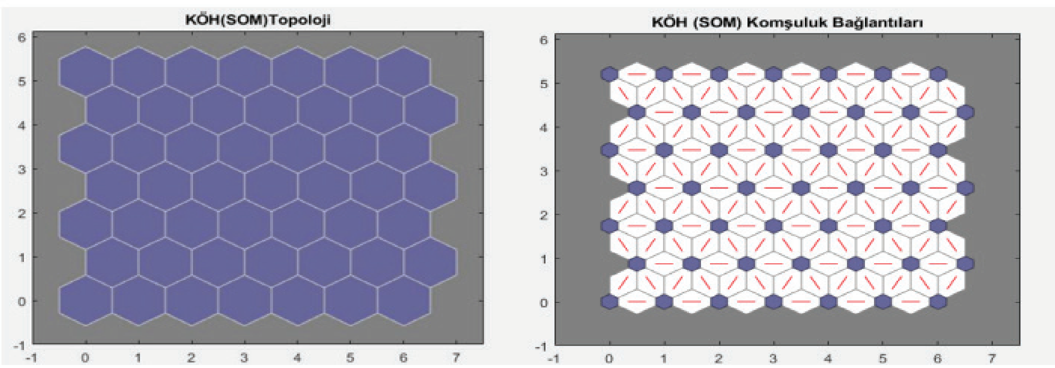

Figure 4. Topology and neighborhood connections images for the Tuzla district.

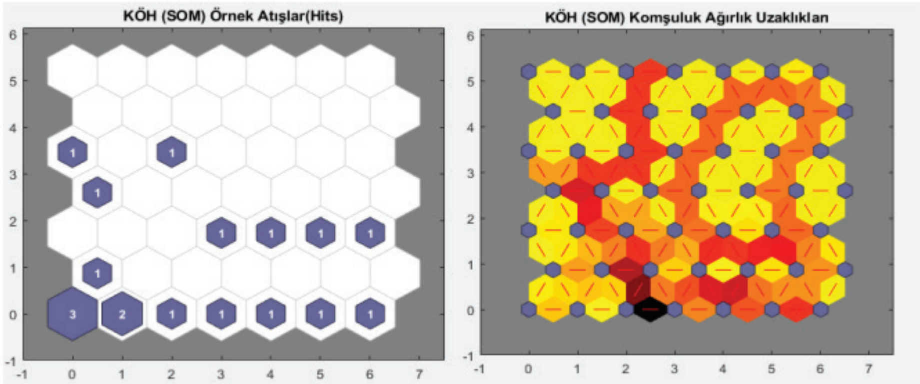

Figure 5. Sample shots and neighborhood weights graph for the Tuzla district.

Table 4. Neighborhood clusters for the Tuzla district

Cluster 1	Cluster 2	Cluster 3	Others
Anadolu	Orta	İstasyon	Cami
Askeri Bölge	Aydınlı	Aydıntepe	Orhanlı
Fatih	Şifa	Evliya Çelebi	İçmeler
Mescit	Mimar Sinan	Yayla	
Tepeören	Postane		
Akfırat			

the neighborhood weights graph, 3 regions separated by red borders draw attention. Table 4 shows the clusters obtained at the end of the clustering process and the neighborhoods belonging to each group. While the first cluster consisted of six members, the second cluster had five, and the third had four. Cami and Orhanlı formed a duo, and İçmeler was not included in these groups.

When the clusters formed are evaluated as locations, it is possible to obtain very close and effective groups by changing the clusters of some neighborhoods. As in other examples, three clusters can be updated with minor changes in line with expert evaluation, and a reorganization can be done to include the exposed neighborhoods. The point that draws attention here is that all three clusters show a homogeneous distribution regarding the number of elements. As a result, it has been shown that there may be 3 clusters for 18 districts of the Tuzla district, and these clusters are partially homogeneous. In the case of conducting research with the UAV in the Tuzla district, homogeneity will be achieved if the neighborhoods are considered as suggested groups.

CONCLUSION

In this paper, the clustering problem for a post-earthquake UAV intervention is considered by focusing on Tuzla, one of the riskiest districts of Istanbul, according to the study conducted by Gulum and others [23]. Considering previous studies and expert evaluations, seven criteria have been identified to find similar neighborhoods and propose clusters for a possible UAV operation for post-earthquake fire. Self-Organizing Maps (SOM), a special artificial neural network type, have been preferred to cluster 18 neighborhoods using the Neural Network tool in the MATLAB program. After 1000 iterations, the neighborhoods were assigned to three main clusters. As suggested in many applications of SOM-based clustering studies, such as [17,18,26] the final clusters have been discussed with a group of experts. Considering the neighborhoods' location, characteristics, and risk levels, the required arrangements have been completed. The findings of this application show that in a possible post-earthquake fire disaster in the Tuzla district, the UAVs may be operated from three main centers, and 18 neighborhoods can be divided into three groups. Since this clustering was conducted according to the risk similarities of the areas, it has been thought that operational plans will be pursued more smoothly and effectively. The findings of this study will support various places and people, such as disaster institutions in Istanbul, as a preliminary warning application. When we think of the promising performance of UAVs in many stages of disasters, this study is essential to give ideas to decision-makers while making plans. The proposed approach will be helpful in Istanbul and other cities in further studies. The study's main limitation is using datasets in the published estimated earthquake losses booklet. Even if these data are based on scientific simulation applications, they are not actual data and have limitations. In future studies, the application can be integrated with a geographic information system, and clustering performance can be increased by considering more variables. In addition, specific command points can be determined in the district, and routing of vehicles can be implemented for UAV intervention.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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