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Design and Implementation of UAV-Assisted Communication in Remote Disaster Areas using AI for 5G Network

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***Abstract*— Use of drones for a variety of functions has recently come to light. Drones are used by businesses to deliver products to clients, by academics and scientists to monitor and find endangered species, and by the military to carry out crucial missions. Powerful, clever, and well-managed Network Functions (NF) and Artificial Intelligence (AI) systems can be used in Search and Reconnaissance (SAR) operations employing Unmanned Aerial Vehicles (UAVs) to study the fifth generation mobile phone (5G). How rapidly people can change circumstances FBS can improve the region's 5G networks by increasing perfo rmance in many different apps as IoT data collection, data tra nsmission and communication technology. The issue of artifici al intelligence-assisted multi-agent planning is discussed locating of users served by UAV with impact of UA Vs. This article describes how a drone can act as a base station in a 5G network and conduct an experiment to demonstrate th e potential of drone communications. From the simulation results it was found to be that the co-operative MADRL was stable at around 14.85 average sum rate.**

Index Terms— UAV, AI, 5G

I. Introduction

Human life will be in risk from destructive natural calamities including climatological (forestfires, droughts), biological (animal plague, illness), geophysical (volcano, earthquake), and hydrological (avalanches, floods). As a result, the emergency team will work quickly to assist those in the impacted region by finding survivors, restoring the damaged structures, and giving connections, food, water, and medication. [1-2]. operating as airborne base stations in the event that the communication infrastructure is disrupted and distributing emergency supplies [3–8]. because of their many characteristics, like their quick launch and vast area to ground and 3-dimensional mobility [10-12]. Many problems like scalabe, robust, and performance of quick response, communication to use (UAVs) in disaster operations [13-15]. The FBSs can be used to support high communication demand areas such as large events or highly dense regions. ubiquitous connectivity at any location, potentially well beyond the coverage area of terrestrial MBS. This will improve the network efficiency and flexibility and thus ease the growth in high data demand. To perform a trajectory planning for UAVs as a base stations while dealing problems such as interference management optimization, it makes advantage of multi-agent deep reinforcement learning.

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A multi-agent deep reinforcement learning algorithm is used, a simulation which consists of number of UAVs as DRL agents and an environment have developed. Environment contains a system model which has of mobilityand transmission models to calculate transmitrates, rewards and states to meet the fundamental needs of reinforcement learning and provide agents to train properly for planning their trajectory optimally even on the environment with different user locations.

II. Literature Review

Unmanned aerial vehicle (UAV) systems may perform a variety of tasks during or following catastrophes, includingspeedy aerial assessments of damaged areas and search andrescue in challenging circumstances and difficult-to-reach places in [1] the technical challenges in UAS To solve these issues, technical solutions like D-NET/UTM integration have been created. [2] the performance and efficiency of K-Means clustering [4] explains the coalitionmain is a UAV that observes UAV with a lot of using sensing and imaging capabilities, aircraft may fly in circles and gather images of the afflicted areas. In contrast to computationally costly methods, the suggested algorithm's light-weight image processing for fire edge identification isvery desirable, according to Razi [5]. resource-constrained drones. Ng [6] investigates In order to determine the best power and time allocation method for the relay-assisted cooperative system, an energy efficiency optimization problem is developed. [7] offers a collection of drone-captured images of a controlled fire that was lit on piles of debris in an Arizona pine forest. [8] examines the primary driver for the use of artificial neural networks [9]researches critical applications for huge autonomous control of (UAVs). [10] There are many different analytical frameworks and mathematical methods discussed, including game theory, stochastic geometry, optimization theory, machine learning, and stochastic geometry. [11] Recently, there has been a lot of interestin investigations to carry out different tasks. In order to facilitate effective UAV-based SAR operations, Lins [12] offers the System Intelligence (SI) and Edge Intelligence (EI) ideas as related 5G components and AI modules.

[13] suggest attempting to maximize the average secrecy rate of the system under consideration. The main issue for 5G and beyond 5G (B5G) is providing ubiquitous connection to various device kinds. M. Usman, A. A. Gebremariam, M. Qaraqe [20] Identify the relevant AI approaches used and classify the major developments in the field into several groups based on their application history. We emphasize that AI and ML are opening the door to networks that are self-configured, self-adaptive, and self-managed. The UDSF implementation has been described in [21]. [22] describes in detail how the diameter protocol is used during message transmission between nodes, to test the effectiveness and functioning of IMS-LTE network components, and to assess call simulation.

III. Methodology

For a UAV connection in a sparsely inhabited area where base stations have been entirely destroyed by natural or man-made disasters like floods or earthquakes, a model- free technique is used. For the FBS to serve all user nodes in the region appointed to it, the route of travel must begin from the MBS and visit every node only once before returning to the MBS. The cost of travel for the FBS, which is the total distance covered when traveling, must be minimized to optimize the FBS' trajectory. The lower the cost, the more efficient the trip will be with regards to the limited power, energy and speed of the FBS. This is an example of the Traveling Salesman Problem (TSP), a combinatorial optimization problem that is NP-hard (Non- deterministic Polynomial Time Hardness). Each user communicates with using their user equipments (UE) with UAV and gets served by nearest UAV dynamically. UAVs will be connected to a signal by another working base station and each one of the UAV communicates continously with users served by themselves by using FDMA system. Also to solve energy problem of UAV, their energy assumed to supplied by using laser charging from base station which will not be detailed in the problem formulation.

A. System model

To keep the environment more realistic, During the flight of the UAV, EU will be allowed to maneuver. Both to maintain the continuation of the discretely specified simulation and because UAVs are quicker than users, the movement of the users is fixed according to the user-UAV velocity ratio. All users have action vector consists of moving right, left, forward, back and remaining static with same length but with a different sequence. Paths users follow is predetermined before simulation randomly by using a random distribution on each users' own action vector so that environment's user mobility model is stationary and accurate.

The proposed work will take into account a downlink transmitting modelin D2D functionality as shown in Figure 1, where the mobile communication shares its wide range of spectral band with the D2D communication.

B. Multiagent reinforcement learning

Considering real-world problems with high complexity that require multiple entities in the same environment to solve or reach a more optimal solution, it is appropriate to use MAR learning approach. In this approach, multiple agents in same cooperative, competitive or mixed. Due to multiple agents being environment, reinforcement learning with many agents has many difficult problems compared to reinforcement method single agent such as the challenge is environment is non-stationary since the actions of the agents in current state affect each other and all of the agents may behave differently from previous trials [7]. To remove non-stationary problem, the state information to be given per step to each UAVs should cover the environment state any ambiguity in the absolute Q function, so UAVs should not be able to get multiple different reward values from same state information andsame action [8]. Mentioned situation causes agents to have to make the optimal action about more states than usual dynamic environment which means agents in MARL have more workload than single agent in the basic reinforcement learning.in same environment can be cooperative, competitive or mixed. Due to multiple agents being in the same environment, reinforcement learning with multiple agents has many difficult problems compared to reinforcement learning with a single agent such as the challenge is that the environment is non-stationary since the current state affect each other may behave differently from previous trials [7]. non-stationary problem, the state information to be given per step to each UAVs should cover the environment state ambiguity in the absolute Q function, so UAVs should not get multiple different reward values from same state information andsame action [8].

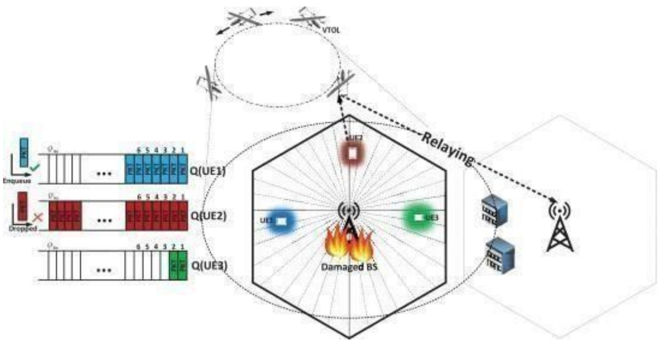

Figure 1: System Model

C. Deep Q learning

Since environments with large state space can cause a serious resource problem in Q-Learning by requires too much space for q-table, basic q-learning can only be used in problems with limited state space. To get rid of resource problem and improve learning performance, using a neural network to estimate action- state values instead of a Q-Table is one of the solution for it[10].

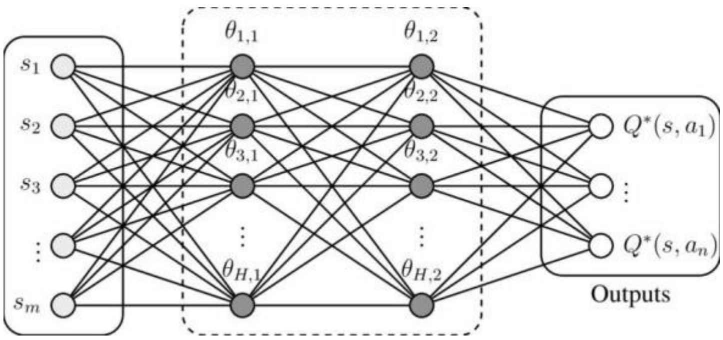

Figure 2: Instead of a Q-Table, Deep Q Network employs a neural network to link state-action pairings to corresponding Q values.

Deep Q-Learning is an approach that takes advantage of both deep learning and q-learning. In Basic Q-Learning, a table maps each state-action pair to its corresponding Q-value. In deep q- learning, instead of a table, a neural network maps input states to the action with Q values which makes deep Q-Learning more appropriate in complex environments which have high dimensional discrete or continuous spaces.

D. 5G implementation of UAV

K-means Clustering will be used as the standard of evaluation of the proposed algorithms to verify the efficiencies and performances of the algorithms. K-means uses the spatial distribution of n points to partition the points in to k clusters. The algorithm works by randomizing locations of k centroids and calculating the distances between every point and every centroid, assigning points to the clusters centered at the centroids closest to the points [20]. The algorithm then replicates new centroids located at the centres of gravities of the points assigned to each cluster. The algorithm completes once the centroids are located at the mean of all points in the cluster assigned to the centroid, and no more changes can be made. K- means is known to have a complexity O(n 2) The pseudocode of the algorithm is below [25].

Figure 3 can be used to visualize how the algorithm will run. The net distance covered by the FBS will be calculated at seven locations of the boundary. The first boundary is located at the dashed line on the left and the last at the dashed line on right.

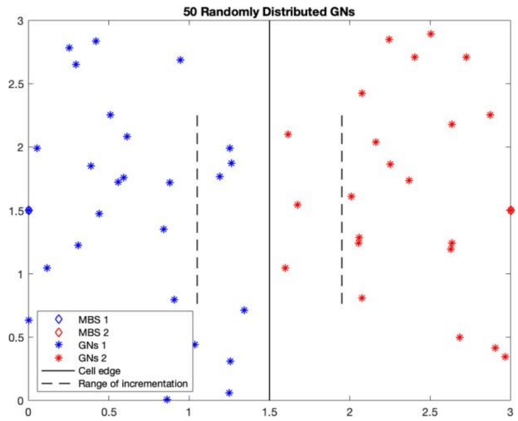

Figure 3: Boundary Incrementation Range

E. Transmission Model

In transmission model, formulations described on are used. It is possible to define the overall total rate at time unit t as

$$R_{\text{sum}} = \sum_{n=1}^{|N|} \sum_{k_n=1}^{K_n} r_{k_n}(t) \tag{1}$$

where N is set of UAVs, K n is all user count which serving by UAV n and rkn(t) by bps/Hz and expressed as

$$r_{k_n}(t) = B_{k_n} \log_2\left(1 + \Gamma_{k_n}(t)\right) \tag{2}$$

where Bkn is the bandwidth of user kn and Γkn (t)

SINR a quantity used to give upper bounds on channel capacity in wireless communication systems, theoretically and in our problem

$$\Gamma_{k_n}(t) = \frac{p_{k_n}(t) g_{k_n}(t)}{I_{k_n}(t) + \sigma^2} \tag{3}$$

where pkn (t) = Pn (t)/ |Kn | has user kn received the transmit power at time t where Pn (t) is transmit power of UAV n at time t and |Kn | is the number of users serving by UAV n. σPower gain of channel between user kn and UAV n given b

$$g_{k_n}(t) = K_0^{-1} d_{k_n}^{-\alpha}(t) [P_{\text{LoS}}\mu_{\text{LoS}} + P_{\text{NLoS}}\mu_{\text{NLos}}]^{-1} \tag{4}$$

where dkn is the euclidean distance between user kn and. Line-Of-Sight(LoS) and Non-Line-Of-Sight(NLoS) conditions are assumed to encountered randomly and probability of LoS denoted as

$$P_{\mathrm{Los}}\left(\theta_{k_n}\right) = b_1\left(\frac{180}{\pi}\theta_{k_n} - \zeta\right)^{b_2}$$

where b1, b2 and ζ is constant
.Inherently, interference Ikn (t) expressed as

$$I_{k_n}(t) = \sum_{n' \neq n} p_{k_{n'}}(t) g_{k_{n'}(t)}$$

V. IMPLEMENTATION

A demo application was made to run the trained models on the location data of the users on earth given by the person using the program. In this demo application, the user selects the path of a trained model folder and the file containing the user data from the dialog. Then user starts the simulation by clicking the "Start Simulation" button. Also user can choose to generate random location data by ticking the "Random Environment" checkbox

Figure 4. Home window of simulation software

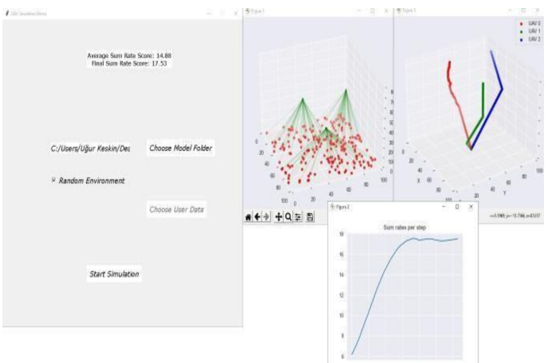

Figure 5. Screenshot of software after the end of simulation After the simulation starts, the location of the UAVs and their connecting with the users on the ground, the instantaneous total sum rate of that step and the trajectories of the UAVs along the way graphs in real time. Charts areinteractive and images can be saved, perspectives of 3D charts can be changed by dragging interactively. After simulation ends, instantaneous sum rate at the last state and average sum rate of trial in window. Screenshots of software in 6

Piecewise cell edge algorithm for 5g

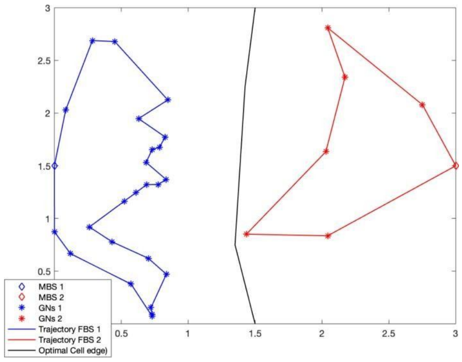

Figure 6: Optimal Piecewise Cell Edge for 30 GNs - Instance 1 Trajectory Representation

For 30 GNs, the optimal boundary location shifted from maintaining the central locations in both Simulations 1 and 3 to a location closer to the flash-crowd. The results displays that from 30 GNs onwards, all optimal boundaries move closer towards the flash-crowd rather than maintaining the traditionally positioned cell edge location. Figure (7) depicts a higher GN density scenario with the optimal edge at 70 GNs.

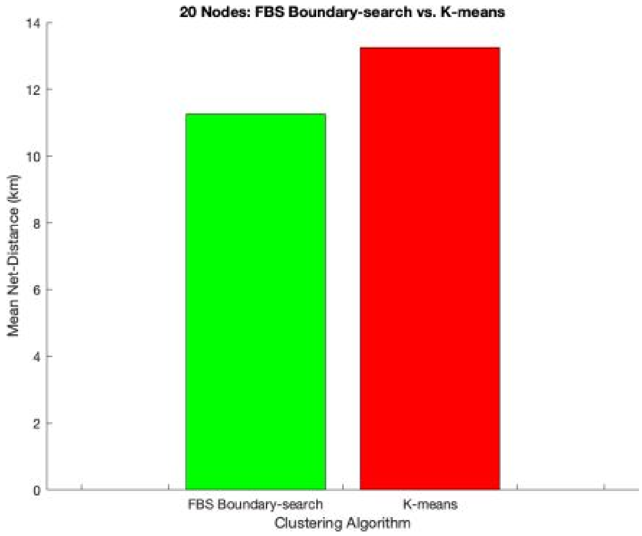

Figure 7: Comparison of Algorithm 2 and K-means Clustering - Mean Net Distance

In above result shows a significant difference in the performance between both algorithms. For all GN sizes, Algorithm 2 output a lower net distance than K-means clustering.

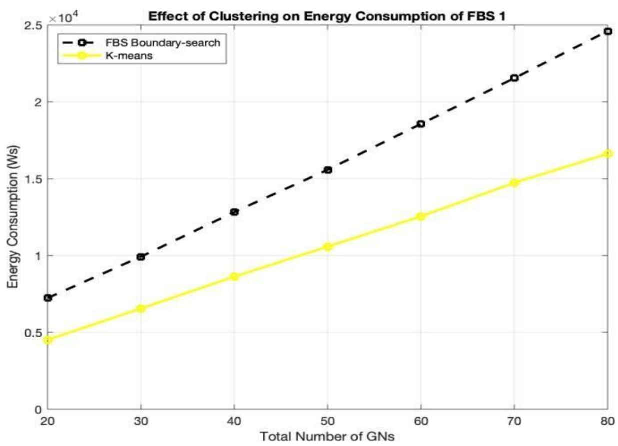

Figure 8: Effect of Clustering on Energy Consumption of FBS 1 after 1,000 Instances

The above results display dynamic advantages and disadvantages of the implementation of each algorithm when dealing with the flash-crowd scenario. When assessing the energy consumption of FBS 1, Algorithm 2 produces results that are significantly more detrimental to the FBS's energy consumption than K-means does. The algorithm also outputs a larger increase in energy usage as the GN size increases than K-means. Slope of Algorithm 2 surpassing that of K-means by approximately 62%.

A. Parameters

1. Simulation parameters

The environment is modeled as a square with 100 units on each side. Each unit is equivalent to 20 meters The movement speed of UE is fixed and considered as 1 meter per second and the speed of UAVs is considered as 20 meters per second, so while UAVs move 1 unit per step, users move 1 unit per 20 steps. Initial horizontal location of UAVs are same and in the center of the environment area. UAVs have different altitudes 1 meter apart also UAV with highest altitude's altitudeis 400 meter. Simulation parameters are shown in Table 7.1.1

TABLE I.

Parameter	Description	Value
α_{lr}	Learning Rate	1e-06
γ	Discount Rate	0.95
ε	Initial epsilon greedy	1
BS	Batch Size	10
$LossFunction$	Loss Function of NeuralNetworks	Huber
$minEpsilon$	Minimum Epsilon	0.1
$epsilonDecayRate$	Epsilon greedy decayrate	0.96
$PENALTY$	Penalty Coefficient	-100

TABLE II.

Parameters	About	Rate
N	Total Number of UAV	3
K	Total Number of users	200
P	Transmit power of UAV	0.08W
B	Bandwidth	1MHz
N_0	Noise power spectral	170dBm/Hz
f_c	Carrier frequency	2GHz
α	Path loss exponent	3
u_{LoS}	for LoS, additionalroute loss	4dB
u_{NLoS}	for nLoS, additionalroute loss	24dB
b_1, b_2, ζ	Environmental parameters	0.36, 0.21, 0
$UNIT$	Meter value correspondingto 1 unit	20
ALT	Initial altitude of highestUAV (in meters)	400
$iterationCount$	Number of iterations for simulation	100
$stepCount$	Number of steps for simulation	64

2. Training parameters

Parameters of DRL are shown in Table 7.1.2. Each UAV takes a state input from environment at each step. State input consist of the horizontal locations of each UAV and the time information to avoid non-stationary states by considering both user movements (with giving time information) and UAV movements (with giving UAV locations). Each iteration, The environment is reset by changing user and UAV locations to their initial positions. Huber loss function was chosen.

VI. Performance Anaysis And Results

Evaluation scores after each iteration is shown below in Figure 9. Also sum rates per step during the trial where UAVs gets the highest score is shown below in Figure 9

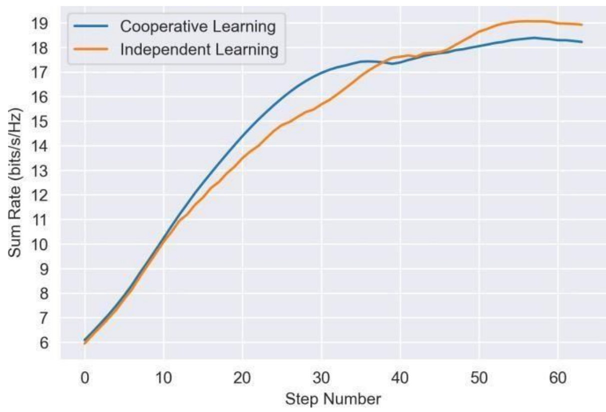

Figure 9. Sum rates per step during trial with the high average sum rate score

Last location (location on the last step of trial with the highest average sum rate score) of UAVs and their association with users' is shown in 3D chart 10. Comparison of Independent MADRL and Cooperative MADRL results shown in Table III

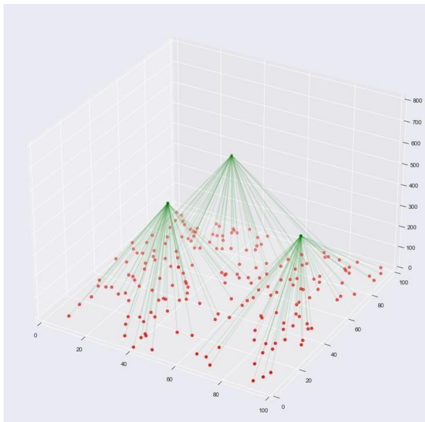

Figure 10. UAVs' final positions (green) and their connections to users on the ground (red) that deliver the greatest instantaneous sum rate on the last step

TABLE III.

MADRL Method	Highest instantaneoussum rate	Highest averagesum rate
Independent	19.16	14.85
Cooperative	19.30	15.04

As can be seen in figures above, Cooperative MADRL is more stable than Independent MADRL but it gets lower scores on first iterations which may be due to the fact that unlike independent MADRL, UAVs (agents) learn by interacting with each other by using each other's network to predict future rewards even agents are unstable and prone to make wrong decisions in the first iterations.

V. CONCLUSION AND FUTURE WORK

UAVs trajectory design as base stations is very detailed and difficult process. Taking cognizance of interference, user locations, user movements and time makes trajectory design more complicated. To make available to get better results on distinct, tougher environments, models must be trained on a lotof distinct environments. Another ways to increase success of MADRL are increasing batch size, increasing iteration number, tuning parameters such as epsilon decay rate, initial epsilon greedy, minimum epsilon greedy learning rate, discount rate and using prioritized experience replay buffer. Increasing batch size and iteration number significantly increases duration of training that is also the reason for batch size was set low in this project.
A further improvement can be made to the experiments would be the application of K-means to find optimal hover locations, rather than flying overall GNs. This would be significant in a flash crowd event as the FBS would be to serve denser crowd more easily from the same location.

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