Drone-Edge Coalesce for Energy-Aware and Sustainable Service Delivery for Smart City Applications

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Abstract

In a typical smart city, drones can collect (or sense) massive amount of data, that is sent to a computing capability for further analysis to make useful decision making without human intervention. This data is relayed to the Cloud for processing and analysis due to its large-scale infrastructural capabilities. However, the key goal of the drone deployment in smart city scenarios or urban environments is to provide timely and quick response alongside providing an energy-efficient service delivery. Thus, we need a sustainable solution that can be deployed locally (closer to the data source) in a smart city, to process or analyze the data (generated from smart city sources) and provide timely decision making for smart city applications. Edge computing, popularly known as the "cloud close to the ground", can provide computational and processing facilities at edge of the network in a smart city. Hence, Edge computing act as an effective alternative solution to process and analyze the data closer to the point of it's generation. Looking into the above discussion, We propose a novel drone-edge coalesce that provides an energy-aware data processing mechanism for sustainable service delivery in the multi-drone

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smart city networks. In this model, the edge computing layer is deployed to process and store the data sensed and collected by drones in a smart city. In this context, an adaptive edge node selection mechanism has been designed on the basis of decision tree approach. In this coalesce, we have to deal with the conventional problems related to the collision and congestion while providing low-latency and sustainable data transmission in a smart city. So, We have designed an energy-aware multi-purpose algorithm that avoids collisions and provides a congestion free data transmission. The proposed coalesce is validated in a simulated environment on the basis of several performance metrics such as, throughput, end-to-end delay and energy consumption.

Keywords: Drone Networks, Edge Computing, Energy Efficiency, Quality of Service, Smart City, Sustainable City

1. Introduction

In the past decade, due to the emergence of various kind of smart city use cases, the consumer grade drones or Unmanned Aerial Vehicles (UAVs) have been gained tremendous popularity in various applications ranging from aerial photography to environmental protection and further to the delivery of goods [51, 50]. The capability to improvise the overall efficiency and productivity and redefining the smart city services along with a reduction in the operation costs has increased the demand for drones in an exponential manner. Thus, the adoption of drone technology among various civilian, commercials and government services moved ahead from the experimental stage to the implementation stage quickly. From the past few decades, the smart city concept is trying to gain a wider attention by providing sustainable chain of end user services, Drones are seen as key enabler for the smart city applications by offering a cost-effective solution for almost everything. The growing interest from a number of consumer-oriented commercial activities expanded the scope and scale of drone applicability in multi-varied smart city environment [12, 47]. As a result, the integration of drones with 5G technology paved the way to provide an on-demand uninterrupted Internet services to various consumers with minimal capital and operational investment [49]. Moreover, with advancement sin the Internet of Things (IoT), these days the drones are being utilized to collect data from smart devices and sensors deployed in various smart city use case scenarios (such as smart grid, smart electric meters, large-scale industrial setup, intelligent transportation, etc)

[46, 4].

Moving further, drones can very useful by enabling the live video, capturing the sensors data and performing lightweight analytic on board. For instance [1], recently a natural disaster hit the Uttarakhand region in India, where an avalanche barrelled down from a breaking glacier. Here, there drones were flown to examine the large affected area and a human detection algorithm on live video streaming helped in the search and rescue mission. In such scenarios, a swarm of drones or multi-drone network can be utilized for efficient and successfully accomplishment of the given tasks in timely manner. The swarm of drones can be deployed as aerial base station to capture the data from sensors, inspection of gas pipelines, analyzing traffic movement and to conduct the various geographical surveys on hard-to-reach places. Despite its numerous benefits, there are some concerns that need to be understood and addressed in a timely manner in order to utilize the full drone capabilities. Drones can collect (or sense) massive amount of data, that is sent to a computing capability for further analysis to make useful decision making with human intervention.

1.1. ***How can drones contribute towards a sustainable smart city?***

Smart city is a concept that prioritizes technology to improve the life of citizens by providing them with efficient and cost-effective services. According to a report by IDC [27], the spending on smart city technology is expecting to reach $135 billion by the end of 2021. In this regard, one of the most fascinating combination is related to the integration of drones in every vertical of a smart city. If we weave the drones in to the smart city fabric, it would act as a game changer for a wide range of smart city applications. In the past, drones were considered as a machine of destruction (like warfare or defence activities), but these days the drones are flying beyond the initially conceptualized horizons. Drone are capable to provide and sustain key services related to smart cities in a cost-effective manner. Even more, the drone-supported day-to-day municipal operations in smart cities can help to achieve the larger sustainable smart city goals concerning the improvement in the living of residents. Drone are expected to play a key role in many smart city applications, like, merchandise delivery, infrastructure planning and inspection, crowd management, natural disaster management, health emergencies, smart transportation, civil security and safety, and smart transportation. Fig. 1 shows different verticals of drone applications in smart city. A brief discussion on the application of drones in smart city use case scenarios is provided below.

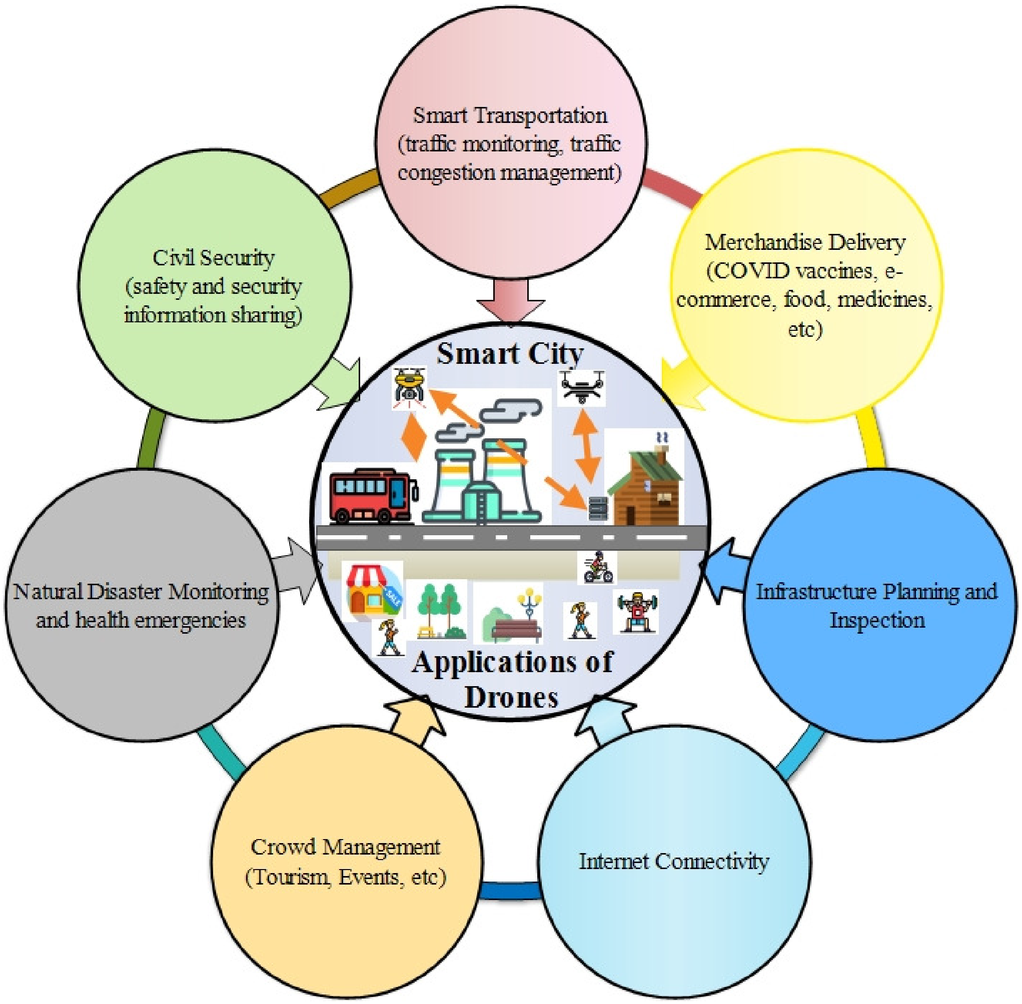

Figure 1: Applications of drones in a smart city.

1.1.1. Smart Transportation and Traffic Management

The biggest contribution of drones in smart city revolves around the concerns of smart transportation. One of the key challenges of transportation sector that has scourged smart city is traffic, ever-reliable rush hour and congestion [29]. The core and reasonable solution to this problem is related to the provisioning of basic information concerning the reasons behind the congestion and traffic chaos, the active status of road conditions, and other unpredictable reasons. The on-road cameras can be useful to collect such information, but they lack in advanced intelligence required for traffic regulation decision making. Here, the drones can play a key enabler as they can collect data and then deliver it to the decision making controller (the cloud) in almost near to real time. Even, drones can collect the data and provide live feeds (even from hidden angles that cameras cant cover) through their high visibility and mobility. This can help to sustain the basic requirements or the backbone of a city by uniformly regulating the traffic. *Traffic, congestion and road chaos has direct or indirect impact of the day to day routine or mind set of the smart city citizens also. Even, a fully regulated traffic can help to reduce the overall carbon emissions and fuel spending of citizens. So, this way drones not only act as enabler for sustainable cities but also impacts the overall society.* Drones can help to find parking slots, cutting the travel time to find a parking slot, help create transit routes in emergency conditions, and identify green routes.

1.1.2. Natural disaster monitoring and Health Emergencies

The next biggest area of drone application is related to the natural disasters or any unconventional emergency situations (like health emergencies, pandemics like COVID). Drones can help to monitor in a more comprehensive manner covering every nook and corner and the monitored information can be analyzed to take precautionary actions as and when required. They help in real time critical situation analysis, circumstance analysis, and even control measures is unconventional situations that can he harmful to lives. Moreover, drones can be used to provide emergency medical supplies and life supporting equipment in a quick manner and at locations where any delay in supply can endanger human lives. For instance, Zipline, a drone delivery service has collaborated with the Government of Ghana to deliver the COVAX vaccines in order to handle the logistic challenges [9, 3, 2, 48]. *This helps to enhance and improvise the response of cities to the health needs and emergency governance concerning the public.*

1.1.3. Drone Delivery Industrial/Commercial Use Cases

These days drone are very popular for providing quick and cost-effective deliveries related to various segments like, medicines, merchandise, food, parcel, etc. Some examples are discussed below based on there categories.

- **Essential Stuff and Medicine**: There are some instances where a contact less delivery is the biggest requirement without any human intervention. For example, in COVID pandemic, contact-less delivery has been on boom but still there was human intervention. Drones can play a vital role in pandemic time and help to provide contact-less deliveries at the consumer door step [25]. Even for an isolating patient, drones can not only contact less delivery of medicines but also provide a quick delivery. Moreover, drones have been used for the delivery of first aid and sensitization drives across cities during the lockdown in many countries [24]. There have been instances where life saving organs were delivered for timely transplants using drones in congested cities [28]. *In this way, the drones can be useful to provide medical delivery and participate in sensitization to benefit the overall city services or society.*

- **e-commerce**: In some major cities, parcel delivery using drones is very popular these days. Topmost logistic companies like, DHL [23], Anavia [18] and Amazon [22] have adopted drone delivery in the cities using automated mechanism. Some instances like [26] have used drones in marine deliveries also where the containers are delivered to consumers locations. *In context to cities, it is expected that drones can help to reduce the carbon footprints and provide timely services to the citizens.*

- **Grocery and Food delivery**: There have been several instances where food and grocery has been delivered using drones. For example, 7 Eleven [21] have relied on drones to deliver the grocery to their customers. Even more, the famous pizza company, Dominos, have adopted drones to deliver pizzas to its customers in a timely way [19, 33]. A famous taco outlet have designed a special tacocopter to deliver tacos in San Fanscisco [20].

1.1.4. Infrastructure Planning and Inspection

One of the key areas of concern in cities is to inspect the ageing build infrastructure as normal eye or cameras cant reach every nook and corner. Drones can be useful in inspecting such cites and using theta information, the city authorities can take remedial actions. This can be very useful at historic sites which are old and any damage can hamper the tourist lookout and even endanger tourist lives. Moreover, drones can even help to monitor the development of new buildings by collecting the real time information related to the construction site and send them to the development team to plan effectively. *This way drones can contribute is the planning, construction and inspection of build infrastructure in cities.* In Canada [38], the use of drones for the above mentioned concerns is legal under the current regulatory framework. For example, Industrial Skyworks, a Canadian company is already assisting and conducting inspections [38].

1.1.5. Civil Security and Safety

Drone provide a promising contribution in the security and safety of citizens, like the information shared by drone scan be useful to protect people from being caught in extremely uneventful situations (such as, disasters). Drones can help to provide quick response in emergency conditions and can hover across various locations in cities to monitor the security situation. *This way drones can be extremely beneficial to ensure citizen security and safety and protect cities from critical situations.*

1.1.6. Crowd Management

In major events like concerts and sports tournaments, drones can help to manage the crowd and monitor any uneventful activities. Generally, after such crowded events, cities face a huge rush on road and drone scan be helpful in such scenarios to assist, diver and provide transit routes to traffic. *This way it can help the city authorities to monitor the large crowd events and help to protect citizens from any mundane (like traffic chaos).*

1.1.7. Internet Connectivity

One of the initial use case where drones have been very popular was to provide temporary Internet connectivity (like 5G network) in areas that are considered black spots. The connectivity provided by drones can enable faster connection speeds and allow citizens to connect to the Internet in an un-disrupted manner. *In case of any fault or failure in connectivity, drones can be deployed to provide temporary connectivity so as to facilitate citizens seamless services and avoid disruption in city operations.*

1.2. ***How to process the massive data collected by drones in a smart city?***

After looking into the above drone applications in a smart city, one of the key concern is the data collected by the drones. This data comes under the category of big data as it satisfies all the major attributed related to volume, velocity, variety, value and veracity. Now, the key challenge is to process this data in a timely manner in order to provide effective service delivery in the smart cities. Generally, this data is relayed to the Cloud for processing and analysis due to its large-scale infrastructural capabilities. However, the key goal of the drone deployment in smart cities or critical environment is to provide timely and quick response. Like, for a rescue mission (due to land slide) in a densely populated forest, any delay in the identification of humans or critical infrastructure can be damaging. Thus, we need a solution that can be deployed locally (closer to the location of the data source), to process or analyze the data and provide timely decision making.

Edge computing, popularly known as the "cloud close to the ground", can provide computational and processing facilities at edge of the network [17, 53]. The edge devices are widely distributed to support real-time data processing and reduces the need to relay data to the Cloud to a large extent [6, 57]. The close proximity of the to data and the compute facility can provide numerous benefits such as, faster insights and quicker response times [36, 37]. Moreover, in the past few years, the modern technology are focusing to automate the systems and processes by relying on the data collected by drones from the connected devices. However, the anomalous scale and complexity of data produced by the connected devices often suppress network bandwidth and burdened the infrastructure capabilities [8]. Transferring of all device generated data to and fro cloud may results into the bandwidth and latency bottlenecks. Hence, Edge computing act as an effective alternative solution to process and analyze the data closer to the point of it's generation [13, 45]. This way we can reduces the latency as there is no need of transfer data over the network to the cloud, thereby omitting the round-trip delay between data source and the remote cloud. These benefits are not restricted to just hosting, but it also helps to improves the Quality of Service (QoS) and assists the communication during the critical circumstances, on-the-go or on-the-demand communications (ad-hoc) [7].

Looking into the above discussion, we have created a novel drone-edge coalesce for efficient data processing in drone networks. However, in such an integration, we have to deal with the conventional problems related to the collision and congestion while providing low-latency data transmission. Various state-of-the-art solutions [11, 5, 30] have been proposed in the literature to handle the problems related to collision-avoidance and congestion control in drone networks. However, none of these solutions have focused on the design of an energy-aware and sustainable solution in the multi-drone networks. Moreover, the adaption of such solutions in the drone-edge coalesce has not been validated yet. The impact of collision and congestion on drone networks is quite high due to unpredictable mobility control, routing conditions, and transmission control mechanisms. However, the high dynamics of these factors has strong impact on connectivity and operations of drones in any deployment. Most of the existing solutions fail to understand and address the energy consumption related problems in drones. Due to limited battery capacity, an inefficient solution that consumes additional energy cannot be deployed in realistic scenarios. Moreover, the energy dynamics of drones are wide due to the dependence on multiple factors, like flight time, link, link state, processing, and transmission. Thus, we need an efficient solution to provide an energy-aware, congestion and collision-free transmission in drone-edge coalesce.

1.3. ***Motivation***

In a smart city, the sharing of timely information is very important to handle various unexpected event and protect the citizens from extreme situations (like, disruption in services or traffic chaos). Drone can be easily deployed at any location irrespective of application domain and can cover all the dead end and corners where even human eye or cameras cant reach. Moreover, they provide a cost-effective, flexible and timely service to gather the information and transmit it to the edge-cloud infrastructure for efficient decision making. This can help the city planners and Government administrators (related to Municipals) to use this data and analyze it to improve the city services and governance. In the past there were some challenges and concerns related to the legal provisions under regulatory framework for realizing the drone deployment in the cities for supporting essential and emergency services. But, these days most of the countries are considering to modify the policy or cover the drone drone deployment under existing policies. For example, the law enforcement agencies in Canada have coordinated with the drone industry to quickly develop drone laws to facilitate such deployments. In this context, the RCMP is already using drones for their necessary mandates [38]. However, the key barriers for the amalgamation of drones into smart cities is related to the unprecedented and seamless volume and varied data. There are several challenges related to the handling or processing of this data in an effective manner. One of the solution was to adopt Cloud technology, but the round trip delay can hinder the key goal of drone deployment concerning timely and quick response. Thus, there is a need to device an alternative way. As discussed previously, the Edge computing has been very popular in smart city applications due to its dual functionality, i.e., processing and storage at the edge, and providing edge intelligence for quick analysis of data. Moreover, the edge can smoothly coordinate with the Cloud whenever higher processing capabilities are required. However, due to distributed deployment of edge nodes across smart cities and the mobility of drones, the selection of a suitable edge nodes becomes a challenge.

1.4. ***Contributions***

Keeping in view of the above considerations, We propose a novel drone-edge coalesce that provides an energy-aware and sustainable data processing mechanism in the multi-drone networks in a smart city. Drone-Edge coalesce can help to develop an effective infrastructure platform supported by the cutting-edge technologies at no additional cost, with an overall goal of improving the smart city sustainability and providing services to citizens at no additional cost. The major contributions of this work are as follows.

- We have proposed a novel drone-edge coalesce model wherein the edge computing layer is deployed to process and store the data sensed and collected by drones.
- We have designed an energy-aware multi-purpose algorithm that avoids collisions and provides a congestion free data transmission
- An adaptive edge node selection mechanism has been designed and developed on the basis of decision tree approach.
- The proposed coalesce is validated in a simulated environment on the basis of several performance metrics such as, throughput, end-to-end delay and energy consumption.

2. Related Work

Various proposals have tried to cover some of the above raised issues but still there are many loopholes to be considered and handled effectively. A brief discussion on these proposals is provided below.

2.1. Deployment of Drones in Smart Cities and Societies

Various representative research proposals have highlighted the use of drones in the context of smart cities and societies. In [40], the authors proposed the use of drones for logistics in a city. The ground based transportation is under huge pressure, the delay in shipments of cargo due to traffic leads to the loss of revenue, time and most importantly the fossil fuel. This hampers the overall vision of smart cities and growth of society through timely delivery of services and goods. So, today it is worth to utilize the drones for logistics delivery. Similarly, in [43], the drones have been utilized for delivering healthcare products to different needy communities and societies in Africa. The major objective of this research is the timely deliver of blood, drugs, vaccines, and laboratory test samples. This clearly indicate the support of drones to the society. Moreover, in comparison to the conventional methods, drones help to reduce the response time and CO2 emissions. Nevertheless, in [14], a technique for delivery of food and small express package in urban cities was proposed. This technique for product delivery worked very well in the very low level and congested airspace and it is also able to cope up with the high density drone delivery. The authors presented a case study of Paris metropolitan city to demonstrate their delivery technique and its applicability in context of cities. In another article [35], the authors proposed the delivery of goods using drone and ground autonomous delivery devices in the two major cities first is Paris suburbs, and second is the Barcelona (Spain). The drones were launched from the rooftop of the truck and were deployed in the dense areas where the reach ability of the trucks is not possible. In [56], the drones were used for delivering the products in cities during COVID 19 pandemic . The person-to-person transmission of this disease, leads to a less interactive way of deliveries the goods. The authors also presents a study on customers perception, behaviour and attitude towards the acceptance of delivery by drone. In [32], the authors focus on the providing real-time based route information to perform various operations in smart cities. The route detection is based on the an agile optimization, which works for both drones and other autonomous vehicles. ***In summary, the above discussed proposals clearly indicate the role and contribution of drones in the fulfilment of sustainable goals in smart cities and societies. Starting from the timely provisioning of services, to reduction in carbon emissions, and further leading to cost-effective way of providing services.***

Moving ahead to other applications of drones, in the [15], drones were utilizes to click the pictures for calibration of outdoor microclimate simulations models. In this, the thermal images captured by drones used in measuring the surface temperatures. Afterwards, the calculated values are used in calibrating numerical models. This clearly indicate that the collected information (i.e., images) are important and are further analysed to measure the surface temperature. Likewise, in [34], an the intelligent processing systems was introduced for the cameras mounted on the drones. The primary task of this system is the data acquisition and analysis, which helps to improve and predicts the urban transportation systems and its sustainability. The results shows that the detection ratio for both human and drones are similar and can be utilized to manage public and fright transport in cities. Further, utilizing the capabilities of the drones, in [42], a technique was designed to build a urban landscape from LiDAR sensors and digital orthophotography from the drone. The designed technique helps to estimating risks, maintaining infrastructure systems and improve the planning for various plannings such as solar energy. The results presented in the paper, witnessed a significant improvement in the prediction of radiation by 36%. ***The above discussed proposals clearly indicate the usefulness of drones in manifold applications related to smart cities and society. However, one key challenge common in all these proposals is data acquisition, storage and processing.***

2.2. Drone and Edge Integration

A wide range of researchers are utilizing drones in amalgamation with the edge computing for processing data generated by IoT devices in the local domain. This amalgamation is very popular in smart healthcare, Industry 4.0, intelligent transportation, smart grid and many other areas of research. As discussed in the previous section, one of the key challenge for drone deployment in smart cities is related to collection, storage and processing of data. Edge computing can resolve this issue to a great extent looking into the promising contributions in other similar domains. A few researchers has foccussed in this direction and tried to integrated drones and edge computing for common benefits. For example, in [57], the authors considered the use of drones in caching data for fog-based IoT systems for realizing sustainable smart cities. It is found that the integration of the fog computing can support the computational demand and reduce the delays and may enhance the energy efficiency. In another work [54], the authors employ drones for autonomous crop scouting techniques for rice. The data gathered by employing the UAVs was used to simulate using deep neural networks and generate further analysis. The authors believe that by using the edge computing for autonomous scouting and lodged rice detection will result in good yield. In [39], the authors introduce the new message transfer concept for the drones those are participating in edge computing. A new term "Edgedrone" is also given to the participating nodes. From the results, it's advent that the QoS parameter results shows 30% improvement. Similarly, due to the wide adaptability of the drones, in [10], the authors utilize them for surveillance in underwater and termed as Internet of Underwater Things (IoUT). The primary focus of the research was to minimize the battery or energy consumption, drones consume energy to gather, hover, and in computation. Based on the above discussions, it is clear that drone-edge integration has witnessed some fascinating results and benefits. But, there are several challenges that arise due to the distributed deployment and resource constraints of edge devices alongside the intermittent mobility of drones.

3. System Model

In the proposed work, the system model consists an array of drones ($\mathcal{D}$), that are used to collect data (like video streams) and transmit the same to the edge nodes (local servers) in a typical smart city. Another task of the drones is to handle user application requests and then process them at the edge and relay the response back to them. Here, we have considered a set of users ($\mathcal{U}$) are connected to the drones. In this setup, the drones are equipped with omni-directional antenna for communication purposes as they are least effected due to the drone's drifts. This model considers multiple drones to support the transmission of sensed data related to different end user applications from source to the edge nodes whereas the communication and drone control is managed through base station. The entire transmission considers issue of interference concerning different communication technologies and energy consumption for different links. The network model and preliminaries including the problem formulation related to the proposed system model are discussed in this section.

3.1. Network Model

As the drones fly at different altitudes, so for the considered network, the observed interference for i^{th} drone at j^{th} location is represented in the form of Signal to Noise Ratio ($\mathcal{SINR}$) based on the transmission power ($\mathcal{P}$), the

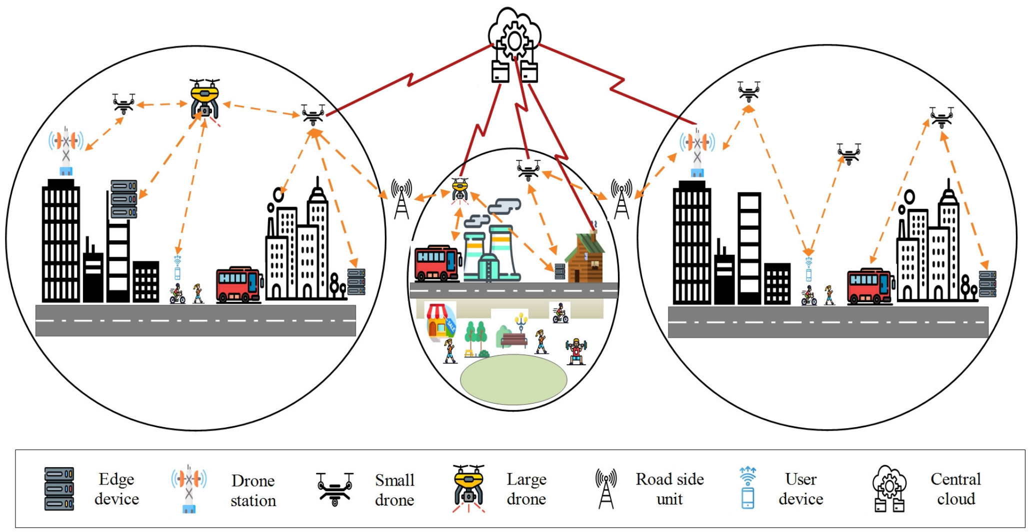

Figure 2: Proposed System Model in a Smart City Scenario

antenna characteristics ($\mathcal{K}$), height of drone (h), the path loss (α) and the noise power spectral density (N). Thus, the $\mathcal{SINR}$ is defined as below [52].

$$\mathcal{SINR}_i = \frac{\mathcal{PK}h^{-\alpha}}{\sum_{i=1,j_1\neq j_2}^{|D|} \mathcal{PK}h^{-\alpha} + N} \tag{1}$$

s.t.

$$\frac{1}{|\mathcal{D}|}\sum_{|\mathcal{D}|} \mathcal{SINR} \geq \mathcal{SINR}_N^t \tag{2}$$

where, $\mathcal{SINR}_N^t$ represents $\mathcal{SINR}$ for the network wherein the drones are flying at same altitude and configuration.

In the proposed model, the total number of connection in the network are given as below.

$$\mathcal{L}_T = \frac{|\mathcal{D}|(|\mathcal{D}|-1)}{2} + 1 \tag{3}$$

At time t, the above equation is transformed as below.

$$\mathcal{L}_T(t) = \frac{|\mathcal{D}^*|_t(|\mathcal{D}^*|_t - 1)}{2} + 1 \tag{4}$$

where, $\mathcal{D}^*$ is the subset of drones satisfying Eq. 1

Now, in order to realize a sustainable network, the required number of connections should exhibit minimum duration of links. Thus, we need to satisfy the following condition.

$$MIN \lim_{t_z \to \infty} \sqrt{\frac{1}{t_z} \sum_{i=1}^{t_z} \bigg(\Big(\frac{|\mathcal{D}^*|_i(|\mathcal{D}^*|_i - 1)}{2} + 1 \Big) - \Big(\frac{\mathcal{L}_a + \mathcal{L}_z}{2} \Big) \bigg)^2} \tag{5}$$

where, t_z represents the maximum time duration for which a network can operate, $\mathcal{L}_a$ and $\mathcal{L}_z$ denote the minimum and maximum number of inactive links in the network, respectively. We have used a and z for minimum and maximum values throughout the paper. Here, the number of links $< \mathcal{L}_a$ as it help to achieve stronger recovery in case of failure.

Now, for each request arising in the network, let us consider the mean packet size as $\frac{1}{\mu}$, then the transmission rate ($\mathcal{T}_R$) is defined as below.

$$\mathcal{T}_R = \frac{\lambda}{\mu} \tag{6}$$

where, λ denotes the arrival rate of each request.

Here, to sustain the network operation at a given rate, the best way is find the probability of connectivity. Based on [52], we can find the probability of average connectivity ($\mathcal{P}_{CN}$) of the network as below.

$$\mathcal{P}_{CN} = 1 - \Big[\sum_{j=1}^{t} \prod_{m=1}^{C} \Big((\, \mathcal{L}_T \,) \, \mathcal{L}_A \Big(P_{CR} \Big) \Big(1 - P_{CR} \Big)^{\mathcal{L}_T - \mathcal{L}_A} \Big) \Big] \tag{7}$$

where, the time slots are represented as t, number of channels for connected entities is given by C, $\mathcal{L}_A$ denotes the actual number of used connections, and P_{CR} represents the probability that $\mathcal{T}_R$ is above a certain threshold for a given connection.

Based on the above formulation, we can check the network failure rate and define the rate of decline ($R_{(\mathcal{L}_T)}$) for a given link as below.

$$R^0_{(\mathcal{L}_T)}(t) = \mathcal{L}^0_T \times e^{-\mathcal{P}^0_{CN}(t_0)} \tag{8}$$

$$R^1_{(\mathcal{L}_T)}(t) = \mathcal{L}^1_T \times e^{-\mathcal{P}^1_{CN}(t_1)} \tag{9}$$

Now, substituting the second equation with the first, we get

$$R^1_{(\mathcal{L}_T)}(t) = R^0_{(\mathcal{L}_T)}(t) \times e^{-\mathcal{P}^1_{CN}(t_1)} \tag{10}$$

This can be generalized as given below.

$$R^t_{(\mathcal{L}_T)}(t) = R^t_{(\mathcal{L}_T)}(t-1) \times e^{-\mathcal{P}^t_{CN}(t_t)} \tag{11}$$

The above defined conditions check the intermediate network states starting from $\mathcal{L}^0_T$

3.2. Energy Model

Let us consider that energy consumed by each transmitted bit is $\mathcal{E}_{bt}$ and the transmission speed for each link is $\mathcal{V}$ (bits/sec), then the energy consumed by each link ($\mathcal{E}_l$) is defined as below.

$$\mathcal{E}_l = \frac{|\mathcal{D}^*|(|\mathcal{D}^*|-1)}{2} \times \mathcal{V} \times \mathcal{E}_{bt}. \tag{12}$$

It is worth noting that the energy consumption for drones is discrete even though they depict continuous mobility pattern. Thus, for energy modelling, it should be handled individually for each occurrence. Let us say that the energy consumed by a drone to sustain its flight is given as $\mathcal{E}_f$, then at time t, the average energy consumption ($\mathcal{E}_c(t)$) is defined as below.

$$\mathcal{E}_c(t) = \mathcal{E}_f + \sum_{i=1}^{\mathcal{V}} (\mathcal{P}_{bp} \times t_t) + (\mathcal{P}_{fl} \times t_{fl}) + (\mathcal{P}_{cl} \times t_{fl}), \tag{13}$$

where, $\mathcal{P}_{bp}$, $\mathcal{P}_{fl}$, and $\mathcal{P}_{cl}$ represents the power consumed for processing each bit, flying, and transmission of control messages, respectively, t_t denotes the period for which a drone transmit each bit, and t_{fl} represents the time for which a drone flies or hover in the sky between two way-points.

Now, to check the energy consumption of the connections with its neighbouring drones, let us consider drones at two locations (i.e., l_i and l_j) to model the energy consumption. Thus the energy consumption ($\mathcal{E}_{i,j}$) to sustain the connection between i and j is defined below.

$$\mathcal{E}_{i,j} = \left[\mathcal{E}_{st} + \left(\mathcal{E}_{st} \times e^{-\mathcal{P}_{ds}(t)}\right) + \mathcal{P}_{ds}\left(\frac{f\,(l_i, l_j)}{v}\right)\right] \tag{14}$$

where, $\mathcal{E}_{st}$ represents the energy consumption to sustain required link state, $\mathcal{P}_{ds}$ denote the power rate between two locations, and v is the velocity of the drone.

Now, the below mentioned condition must be sustained to achieve energy-efficient transmission.

$$\mathcal{E}_{i,j} << \mathcal{E}_c(t) \tag{15}$$

3.3. Problem Formulation

The key objectives of this work revolves around QoS and energy efficiency. Thus, in order to sustain a link in drone-edge coalesce, the following two condition exists.

$$\Big(\mathcal{T}_R\Big)_L \geq \Big(\mathcal{T}_R\Big)_{minL} \tag{16}$$

$$\Big(\mathcal{E}_{i,j} + \mathcal{E}_c(t)\Big) \leq \mathcal{E}_{MAX}(t) \tag{17}$$

where, $\mathcal{E}_{MAX}(t)$ represents the maximum available energy for drone per charge. Based on these condition, we have defined the following objective function for link connectivity to sustain a flight.

$$max\Big(\mathcal{T}_R\Big) \tag{18}$$

Similarly, we have defined the following objective function for energy consumption required to sustain a flight.

$$min\Big(\mathcal{E}_{i,j} + \mathcal{E}_c(t)\Big) \tag{19}$$

Now, the above two objective functions are competing objective, So, combining both the objective functions, we get.

$$max\mathcal{X}_{ij}\Big[-\Big(\mathcal{E}_{i,j} + \mathcal{E}_c(t)\Big), \Big(\mathcal{T}_R\Big)\Big] \tag{20}$$

s.t.

$$\mathcal{P}_{CN} > THR \tag{21}$$

where, $\mathcal{X}_{ij}$ is the decision variable and THR is the threshold.

4. Proposed Energy-aware Data Transmission Approach

In this paper, we have proposed an energy-aware data transmission approach that reduces the unwanted energy consumption to provide a congestion and collision-free transmission control. This approach provides a balanced or optimal solution for QoS and energy sustainability for drone-edge coalesce. In this approach, we have been inspired by fire-fly optimization algorithm [55, 52] to establish a reliable connection among two drones. The proposed approach works in three phases, i) collision avoidance (criteria 1),

ii) congestion control (criteria 2), and iii) energy awareness (criteria 3). Algorithm 1 provides the flow of the proposed approach across these three phases.

In the first phase, the accurate positioning beacons are used to define the collision avoidance criteria. The average light intensity ($\mathcal{I}_{i,j}$) gained by tho drones flying at two different locations (let us say, loc i and loc j) is used define the collision avoidance criteria. Moreover, the level of attraction ($\mathcal{A}_i$) between these two drones from one's prospective is also important factor to define $\mathcal{I}_{i,j}$. Thus, $\mathcal{I}_{i,j}$ is represented below.

$$\mathcal{I}_{i,j} = \mathcal{A}_i(t) + \mathcal{A}_i(t_0)e^{-\Delta\theta^2}\,(C_i - C_j) + \rho, \tag{22}$$

where, the rate of change of current heading of a drone is given by Δ, the θ is used to represent the inverse probability of connectivity between drones, and ρ represents the density of all the drones in the neighborhood.

Due to the variation in the number of inter-connected drones, the value of ρ is unpredictable and keep on changing, so the $\mathcal{I}_{i,j}$ is computed for all the drones. The higher value of $\mathcal{I}_{i,j}$ may result in a collision so we operate the firefly optimization algorithm in a reverse pattern to avoid collision. Using $\mathcal{I}_{i,j}$, the proposed algorithm checks the possibilities of any collision based on the following condition.

$$\mathcal{I}_{i,j} \leq \mathcal{I}_{i,j}^{THR} \;\; \forall\; \mathcal{D}. \tag{23}$$

The above condition helps to achieve the following objective,

$$min\;(\mathcal{I}_{i,j}) \;\; \forall\; \mathcal{D}. \tag{24}$$

The criteria 1 is satisfied if the above condition is satisfied, otherwise it will end up in collision (line 8-14). If the criteria 1 is satisfied, we continue with same state (S_0), i.e., the initial state and check criteria 2. For this purpose, we define the congestion control criteria to coordinate the transmission. Let us say that the traffic rate among two drones is defined as $\mathcal{R}_{i,j}^{TR}$. Now, based on the incoming traffic, we use the intensity scheme to alter (increase or decrease) the congestion window (CW) to control the network congestion. The congestion control criteria operates on both the drones in a simultaneous manner and can be described as below.

$$\mathcal{C}_{i,j} = \mathcal{R}_{i,j}^{TR}(t) + \mathcal{R}_0^{TR}e^{-v\delta^2}\Delta L + \mathcal{C}_{CC} \tag{25}$$

where, $\mathcal{R}_0^{TR}$ is the initial traffic rate, δ denotes the path loss factor, ΔC represents that a connection exists between two drones and its value range lies between 0,1, and $\mathcal{C}_{CC}$ depicts the number of channels in the connected components (CC) in a network.

Based on the above discussion, a congestion free route depends on the following condition.

$$\mathcal{C}_{i,j} \leq \mathcal{C}_{i,j}^{THR} \tag{26}$$

The above defined condition is used to set up CW and thus the criteria 2 is satisfied (line 15-25). If the criteria 2 is satisfied, we check the final criteria 3. This is the most important criteria for the proposed scheme as it conserves the energy consumption. We define the following energy conservation based on the light intensity mechanism.

$$\mathcal{E}_{i,j} = \mathcal{E}_{MAX}(t) + \mathcal{E}_0(t)e^{-\mathcal{P}_{CN}\delta^2}\left(l_i - l_j\right) + \mathcal{C}_{CC} \tag{27}$$

where, $\mathcal{E}_0(t)$ depicts the energy consumption at S_0 at time t.

Now, to achieve an energy-aware or energy-efficient data transmission, the Eq. 16 must be satisfied. If the criteria 3 is satisfied, then CC are added to the route matrix (R[]), otherwise the CC are removed from R[] (line 27-35). After this, the data packet is transmitted over the selected congestion and collision-free and energy-efficient route (line 40).

5. Decision tree based Edge Selection, Allocation and Recovery Scheme

The data collected and transmitted by the drone is scheduled for processing and analysis at the edge nodes. Now, edge nodes are also resource constrained devices and thus their resources must be allocated using an optimal strategy. For this reason, we need to select an optimal edge node that can handle the data processing tasks in an efficient manner and provide desired QoS guarantee. There are many factors (like, edge state, current workload, available resources, QoS requirements, etc) that influence this decision making. To achieve an efficient edge node selection and scheduling, we have defined the following states for edge that exist during its lifetime.

The edge states depict the working condition of an edge node and these are described as below.

- **Normal State (ST_N)**: In this state, an edge node is running normally but it do not have enough resources to be allocated to another task or workload. This state can also be called as a perfect state.

Algorithm 1 Energy-aware Transmission Algorithm

Input: Initialize the drone network attributes
Output: Optimal transmission route

Initialize the networks to initial state == S_0
while (Transmission==continue) **do**
  Share beacons and find location
  i=1
  while $(i \leq |\mathcal{D}|) < parallel >$ **do**
    Calculate $\updownarrow_{i,j}^{(r)}$
    Input metrics from neighboring drones
    Check **criteria 1**
    if $(\mathcal{I}_{i,j} > \mathcal{I}_{i,j}^{(TH)})$ **then**
      Possibility of collision == TRUE
      Update incidence and adjacency matrices
    else
      Continue with S_0
      if Criteria 1 == satisfied **then**
        Check **criteria 2**
        Calculate $\mathcal{C}_{i,j}$
        Input metrics from D_{nb}
        if $(\mathcal{C}_{i,j} > \mathcal{C}_{i,j}^{THR})$ **then**
          CW = CW - 1
        else
          CW = CW + 1
        end if
      end if
      if criteria 2 == satisfied **then**
        Initialize traffic and set timing diagram
        Check timing diagram and available slots
        Check **criteria 3**
        Set energy metrics
        Calculate $\mathcal{E}_{i,j}$
        Calculate $\mathcal{E}_c(t)$
        Input metrics from all the channels
        if $(\left(\mathcal{E}_{i,j} + \mathcal{E}_c(t)\right) < \mathcal{E}_{MAX}(t)_{(TH)}$ **then**
          Add CC $\rightarrow$ R[]
        else
          Remove CC $\leftarrow$ R[]
        end if
      end if
    end if
    i=i+1
    Ready for transmission (R[])
  end while
end while=0

- **Active State (ST_A)**: In this state, an edge node is running and is neither overloaded nor in a failed state. Such an edge node is assumed to be is a condition to meet the QoS requirements concerning the data relayed from the drones for processing.

- **Backup State (ST_B)**: Some of the edge nodes are kept in this state to handle the failure or an overloaded condition of the active state edge nodes. If edge node is overloaded or in a failed state, the data being processed by that node is migrated to the nodes in the backup state.

- **Failure State (ST_F)**: In this state, an edge node fails and is not capable to performs its routine tasks. Such a node should be recovered using an suitable strategy. An edge node can fail due to overload or a fault or some attack.

- **Overloaded State (ST_O)**: This state is concerned with the edge nodes that are overloaded with the ongoing tasks and are not in a state to handle any additional workload. Also there may be a need to migrate some of the load from this node to move it into normal state. This state can fail if the workload is not migrated on time.

- **Transition State (ST_T)**: Here, a failed edge node migrates the data to another edge node selected from the backup edge nodes.

The proposed scheme is divided into two phases depicted using Algorithm 2 and Figure 3). The first phase is responsible for the entire workflow including edge selection, allocation and recovery scheme. The second phase is responsible for selection of optimal edge from the active edge nodes (ST_A) using a decision tree.

5.1. The Proposed Scheme [Phase 1]

The phase one includes three procedures, a) an edge state checking procedure, and b) an edge resource allocation procedure, and c) an edge recovery and allocation procedure. In the procedure 1, the algorithm checks the various states (ST_k, where k edge nodes are considered) defined in the previous sub-section based on a pre-defined threshold value (THR). Once the edge nodes are classified in to different states, then incoming workload (from drones) is allocated to the selected active state edge nodes. For this purpose, the procedure 2 is initiated. In this procedure, the resources required (R_{rq}) for handling drone tasks are checked alongside checking the resources available (R_{avl}) at edge nodes with ST_A. The appropriate edge node for allocation from all the active nodes is selected using Algorithm 2. The Algorithm 2 is based on decision tree and provides the edge nodes with positive or negative labels. The positive nodes are best match for the drone workload among all the active state edge nodes. So, R_{rq} are allocated from edge nodes having ST_A accordingly. In case, a suitable edge nodes having ST_A state is not available, then edge nodes having ST_B state is activated and resources are allocated from it.

Additionally, this scheme also keep a track of overloaded or failed states and migrate their workload to ensure the data generated by the edge nodes is processed on time and within the desired QoS limitations. For this purpose, the last procedure is adopted to recover from a situation when edge nodes are in ST_F or ST_O states. To overcome failure and overloading, the procedure 3 is used to edge nodes having ST_A state. In case, a suitable edge nodes having ST_A state is not available, then edge nodes having ST_B state is activated and resources are allocated from it. The working of the proposed scheme is shown in the Algorithm 2.

5.2. The Proposed Scheme [Phase 2]

The second phase is based on the decision tree approach. This approach constructs a tree-like structure during the classification of the edge nodes (objects) into various states. The internal nodes in the tree-like structure perform test on the objects, the leaf nodes on the tree serve the class labels and the different branches on the tree represents the features. To construct the tree, an algorithmic approach is used to divide the edge nodes into various categories by adding labels [16] and assigning the incoming data to them for further processing. In decision tree-based classification technique, the input from the edge nodes (like, edge state, current workload, available resources, etc) is provided to the decision tree as shown in Fig. 3. The Iterative Dichotomiser 3 (**ID3**) algorithm is used to build the decision tree. After this, a top to down greedy approach is used for decision node selection [31]. Initially, the all data is considered as root node. The incoming data is in the form of records $(\curvearrowleft, \mathbb{Y})$ i.e. $(\curvearrowleft, \mathbb{Y} = \curvearrowleft_1, \curvearrowleft_2, \curvearrowleft_3, ..., \curvearrowleft\daleth, \mathbb{Y})$, where $\curvearrowleft$ is the input vector to define the features of the data and $\mathbb{Y}$ is the expected value q after classification. To get the expected value, *Entropy* and *Information Gain* are used to partition the data set into similar feature subsets and selection of weightage features at various decision nodes respectively [41].

5.2.1. Entropy

In top-down approach, it is a required to partition the data into subsets with similar properties. Entropy is used to identify the similar properties instances in the data. If all the data is of similar nature, entropy is zero,

Algorithm 2 Proposed Algorithm

```
procedure CHECK−STATE(Procedure 1)
    for k==1, k<n, k++ do
        if (MODE == RUNNING) then
            if ($ST_k \leq$ THR) then
                STATE == ACTIVE ($ST_A$)
            else
                STATE == OVERLOADED ($ST_O$)
            end if
        else
            STATE == BACKUP ($ST_B$)
        end if
    end for
    ————————————————————————————————————————-
    procedure ALLOCATE−RESOURCES(Procedure 2)
        for i==1, i<n, i++ do
            CHECK == ($R_{rq}$)
            CHECK == ($R_{avl}$) → $ST_A$
            if $R_{rq} < R_{avl}$ then
                SELECT ($R_{RQ}$) ← $ST_A$ using Algorithm 2
                for Decision Tree NODE == POSITIVE → $ST_A$ do
                    ALLOCATE ($R_{RQ}$) → $ST_A$
                end for
            else
                ACTIVATE ($ST_B$)
                ALLOCATE ($R_{RQ}$) → $ST_B$
            end if
        end for
        ————————————————————————————————————————-
        procedure FAULT−RECOVERY(Procedure 3)
            for k==1, k<n, k++ do
                CHECK STATE using Procedure 1
                if STATE ∈ ($ST_A$, $ST_B$, $ST_N$) then
                    FOLLOW NORMAL PROCEDURE
                else if STATE ∈ ($ST_O$, $ST_F$) then
                    Send HELLO beacon
                    if NO RESPONSE then
                        STATE == FAILURE ($ST_F$)
                        CHECK == ($R_{all}$) → SCHEDULER
                        CHECK == ($R_{avl}$) → $ST_A$
                        if $R_{all} < R_{avl}$ then
                            SELECT ($R_{all}$) ← $ST_A$ using Algorithm 2
                            CHANGE STATE == ($ST_T$)
                            for Decision Tree NODE == POSITIVE → $ST_A$ do
                                ALLOCATE ($R_{all}$) → $ST_A$
                            end for
                        else
                            ACTIVATE ($ST_B$)
                            ALLOCATE ($R_{all}$) → $ST_B$
                        end if
                    end if
                end if
            end for
```

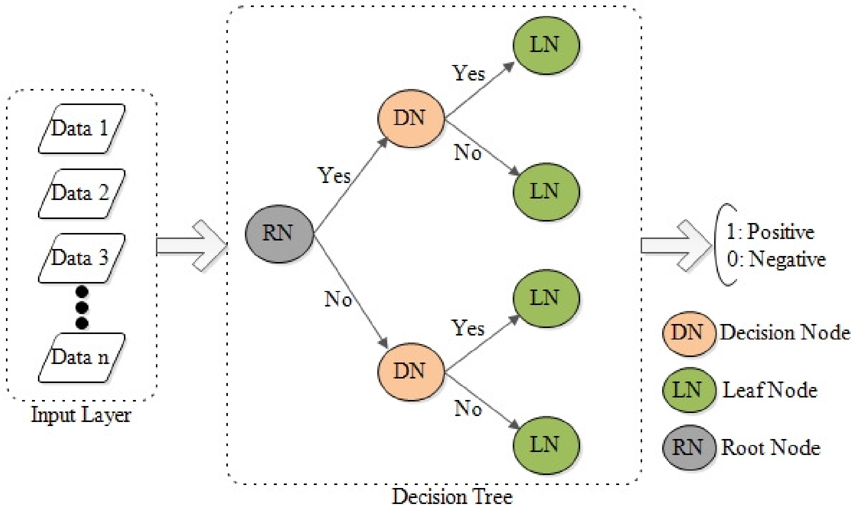

Figure 3: Decision tree classification

otherwise, data is divided into subsets and the calculated value of entropy is one. To calculate the entropy on single parameter and two parameter of the selected data, frequency table is required.

- Entropy on single parameter:

$$E(\mathbb{S}) = \sum_{i=0}^{c} -\mathbb{P}_i log_2 \mathbb{P}_i \tag{28}$$

- Entropy on two parameters:

$$E(\mathbb{X}_{\nVdash}, \mathbb{X}_{\nvDash}) = \sum_{c \in \mathbb{X}_2} \mathbb{P}(c) E(c) \tag{29}$$

where, S is the current state of the data, $\mathbb{P}_i$ is the probability of the i^{th} item in state S, $\mathbb{X}_1$ is the current state of the data and $\mathbb{X}_2$ is the selected parameters.

5.2.2. Information Gain

It analyse how effectively the selected parameter differentiate the incoming data. The parameter with the maximum information gain is selected as a decision node in the tree. Initially, the entropy of the target node is calculated using Eq. 28. In next phase, we divide the data according to the features or parameters. Then, we calculate the entropy of the next coming node and so on. After this, we add all the calculated entropy and subtract the calculated entropy value from the initially calculated entropy value as shown in Eq. 30

$$Gain(\mathbb{X}_1, \mathbb{X}_2) = E(\mathbb{X}_1) - E(\mathbb{X}_1, \mathbb{X}_2) \tag{30}$$

The parameter with the maximum information gain is opted as a decision node. The nodes with zero entropy are the leaf nodes and entropy more than zero require further splitting. The same approach is processed from top-down tree till all the data is categorized.

5.3. Training and Testing

The proposed approach works according to the following steps for training and testing of the classification model [44]:

- Initially, consider the input data as root node ($\mathfrak{R}$).
- Traverse each parameter of the dataset for Decision node selection.
- Calculate the **Entropy** of the selected parameter using Eq.29.
- Calculate the **Information Gain** of the selected parameter using Eq. 30.
- After traversing all parameters of the selected subset, selected the parameter with minimum entropy value and maximum information gain value.
- The above mentioned steps are iterated on each subset of the data, till the data is not classified.
- When, the tree is classified with proper decision nodes, test the data to check the accuracy of the trained model.

6. Results and Discussion

This section covers the evaluation of the proposed work in a simulated environment. The results obtained and discussions are provided to prove the effectiveness of the proposed work. For network modelling, we have selected the standard metrics irrespective of their application domain. As there are limited options for drone simulations, so we have performed our simulations using Network Simulator (NS-2). The simulation configurations and settings are provided in Table 1.

Table 1: Parameter Configurations

Parameter	**Value**	**Description**
Area	3000x3000 sq. m.	Area under evaluations
Maximum speed	60 Kmph	Maximum speed of drones
h	100 - 300 feet	Height
E_{MAX}	3000 J	Energy per charge
$\mathcal{P}$	30 dBm	Transmission power
$\|\mathcal{D}\|$	5-25	Number of drones
$\|\mathcal{U}\|$	100-300	Number of users
N	-174 dBm/Hz	Noise power spectral density factor
ρ	2-25	Density of drone in its neighbour
$\mathcal{T}_R$	256 kbps	Transmission rate
$\mathcal{K}$	-11dB	Antenna characteristics
δ	4	Path loss factor
t_t	1000s	Time for which a drone transmits
v	10-40 mps	Velocity
$\mathcal{C}_{CC}$	1-3	Number of connected channels
$\mathcal{E}_{st}$	1-2 J	Required link state energy
Δ	0.1	Rate of change of current heading
Simulation Time	1000s	Operational time
Agent	TCP New Reno	TCP agent between nodes
Pause time for $\|\mathcal{D}\|$	0	Halts for drones
Pause time for $\|\mathcal{U}\|$	2-5s	Halts for users
Routing Agent	Link state	Routing strategy
RTS, CTS, ACK	170, 120, 120 bits	Packet lengths

We perform simulated experiments according to the above mentioned settings and gather results in rems of energy conservation, packet delivery ratio (PDR), average network throughput, and average end-to-end delay. First, we discuss the energy conservation achieved due to the proposed scheme with respect to the probability of connectivity. Figs. 4 shows the energy conservation with an increase in the probability of connectivity. It is visible that with an increase in the probability of connectivity (maximum transmission rate), in ideal conditions up to 1, the energy conservation decrease but the proposed scheme sustains this decrease to a slight level. This means that the energy conservation achieved is higher disregarding all sort of drone operations.

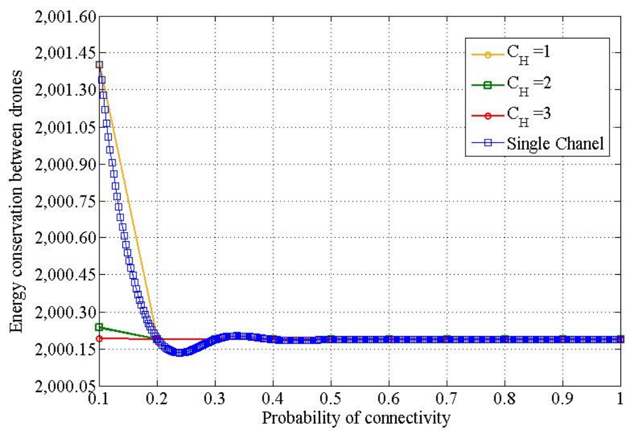

Figure 4: Variation of energy with respect to the probability of connectivity.

The results obtained depict that the proposed work helps to manage a higher PDR even with an increase in the number of users pertaining to the drones. Fig. 5 shows the variations with respect to an increase in the number of drones (5 to 25) and number of users (100-300). Is is evident that for each case of drones, the PDR decreases with an increase in the number of users but this variations remains between 3.8% to 84%. The PDR ranged between 85% to 99.5%. This shows a significant performance with respect to the proposed drone-edge coalesce.

Now, the next important QoS metric is related to the maximum utilization of resources with an increase in the transmission rate (average). The network throughput increases when the transmission rate is closer to the maximum permissible rate. But, thee is another factor that impacts the throughput, i.e., the number of users. An increase in the number of users can end up in a significant drop in the throughput. Fig. 6 shows the average network throughput achieved with the proposed work considering an increase

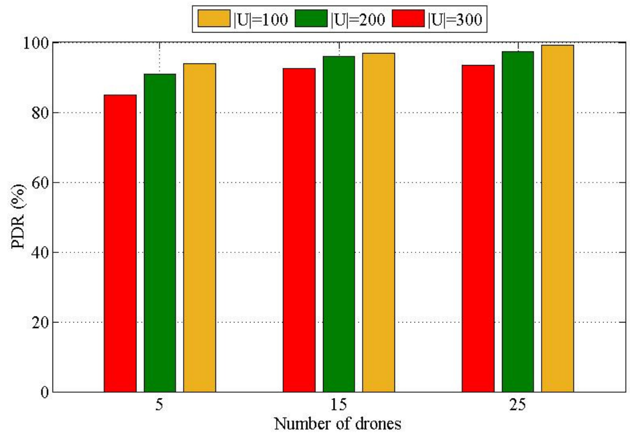

Figure 5: PDR

in the number of drone as well as the number of users. It is visible that the proposed work helps to sustain the throughput (maximum at a value of 31.5 Mbps) at a high value even with a variation of users from 100 to 300.

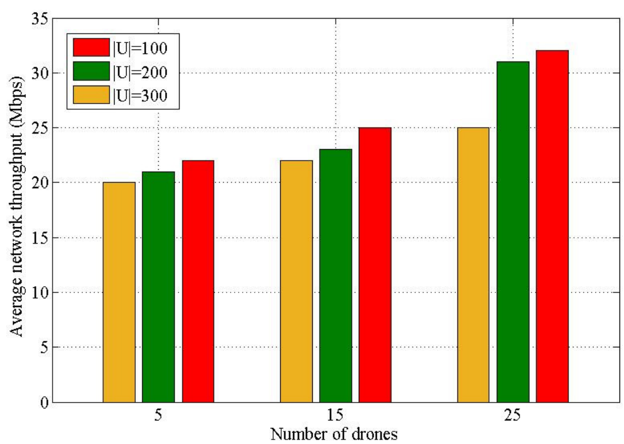

Figure 6: Average network throughput

Finally, we look into the most important metric in the drone-edge coalesce, i.e., end-to-end delay. Fig. 7 shows the average end-to-end delay witnessed in the experiments with respect to an increase in the number of drones as well as users. It is visible that the average end-to-end delay ranged between 12.00 ms (highest) to 2.50 ms (lowest). The delay is seen to be lower with an increase in the number of drones serving the users in contrast to a lower number of drones.

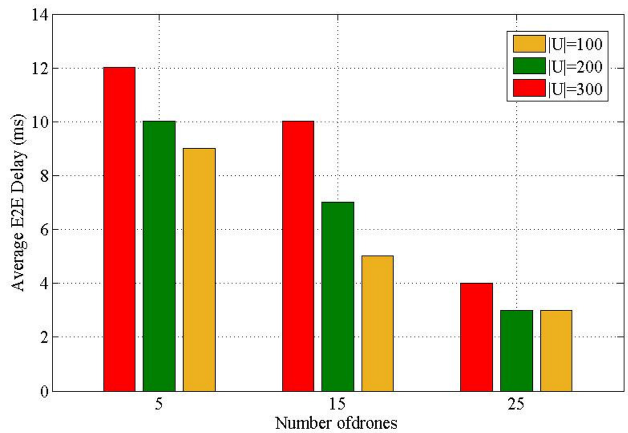

Figure 7: Average end to end delay

Table 2: Simulation results for observed delay.

$\|\mathcal{D}\|$	$\|\mathcal{U}\|$	**Message exchanged**	**Observed Average Delay (s)**	**Netweork sustaining time (s)**
	100	148	0.0112	995.54
5	200	201	0.0119	995.90
	300	251	0.0126	996.26
	100	187	0.0105	996.28
15	200	219	0.0110	996.31
	300	265	0.0115	996.34
	100	393	0.0050	996.89
25	200	407	0.0055	997.29
	300	451	0.0060	997.69

Apart from the above results, we have provided some information on the average number of messages exchanged drones and the ground nodes. Here, we try to understand the average delay that was observed during the exchange of these messages. Table 2 depicts that the obtained results show a minimal fluctuations even with a considerable effect of the number of drones.

7. Conclusion

In this work, we have envisioned a drone-edge coalesce wherein the drones are deployed to provide services to the end users and the edge act as data processors for all the requests. There are several challenges related to this coalesce regarding the drone networks and edge selection. In context of the drone communications, the key challenges handled in this work are related to the congestion control and collision avoidance. Over the top of this, we have tried to provide a energy-aware data transmission in the proposed setup. Secondly, we have utilized a decision tree mechanism to select an optimal edge node for data processing. The proposed work was validated using a simulated environment. The results obtained depict the effectiveness of the work with respect to several performance metrics, like, energy conservation, packet delivery rate, average network throughput, average end-to-end delay. The results obtained look promising and prove the effectiveness of the work.

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