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An Optimal Energy Competent Mission based Collision Avoidance Protocol Scheme for Multi-Rotor UAV's

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***Abstract*—Currently, with the advancement of computer control technology, unmanned aerial vehicles (UAVs) have developed greatly. In contrast to the remote manipulation used in the early stages, most UAVs can now fly autonomously. As the number of potential applications for Unmanned Aerial Vehicles (UAVs) keeps rising steadily, the chances that these devices get close to each other during their flights also increases, causing concerns regarding potential collisions. To solve the problem of intercepting a moving target by a multirotor unmanned aerial vehicle (UAV) swarm, an optimal strategy along with clustering strategy is proposed. This paper proposed the Energy Competent-Mission Based Collision Avoidance Protocol (EC-MBCAP) using Adaptive whale optimization approach. The clustering technique is carried using Gradient clustering metric based passive clustering method (GCM-PC). This optimization process is employed so as to enhance and optimize the energy in collision avoidance protocol. Experimental and simulation results demonstrated the validity and effectiveness of the proposed solution, which typically reduces the energy consumption and in turn optimizes the protocol efficiency thereby reducing the collision for each risky situation successfully handled.**

***Index Terms*— unmanned aerial vehicles, multirotor, Energy Competent-Mission Based Collision Avoidance Protocol, Gradient clustering metric based passive clustering method, Adaptive whale optimization.**

I. INTRODUCTION

With an increasing Unmanned Aerial Vehicles (UAVs) that were elevated over our heads, there is a growing necessitate for safety, coordination, information sharing, and communication between these strategies so as to subsist a sensible option for a range of application that covers rescue and search, military, patrolling, and delivery of goods. Based on IEEE 802.11, Wireless sensor network is systematized in two common categories. The first one is the Infrastructure network which handles a number of trust dependent stationary or immobile nodes. In these networks, one peculiar node is in center called as access point and through it data transmission within or outward network is done. The second is Infrastructure-less or ad-hoc network which is similar to infrastructure except without having a centralized authority (i.e.) there is no need of access point. The nodes in these networks are free to move anywhere as desired within the constrained transmission range. The increasing current in the small commercial Unmanned Aerial Systems (UAS) availability has led to the growth of several

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different applications [1-3]. These applications expand to the many different types of UAVs development, together fixed wing and multirotor platform, for the aerial monitoring purpose, image processing, and object detection. Significant investigate has been conducted on platforms of aerial robotic in addition to increasing the operations area for these small-scale UAVs intended for remote sensing [3-5]. One such application is employing the detection of target and image processing for the location of an air samples target source. UAVs Research on path design, planning and remote sensing is a dynamic research field [6, 7].

The main intention of this work is to avoid collision in multi-rotor UAVs with the use of an effective optimization and energy competent approach.

The remaining sections of the proposed study are illustrated as follows: section II deals with related works. The specific and several phases of the proposed methodology are briefly explained in section III. Experimental results are furnished in section IV. Finally, the conclusion of the proposed research study is given in section V.

II. RELATED WORKS

[8] recognized the optimal route on taking into account the UAVs with superior stability and residual energy in the network of 5G so as to augment lifetime of network, and decrease consumption of energy and the number of broken relations.

[9] suggested a multiple UAVs that were permitted for communication accordingly that an ad-hoc network was being recognized among them. The entire UAVs in the network in turn carry communication from UAV-to-UAV and only the UAVs groups relate the ground station. This feature in turn eliminates the deployment of complex hardware wants every UAV. Furthermore, through the UAV communication that relates breaks down; there is no breakage of link by the base station because of ad-hoc network among UAVs.

[10] supported the employment of information movement and a level of residual energy with every UAV so as to assure a communication stability highly on the prediction of a rapid breakage of link before their incidence. A strong process of route discovery was employed for the exploration of routing paths at which the balanced consumption of energy, the prediction of link breakage, and a connectivity paths degree exposed were estimated.

[11] study how UAVs operating in ad hoc mode can cooperate with VANET on the ground so as to assist in the routing process and improve the reliability of the data delivery by bridging the communication gap whenever it is possible. In a previous work, we have proposed UVAR – a UAV-Assisted VANETs routing protocol, which improves data routing and connectivity of the UAVs on the ground through the use of UAVs.

[12] proposed a lot of routing protocols for Vehicular Adhoc Networks' (VANETs) through taking into account their specific distinctiveness. The protocols depending on the positions of vehicles', termed protocols of geographic routing (GR) or position-based routing protocols *(PBR)*, were exposed to be most sufficient to the VANETs because of their strength in managing the active atmosphere change and high mobility of the vehicles. In place of using IP addresses, the same as in the case of Mobile Ah hoc Networks (MANETs) protocols, routing protocols based on position depends on the environmental vehicles position once choosing the best path to transmit the data.

[13] implemented a methodology of hybrid design, where features of reactive routing (AODV) with geographic routing and proactive routing protocol syndicated. Adaptive Hybrid Routing Protocol (AHR), vehicles employ proactive routing protocol for reactive routing protocol and V2I communication by geographic routing protocol for V2V communication. The systems integrate of both reactive and geographic routing protocols features with schemes of proactive routing.

[14] reviewed propagation models, mobility, and positioning that were presented for FANETs in the correlated technical literature. A general restriction that influences these three topic is be short of studies that estimates the manipulation that an unmanned aerial vehicles (UAV) might have the communication devices that were embedded /on-board, typically assuming omnidirectional or isotropic emission pattern presently.

[15] presented a complete of position-based routing protocols evaluation for FANETs by their different categories. a taxonomy classification of these protocols, that covers a thorough routing schemes description employed in all kind. We suggested a relative review depending on a range of criterion, and present the weaknesses and advantages of all protocol.

[16] projected a strategy of optimal link that is self-sufficient of arrival time of message and be capable of executing in a dispersed manner. After that, the expected path delay is derived by considering delay components dependence alongside the path, and proposes the strategy of optimal routing for the minimization of estimated path delay. The simulations on Trace-driven has been employed for the validation of thorough analysis, and demonstrate the better proposed strategies performance that outcome in a considerable reduction of delay and greatly a high delivery ratio on comparing with existing solutions devoid of drop boxes.

[17] developed three separate techniques for the computation of fractal dimension. Tiles with targets were related to others from same textures of background devoid of targets. The dissimilar dimension of fractal feature approaches were being regarding how well they might be employed for the detection of targets vs. false alarms in the similar context.
[18] presented a new model of spatiotemporal saliency to deal with the moving infrared dim target recognition issue. As per the solution of closed form attained from the feature reconstruction regularization, an adaptive local function was presented at which the estimation of temporal saliency map and the spatial saliency map was made on the temporal domain and the spatial domain.
[19] developed a method of automatic processing that allows an effective detection of target by high sensitivity throughout the varying acoustic forms. The technique depends on scale-dependent adaptive filtering of information and analysis of short-scale backscatter contributions in a morphological manner for the extreme unstable exclusion of features and biological targets separation. The platform of Echo sounder deployments just about the infrastructure of marine energy in a tidal control offers test data that exhibit the proposed approach effectiveness.
[20] considered an effectual approach of small-target detection depending on the biased image entropy. The approach weights the measure of local entropy through the multistage grayscale distinction followed by an adaptive operation of threshold that intends at enhancing the SNR for cases at which jamming items in the prospect contain thermal intensity measure comparable regarding the environment as small target.

III. Proposed Work

This section is the detailed depiction of overall working of the proposed scheme.
The Unmanned Aerial Vehicles (UAV) is indispensable for various applications where human intervention is impossible, risky or expensive e.g., hazardous material recovery, traffic monitoring, disaster relief support etc. Recently, the applications of unmanned aerial vehicles are diverse, ranging from search and rescue, reconnaissance and surveillance. Therefore, it has been very much desired to avoid collision in Multi-rotor UAV's, preferably without using expensive aiding systems.

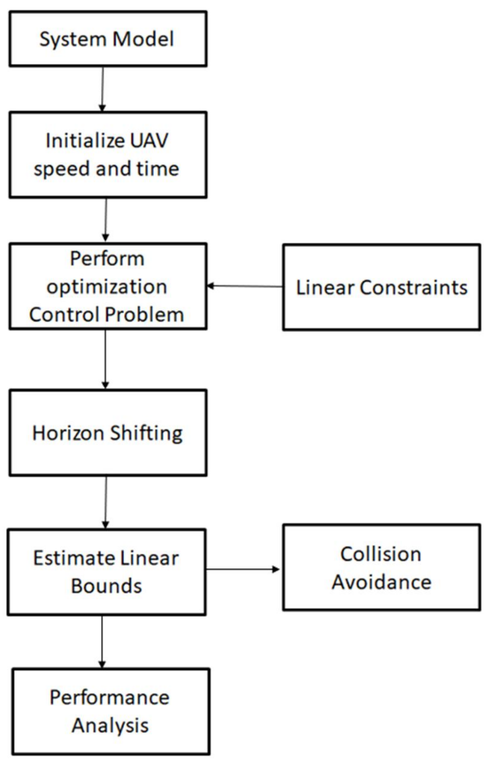

Figure 1 Flow of the proposed system

A. System Model

Initially, the system model is being initialized by initializing the parameters employed in the communication process of the network. The parameters like number of nodes, number of UAV's, energy constraints, number of rotors, movement speed, communication radius, and number of packets were considered. Thus, the initialized parameters were taken for the process of communication.

B. Prediction of Geographic Location and path availability for multi-rotor UAV's

Initially, the geographic locations of the nodes employed in the network should be identified by setting a limit/range. The nodes within that specified range are assigned with their respective base station accordingly. For e.g., the limit of user is set as 100 in a specific range, then the users within this area are grouped and were connected to their respective base station and the communication will be taken place among these nodes. In the proposed mechanism geographic location identification is segregated by three stages. At first, the spatial correlation among the node is identified with the use of Euclidian distance metric. Then, the predictions of neighboring nodes are carried out. In the next stage, temporal correlation among two nodes will be estimated within the primary user's coverage criteria. The third stage is the prediction of common idle channels. After that, the confidence level regarding the idle channel sensing is estimated thereby broadcasting the information of channel to the cluster head. At last, the residual energy is being updated to check the energy efficiency of routing and communication system.

C. Perform Energy competent optimization control problem using Adaptive Whale Optimization based passive clustering Algorithm

The better path of selecting a route is usually to predict traffic between the source and the destination points in network routing. The direction of a low traffic density is favored for optimum route choice, as a high traffic density increases the flow of vehicles on the road. An active prediction method is necessary to choose the best path. Route exploration is the central process in the current implemented optimization method. The optimization algorithm finds the right route, from source to destination, which meets the entire considered multiple limitations. For optimizing multipath, an algorithm can be used to provide reliable data delivery. During the route selection, the data transfer to the destination can be postponed if the nodes are not energy efficient and overloaded because of high traffic. In network, the vehicle nodes can only travel along fixed paths due to some constraints on the roads and streets.

The Whale Optimization Algorithm (WOA) is a new optimization technique to solve optimization problems. The Whale Optimization Algorithm consists of three operators to simulate the search for prey, encircling prey, and bubble-net foraging behavior of humpback whales to reduce the clusters and also achieves the reduced end-to-end delays. Road Side Units (RSU) will allow the planners to deploy effective communication without any link breakage. The QoS in the network is measured using various parameters like end-end delay, energy consumption, packet loss, and throughput.

Initially, clustering the vehicles are non-linearly set into motion through the fitness value of own and their neighbors thus emulate effective neighbors by attaining the optimal path between the vehicles. The clustering of vehicles uses for continuous herds or each vehicle can belong to a single global flock. Clustering begins with gathering arbitrary particles to enhance the cluster stability as well as to reduce the cluster regeneration timing. The wireless-enabled vehicle nodes get clustering according to the encircling prey, Let the optimal path for clustering the vehicle nodes considered as,

$$\vec{V} = \left|\vec{D}.w^{better}(t) - w(t)\right| \quad (1)$$

$$w(t+1) = w^{better}(t) - \vec{B}.\vec{V} \quad (2)$$

Where, V as vehicle nodes

t as time is taken during clustering

w (t+1) as optimal path

When a source node needs to send packets to a destination node with no routes to the destination node in its routing table, the route discovery phase will be started. The source node broadcasts a Route Request (RREQ) packet to its neighbors. The neighbors that receive the RREQ packet are divided into three categories: the receiver node is the destination node, the receiver node has a route to the destination, and none of both. In this situation, the receiver node forwards the RREQ packet to its neighbors until the destination node receives the RREQ packet or a node has a route to the destination node, and the process repeats with the reduced overhead problem.

To achieved the optimal routing path, the constant number of clusters in a vehicle node gets enabled for AODV protocol improvement. For the Trust-based routing path by making the cluster creation, a Trust-based rule manager never considered for the clustering process, and all vehicle nodes imagined as trust nodes. Moreover, the routing processes enable each trust-based vehicle nodes. The large differences in speed of any two vehicles may result in short link-time taken and the links are break easily. Based on the previous knowledge, we will illustrate our proposed AODV protocol in detail in the following as trust-based route calculation, link breakage among the vehicles, and the threshold assignment according to the vehicle nodes in the wireless network.

Now, the trust-based routing enables through the threshold assignment among the vehicle nodes with the optimal path estimation. The Threshold assignment depends on the residual energy mean value and overall Trust based score mean value for each vehicular nodes. By using the overall trust scores to find the mean trust-based score value for each vehicular node

$$TM_i = \frac{\left(\frac{TS_i + \sum_{j=1}^{n} TN_i}{n-1}\right)}{n},\ j! = i \qquad (3)$$

Where,

TM_i = Trust Mean value (i_{th} node).

TS_i = Summation of trust scores

TN_j = Trust Value of the Neighbor,

n = Number of nodes in the network

Threshold value that helps for routing path calculation, i.e., Mean value >Threshold to participate The DV for vehicular nodes selection through the formula as,

$$\text{Decision value}_i = \frac{(W1*TM+W2*RE*W3*(\frac{1}{D}))}{(W1+W2+W3+} \qquad (4)$$

Where TM > Threshold

RE is residual energy

D is Distance from the neighbor vehicle nodes

The threshold values assigned to the vehicle nodes and stable to enable the trust-based calculation over the neighbor nodes without any link breakage. The trust-based calculation among the vehicle nodes used to find the Trust based score for each vehicle nodes considering the two limitations.

1. The vehicle nodes are sending an ACK to neighbor vehicle nodes when it receives the packets.
2. The vehicle nodes that drop more packets.

$$TSC_{i1} = \left(\frac{ACK}{RP}\right) * 100 \qquad (5)$$

Where TSC_i = The percentage of the initial trust-based score for the i_{th} node. ACK = Acknowledgements sent to the nearby vehicle nodes. RP = Total number of received packets.

$$TSC_{i2} = 100 - \left(\left(\frac{DP}{TDP}\right) * 100\right) \qquad (6)$$

Where, DP = Dropped packets, TDP = Overall dropped packets.

$$TSC_i = \frac{(TSC_{i1} + TSC_{i2})}{2} \qquad (7)$$

After trust-based score evaluation, the Cluster Head Selection will do for the effective nest preparation over the nodes. The selection of Cluster Head algorithm to calculate the high residual energy optimization and Trust-based score values, but with the reduced distance from all participated vehicular nodes for distance evaluation. The distance of the vehicle nodes as,

$$D_i = |avg\ dist\ of\ nodes\ (v1) - \max dist\ of\ nodes| \qquad (8)$$

Where, D_i as the average distance of vehicle nodes

The traffic system on each vehicle reduced and the average distance helps to enable the Cluster Head (CH) Selection. The sum of distance in each vehicle between the sensor nodes enables the efficient CH selection to predict the path and less-cost system.

The sum of distance among the vehicle nodes provides the necessary information for the adaptive feasible communication that used for finding the sensor node distance. The sensor node distance is,

$$S_i = \frac{Number\ of\ sensor_j}{Maximum\ sensors\ used_j} \qquad (9)$$

The sensor nodes help to establish the optimal position of the vehicle using the vehicle's sensor and to enable the AODV protocol gets improved based on the least traffic occurrence and energy efficiently. The area of the best hunt used to estimate the clustering enabled CH selection with the updating of adjusting the proximate distance over the vehicle nodes. The fitness value calculated by using the formula as,

$$\text{Fitness} = \{\text{Max\_stability of cluster}\} \qquad (9)$$

The fitness value helps to improve the channel capacity among the vehicle nodes. An Adaptive Whale Optimization aim is to maximize the channel capacity with minimum time by selecting the suitable requirements of radar sensing and communication and the equation as follows,

$$CC = \max_{cc} \frac{N_c\,(T_g|+T) f * M * S_c}{T} * \log_2(1 + \frac{\delta TP}{N_0 . S_c}) \qquad (10)$$

Where,
N_c as spacing of subcarrier nodes
S_c as number of subcarrier nodes
T_g as yclic prefix
f as frequency among the vehicle nodes
Here, the Whale Optimization Algorithm Encircling prey, Bubble net attacking model used to enable the shortest path among the vehicle nodes, without any traffic, improved data loss, the shortest path to be estimated.

Encircling prey

Humpback whale encompasses the prey (little fishes) by then revives its situation towards the optimal course of action all through extending the number of iteration from starting to the best number of iteration; it is depicted by

$$I = \lfloor \vec{x}.\vec{b}(t) - \vec{b}x(t) \rfloor \qquad (11)$$

$$b(t+1) = b^{better}(t) - H.\ x\,\vec{1} \qquad (12)$$

where, t as recent CH selection
H, x as coefficient vectors
$\vec{b}(t)$ as better CH selection arrangements with respect to the position of vectors.
$x\,\vec{1} = 2x\bar{2}.\vec{s}$ and
$x = \bar{2}.r$
where x2→ randomly decreased from 2 to 0 throughout iterations r→ is a non-linear vector in (0, 1).

Bubble net attacking model

In UAV's clustering model, updating the new CH values is done by two steps.

a. Shrinking encircling mechanism
b. Spiral updating position

Both the methods are used to enable the better CH selection with the accordance of UAV's nodes. The position of humpback whales seem haphazard as indicated by the position of each other for optimal shortest path estimation as given below:

$$\vec{N} = |x.\,c_{rand} - \vec{c}| \qquad (13)$$

$$C(t+1) = c_{rand} - y1.\vec{H}\ ]\text{correlation} \qquad (14)$$

This process is employed by decreasing linearly the value of y2 from 0 to 2; the random value of vector k1 ranges between −1 and 1.

The correction factor makes the whales move in small steps towards the prey to explore the search space efficiently for better and efficient shortest path selection. The UAV's reliability is maintained in a cluster-based CH and cluster member. The cluster members send messages to the optimal CH to ensure it is still within the cluster to investigate the development of the UAV's. If the CH selection never responds or the CMs identify that the CH has abnormal behavior, the clustering system is propelled between a group of individuals as per the beforehand characterized CH decision process. Then, to find the trust-based degree of UAV's nodes with the respective shortest path equation based on the RSU system as,

$$D_{RSU\text{-}U} = \sqrt[2]{(U_{RSU} - U_i) + (V_{RSU} - P_t)^2} \qquad (15)$$

The proposed algorithm considers the trust aware score values, distance, and residual energy for the unique routing path, which is optimum. The limitation of CH is that the speed and mobility < average mobility speed of all the vehicular nodes. Finally, the UAV's communication established the efficient routing path with the improvements and modification on AODV protocol according to the UAV's stability and the primary and essential parameters such as energy consumption, delay time reduction, and the least traffic also attained.

D. Congested path prediction to avoid collision in Multi-rotor UAV's using GCM-PC

Clustering is an effective technique for an ad hoc network partitioning through grouping the geographically adjacent nodes into clusters dynamically. The mechanism of clustering offers a competent allocation of radio resources, energy and location management, and routing and backbone formation and is an effective method for scalability issues tackling relevant to the networking domain of networking.

Networks have implemented several clustering algorithms. Passive clustering is one such algorithm. It is a mechanical cluster formation that adapts effectively in mobile ad hoc networks, where resources (such as electricity, bandwidth) are limited, to dynamic topology changes. Passive clustering uses outgoing data packets to build and manage clusters rather than unique control packets. In other words, it offers an effective way to passively partition an ad hoc network into multiple clusters. Passive piggyback clustering eliminates the overhead of explicit control packets through the control knowledge in the out coming data packet. Any node can read piggybacked data through promiscuous receiving packets and can determine their position in a cluster.

The predicted congestion never specifies the actual coordinates also for the congestion time. For congested path identification, the passive Clustering-based Congested Path Detection Algorithm (CCPDA) to be used by estimating linear bounds. This algorithm detects congestion due to traffic, location, and congestion time.

For path clustering, path algorithm enables one to cluster the path. The algorithm performs the longitudinal paths clustering, and it follows 3 steps. Firstly, it describes the features. Secondly, to select a subset of data through the factor analysis. Finally, the performance of cluster evaluation to find the cluster path and allocate each cluster in all ways. The path clustering method consists of path range, SD, Mean change/time.

The path distance calculated through the Harvesine formula such as, For any two points of UAV's, the central angle among the two UAV's as,

$$\theta = \text{hav}(\phi 1 - \phi 2) + \cos(\boldsymbol{\phi} 1) + \cos(\boldsymbol{\phi} 2)\text{hav}(\lambda 1 - \lambda 2) \quad (16)$$

Where θ referred to as Harvesine function (θ):

$$\theta = \sin^2\left(\frac{\theta}{2}\right) = \frac{1-\cos(\theta)}{2} \quad (17)$$

After the distance of each path to be found through the Havesine formula to calculate the distance and path traveling time. The time to travel the path distance and the time estimation as,

$$t = t_i - t_{i-1} \quad (18)$$

The formula for cluster speed and path for least congestion of traffic path that can be found using below as;

$$S = \frac{d}{t} \quad (19)$$

By considering each cluster paths, the average speed/cluster computed by using;

$$Cs = \frac{T_S}{n} \quad (20)$$

The congestion depends on the threshold value with its bandwidth, and residual energy If the averages speed of a cluster < the speed of the threshold, it attain less than 1 km/h and the time is important than a threshold time. The duration of stopping congestion event < the threshold duration, which is not congestion, it has a stoppage of traffic. If cluster speed < 1 km/h and the event duration > threshold duration, the UAV's to stop for while a time, then that are locked. If stoppage duration ≥ threshold duration, which is not a traffic stoppage or passengers to be picked, which is a congestion occurrence. The results of congested events performance conducted in terms of the positions like longitudinal and latitude of time occurrence.

IV. Performance Analysis

The overall success of the proposed approach will, therefore, be measured in this portion. The findings and the feasibility of the suggested approach are measured and contrasted with methodologies by the following measurement criteria.

A. Time overhead

Time overhead: The time taken by number of generated packets by the data volume is sent to the destination.

Figure 2 is the representation of time overhead performance analysis. The time overhead is estimated in terms of UAV speed.

B. Throughput

The volume of data transmitted successfully throughout the communication cycle

Throughput = (Received packets *packet size)/simulation time (21)

Figure 3 shows that, the suggested Protocol achieves a higher throughput rate. The shortest path can be identified quickly before the data passes through the route. Figure 4 is the representation of throughput in terms of time overhead.

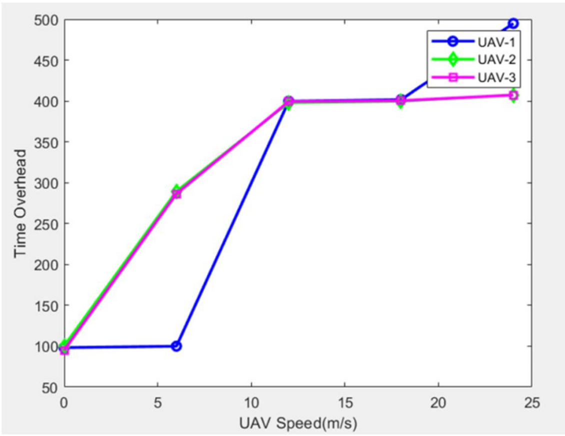

Figure 2 Time overhead performance analysis

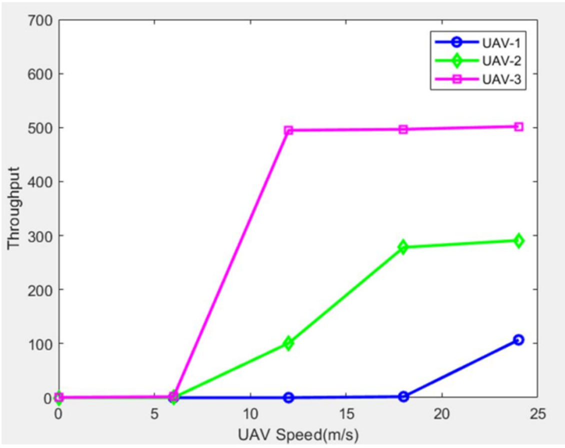

Figure 3 Performance analysis of throughput

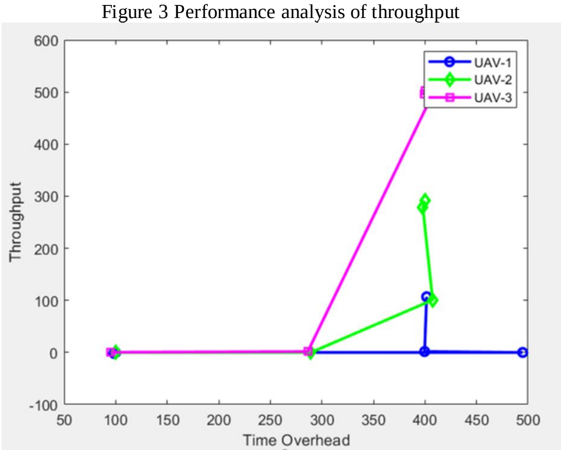

Figure 4 performance analysis of throughput in terms of time overhead

C. Delay performance

That's the length of the transmission process, regardless of the amount of time it takes to transmit the signals.

$$AD = (Ps-Pr) / Pr \tag{22}$$

Here Ps is the time taken to the sent packet, and Pr is the overall time consumed.

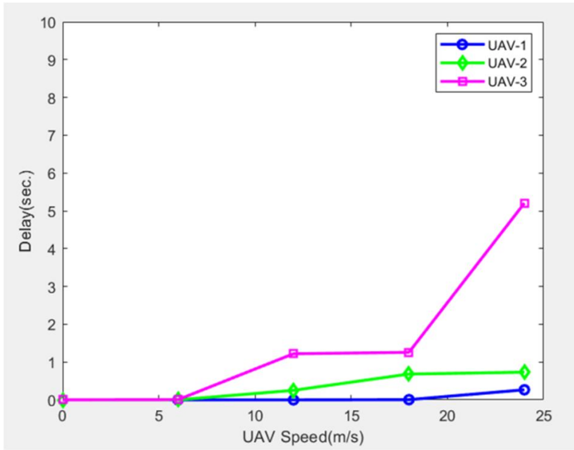

Figure 5 Performance analysis of delay

Figure 5 reveals that the end-to-end latency of the suggested Protocol is shorter than the other Protocol. This technique prevents overcrowding. Due to the complexity, crowding of a huge number of nodes adds to the difference in the dissemination of information. And even though the link is broken, the data can be returned to the source again, and the new route can be found, and the cycle can be recovered. But as a result, the short route and the breakdown of the link were noticed here in the solution before the loop began. Therefore, the time difference here has been removed.

V. Conclusion

In this approach, an optimal strategy along with clustering is proposed. This paper proposed the Energy Competent-Mission Based Collision Avoidance Protocol (EC-MBCAP) with the use of Adaptive whale optimization approach. Gradient clustering metric based passive clustering method (GCM-PC) was employed. To enhance and optimize the energy in collision avoidance protocol, this optimization technique was carried out. Simulation Outcomes illustrates the validity and effectiveness of the presented approach that in turn reduces the energy consumption thereby optimizes the protocol efficiency and thus reducing the collision in multi-rotor UAV's.

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