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Multi-objective Optimization in Satellite-Assisted UAVs

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Abstract

Nowadays, Vehicular communication is used in intelligent transmission applications. The number of vehicles used in a particular region has numerously increased energy consumption, computation delay, and computation overhead. In this paper, Multi-Objective Optimization in Satellite Assisted UAVs (MO-SAUVs) is proposed under an improved Ant Colony Optimization (IACO) algorithm. The procedures that are considered for the process of MO are optimal logistics distribution, path prediction-based pheromone deposition, and evaporation. Using this method, effective region selection for the UAVs is performed which leads to improving the network energy efficiency by decreasing energy consumption and delay. The simulation is performed in NS2 and the proposed MO-SAUAVs method is compared with the TA-SAUAVs method and PL-SAUAVs method according to different parameters. The results show that the proposed MO-SAUAVs method achieves lower computation delay (70ms to 110ms), higher energy efficiency (6% to 16%), lower energy consumption (7% to 14%), and packets lower computation overhead (500 packets to 700) when we were compared with TA-SAUAVs and PL-SAUAVs.

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Keywords: Unmanned Aerial Vehicles (UAVs); Vehicular communication; Ant Colony Optimization (ACO); Multi-objective Optimization

1. Introduction

Nowadays, vehicular communication is applied in intelligent Transportation (IT) Systems. A huge number of vehicles that are interconnected together makes it difficult to control and monitor the network. Through the time of vehicle-to-vehicle transmission ground-level obstacles and interference are so high and infrastructure-based communication performance is not satisfied [1-3]. In both this kind of communication energy consumption, computation delay, and computation overhead more directly affect the energy efficiency network [4-22]. To overcome these drawbacks UAVs are introduced in vehicular communication. Through UAVs, ground-level threads are managed, and a UAVs-based network is used in several applications. Therefore, it is cost-effective, highly secure to capture confidential data, and used for disaster management [6-8]. Further development satellite-assisted UAVs are used so that the coverage area of the UAVs is increased which leads to the reduction of UAVs count to monitor the entire network [9]. Therefore, it is very essential to place the drone's coverage area properly to get quick access to the communication between the vehicles. In this paper, Multi-objective Optimization is presented with the help of an improved Ant Colony Optimization (ACO) process. The main objectives in the paper are:

- Satellite Assisted UAVs in Vehicular Communication are proposed to reduce energy consumption, computation delay, and computation overhead.
- Coverage area analysis of the UAVs is complicated in satellite-assisted UAV networks.
- Multi-objective Optimization is proposed using the Ant Colony Optimization (IACO) algorithm to perform this process effectively.

2. Related Works

In [10], proposed a method using Deep Q-Network (DQN) technique. In addition, the proposed method used Actor-Critic (AC) mechanisms to maximize the QoE performance in rescue operations. Compared to the greedy approach, this framework reduced the delay and improved the video transmission. Nevertheless, when the communication range is increased, it is unable to maintain the Packet Delivery Ratio (PDR). In [11], a proposed SECMOP method to avoid the effects of known and unknown eavesdrops. However, in network collision scenarios, it is unable to provide high PDR, which further lengthens the transmission latency. In [12], presented CES-UAV-VIN method to minimize the energy consumption for communication. This approach progressively increased energy efficiency while reducing the volume of backhaul transmission. However, this method has a small cache and causes computational overhead. In [13], presented a solution based on successive convex approximation (SCA) tools. This method effectively enhanced the security performance of the system. In situations where the network was very crowded. In [14], present LEO method with UAV communications for content delivery in terrestrial networks are presented. Throughput was increased, and this structure made connectivity universal. The primary drawback of this architecture is that it cannot be used for large-scale networks in a real-time scenario. In [15], proposed an EEAO framework for effective UAV communication. This framework performs well in terms of PDR and transmission rate. The main disadvantage of this paradigm is that it makes long-distance communication more computationally complex. In [16-19], presented multi-objective optimization-based robust beamforming to increase the security of UAV communication. This system reduced overall transmission power while ensuring security. However, this framework's primary shortcoming is its inability to raise the PDR. In [21], presented a dual-hop cooperative satellite UAV framework to improve the omnidirectional coverage of Radio Frequency (RF). In terms of network coverage and connection connectivity, this framework performs superbly. However, as the distance is extended, it takes more energy to maintain the same performance. In [23], a new method to enhance the optimization in VANETs using the principle of GMHS (Gaussian Mutation Harmony Searching). It produces reasonable performance but is inappropriate for the high-speed VANETs. In [24-26], proposed Multi-Objective Optimization in VANETs to improve effectiveness and stability. The Firefly algorithm is used for this process and produces rational performance, but it is not valid for VANETs with enormous density. In [27], proposed a transmission control protocol with hybrid automatic repeat request protocol in emerging UAV-based networks. This method produces good overall performance, but transmission losses and congestion losses occur.

3. Network Environments

3.1 UAVs to GVs Communication

It is a two-way communication model where UAVs to GVs and GVs to UAVs are possible to communicate. UAVs are mainly presented to secure the network. UAVs have access to connect with any GVs whenever. It monitors and controls the network and makes all decisions according to communication

3.2 UAVs to UAVs Communication

UAVs are introduced in VANETs. Effective deployment of UAVs is essential to perform stable communication in VANETs and create obstacle-free communication between vehicles. Improper employment may create a loss of information, affect the utility of the UAVs, and increase the deployment cost, which is not an effective process.

3.3 Satellite to UAV Communication

After collecting the data from the GVs, the UAVs transmit the information to the satellite. Satellites will act as if a collection authority, and it gather all the information from the UAVs for future reference. The major challenge in this network model is providing a proper coverage area for the UAVs. For this purpose, MO-SAUAVs in the next section.

4. Multi-objective Optimization in Satellite Assisted UAVs (MO-SAUAVs)

MO-SAUAVsis performed in the network using the Improved Ant Colony Optimization (IACO) algorithm. The figure shows the proposed MO-SAUAVs. Traditional Ant Colony Optimization (ACO) is improved with multiple objectives to perform UAV coverage area analysis in the MO-SAUAVs method. ACO is the nature-inspired approach that works using the principle of the behaviour of ants to discover the optimal route from source to destination. The ground process in this algorithm is distance calculation using Euclidean distance, pheromone deposition, pheromone updating, and pheromone evaporation. Through multi-objective ACO strong ants are introduced which provide mobility prediction during the pathfinding process. To perform mobility prediction-based route optimization the process of optimal logistics distribution is performed. The process of optimal logistics distribution is elaborated using the pseudo-code below. Followed by the optimal logistics distribution process, a random food search process of ants is preceded. Once the ant initiates from the source to reach the destination for food search a stable portion of pheromone is deposited in the path that provides an entryway for the other ants to follow the path to reach the destination after finding the optimal path. If the pheromone deposition is not updated periodically then it is understood that the corresponding path is not optimal. If the path is observed incrementally then the quantity of pheromone deposition of that path needs to be calculated. Then the mathematical expression for the process of pheromone deposition from the source (S) to destination (D) is expressed in equation (1) below.

$$PD_{(S,D)} = \sum_{i=1}^{N} (\alpha * TH_{(S,D)}) - (\beta * ER_{(S,D)}) \tag{1}$$

where the terms $TH_{(S,D)}$ denotes the transmission history of the path between the source and the destination, $ER_{(S,D)}$ denotes the evaporation rate of the source and the destination and $\alpha \, and \, \beta$ are the trial numbers suit the specification $\alpha + \beta = 1$. In all cases, the amount of evaporation lies between 0 to 1. According to the equation (1) the optimal solution is provided. So that the UAVs can travel in an optimal path to cover the uncovered regions of the network. In the network, the transmission is performed effectively so that it can be able to achieve high efficiency during the communication process.

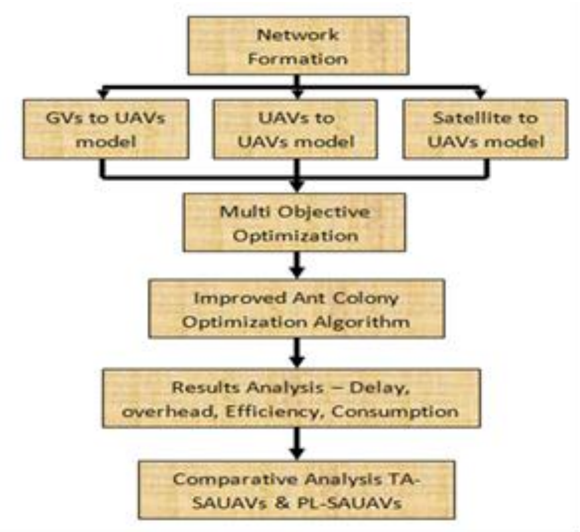

Figure 1. Workflow of the proposed MO-SAUAVs

Pseudo code for Ant optimization

START

Initiate food search;

Parameter used for ant food search;

ze, pheromone value, pheromone evaporation factor, considered constant values;

Ant behavior – random;

Initiate ant,

While iteration=iteration+1; finish iteration=50 do

For i - number of ant and anti – root node

For anti = anti +1; ant i++;

Initial pheromone deposition 〖P〗_i at iteration =0

P_i=1 to t+1;

Process considered;

length calculation, current iteration count, best probability value calculation, store the optimal value;

:e pheromone for ants and the path;

Iteration ++;

Optimal solution can be obtained for greater number of iterations;

End for

End while

Followed by the optimal logistics distribution process, a random food search process of ants is preceded. Once the ant initiates from the source to reach the destination for food search a stable portion of pheromone is deposited in the path, which provides an entryway for the other ants to follow the path to reach the destination after finding the optimal path. If the pheromone deposition is not updated periodically then it is understood that the corresponding path is not optimal. If the path is observed incrementally then the quantity of pheromone deposition of that path needs to be calculated. Then the mathematical expression for the process of pheromone deposition from the source (S) to destination (D) is expressed in equation (1).

$$PD_{(S,D)} = \sum_{i=1}^{N} (\alpha * TH_{(S,D)}) - (\beta * ER_{(S,D)}) \tag{2}$$

where $TH_{(S,D)}$ indicates the communication history among the source and destination, $ER_{(S,D)}$ denotes the evaporation rate of the source and the destination and $\alpha \ and \ \beta$ are the new constants which content the form $\alpha + \beta = 1$. In all cases, the amount of evaporation lies between 0 to 1. According to the equation (1) the optimal solution is provided.

5. Performance Evaluations

In this work, the NS-2 version 2.35 under Ubuntu 16.04 Operating System are performed in simulation. The vehicular mobility is generated using SUMO-1.1.0. The result of the MO-SAUAVs is performed by measuring the parameters [26]. The TA-SAUAVs [17] and PL-SAUAVs [18] are considered for the comparative analysis process. Table 2 shows the simulation setting.

Table 1: Simulation setting.

Parameters	Values
Running Time	500 ms
Network Size	10000m*10000m
Transmission Power	0.500 Joules
Vehicles number	5000 vehicles
UAVs number	5 UAVs
Traffic Flow	CBR
Vehicles Speed	100 km/hr
Packet Size	510 Bytes
UAVs Speed	150 km/hr
Receiving Power	0.050 Joules

5.1 Computation Delay (CD)

CD is the time taken to transfer the data from one place to another for the entire network. Figure 2 shows the CD calculation performance of the considered TA-SAUAVs PL-SAUAVs and proposed MO-SAUAVs. The graphic out shows that the proposed MO-SAUAVs produce low CD when compared with TA-SAUAVs and PL-SAUAVs. The proposed method is achieved with the multi-objective better ACO algorithm.

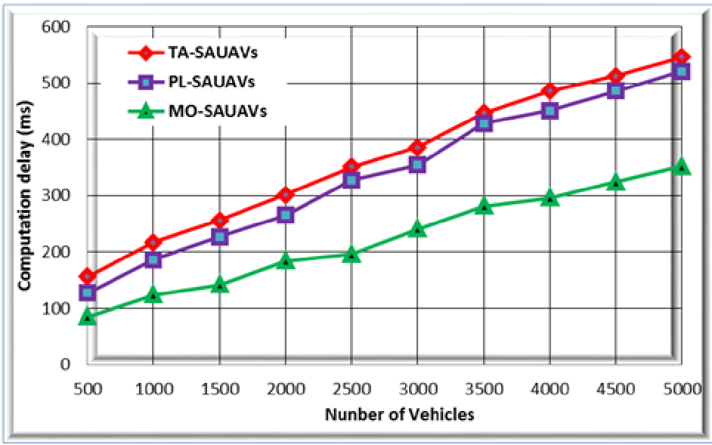

Figure 2. CD Calculation.

Table 2 shows the CD measurements of the MO- SAUAVs with TA-SAUAVs and PL-SAUAVs. The CD produced with 5000 vehicles by the TA-SAUAVs, PL-SAUAVs, and proposed MO- SAUAVs are 546ms, 521ms, and 352ms respectively. The MO-SAUAVs produced lower computation delay (70ms to 110ms) compared with TA-SAUAVs and PL-SAUAVs.

Table 2: CD Measurements.

No of vehicles	TA-SAUAVs	PL-SAUAVs	MO-SAUAVs
500	156	127	85
1000	217	186	124
1500	256	227	142
2000	302	265	184
2500	351	328	196
3000	386	354	241
3500	447	428	281
4000	486	451	296
4500	513	486	324
5000	546	521	352

5.2 Energy Efficiency (EE)

Figure 3 shows the performance of the TA-SAUVs considered, PL-SAUVs, and proposed MO-SAUVs in terms of EE. The graphical output shows that the proposed MO-SAUAVs achieve high EE when compared with the TA-SAUAVs and PL-SAUAVs. Using a multi-objective improved ACO algorithm overhead and delay of the network are reduced leading to achieving high EE of the network.

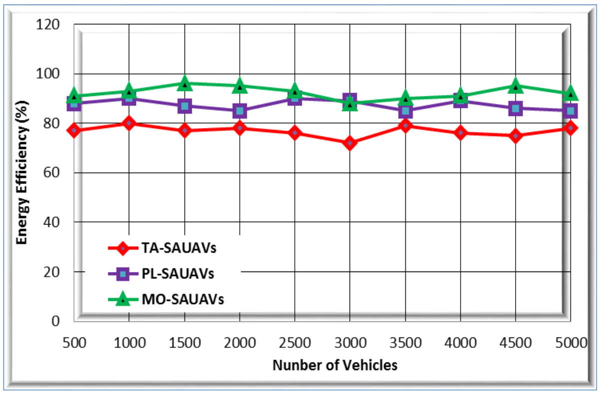

Figure 3. EE Calculation.

Table 3 shows the EE value calculation of the proposed MO- SAUAVs with TA-SAUAVs and PL-SAUAVs. The EE achieved with 5000 vehicles by the TA-SAUAVs, PL-SAUAVs, and MO- SAUAVs are 80%, 90%, and 96% respectively. The proposed MO-SAUAVs achieved 6% to 16% higher EE associated with the TA-SAUAVs and PL-SAUAVs.

Table 3: EE Measurements.

No of vehicles	TA-SAUAVs	PL-SAUAVs	MO-SAUAVs
500	77	88	91
1000	80	90	93
1500	77	87	96
2000	78	85	95
2500	76	90	93
3000	72	89	88
3500	79	85	90
4000	76	89	91
4500	75	86	95
5000	78	85	92

5.3 Energy Consumption (EC)

Figure 4 shows the performance of the TA-SAUVs considered, PL-SAUVs, and proposed MO-SAUVs in terms of EC. The graphical output shows that the proposed MO-SAUAVs produce lower EC when compared with the TA-SAUAVs and PL-SAUAVs. Communication is performed optimally with the presence of multi multi-objective improved ACO algorithm that reduces the EC during communication.

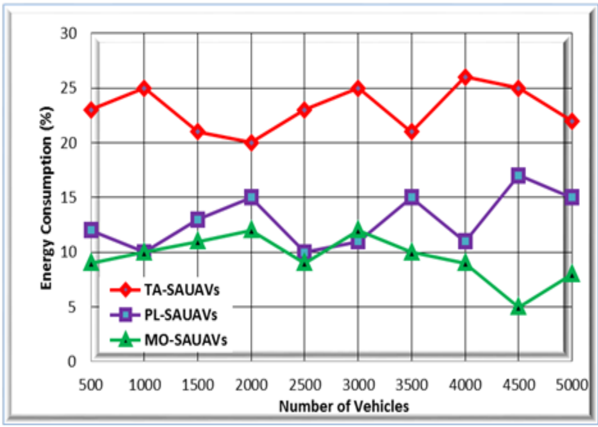

Figure 4. EC Calculation.

Table 4 shows the energy consumption value calculation of the proposed MO- SAUAVs with TA-SAUAVs and PL-SAUAVs. The energy consumption produced with 5000 vehicles by the simulated methods such as TA-SAUAVs, PL-SAUAVs, and proposed MO-SAUAVs are 26%, 17%, and 12% respectively. The MO-SAUAVs produced around 7% to 14% lower energy consumption when compared with the earlier works.

Table 4: EC measurements.

No of vehicles	TA-SAUAVs	PL-SAUAVs	MO-SAUAVs
500	77	88	9
1000	80	90	10
1500	77	87	11
2000	78	85	12
2500	76	90	9
3000	72	89	12
3500	79	85	10
4000	76	89	9
4500	75	86	5
5000	78	85	8

5.4 Computation Overhead (CO)

Figure 5 shows the performance of the considered TA-SAUAVs, PL-SAUAVs, and MO-SAUAVs in CO. The graphical output shows that the MO- SAUAVs produce lower computation overhead when associated with the TA-SAUAVs and PL-SAUAVs, which are achieved using the multi-objective improved ACO algorithm in UAVs to satellite-based network model.

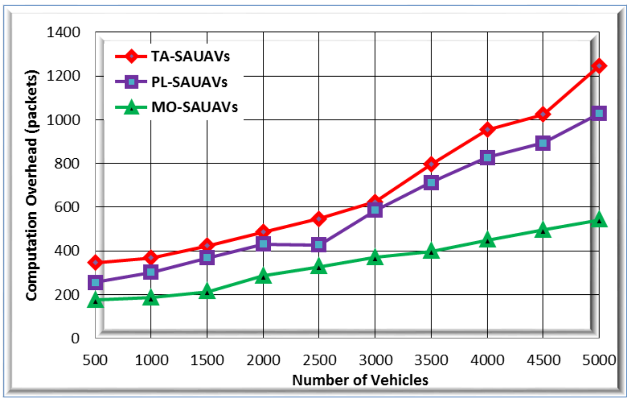

Figure 5. CO Calculation.

Table 5 shows the CO value calculation of the MO- SAUAVs with the TA-SAUAVs and PL-SAUAVs. The computation overhead produced with 5000 vehicles by the TA-SAUAVs, PL-SAUAVs, and proposed MO-SAUAVs are 1245 packets, 1028 packets, and 542 packets respectively. The MO-SAUAVs produced around 500 packets to 700 packets lower CO when compared with the TA-SAUAVs and PL-SAUAVs.

Table 5: CO Measurements.

No of vehicles	TA-SAUAVs	PL-SAUAVs	MO-SAUAVs
500	347	256	175
1000	369	302	186
1500	425	368	214
2000	486	431	286
2500	547	428	328
3000	624	586	371
3500	796	714	398
4000	954	827	449
4500	1024	894	496
5000	1245	1028	542

6. Conclusion

This paper provides effective communication in vehicular network UAVs assisted VANETs are introduced and followed by that satellite assisted UAVs are introduced to improve the stability of data transmission. Region division in UAVs becomes a challenging task in this network model. Improper fixing leads to the increase of energy consumption, computation delay, and computation overhead. The parameters that are considered for the process of Multi-objective Optimization are optimal logistics distribution, path prediction-based pheromone deposition, and evaporation. By the use of the multi-objective improved Ant Colony Optimization algorithm, the communication becomes more stable and flexible according to UAVs positioning process. The results of the proposed MO-SAUAVs are compared with the earlier works SAUAVs and PL-SAUAVs. The results show that the proposed MO-SAUAVs produced 110ms lower computation delay, 16% higher energy efficiency, 14% lower energy consumption, and 700 packets lower computation overhead when compared with TA-SAUAVs and PL-SAUAVs. For the process of research continuation security of UAVs are concentrated.

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