Sigma J Eng Nat Sci, Vol. 40, No. 1, pp. 108–117, March, 2022

Sigma Journal of Engineering and Natural Sciences
Web page info: https://sigma.yildiz.edu.tr
DOI: 10.14744/sigma.2022.00009

Research Article

Optimization of drones communication by using meta-heuristic optimization algorithms

A. F. M. Shahen SHAH[1,*], Muhammet Ali KARABULUT[2]

[1]*Department of Electronics and Communication Engineering, Yildiz Technical University, Istanbul, Turkey*
[2]*Department of Electrical and Electronics Engineering, Kafkas University, Kars, Turkey*

ARTICLE INFO

Article history
Received: 14 December 2020
Accepted: 04 January 2021

Key words:
Cuckoo search algorithm; Drones; Differential evolution algorithm; Honeybee algorithm; IEEE 802.11; Optimization

ABSTRACT

Unmanned aerial vehicles (UAVs), more generally known as drones or remotely piloted aircraft, have been extensively used in both civilian activities and military missions because of their high mobility and low cost. Multi-UAV systems structured in an ad hoc manner called UAVs ad hoc network which is also familiar as flying ad hoc Network (FANET). For FANETs, the IEEE 802.11 standard offers Medium Access Control (MAC) layer requirements. Optimization of the contention window (CW) size will optimize the output. Three distinct meta-heuristic optimization algorithms are used in this paper to improve the efficiency of FANETs, which are the Cuckoo Search Algorithm (CUCO), the Differential Evolution Algorithm (DEA)\ and the Honey Bee Algorithm (HBA). Optimum CW size is defined through meta-heuristic optimization algorithms. Performance comparison among CUCO, DEA, HBA, and traditional MAC based on IEEE 802.11 is presented. Relationships among parameters are obtained through Markov chain based analytical study. Performance metrics such as successful transmission probability, collision probability, channel busy probability, throughput, packet dropping rate (PDR), and delay expressions are derived. Simulation results reveal that meta-heuristic optimization algorithms improve the quality and reliability of communication by increasing throughput and decreasing PDR and latency.

Cite this article as: Shahen A F M S, Mehmet A K. Optimization of drones communication by using meta-heuristic optimization algorithms. Sigma J Eng Nat Sci 2022;40(1):108–117.

INTRODUCTION

Drones, also well-known as unmanned aerial vehicles (UAVs), offer protection for humans relative to the usage of manned vehicle missions. Drones support a wide variety of applications in military and civil tasks such as environmental and meteorological monitoring, forest fire management, agricultural monitoring, surveillance support, search and rescue missions, radar localization, border surveillance, aerial photography [1-8]. Drone-to-Drone

***Corresponding author.**
*E-mail address: shahen.shah@hotmail.com

This paper was recommended for publication in revised form by Regional Editor Tülay Yıldırım

Published by Yıldız Technical University Press, İstanbul, Turkey

(D2D) communication and Drone-to-Infrastructure (D2I) communication are enabled by UAV ad hoc networks, also known as flying ad hoc networks (FANETs), as seen in Fig. 1. Communication in FANETs should be effective in order to provide useful applications. Due to excessive mobility and low density, drones are rarely connected, which can be addressed through an ad hoc network between drones, resulting in extension of coverage [9]. FANETs will allow contact with the ground through other drones if the drone is unable to communicate with the ground. The IEEE 802.11-2016 standard [10] defines specifications for physical (PHY) and MAC layers for FANETs. To access the medium, carrier-sense multiple access with collision avoidance (CSMA/CA) is employed. The Request to send/ clear to send (RTS/CTS) mechanism is utilized to prevent the problem of hidden nodes. Performance analysis of FANETs is challenging [1].

In several areas, such as science, commerce, and engineering; artificial intelligence i.e. nature-inspired intelligence algorithms have recently been commonly utilized as straight search and optimization methods. Optimization is the method of finding the most effective approach for a particular intent or target by having certain constraints. A new theory has been put forward by scientists, and it has been established by optimization. In optimization terminology, there is an aspiration to get best every time. The strongest interpretation is focused on research, the form of solution and allowable tolerance. Many optimization methods have been developed and adapted to different fields in order to overcome the challenges faced in the past [11]. In the formulation of optimization problems, mathematical methods or classical methods are commonly utilized. The disadvantages of such methods, such as the inelasticity and the necessity to recognize them with mathematical functions, attracts scientists to evolve general-purpose as well as high-performance approaches which have been inspired by natural phenomena. In optimization problems, Cuckoo Search Algorithm (CUCO), Differential Evolution Algorithm (DEA) and Honey Bee Algorithm (HBA) are broadly used [12–16].

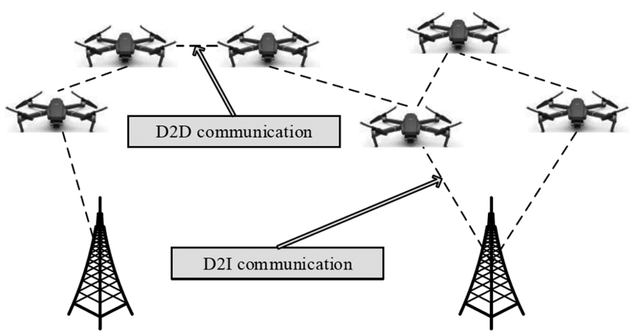

Figure 1. A basic FANETs structure.

The impact of IEEE 802.11 in FANETs has been studied recently in [2]. It is apparent that the performance is contingent on the size of the contention window (CW) [2, 17–19]. In this article, in order to optimize performance, CW size is optimized using three meta-heuristic optimization algorithms. The key goal of the study is to increase the efficiency and reliability of communication by improving throughput as well as reducing packet dropping rate (PDR) and delay. Optimization algorithms such as DEA, CUCO and HBA are employed in FANETs. Markov chain based theoretical study is sketched to show the association among parameters. Crucial performance metrics expressions such as collision probability, successful transmission probability, channel busy probability, throughput, PDR and delay are derived. Simulation results are presented. Comparison with IEEE 802.11 based conventional MAC is given. Simulation results show that meta-heuristic optimization algorithms improve performance.

The reminder of paper is organized as given below: Section II shows meta-heuristic optimization algorithms. Section III describes system model and an analytical study based on Markov chain model. Throughput, PDR and delay analysis is carried out in Section IV. Section V demonstrates numerical results. Section VI provides conclusion.

META-HEURISTIC OPTIMIZATION ALGORITHMS

Cuckoo Search Algorithm (CUCO)

Basically, CUCO is an algorithm focused on herd intelligence. It is observed that there are drones operating in ad hoc networks. The CUCO algorithm is focused on exchanging social information among drones. Depending on the number of generations in the genetic algorithm, the search is completed. Each *CW* size uses previous experience to adjust its size to the best size on the system. The CUCO algorithm is mainly based on approximating the position of drones in ad hoc networks to drones with the best position in ad hoc networks. CW size is random and drones in the herd are better positioned in their new moves than the previous position, and this process carries on until the goal is achieved. In several optimization problems, the CUCO algorithm has been used effectively [19–21].

Algorithm 1. Cuckoo Search Algorithm

1. Initiate *CW* size
2. Calculate the *CW* size value of all drones in FANETs
3. Compare all *CW* size to have the better of previous in FANETs
4. IF *CW* size is better,
5. Then take the *CW* size place
6. End IF
7. Compare values of best *CW* size among FANETs and select the best one as the global best

8. Update values of *CW* size
9. Discard

Algorithm 1 presents algorithm of CUCO for FANETs. Basically, the algorithm comprises of the steps below:

i. A starting swarm is created with an arbitrarily generated initial *CW* size.

ii. Exchange of values of all drones in FANETs.

iii. There is a local best of the present generation for each drone (p_{best}). The best in pack are as many as the drones.

iv. The global best (g_{best}) is taken from local best in current ad hoc networks.

v. The CW size has been updated as follows.

Here, X_{id} is position and CW_{id} is *CW* size values, while $rand_1$ and $rand_2$ values are arbitrarily generated numbers. The value of inertial weight is w and c_1, c_2 are scaling factors.

vi. Until requirement for stopping is satisfied, repeat steps 2, 3, 4, 5.

$$V_{id} = wCW_{id} + c_1(P_{id} - X_{id})rand_1(0,1) + c_2(P_{gd} - X_{id})rand_2(0,1), \tag{1}$$

$$X_{id} = X_{id} + CW_{id}. \tag{2}$$

Differential Evolutionary Algorithm (DEA)

A popular population-based algorithm is the DEA that is commonly utilized in different optimization problems [22]. These algorithms are also utilized with numerical optimization algorithms for general purposes. Through utilizing advanced throughput efficiency, DEA differs from genetic algorithms. The output of the task, which is centered on variation between target vector pairs, is calculated by its own distribution of target vectors. It is often utilized for generating a reference vector from a parental vector in combination with mutation and crossover. Algorithm 2 presents algorithm of DEA.

Algorithm 2. Differential Evolutionary Algorithm

1. Initiate *CW* size
2. Get awareness of two arbitrarily chosen *CW* size values from ad hoc networks
3. Gather the difference vector as third *CW* size
4. Compare target vector with the total vector
5. IF new value of *CW* size is better than the target vector
6. Then replace it
7. End If
8. Discard

DEA varies in the efficiency of throughput and recombination phases from other optimization algorithm. DEA utilizes weighted variations between solution *CW* size to mix.

$$u_{id+1} = x_{i,G} + C(x_{r3,G} - x_{i,G}) + V(x_{r1,G} - x_{r2,G}), \quad r1 \neq r2 \neq r3 \neq i. \tag{3}$$

Eq. 2 is invariant rotationally [22]. Under the initial *CW* size limits, a DEA population is generated arbitrarily. FANETs experience perturbation in each *G* generation. The solution vectors are arbitrarily chosen, shown by three separate *CW* sizes or *x*. *C* coefficient x_{r3} denotes association level between *G* and current CW size $x_{1,G}$. Coefficient *V* represents step size scaling from difference of vectors $x_{r1,G}$-$x_{r2,G}$.

Honey Bee Algorithm (HBA)

The actions, understanding, knowledge exchange and memorization of Bee's food search attribute have recently turned one of the most important herd intelligence research fields. In a natural bee colony, there is a role shared between bees. The bees do this job without a central unit, sharing it on their own which is similar to ad hoc networks. Two major aspects of herd intelligence are the exchange of business and self-organization.

In the minimal *CW* size search model, there is a simple aspect that enables common intelligence to appear. To get optimum throughput, bees i.e. drones take the *CW* size. There are two styles of bees (drones and network system), based on an internal instinct or an external influence, like random bees looking for arbitrary opportunities, beekeepers (system) waits for bees (drones) in the FANETs, observing bees (drones), and utilizing the knowledge exchanged by bees (drones) and switching to a new size of the *CW*. Sharing details among drones is the most significant element in the creation of common knowledge. Honey bee algorithm (HBA) is the latest algorithm generated by modeling the behavior (*CW* size) of bees (drones). By trying to find the *CW* size with the higher throughput, HBA tries to get the result by the maximum or minimum in the set [23]. Algorithm 3 presents the algorithm of HBA.

Algorithm 3. Honey Bee Algorithm

1. Initiate CW size
2. A CW size is defined

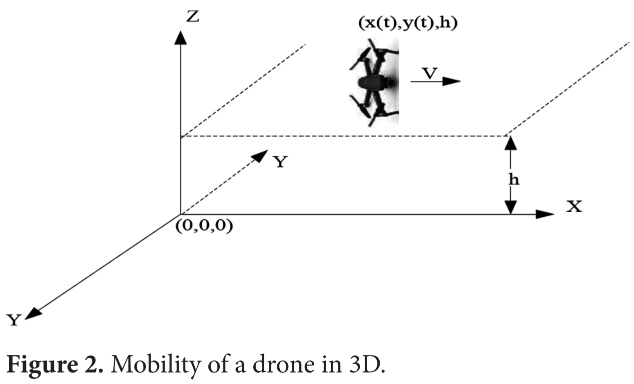

Figure 2. Mobility of a drone in 3D.

3. Compute throughput
4. IF all drones are distributed
5. Take *CW* size in memory
6. Define the *CW* size to be published
7. Generate new CW size in place of published *CW*
8. Discard
9. Else IF
10. Identify the *CW* size by the drone
11. Go step 3
12. End Else IF
13. End IF
14. Discard

The initial *CW* is computed arbitrarily inside the search space, according to the HBA. The initial generation of *CW* can be written as

$$CW_{i,j} = b_j^l + (b_j^u - b_j^l) rand(0,1), \tag{4}$$

where j is problem size, the b_j^l and b_j^u are lower and upper limits of jth dimension the population of ith in ad hoc networks. An optimum *CW* size will be searched near *CW* size while carrying throughput performance with the current *CW* size. The old *CW* size is kept in memory, and if a better *CW* size is found, then old one is replaced with the better *CW*. The call is made randomly. If any *CW* size is better than current best *CW* size, then it will be saved in memory, information is exchanged in FANETs.

SYSTEM MODEL

It is assumed that there is a FANET with N drones in the *TR* transmission range. Saturated state is considered. The key attributes of FANETs are their three dimensional (3D) appearance and excessive mobility. In 3D space, drones travel, which is beneficial for moving through obstacles. 3D space mobility is explained in Fig. 2. For a time T, the constant altitude h is assumed. The drone's position is represented by $(x(t), y(t), h)$, where $x(t)$ and $y(t)$ indicate time varying coordinates of x and y, respectively. The drone's position depends on the position of launch and landing or pre- and post-mission. Let (x_i, y_i, h) and (x_f, y_f, h) respectively be the original and final positions. Let the distance between the original and the final position be d. The minimum d is $d_{\min} = \sqrt{(x_f - x_i)^2 + (y_f - y_i)^2}$ between the original and final position. The maximum velocity of the drone is $v_{\max} \geq \frac{d_{\min}}{T}$. Therefore, from original to final position, there is at least one possible trajectory.

IEEE 802.11 DCF

In IEEE 802.11 standard, MAC protocol is utilized to manage access to a shared channel by multiple drones. The primary access mechanism, which is a contention-based access process utilizing a random access technique, is the IEEE 802.11 Distributed Coordination Feature (DCF), where each station will start transmission without any infrastructure assistance. Therefore, this technique can support both infrastructure type wireless local area network (Wireless LAN, WLAN) and wireless ad hoc networks.

The basic access method of IEEE 802.11 DCF is CSMA/CA. In wireless networks, the CSMA/CA method is used since the collision can not be detected, so collision avoidance is the only remedy. The CSMA/CA approach eliminates collisions by utilizing the methodology presented in Fig. 3. After awaiting DCF inter-frame space (DIFS) duration and completing the backoff process, the source drone transmits data to the destination drone. Destination drone holds for the short internal frame space (SIFS) and after that replies with an acknowledgment (ACK) to endorse the successful transmission, irrespective of the busy or inactive state of the channel. When the source drone and destination drone are in communication, the network allocation vector (NAV) blocks the channel and closes it to other drones.

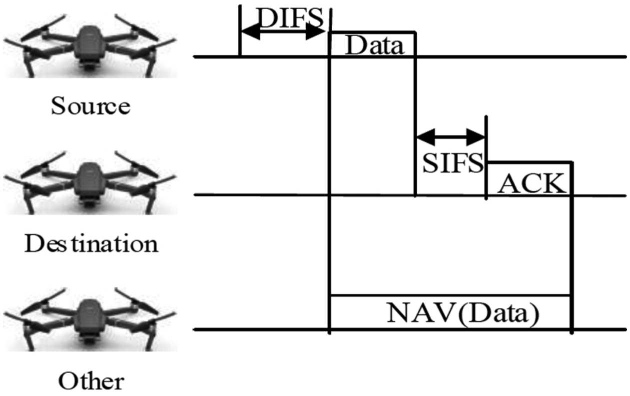

Figure 3. CSMA/CA technique.

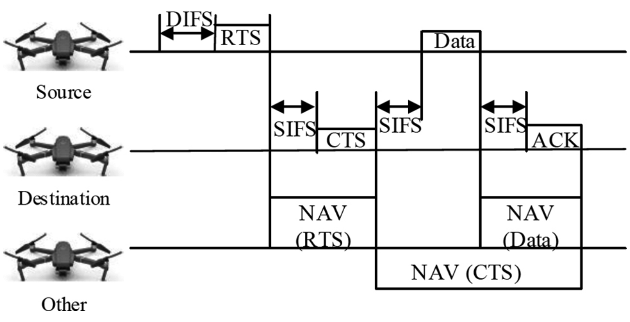

Figure 4. RTS/CTS technique.

Another access mechanism used in the DCF is the RTS/CTS mechanism, seen in Fig. 4. The source drone sends an RTS after waiting for the DIFS period and finishing the backoff process. After the destination drone receives RTS, after SIFS period, it responds to the source drone with a CTS. The CTS is detected by the source drone and awaits for SIFS time, and then transmits data. If the destination drone successfully receives data, to affirm the transmission, it answers with ACK. Each other drone that senses RTS or CTS frames sets the NAV until the end of ACK to postpone transmission.

Markov Chain Model

If there is a packet to send in FANETs, drone initiates to listen the channel. Drone transmits while channel is listened idle for DIFS time (δ_{DIFS}). Otherwise to prevent collision, the drone takes an arbitrary backoff. Let counter of backoff time as well as backoff stage for drone at time δ are denoted by $c(\delta)$ and $s(\delta)$, respectively which are stochastic processes. c and j represent the backoff counter value and backoff stage value, respectively. If maximum retransmission limit and CW size are denoted by mr and CW, respectively, then c and j can be defined as $C \in (0, CW - 1)$, $J \in (0, mr)$. The initial value of c, which can be expressed as CW_{min}, is uniformly chosen from $[0, CW_0\text{-}1]$. c is decreased by 1 when the channel is sensed inactive for a slot time (δ_{slot}), and if channel is sensed busy, then c is paused in the current value, and if the channel is sensed free again for more than δ_{DIFS}, c restart to decrease. If c is 0, drone will transmit the packet. When a collision happens after a transmission, j is increased by 1. After each unsuccessful transmission, CW doubles and can have $CW_{\max} = 2^{mr}\, CW_{\min}$ highest value. Let P_B and P_C be channel busy probability and collision probability, respectively.

Let $b_{j,c} = \lim_{t\to\infty} P\{s(t) = j, c(t) = c\}$, $(j \in [0, mr]$, $c \in [0, CW_j - 1])$ be the stationary distribution of the Markov chain. Fig. 5 shows two-dimensional (2D) Markov chain model. From Markov chain, the following expression can be derived as

$$b_{j,c} = \frac{CW_j - k}{CW_j} b_{j,0}. \tag{5}$$

As total probability is one,

$$\begin{aligned} 1 &= \sum_{j=0}^{mr} \sum_{c=0}^{CW_j-1} b_{j,c} = \sum_{j=0}^{mr} b_{j,0} \sum_{c=0}^{CW_s-1} \frac{CW_j - k}{CW_j} \\ &= \sum_{j=0}^{mr} b_{j,0} \frac{CW_j + 1}{2} \\ &= \frac{b_{0,0}}{2}\left[CW\left(\sum_{j=0}^{mr-1} (2P_C)^j + \frac{(2P_C)^{mr}}{1-P_C}\right) + \frac{1}{1-P_C} \right], \end{aligned} \tag{6}$$

and

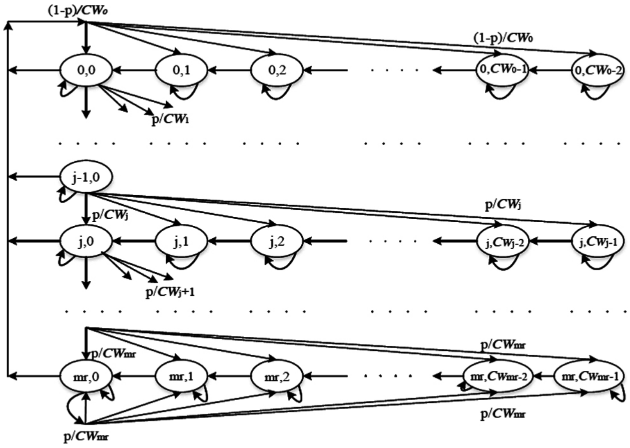

Figure 5. Illustration of backoff technique with 2D Markov Chain model.

$$b_{0,0} = \frac{2(1-2P_C)(1-P_C)}{(1-2P_C)(CW+1) + P_C CW(1-(2P_C)^{mr})}. \tag{7}$$

Let P_{TR} be the probability of packet transmission at a random slot time that can take place only if c becomes 0 regardless of j. Therefore, P_{TR} can be written as

$$\begin{aligned} P_{TR} &= \sum_{j=0}^{mr} b_{j,0} = \frac{b_{0,0}}{1-P_C} \\ &= \frac{2(1-2P_C)}{(1-2P_C)(CW+1) + P_C CW(1-(2P_C)^{mr})}. \end{aligned} \tag{8}$$

If any of N drones transmit a packet, the channel will be busy which can be given as

$$P_B = 1 - (1 - P_{TR})^N. \tag{9}$$

If any of remaining $N\text{-}1$ drones sends a packet when a packet is sent by a drone, then collision will happen. Thus, collision probability P_c can be defined as

$$P_C = 1 - (1 - P_{TR})^{N-1}. \tag{10}$$

Let P_s be probability successful of transmission that after a packet transmission, it is received successfully by the receiver which can be expressed as

$$P_S = \frac{N P_{TR} (1 - P_{TR})^{N-1}}{P_B}. \tag{11}$$

Packet arrival probability can be expressed by the Poisson distribution with average arrival rate λ which can be given as

$$P_p = 1 - \exp(-\lambda \delta_{Ex}), \quad (12)$$

where δ_{Ex} is expected period of drone in a Markov state which can be expressed as

$$\delta_{Ex} = (1-P_B)\delta_{Slot} + P_B P_S \delta_S + P_B(1-P_S)\delta_C, \quad (13)$$

where δ_S and δ_C are the duration of successful transmission and collided, respectively. δ_S, and δ_C can be given as

$$\delta_S^{RTS/CTS} = \delta_{DIFS} + 3\delta_{SIFS} + \frac{(N-1)L}{R_D} + (N-1)\left(\delta_{RTS} + \delta_{CTS} + \delta_{ACK}\right) + \delta_{Del}, \quad (14)$$

$$\delta_S^{CSMA/CA} = \delta_{DIFS} + \delta_{SIFS} + \frac{L}{R_D} + \delta_{ACK} + \delta_{Del}, \quad (15)$$

$$\delta_C^{RTS/CTS} = \delta_{DIFS} + \delta_{RTS} + \delta_{Del}, \quad (16)$$

$$\delta_C^{CSMA/CA} = \delta_{DIFS} + \frac{L}{R_D} + \delta_{Del}, \quad (17)$$

where δ_{SIFS}, δ_{DIFS}, δ_{RTS}, δ_{CTS}, δ_{Del} and δ_{ACK} are are duration for SIFS, DIFS, RTS, CTS, delay, and ACK, respectively. RD and L are presents transmission rate and packet size, respectively.

THROUGHPUT, PDR, AND DELAY ANALYSIS

Let S be the system throughput which is the ratio of mean transferred data and mean duration of slot time which can be written as [24]

$$S = \frac{P_S P_B L}{\delta_{Ex}}. \quad (18)$$

S for RTS/CTS and CSMA/CA can be given as

$$S^{RTS/CTS} = \frac{P_S P_B L}{(1-P_B)\delta_{Slot} + P_B\begin{pmatrix} P_S\delta_S^{RTS/CTS} \\ +(1-P_S)\delta_C^{RTS/CTS}\end{pmatrix}}, \quad (19)$$

$$S^{CSMA/CA} = \frac{P_S P_B L}{(1-P_B)\delta_{Slot} + P_B\begin{pmatrix} P_S\delta_S^{CSMA/CA} \\ +(1-P_S)\delta_C^{CSMA/CA}\end{pmatrix}}. \quad (20)$$

After mr, the packet will be dropped. Thus, PDR can be defined as [25]

$$\eta_{pdr} = (1-P_S)^{mr}. \quad (21)$$

Let $E[D]$ be mean delay of a packet that has been delivered successfully, which can be written as [26]

$$E[D] = E[\delta_{Int}] - E[P_{Dr}]E[\delta_{Dr}], \quad (22)$$

where $E[\delta_{Int}]$ indicates mean duration at a receiver between two successfully received packets, $E[P_{Dr}]$ is average dropped packets number in relation to a successful delivery, $E[\delta_{Dr}]$ expresses mean period to drop a packet. $E[\delta_{Int}]$ can be obtained for RTS/CTS and CSMA/CA as

$$E[\delta_{Int}^{RTS/CTS}] = \frac{NP_S P_B L}{S} = N\delta_{Ex}^{RTS/CTS}, \quad (23)$$

$$E[\delta_{Int}^{CSMA/CA}] = \frac{NP_S P_B L}{S} = N\delta_{Ex}^{CSMA/CA}. \quad (24)$$

If P_{Fd} is probability that a packet is dropped finally, then $E[P_{Dr}]$ can be given as

$$E[P_{Dr}] = \frac{P_{Fd}}{1-P_{Fd}}. \quad (25)$$

$E[\delta_{Dr}]$ can also be written as

$$E[\delta_{Dr}^{RTS/CTS}] = E[X_{Dr}]\delta_{Ex}^{RTS/CTS}, \quad (26)$$

$$E[\delta_{Dr}^{CSMA/CA}] = E[X_{Dr}]\delta_{Ex}^{CSMA/CA}, \quad (27)$$

where $E[X_{Dr}]$ denotes average number of slot times for a dropped packet which can be given as

$$E[X_{Dr}] = \frac{CW+1}{2}. \quad (28)$$

Therefore, $E[D]$ can be attained by utilizing equations from (22) to (27) as

$$E[D^{RTS/CTS}] = \delta_{Ex}^{RTS/CTS}\left(N - \frac{P_{Fd}}{1-P_{Fd}} \times \frac{CW+1}{2}\right), \quad (29)$$

Table 1. Parameter values used in numerical analysis

Parameters	Value
δ_{Slot}, δ_{DIFS}, δ_{SIFS}, δ_{Del} (μs)	20, 10, 50, 1
RTS, CTS, L_h, *L, ACK* (bytes)	26, 20, 50, 1024, 14
R_c, R_{dat} (Mbps)	1, 11
mr, N, TR (m)	5, 0–50, 300
CW for traditional MAC	64

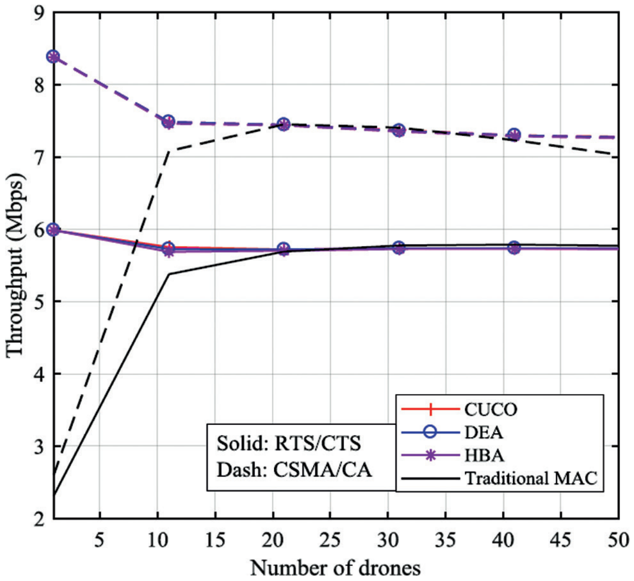

Figure 6. Comparison of throughput against the number of drones for each algorithm.

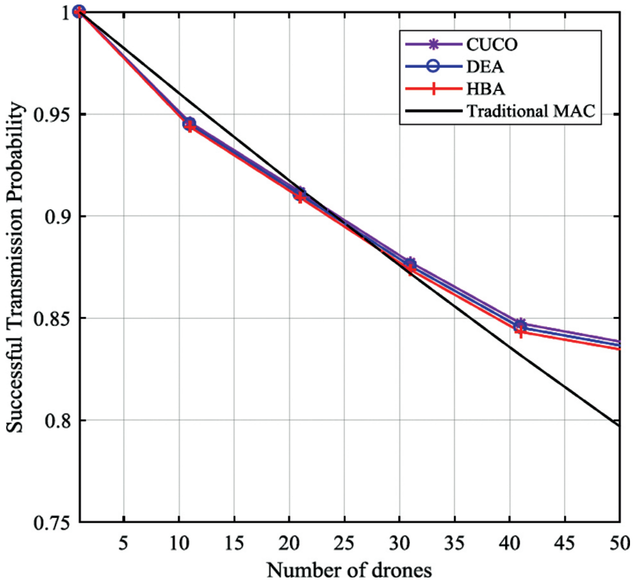

Figure 7. Comparison of successful transmission probability versus number of drones.

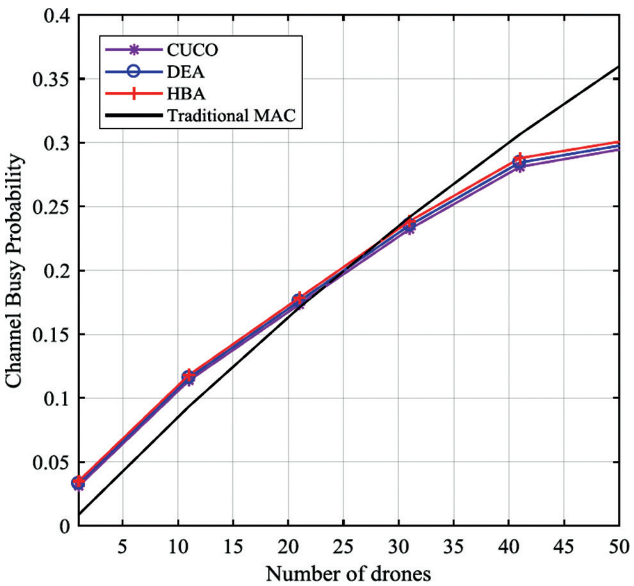

Figure 8. Channel busy probability against number of drones.

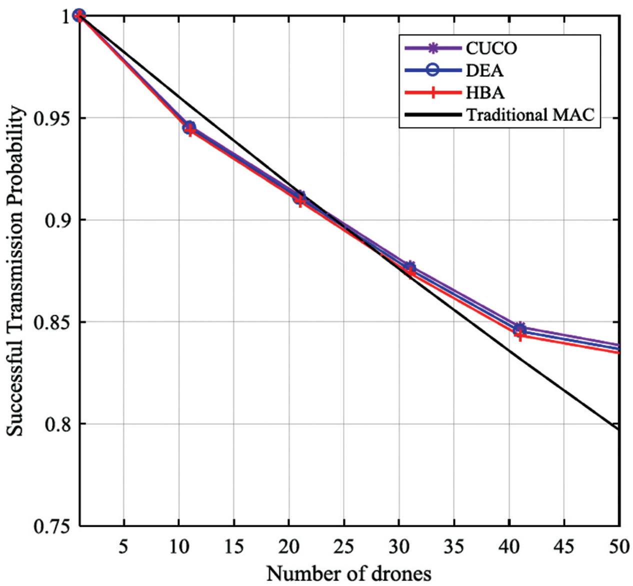

Figure 9. Collision probability versus number of drones.

$$E[D^{CSMA/CA}] = \delta_{Ex}^{CSMA/CA}\left(N - \frac{P_{Fd}}{1-P_{Fd}} \times \frac{CW+1}{2}\right). \quad (30)$$

NUMERICAL RESULTS

In this section, the impact of different meta-heuristic optimization algorithms in FANETs is evaluated. A comparison among meta-heuristic optimization algorithms and IEEE 802.11 based traditional MAC is presented. Furthermore, comparison between two access mechanisms CSMA/CA and RTS/CTS is provided. The numerical results are accomplished in MATLAB. Parameter values utilized in numerical analysis are given in Table 1.

Fig. 6 shows throughput according to number of drones. With an increasing number of drones, the throughput rises

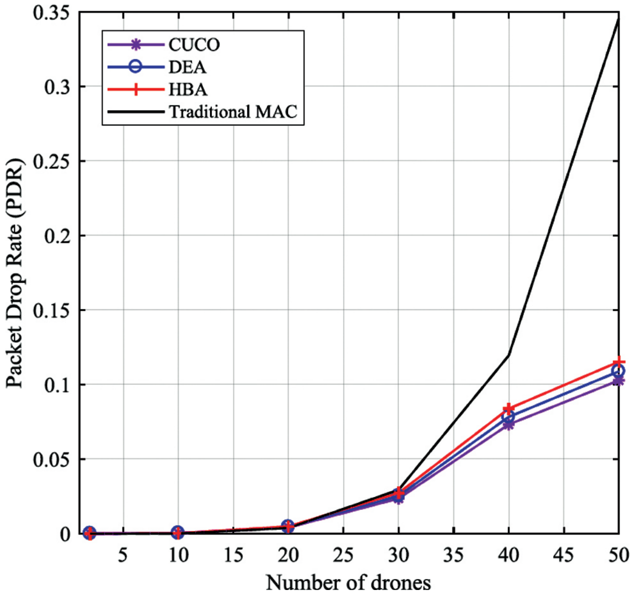

Figure 10. PDR against number of drones.

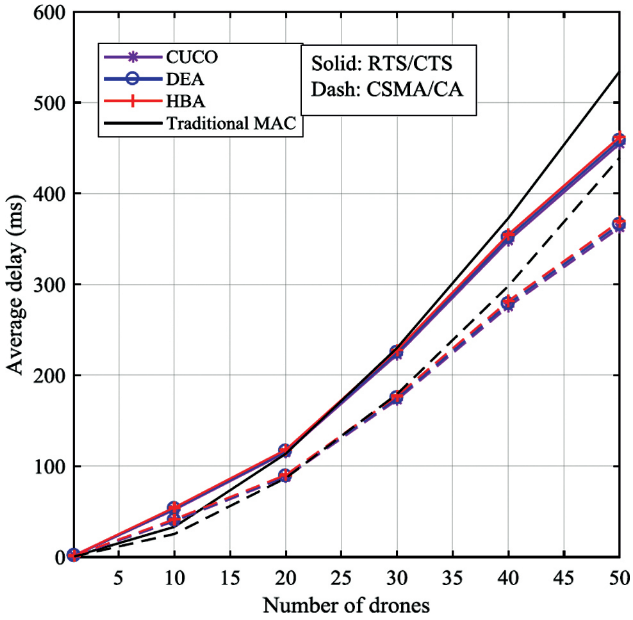

Figure 11. Average delay versus number of drones.

Table 2. Throughput values by using RTS/CTS mechanism

Number of drones	CUCO	HBA	DEA	Traditional MAC
10	5,7520	5,6870	5,7248	5,3775
20	5,7190	5,7022	5,7190	5,6908
30	5,7350	5,7764	5,7750	5,7742
40	5,7357	5,7896	5,7857	5,7874
50	5,7263	5,7763	5,7714	5,7689

Table 3. Throughput values by using CSMA/CA mechanism

Number of drones	CUCO	HBA	DEA	Traditional MAC
10	7,4810	7,4606	7,4810	7,0797
20	7,4512	7,4600	7,4512	7,4506
30	7,4076	7,4297	7,4089	7,4028
40	7,2964	7,2867	7,2964	7,2303
50	7,2746	7,2572	7,2661	7,0073

up to a definite level, then the throughput continues to drop as further collisions arise as more packets contend for channel. Throughput for meta-heuristic optimization algorithms is always greater than traditional MAC. The HBA has greater throughput than CUCO and DEA when the number of drones is low. When the number of drones is high ($N \geq 35$), the throughput of HBA and CUCO algorithms is almost the same, however, higher than DEA. Meta-heuristic optimization algorithms have better efficiency than conventional MAC. It seems that the performance of CSMA/CA is better than RTS/CTS.

Fig. 7 presents the probability of successful transmission versus number of drones. The increase in the number of drones adversely affects successful transmission due to increase in collision. It seems that with the increase of drones the probability of successful transmission is better in cases where meta-heuristic optimization algorithm is used Figs. 8 and 9 show effect of channel busy probability and collision probability for different number of drones, respectively. With the increase of the number of drones channel busy probability is increased. Since more packets will compete for packet transmission, collision probability will increase with the number of drones. Due to increase of collision probability with the number of drones, channel busy probability will increase because of retransmission and increment of CW size. When number of drones is high ($N \geq 35$), probability of channel busy and collision are lower than traditional MAC than meta-heuristic optimization algorithms. Besides, CUCO algorithm is better than HBA and DEA algorithms.

Fig. 10 shows the variation of PDR with drone's number. PDR upturns with the number of drones. When the number of drones is small, HBA has lower PDR than CUCO and DEA. If the number of drones is high, DEA has a lesser PDR. The meta-heuristic optimization algorithms' PDR is constantly smaller than traditional MAC. Therefore, it is palpable that through growing throughput and decreasing PDR, meta-heuristic optimization algorithms improve communication efficiency. Figs. 7, 8, 9, and 10 do not depend on whether it is used RTS/CTS or CSMA/CA.

Fig. 11 illustrates the average delay for the number of drones. The delay increases with increment in the number of drones, mainly due to two causes. First, as the number of drones increases, more packets will compete to transmit, which increases the chances of channel busyness, which increases access time to channel. Second, as the number of drones increases, there will be more packets for transmission, which will create more packet collisions, which will rise retransmission and upsurge backoff for transmission. In order to decrease latency, channel busy probability and collision probability must be reduced. However, meta-heuristic optimization algorithms reduce delay in both RTS/CTS and CSMA/CA.

Table 2 and Table 3 present the throughput values by using meta-heuristic optimization algorithms with RTS/CTS and CSMA/CA mechanism, respectively. CSMA/CA mechanism has better throughput than RTS/CTS mechanism. Tables 4 and 5 demonstrate computation time comparison among CUCO, HBA, DEA and traditional MAC with RTS/CTS and CSMA/CA mechanism, respectively. Time consumption of traditional MAC is less than meta-heuristic algorithms. The time consumption of DEA is less than other metaheuristic optimization algorithms.

CONCLUSION

In this paper, meta-heuristic optimization algorithms are used in FANETs to get optimum throughput performance by optimizing CW size. In order to set up the relationship among parameters Markov chain based analytical study is sketched. Successful transmission probability, collision probability, channel busy probability, throughput, PDR, and delay expressions are provided. Simulation results are illustrated. Comparison between CUCO, DEA, HBA and traditional MAC is presented. It is apparent that efficiency and communication reliability are increased by meta-heuristic optimization algorithms.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

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

CONFLICT OF INTEREST

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

ETHICS

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

REFERENCES

[1] Mozaffari M, Saad W, Bennis M, Nam Y, Debbah M. A tutorial on UAVs for wireless networks: applications, challenges, and open problems. IEEE Communications Surveys Tutorials 2019;21:2334–2360. [CrossRef]

[2] Shah Ilhan H, Tureli U. Designing and Analysis of IEEE 802.11 MAC for UAVs Ad Hoc Networks, in Proc. of IEEE 10th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON), New York City, NY, USA, pp. 0934–0939, 2019.

[3] Mozaffari M, Saad W, Bennis M, Debbah M. Unmanned aerial vehicle with underlaid device-to-device communications: Performance and tradeoffs. IEEE Trans Wireless Commun 2016;15:3949–3963. [CrossRef]

[4] Zeng Y, Zhang R, Lim TJ. Wireless communications with unmanned aerial vehicles: opportunities and challenges. IEEE Communications Magazine 2016;54:36–42. [CrossRef]

[5] Barrado C, Messeguer Lopez R, Pastor JE, Santamaria E, Royo P. Wildfire monitoring using a mixed air-ground mobile network. IEEE Pervasive Comput 2010;9:24–32. [CrossRef]

[6] Maza I, Caballero F, Capitan J, Martinez-De-Dios JR, Ollero A. Experimental results in multi-UAV coordination for disaster management and civil security applications. J Intell Robot Syst 2011;61:563–585. [CrossRef]

[7] Bekmezci I, Sahingoz OK, Temel Ş. Flying ad-hoc networks (FANETs): A survey. Ad Hoc Networks 2013;11:1254–1270. [CrossRef]

[8] Yang G, Lin X, Li Y, Cui H, Xu M, Wu D, Rydén H, Redhwan SB. A telecom perspective on the Internet of drones: From LTE-advanced to 5G, in arXiv preprint arXiv 2018;1803.11048.

[9] Oubbati OS, Lakas A, Zhou F, Güneş M, Yagoubi MB. A survey on position-based routing protocols for Flying Ad hoc Networks (FANETs). Veh Commun 2017;10:29–56. [CrossRef]

[10] IEEE Standard for Information technology--Telecommunications and information exchange between systems Local and metropolitan area networks--Specific requirements - Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications," in IEEE Std 802.11-2016 (Revision of IEEE Std 802.11-2012), pp.1–3534, 14 Dec. 2016.

[11] Leeton U, Uthitsınthorn D, Kwannetr U, Sinsuphun N, Kulwırawanichpong T. Power loss minimization using optimal power flow based on particle swarm optimization, ETI-CON Int. Conference, 19-21, May 2010.

[12] Karabulut MA, Shah AFMS. Ilhan H. Performance optimization by using artificial neural network algorithms in VANETs, 42nd International Conference on Telecommunications and Signal Processing (TSP), Budapest, Hungary, 2019, pp. 633–636. [CrossRef]

[13] Mahouti P. Design optimization of a pattern reconfigurable microstrip antenna using differential evolution and 3D EM simulation-based neural network model. Int J RF Microw C E 2019;29:e21796. [CrossRef]

[14] Das S, Suganthan PN. Differential evolution: a survey of the state-of-the-art. IEEE Transactions on Evolutionary Comput 2011;15:4–31. [CrossRef]

[15] Sarker RA, Elsayed SM, Ray T. Differential evolution with dynamic parameters selection for optimization problems. IEEE Trans Evol Comput 2014;18:689–707. [CrossRef]

[16] Qin Q, Cheng S, Zhang Q, Li L, Shi Y. Particle swarm optimization with interswarm interactive learning strategy, IEEE Transactions on Cybernetics 2016;46:2238–2251. [CrossRef]

[17] Karabulut MA, Shah AFMS, Ilhan H. The Performance of the IEEE 802.11 DCF for different contention window in VANETs, 41st International Conference on Telecommunications and Signal Processing (TSP), Athens, 2018, pp. 1–4. [CrossRef]

[18] Karabulut MA, Shah AFMS, Ilhan H. The effect of contention window size of the IEEE 802.11 dcf for VANETs, 26th Signal Processing and Communications Applications Conference (SIU), Izmir, pp. 1–4.

[19] Karabulut MA, Shah AFMS, Ilhan H. Performance modeling and analysis of the IEEE 802.11 MAC protocol for VANETs. J Fac Eng Archit Gazi Univ 2020;35:1575–1587.

[20] Gunes F, Belen MA, Mahouti P. Competitive evolutionary algorithms for building performance database of a microwave transistor. Int J Circ Theor Appl 2018;46:244–258. [CrossRef]

[21] Ucgun H, Danacı M. Simulation of routing problems by combining queuing network analysis and artificial bee colony algorithms for ad hoc networks, 2nd Int. Symposium on Innovative Technologies in Engineering and Science (ISITES), pp. 1123–1132, 2014.

[22] Reina DG, Ruiz P, Ciobanu R, Toral SL, Dorronsoro B, Dobre C. A survey on the application of evolutionary algorithms for mobile multihop ad hoc network optimization problems. Int J Distrib Sens Net 2016;12:1–13. [CrossRef]

[23] Karaboga D. A survey: algorithms simulating bee swarm intelligence, Artificial Intelligence Review, vol. 2009;31:61–85. [CrossRef]

[24] Shah AFMS, Ilhan H, Tureli U. RECV-MAC: A novel reliable and efficient cooperative MAC protocol for VANETs. IET Commun 2019;13:2541–2549. [CrossRef]

[25] Karabulut MA, Shah AFMS, Ilhan H. OEC-MAC: A novel OFDMA based efficient cooperative MAC protocol for VANETS. IEEE Access 2020;8:94665–94677. [CrossRef]

[26] Shah AFMS, Ilhan H, Tureli U. CB-MAC: A novel cluster-based MAC protocol for VANETs. IET Intell Trans Syst 2019;13:587–595. [CrossRef]