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An Adaptive EDCA Selfishness-Aware Scheme for Dense WLANs in 5G Networks

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ABSTRACT To keep pace with the current rapid evolution of mobile data requirements, IEEE 802.11 was evolved to provide more desirable performance to fulfill the needs of fifth-generation (5G) and Internet of Things (IoT) networks. It provides two different access contention-based schemes; Distributed Coordination Function (DCF) which not differentiates between different services, and Enhanced Distributed Channel Access (EDCA) which provides differentiation between various services through four priority Access Categories (ACs). The dilemma of the conventional IEEE 802.11 networks is the static assignation of parameters in DCF and EDCA regardless of the number of associated stations and no matter what kind of service is required by each station (i.e., the activity of ACs). Consequently, this led to a significant degradation in the performance of the network, especially in the case of ultra-dense load network. Therefore, in this paper, we introduce a novel algorithm for EDCA considering a dynamic assignation of Arbitration Inter-Frame Space Number (AIFSN) and guidance Contention Window (CW) depending on the number of associated stations and ACs activeness status. Based on the analytical models of EDCA, a game-theoretic method is proposed to make each associated station adapts its transmission probability within the guidance CW. The purpose of guidance CW is a pre-stage to detect the selfish stations which pick up a very low CW to maximize its throughput regardless of the overall network throughput. Simulation results show that the proposed game-based algorithm can obtain higher performance than the standard 802.11 networks in terms of normalized throughput, data dropped during retransmissions limit threshold exceeding, and mean average delay for sensitive delay applications.

INDEX TERMS EDCA, high density WLANs, multiple access, selfish nodes, 5G.

I. INTRODUCTION

Recently, IEEE 802.11 networks have become an essential key to deploying dense networks and play a coaxial role for many ongoing technologies such as fifth-generation (5G) and Internet of Things (IoT) technologies [1]–[3]. Due to the rapidly increasing mobile data growth, exploitation of the unlicensed band by the interconnection of the IEEE 802.11and cellular networks could not be dispensed with easily. According to Cisco's white paper [4], Mobile data traffic has grown 17 times between 2012 and 2017 (reached 11.5 EB per month); and will increase 7 times between 2017 and 2022 (will reach 77 EB per month). At the same time, the capacity of cellular networks is keeping increasing; it's anticipated that the increasing rate of mobile data traffic will outstrip the network capacity. So, the network capacity is unable to keep up with the current rapidly evolving mobile data requirements. To keep pace with this, the interconnection of wireless local area networks (WLANs) and cellular networks (e.g. mobile traffic offloading through WLANs, LTE WLAN aggregation (LWA)) can improve the capacity and enhance the overall performance of the network [5].

Mobile traffic offloading [6], [7], where the cellular network traffic is offloaded to the supplementary networks (e.g. IEEE 802.11 Networks [8], Device to Device (D2D) communications [9], [10], small cell networks (SCNs) [7]). IEEE 802.11 Networks becomes the favored supplementary offloading networks due to its advantages: ease of deploying, higher data rates, cost-effective, unlicensed spectrum, convenient because of most cellular network users has equipment

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contains both of 802.11 and cellular modules which mean that there is no need to upgrade the user equipment (UE). LWA has evolved as a promising technology to improve the network capacity and quality of service (QoS) as a step toward 5G networks [5]; it can utilize both WLAN and LTE spectrums at the same time and combined between the advantages of LTE and WLAN access technology [11].

Current IEEE 802.11 networks confront the challenges of inefficient uplink utilization due to contention. IEEE 802.11 Medium Access Control (MAC) adopts carrier sense multiple access with collision avoidance (CSMA/CA). The two basic access methods in IEEE 802.11 networks are called Distributed Coordination Function (DCF) and Point Coordination Function (PCF) [12]. DCF is a contention-based access method and was proposed to support the best effort services, while PCF is a contention-free access method in which an access point (AP) coordinates with associated nodes through sending polling messages.

To extend the support of QoS in IEEE 802.11 networks, IEEE proposed the 802.11e amendment to differentiate between different services. IEEE 802.11e proposed two access methods called Enhanced Distributed Channel Access (EDCA) which is an enhanced version of DCF, and Hybrid Coordination Function Controlled Channel Access (HCCA) which is an extension of PCF [13]. EDCA method differentiates between different services through four different Access Categories (ACs): the highest priority Voice (VO) AC, Video (VI), Best Effort (BE), and the lowest priority Background (BK) AC. The key concept of EDCA is that the differentiated access between different ACs is through assigning different Contention Window (CW) size and Arbitration Inter-Frame Space Number (AIFSN) [14].

The dilemma of the EDCA method is the static assignation of parameters of CW size and AIFSN value regardless of how many stations are associated and the current presence status of ACs, which causes degradation in the network performance in the case of dense load network and causes waste of resources for absent ACs. Another dilemma is the selfish behavior of some nodes which choose a very small CW to increase their channel access and therefore the channel access opportunity for well-behaved nodes decreases [15]. Consequently, these dilemmas led to more collisions which impact on the overall performance of the network.

Therefore, these challenges greatly inspire us to propose a novel algorithm of EDCA for resolving the aforementioned dilemmas, the main contributions of this paper are summarized as follows:

- We propose an ACs presence-aware algorithm to dynamically tune the AIFSN value for each AC by seizing the AIFSN values of the absent ACs and also seizing the IFS value of the unused HCCA mode.
- To take the condition of the dense load AP into account, we adapt the guidance CW size depending on the number of associated nodes in each AC, and then each node will adapt its transmission probability within the guidance CW using a game-theoretic approach to maximize its performance with considering of the overall performance of the network.
- We propose a mechanism to allow the AP to detect and punish selfish and malicious behavioral nodes depending on the guidance CW.

The proposed algorithm simulation results showed that the overall performance of the dense load AP is improved in terms of normalized throughput, data dropped during retransmissions limit threshold exceeding, and mean average delay for sensitive delay ACs.

The rest of the paper is organized as follows. Section II outlines the EDCA scheme, game theory, and related work. Section III details the novel proposed mechanism: determination of ACs presence status, counting of nodes in each AC, tuning of the guidance CW, adaptation of the transmission probability for each node depending on game theory, and detection of selfish behavioral nodes. In section IV, we evaluate the performance of the proposed mechanism via simulation. Finally, we conclude the paper in Section V.

II. PRELIMINARIES AND RELATED WORK

A. DCF & EDCA SCHEMES

The DCF scheme is a contention-based access mechanism designed by IEEE [12]. Every station has to sense the channel before it can send. If the channel is idle longer than a time interval called Distributed Inter-Frame Space (DIFS), the station will initiate the backoff stage as a step towards seizing the medium. In contrast, if the channel is busy, the station has to wait until the medium turns to idle state again for a time longer than DIFS [16]. In the backoff stage, the station will randomly select an initial backoff counter from a range [0, (CW - 1)], where CW value is within a range from the minimum contention window (CW_{min}) to the maximum contention window (CW_{max}). The backoff counter decreases by 1 when the medium state is idle. Once the backoff counter reaches zero, the station can immediately send the data. In case the medium state becomes busy during the decrement of the backoff counter, the counter will be paused until the medium turns to idle state for a time longer than DIFS [17]. The initial CW is set to CW_{min}; in case of collision occurred, the old CW (CW_{old}) of the failed transmission nodes will be multiplied by 2 up to CW_{max}. In contrast, in the case of successful data transmission or reaching the retransmissions limit, the CW is reset to CW_{min} [12]. The updating of CW is given by

$$CW = \begin{cases} CW_{min} & \text{on a success} \\ \min\left(CW_{max}, 2 * CW_{old}\right) & \text{on a collision} \end{cases} \quad (1)$$

IEEE developed the DCF scheme to EDCA scheme to provide a differentiation between different types of services. The EDCA differentiates between different services through four ACs from the highest priority to the lowest as follows: VO (for voice services), VI (for video services), BE (for best-effort services), and BK (for Background data). The EDCA assigns static parameters to each AC which includes

TABLE 1. EDCA ACs parameters.

Access Category		$AIFSN_m$	$CW_{min,m}$	$CW_{max,m}$	$TXOP_m$
AC	m				
VO	0	2	7	15	3.264 ms
VI	1	2	15	31	6.016 ms
BE	2	3	31	1023	0 ms
BK	3	7	31	1023	0 ms

CW_{min}, CW_{max}, Arbitration Inter-Frame Space (AIFS), and transmission opportunity (TXOP) as listed in Table 1 [13]. In EDCA scheme, each station will sense the channel for being idle for a time longer than AIFS instead of DIFS, which is given by

$$AIFS_m = SIFS + AIFSN_m * \delta \quad (2)$$

where $AIFSN_m$ is the AIFSN number for AC class m, SIFS is the Short Inter-Frame Space, δ is the slot time duration.

Besides, the EDCA produces TXOP as a contention-free period (CFP); during this period, each node can seize the channel for a TXOP period and transmit as many data frames as possible until the interval of the data frames transmission does not exceed the limited TXOP period [18].

B. GAME THEORY

Game theory is an effective mathematical tool to study the strategies and decision making in conflict of interest or cooperative situations between multiple players, this theory attracted great attention of many researchers from the wireless community [19]. Every game consists of three main components: players (e.g., people, organizations, network nodes), strategies (i.e., set of decisions), and payoff or utility functions. Each player must take into account the decisions taken by the other players to optimize its decision to maximize its own payoff. A strategic game is represented as follows [20]:

$$G =< K, (S_i)_{i\in K}, (u_i)_{i\in K} > \quad (3)$$

where K is the number of players, S_i is the set of available strategies for player i, u_i is the utility function of player i.

In general, games can be classified into cooperative or non-cooperative games. In a cooperative game, all players collaborate and coordinate their strategies to maximize the system utility and obtain a social equilibrium. On the other hand, in a non-cooperative game, each player takes a decision autonomously to maximize its own utility without knowing the choices of the other players [20]. Non-Cooperative games have been widely used to research several topics in wireless networks (e.g., Medium Access Control (MAC) game, admission control, and power control). The objective of non-cooperative games is to discover the equilibria in wireless networks with self-interested nodes [21].

A game solution, called Equilibrium, explains the players' optimal set of strategies and the resulted utility from these strategies. One of the most known equilibria is the Nash Equilibrium (NE); NE is a combination of strategies such that no player has a motivation to change his/her strategy to achieve a greater utility, which meets the following criterion [19]:

$$u_i\left(s_i^*, s_{-i}^*\right) \geq u_i\left(s_i, s_{-i}^*\right), \quad \forall i \in K, \ \forall s_i \in S_i \quad (4)$$

where, s_i^* is a NE strategy for player i, and s_{-i}^* is NE strategies set for all other players except player i. There are many methods that lead a game towards a NE; the most common are Best Response, Gradient, and Jacobi method.

Game theory has become an effective tool for improving the overall performance of wireless networks. Applications and Challenges of game theory for wireless networks are studied in [22]–[25], and for MAC challenges are studied in [20], [26].

C. RELATED WORK

There have been a lot of researches on addressing the dilemma of performance degradation and providing more QoS support in dense load WLANs. Here we discuss a few which are most related to this paper. In [27], a backoff scheme for WLANs is proposed with QoS support by doubling the CW when the channel is found busy not only on collision state. This procedure may decrease the collisions between the competing nodes, but it will increase the average delay for voice and video ACs. In [28], the authors introduced an efficient back-off scheme to increase energy efficiency and decrease collisions. It adjusts the CW size according to the collision probability and uses temporary back-off within the existing back-off counter. In [29], the authors improved the binary exponential backoff (BEB) based on the estimated number of the competing nodes which adapt the CWmin before the contention phase to enhance the overall network throughput and the packet delivery ratio. The authors of [30] improved the wireless full-duplex cognitive MAC protocol that effectively resolved the problem of reactivation-failure in multichannel non-time slotted cognitive radio networks. In [31], the authors improved the energy efficiency while providing the QoS for 5G networks by maximizing the effective power efficiency (EPE) of SISO and MIMO channels.

In [32], with introducing an analytical model, an adaptive CW algorithm is proposed to consider the estimated number of stations in each AC; an improving shown in the network throughput and retransmissions, but the algorithm used a very large size CW_{min} compared to the number of stations which will cause a degradation in term of delay in dense load condition. In [33], the authors proposed a dynamic CW tuning scheme by considering the collision probability. In [34], the authors proposed an adaptive AIFSN scheme based on the network load to enhance QoS support. In [35], we proposed an adaptive CW and AIFSN tuning scheme by taking into account the number of associated nodes in each AC and the activity of ACs to improve the global normalized throughput of the network and decrease the mean average delay of sensitive delay services.

Within the framework of game theory, in [36], a game-theoretic adaptive CW mechanism is proposed for heavy load DCF WLANs. This mechanism makes each node to adjust its CW size independently to improve the performance of the network in which there will be a tradeoff between the throughput, mean delay, and the retransmission attempts. In [37], the authors proposed a dynamic CW_{min} game-based mechanism called G-EDCA to improve the network throughput and decrease the frame drop rate by considering the problem of selfish behavioral nodes. In [38], the authors proposed a game-theoretic adaptive AIFSN scheme based on the QoS measurements and proposed an admission control algorithm based on the network capacity to increase the throughput of low priority AC.

III. THE PROPOSED ALGORITHM

As discussed in the previous sections, providing high throughput and low delay for sensitive delay services, especially in dense load condition networks, is very critical and considered as a vital key to keeping pace with the current rapid evolution of mobile data requirements. In EDCA mode of the IEEE 802.11 networks, the associated stations access to the channel by adjusting their CWs.

Therefore, unsuitable tuning of CW by some selfish behavioral stations to increase the transmission probability by exploiting small values of CW will lead to more collisions and dramatic degradation in the overall performance of the dense load AP. Besides that, the static assignment of AIFSN values regardless of the absence state of any AC and the activity of HCCA mode will waste resources that can be exploited by the non-absent ACs. So, we proposed an algorithm to adapt the values of CW and AIFSN with detection of selfish nodes by taking into account the number of associated nodes in each AC and the activity of ACs to improve the overall efficiency of the uplink access (i.e., transmissions to the AP) in dense load IEEE 802.11 network with the support of QoS differentiation. Our algorithm includes six phases:

a. Detection of actually present ACs and the number of stations in each AC.
b. Tuning of AIFSN.
c. Tuning of the guidance CW.
d. Advertising the calculated values of the Guidance CW and AIFSN.
e. Game theoretic based adaptation of transmission probability.
f. Detection of selfish behavioral stations.

A glossary of notations used in the proposed algorithm is presented in Table 2.

A. DETECTION OF PRESENT ACs AND THE NUMBER OF STATIONS PER EACH AC

To join the WLAN and start the data transmission process, each station must send an association request to the AP in order to acquire an Association Identifier (AID). Fig. 1 shows the structure of the association request frame, which contains a subfield called QoS Capability includes flags for all types of ACs. These flags are set to 0 or 1 by the stations to inform the AP about needing QoS ACs to data transmission.

At the AP, we created three counters for Voice, Video, and Best Effort ACs to count the number of stations for access category m (K_m), where m is equal to 0, 1, and 2 for voice, video, and Best Effort ACs respectively. For each AC flag equal to 1 received by the AP, the corresponding AC counter will be incremented by 1.

In contrast, the corresponding counter will be decremented by one in case of disassociation. These counters will give us an accurate number of the currently associated station in each AC. In case any counter has a zero value, this means that the corresponding AC is not active (i.e., absent).

TABLE 2. Glossary of notations.

Symbol	Definition
δ	Slot time duration
K_m	Number of stations in AC class m
S_i	Available Strategies for player i
u_i	Payoff of player i
s_i^*	Best response strategy of player i
CW_{maxphy}	Max. CW restricted by the physical layer
$CW_{min,m}$	Min. CW in AC class m
$CW_{max,m}$	Max. CW in AC class m
Ψ_m	Transmission probability of AC class m inside the station
β_m	Probability that backoff counter can be decreased by one for access category m
$\mathbb{C}_m$	Collision probability of access category m for a station
r_m	Retransmissions limit for access category m
$\mathbb{D}_m$	Maximum times for doubling the CW after a collision for access category m
ξ_m	Transmission probability of AC class m outside the station
λ	Probability of at least one transmission in a time slot
μ_m	Probability of a succeeded transmission for AC class m in a time slot
ν	Probability of a collided transmission in a time slot
X_m	Saturation throughput for AC class m
σ	Propagation delay
TS_m	Average time of a successful trans. for AC class m
TC	Average time of a collided transmission
A_m	Average access delay of AC class m

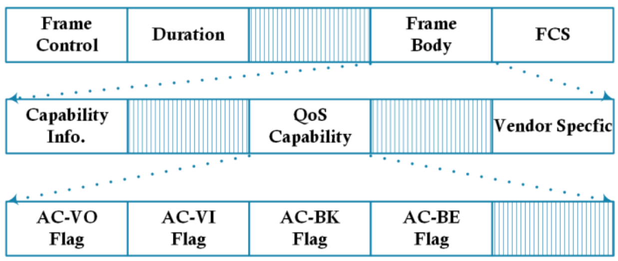

FIGURE 1. Association request frame in IEEE 802.11.

TABLE 3. The dynamic tuning of AIFSN.

Activity Status				AIFSN Value		
HCCA	VO	VI	BE	VO	VI	BE
Disabled	Absent	Absent	Active	-	-	1
Disabled	Absent	Active	Absent	-	1	-
Disabled	Absent	Active	Active	-	1	2
Disabled	Active	Absent	Absent	1	-	-
Disabled	Active	Absent	Active	1	-	2
Disabled	Active	Active	Absent	1	2	-
Disabled	Active	Active	Active	1	2	3
Enabled	Absent	Absent	Active	-	-	2
Enabled	Absent	Active	Absent	-	2	-
Enabled	Absent	Active	Active	-	2	3
Enabled	Active	Absent	Absent	2	-	-
Enabled	Active	Absent	Active	2	-	3
Enabled	Active	Active	Absent	2	3	-
Enabled	Active	Active	Active	2	3	4

B. TUNING OF AIFSN

As mentioned earlier, the allocation of the fixed value of AIFSN to different ACs is considered to be a waste of resources, particularly in the case of inactivity for any AC.

Accordingly, the active ACs can exploit opportunistically the AIFSN values of the absent ACs to improve its performance. According to [39], the best effort AC is the most traffic used in IoT networks.

So, the best effort AC can benefit from the absence of higher priority ACs (i.e., voice and video ACs) by seizing its AIFSN values to decrease the media access delay. In addition, the centralized scheme HCCA is not practically used. In HCCA, the PCF Inter-Frame Space (PIFS) interval is used by stations to transmit data within the Contention Free Period (CFP) and used by the Hybrid Coordinator (HC) to start or end the CFP.

Hence, in our proposed algorithm, the active ACs will seize the AIFSN of the absent ACs and will seize the PIFS interval when the HCCA mode is disabled. But, if the data transmission cannot be completed before the incoming scheduled beacon starts, stations are not permitted to send data. The dynamic tuning of AIFSN is listed in Table 3.

C. TUNING OF THE GUIDANCE CW

As listed earlier in Table 1, IEEE 802.11 standard allocates a static value of CW_{min} and CW_{max} for each AC. So, in the condition of dense load AP, the static allocation will cause a precipitous fall in the network performance in terms of the overall throughput and the average delay during a high number of collisions. This problem also occurs as the selfish stations attempt to select a small CW in order to increase the transmission probability.

Hence, we propose the concept of the guidance CW, which is a preliminary step for two processes as follows:

a. Adaptation of transmission probability: where each station adapts its probability transmission in a game-theoretic approach within the guidance CW

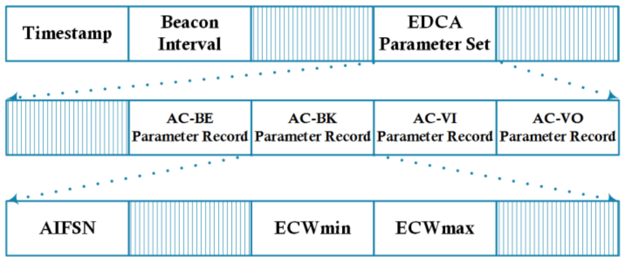

FIGURE 2. Beacon format in IEEE 802.11.

b. Detection of selfish stations: where the AP detects any station adapts its probability transmission with CW value lower than the guidance CW.

In our proposed Algorithm, we adapt the values of CW_{min} and CW_{max} of the guidance CW depending on the number of stations in each AC as follows [35]:

$$CW_{min,m} = 2^{ceil(\log_2(\frac{k_m}{2}))} - 1 \quad (5)$$

$$CW_{max,m} = \min(2^{ceil(\log_2(2k_m))} - 1, CW_{maxphy}) \quad (6)$$

where CW_{maxphy} is the maximum value of CW_{max} restricted by the physical layer.

D. ADVERTISING THE NEW VALUES OF GUIDANCE CW AND AIFSN

In IEEE 802.11 networks, the AP sent a beacon frame periodically (every 102.4 ms) to inform all associated stations about the network information and parameters. Consequently, all stations which are associated with the network can be updated with the Basic Services Set (BSS) parameters. As shown in Fig. 2, the beacon frame contains a field called EDCA Parameter Set, which includes the AIFSN, ECWmin, and ECWmax parameters for each AC. ECWmin and ECWmax are the exponent form of CWmin and CWmax as follows:

$$CW_{min,m} = 2^{ECWmin,m} - 1 \quad (7)$$

$$CW_{max,m} = 2^{ECWmax,m} - 1 \quad (8)$$

In our algorithm, after adaptation of the AIFSN and the guidance CW, the AP will advertise the associated stations with the new values through the fields of AIFSN, ECWmin, and ECWmax. From (5)-(8), the new calculated ECWmin, and ECWmax of the guidance CW will be as follows:

$$ECW_{min,m} = ceil(log_2(\frac{k_m}{2})) \quad (9)$$

$$ECW_{max,m} = min(ceil(log_2(2k_m)),(log_2(CW_{maxphy}))) \quad (10)$$

E. GAME-THEORETIC BASED ADAPTATION OF TRANSMISSION PROBABILITY

In this stage, through a game-theoretic approach, all associated stations will adapt its transmission probability within the guidance CW by tuning only CW_{min} for lower complexity purposes. Game theory is an effective method to clarify the effect of station actions on the others, and on the network performance.

In our proposed algorithm, each associated station in each AC will be considered as a player and the adaptation of its transmission probability will be considered as its strategy. Each associated station will adapt its transmission probability in order to maximize the payoff function which aims to maximize the network throughput, minimize the data dropped during retransmissions limit threshold exceeding, and minimize the access delay in the network.

First, the equations of the throughput and the access delay in the EDCA algorithm should be defined to determine the proposed payoff function. These equations are addressed in some analytical models [32], [40]–[42]. Let Ψ_m refer to the transmission probability of AC class m inside the station, which expressed in (11), as shown at the bottom of this page, [40]; where β_m is the probability that backoff counter can be decreased by one for access category m, $\mathbb{C}_m$ is the collision probability of access category m for a station, r_m is the retransmissions limit for access category m, $\mathbb{D}_m$ is the maximum times for doubling the CW after a collision for access category m. β_m, and $\mathbb{C}_m$ are defined as follows [40]–[42]:

$$\begin{cases}\beta_0 = 1\\ \beta_1 = \left((1-\Psi_0)(1-\xi_0)^{K_{total}}\right)^{(DIFF_1)}\\ \beta_2 = \beta_1 * \left(\prod_{j=0}^{1}\left(1-\Psi_j\right)\left(1-\xi_{\rm j}\right)^{K_{total}}\right)^{(DIFF_2)}\\ \beta_3 = \beta_1 * \beta_2 * \left(\prod_{j=0}^{2}\left(1-\Psi_j\right)\left(1-\xi_{\rm j}\right)^{K_{total}}\right)^{(DIFF_3)}\end{cases} \tag{12}$$

$$\mathbb{C}_m = \mathbb{I}_m + (1-\mathbb{I}_m)\,\Phi \tag{13}$$

where K_{total} is the number of all stations in the network, $\xi_{\rm m}$ is the transmission probability of AC class m outside the station, $\mathbb{I}_m$ is the virtual collision probability of AC class m with a higher priority class within the same station, $DIFF_m = (AIFSN_m - AIFSN_{m-1})$, and Φ is the collision probability between different stations (i.e., the external collision probability). $\mathbb{I}_m$, Φ, and $\xi_{\rm m}$ are defined as follows [40]–[42]:

$$\begin{cases}\mathbb{I}_0 = 0\\ \mathbb{I}_1 = \Psi_0\\ \mathbb{I}_2 = 1-(1-\Psi_0)(1-\Psi_1)\\ \mathbb{I}_3 = 1-(1-\Psi_0)(1-\Psi_1)(1-\Psi_2)\end{cases} \tag{14}$$

$$\xi_{\rm m} = \Psi_m(1-\mathbb{I}_m) \tag{15}$$

$$\Phi = 1-(1-\xi_{\rm total})^{K_{total}-1} \tag{16}$$

where $\xi_{\rm total}$ is the total transmission probability for a station and equal to $\sum_{m=0}^{3}\xi_{\rm m}$.

According to the EDCA analytical models, the saturation throughput is the maximum throughput that the network can reach under saturation conditions. The saturation condition means that all stations always have data to send. Let λ refers to the probability of at least one transmission (succeeded or collided) being in a time slot, μ_m refers to the probability of a succeeded attempt for AC class m in the time slot, and ν refers to the probability of a collided transmission in the time slot, which are defined as follows [40]:

$$\lambda = 1-(1-\xi_{total})^{K_{total}} \tag{17}$$

$$\mu_m = \frac{K_{total} * \xi_m\,(1-\xi_{total})^{K_{total}-1}}{\lambda} \tag{18}$$

$$\nu = \frac{\lambda - K_{total} * \xi_{\,total}\,(1-\xi_{total})^{K_{total}-1}}{\lambda} \tag{19}$$

The saturation throughput for AC class m ($\rm X_m$) is defined as follows [40]–[42]:

$$X_m = \frac{\lambda * \mu_m * E\,[P_m]}{(1-\lambda)*\delta + \sum_{m=0}^{3}\lambda * \mu_m * TS_m + \lambda * \nu * TC} \tag{20}$$

where $E\,[P_m]$ is the mean payload size of AC class m, δ is the slot time duration, TS_m is the average time of a successful transmission for AC class m, and TC is the average time of a collided transmission. TS_m, and TC are calculated as follows [40], [43]:

$$TS_m = TH + T_{E[P_m]} + SIFS + ACK + AIFS_m + 2\sigma \tag{21}$$

$$TC = TH + T_{E[P_m^*]} + AIFS_m + \sigma \tag{22}$$

where TH is the transmission time of the frame header, $T_{E[P_m]}$ is the transmission time of the $E\,[P_m]$, $T_{E[P_m^*]}$ is the transmission time of the longest collided mean payload, and σ is the propagation delay. The average access delay is represented as follows [44]:

$$\begin{aligned}{\rm A_m} = \xi_{\rm total}\,(K_{total}-1)\left[TS_m + TC * \frac{\Phi}{1-\Phi}\right] + TS_m\\ + TC * \frac{\Phi}{1-\Phi} + CW_m * \delta\end{aligned} \tag{23}$$

Finally, after counting the number of stations in each AC (first phase of the proposed algorithm), and also defining the saturation throughput and the medium access delay equations, the proposed game can be defined. In our proposed algorithm, the game is defined as $< K_{total}, (\xi_{\rm i})_{i\in K}, (u_i)_{i\in K} >$, each station will adapt its transmission probability by tuning its CW within the CW guidance to optimize its payoff. The payoff function of each station is formulated as the performance of station in terms of the saturation throughput and the media access delay (i.e., each station will try to increase its throughput and decrease its access delay). The proposed payoff function is formulated depending on the weighted sum method [45] as follows:

$$u_i\,(\xi_{\rm i}) = \alpha_1 \frac{X_m}{X_{m[max]}} - \alpha_2 \frac{\rm A_m}{\rm A_{m[max]}} \tag{24}$$

where α_1 and α_2 are the weighted coefficients. The terms of throughput and access delay are normalized since they do not

$$\Psi_m = \frac{2\beta_m * \left(1-\mathbb{C}_m^{r_m+1}\right)}{(1+2\mathbb{C}_m) * \left(1-\mathbb{C}_m^{r_m+1}\right) + CW_{\rm min,m} * (2\mathbb{C}_m)^{\mathbb{D}_m} * \left(1-\mathbb{C}_m^{(r_m-\mathbb{D}_m+1)} - \frac{1-\mathbb{C}_m}{1-2\mathbb{C}_m}\right) + \frac{1-\mathbb{C}_m}{1-2\mathbb{C}_m}} \tag{11}$$

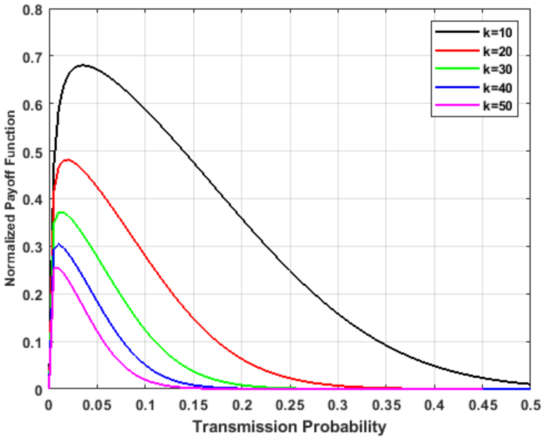

FIGURE 3. The normalized payoff function.

have the same dimension unit. The weighted coefficients can be adapted by stations depending on their objectives.

The normalized payoff function for a different number of associated stations (10, 20, 30, 40 and 50) is shown in Fig. 3. It is clear that this function is concave. According to the formulated payoff function, it is clear that two statements affect on the transmission probability. We assume that all stations can listen to each other, and then they form a coalition. All stations must adapt its transmission probability within the guidance CW to maximize the throughput and minimize the delay. In case of any station adapts its transmission probability outside the range of the guidance CW, the AP can detect the malicious behavior of this station and expelled it from the network. Therefore, every station is forced to cooperate to reach an NE and a satisfying point for all other stations which will affect on the overall network performance. So our proposed game is acting like a cooperative one. Hence, if this problem is optimized, the optimal probability of transmission, which is also a Pareto solution, will be obtained.

In our algorithm, we used the best response method to lead the game towards NE. Therefore, each station selects its best strategy against the other stations' previous strategies. The NE is the point at which each station in the network has selected the best response to the other players' actions. So, each station must maximize its payoff function by solving the following equation:

$$\xi_i\,(t+1) = \arg\max_{0<\xi_i<1} u_i(\xi_i, \xi_{-i}) \qquad (25)$$

By solving $du_i(\xi_i, \xi_{-i})/d\xi_i = 0$, the best response ($\xi_i^*$) can be calculated. As we mentioned before, every station selects its best response against the actions of the other station in the last stage. Hence, each station will select its strategy at stage (t + 1) as follows:

$$\xi_i\,(t+1) = \arg\max_{0<\xi_i<1} (\alpha_1 \frac{X_m}{X_{total}} - \alpha_2 \frac{A_m}{A_{total}}) \qquad (26)$$

After obtaining the optimal transmission probability, the CW_{min} can be adapted through (11) and (15) within the CW_{min} of the guidance CW.

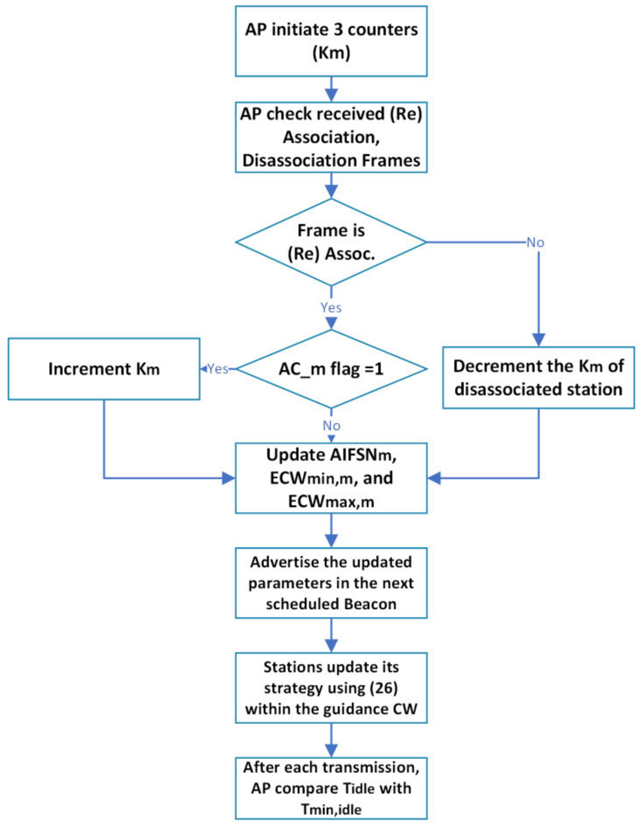

FIGURE 4. The flowchart of the proposed algorithm.

F. DETECTION OF SELFISH BEHAVIORAL STATIONS

As we mentioned before, the selfish behavioral adaptation of the CW by malicious stations results in more collisions and degradation in the overall performance, especially it may cause a rapid collapse in a dense load AP. We introduced the concept of the guidance CW as a preliminary stage to detect the selfish stations. The guidance CW will make the AP able to detect any station that adapts its CW with a lower value than the guidance CW. The minimum time the channel is idle before any class m transmission within the guidance CW is calculated as follows:

$$T_{min,idle} = SIFS + (AIFSN_m + CW_{min,m,guidance}) * \delta \qquad (27)$$

In this stage, the AP senses the channel and calculates how much time the channel is idle before any transmission. In the case of the calculated idle time before transmission by a station is lower than $T_{min,idle}$, this indicates the station is selfish. Consequently, the AP can punish the selfish station by disassociation. In Fig. 4, the flowchart of the proposed algorithm is illustrated.

Since the game theory is known to be complicated, we used it as partial game theory to reduce complexity and offer more simplicity. In the presented scheme, we used the game theory only in the phase of transmission probability adaptation but didn't use it in the rest of the algorithm. Also to reduce the complexity of the scheme, we used a direct

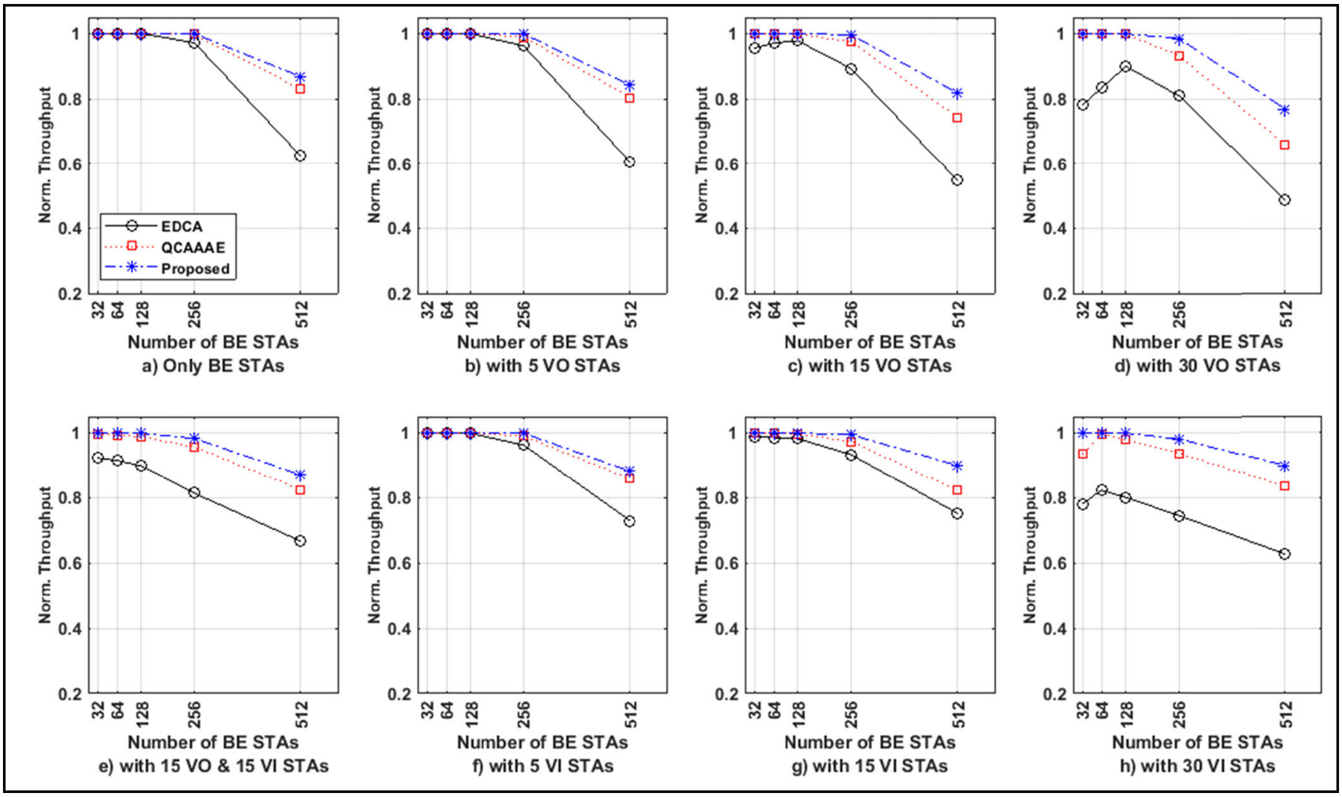

FIGURE 5. The normalized throughput of the network.

method at the AP to count the number of associated stations instead of an estimation method. Additionally, we limited the scheme to 3 ACs and excluded the Background AC for lower complexity.

IV. PERFORMANCE EVALUATION

In this section, we investigate the performance of the proposed algorithm through a set of forty different simulated scenarios considering both low and high density loads. The scenarios consist of 32, 64, 128, 256, or 512 Best Effort (BE) stations and repeated with different combinations of Voice (VO) and Video (VI) stations. We assumed that the network is in saturation condition (i.e. all stations always have data frames to send to AP).

The proposed algorithm is simulated with the Riverbed modeler and compared with the traditional IEEE 802.11 EDCA [46], [47], and QCAAAE algorithms [35]. We assessed the proposed algorithm in terms of the network throughput normalized to the total traffic submitted, the mean average End-to-End delay, and the data drop rate due to exceeding of retransmission attempts. The simulation parameters are illustrated in Table 4.

The simulation results of the global normalized throughput are shown in Fig. 5. It is clear that the proposed algorithm has a higher normalized throughput than the conventional EDCA and QCAAAE algorithms, especially in high-density conditions. In all scenarios that include 512 BE stations, the normalized throughput increased on average 37% compared to the traditional EDCA and 8% compared to QCAAAE.

TABLE 4. Simulation parameters.

Parameter	Value
Physical Layer	IEEE 802.11 OFDM
Spatial Streams	1
Slot Time (δ)	9 μs
Beacon Interval	102.4 ms
CW_{maxphy}	1023
Data Rate	65 Mb/s
α_1, α_2	0.8, 0.2
Voice Payload Size	50 Bytes
Video Payload Size	8738.13 Bytes
Best Effort Payload Size	100 Bytes

Regarding the drop rate due to exceeding of retransmissions limit, it is obvious from Fig. 6 that the proposed algorithm has a lower drop rate than the other algorithms; this improvement is most noticeable in cases of high-density scenarios. In all scenarios includes 512 BE stations, the drop rate of the proposed algorithm decreased on average from 4.82 Mb/s (EDCA), 2.45 Mb/s (QCAAAE) to 1.09 Mb/s.

The simulation results of the mean average delay of the network are shown in Fig. 7, it is clear that the proposed algorithm has a lower mean average delay than the other algorithms, except for two scenarios. In 256 BE with 30 VI and 512 BE with 30 VI scenarios, the delay of

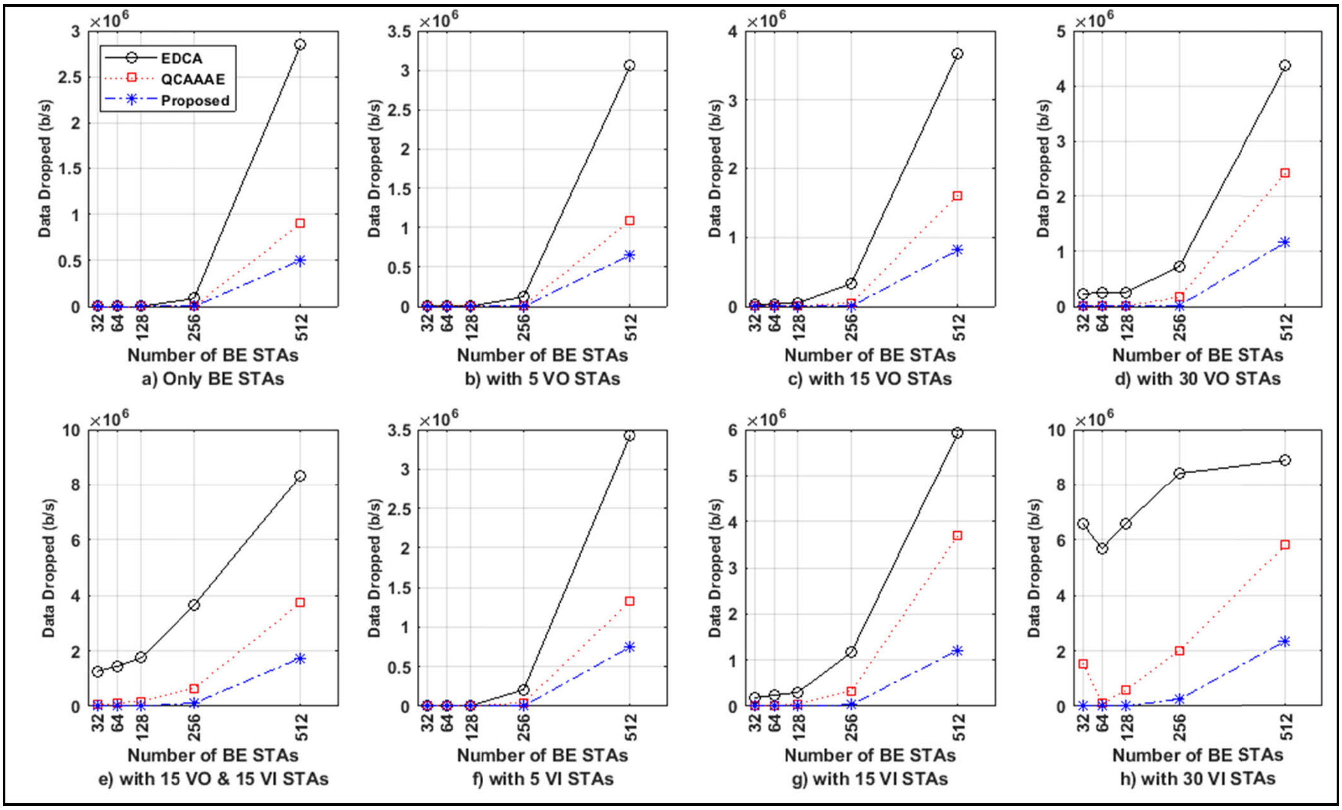

FIGURE 6. The drop rate due to exceeding of retransmissions limit.

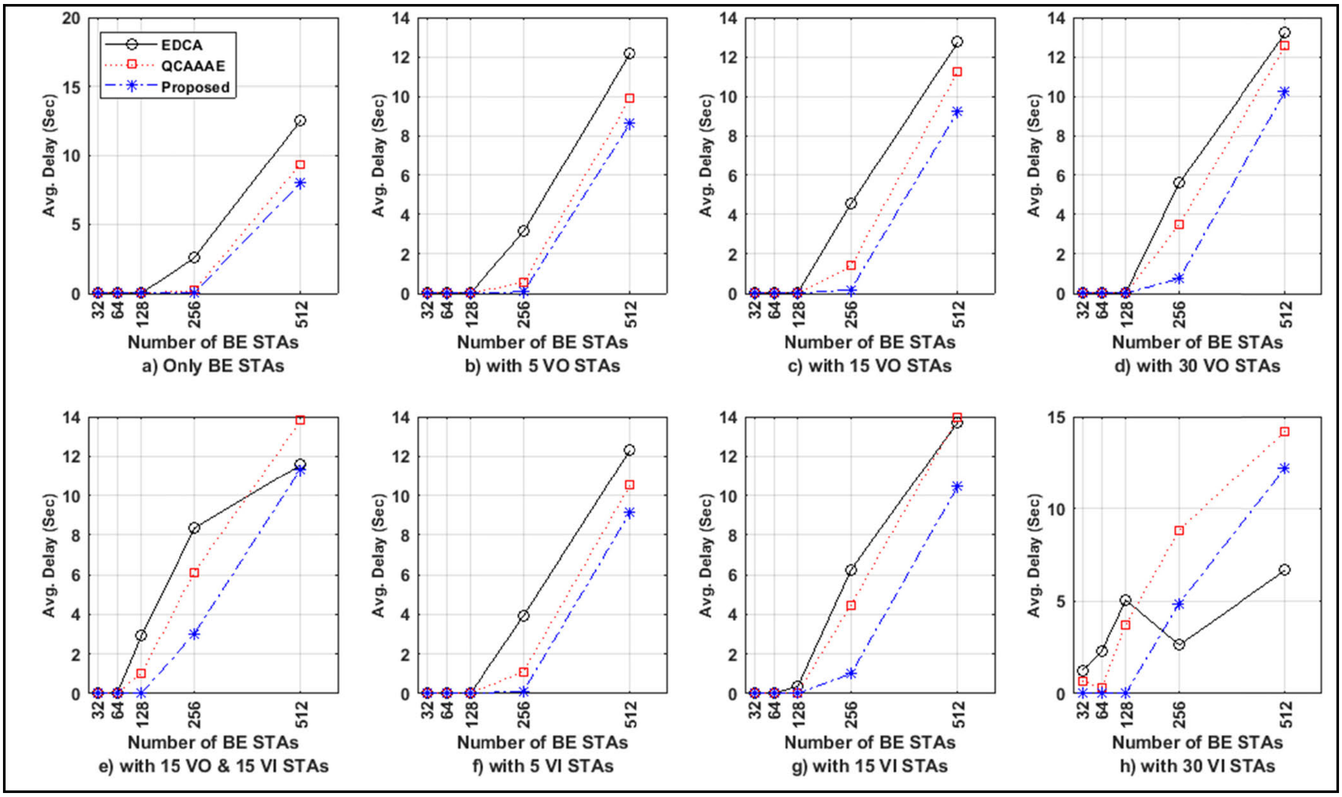

FIGURE 7. The mean average delay of the network.

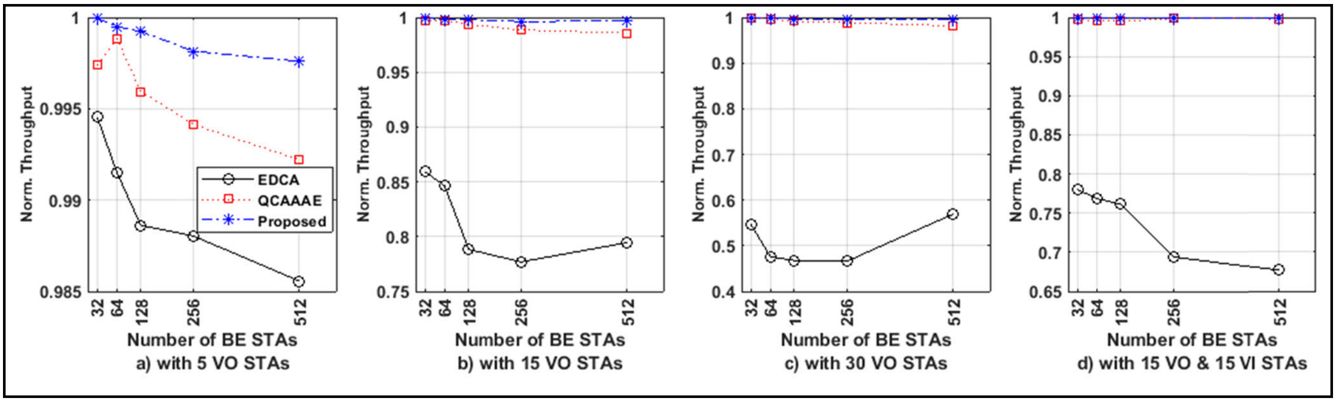

FIGURE 8. The normalized throughput of voice stations.

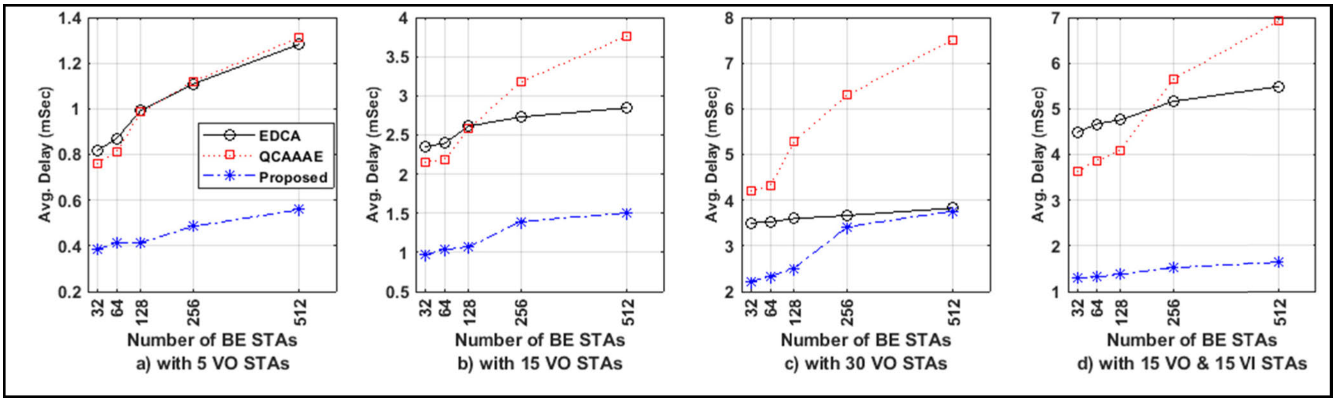

FIGURE 9. The mean average delay of voice stations.

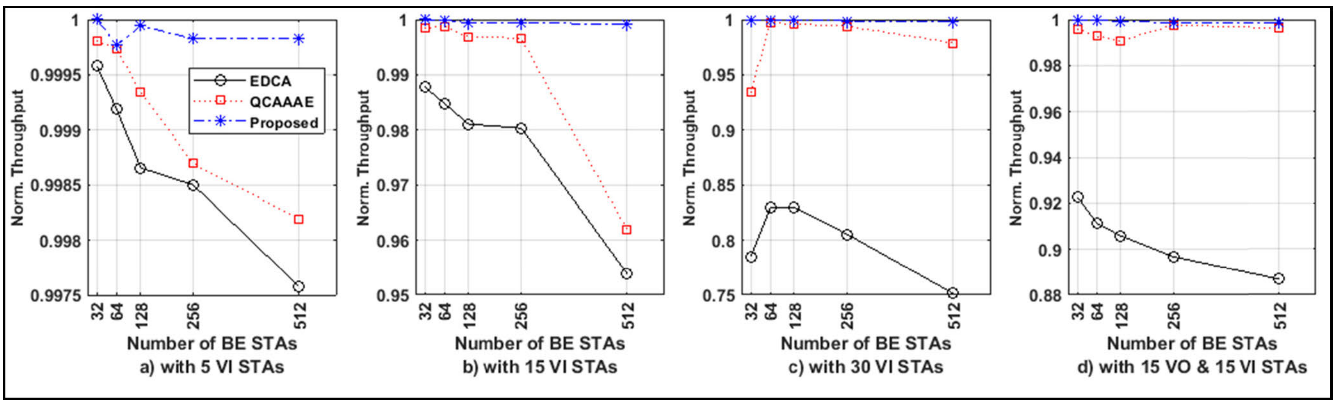

FIGURE 10. The normalized throughput of video stations.

EDCA is lower and decreased from 4.8s to 2.6s from 12.2s to 6.6s, respectively. But on the other hand, the normalized throughput (which has more priority) of the proposed algorithm is increased in these scenarios from 74.4% to 98.1% and from 62.6% to 89.7%, respectively. Also, the data drop rate is decreased in the proposed algorithm from 8.02 Mb/s to 0.25 Mb/s and from 8.47 Mb/s to 1.9 Mb/s, respectively.

Concerning the services that are sensitive to data loss and delay, as shown in Fig. 8 to Fig. 11, it is quite notable that the normalized throughput and the mean average End-to-End delay of voice and video stations are improved compared to the other algorithms. In most of the simulated scenarios, we also have noted that the proposed algorithm has solved the delay caused by the QCAAAE in voice and video services with also maintaining a higher throughput at the same time.

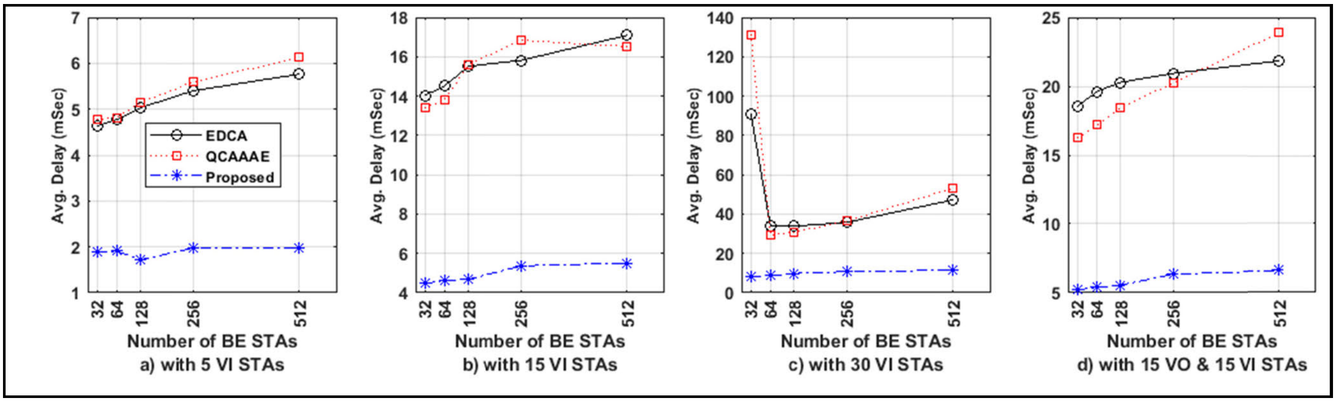

FIGURE 11. The mean average delay of video stations.

TABLE 5. The average retransmission attempts.

Scheme	Average Retransmission Attempts
EDCA	4.3694
QCAAE	2.4188
The proposed scheme	2.2014

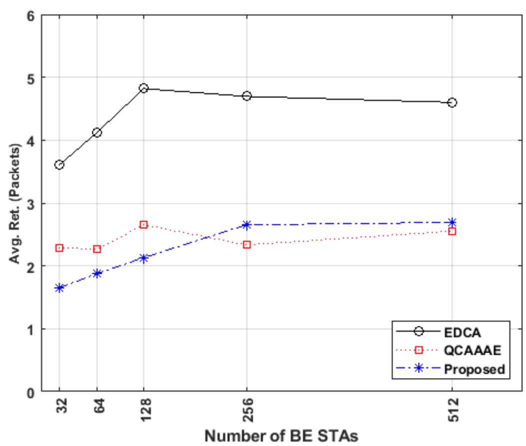

FIGURE 12. The average retransmission attempts of the network.

TABLE 6. The mean average delay in ACs.

Traffic Scenario	ACs Mean Average Delay (Sec)		
	VO	VI	BE
32 BE, 15VO, 15 VI	0.0012	0.0052	0.0061
64 BE, 15VO, 15 VI	0.0013	0.0053	0.0115
128 BE, 15VO, 15 VI	0.0014	0.0055	0.0251
256 BE, 15VO, 15 VI	0.0015	0.0063	4.1561
512 BE, 15VO, 15 VI	0.0016	0.0066	14.008

The average number of retransmission attempts of all scenarios is listed in Table 5. The simulation results of the average retransmission attempts of (32BE, 64BE, 128BE, 256BE, 512BE) scenarios are shown in Fig. 12. It is clear that the proposed algorithm has fewer collisions than conventional

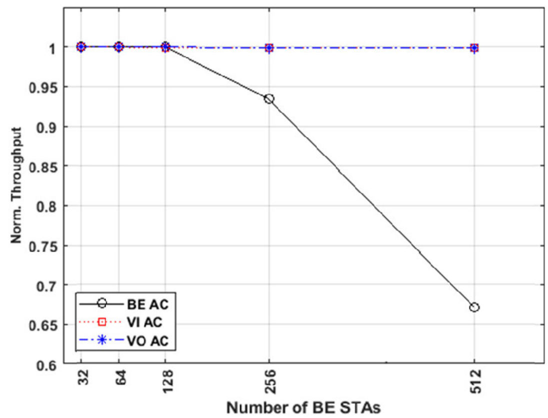

FIGURE 13. The average normalized throughput in ACs.

EDCA. The average number of retransmission attempts decreased on average 49.6% compared to the traditional EDCA and 8.98% compared to QCAAAE.

Fig.13 and Table 6 show the average normalized throughput and the mean average delay in all scenarios in which all ACs have existed; it is quite notable that the proposed scheme satisfies the priority between different ACs.

V. CONCLUSION

In this paper, we proposed a novel mechanism based on the EDCA mechanism to address the dilemma of the rapid degradation in the performance of high-density networks due to the static assignation of CW size and AIFS interval; also to solve the dilemma of selfish stations which select a very small CW to increase its channel access opportunity without considering the performance of the network and other stations. Our proposed algorithm adapted dynamically the CW size and AIFSN value with taking into account the activity status of each AC and the number of associated stations in each AC. We proposed the concept of the guidance CW as a pre-stage for the detection of the selfish stations. So, the AP will be able to detect any station which adapts its CW without considering the guidance CW through comparing between two metrics:

the actual idle time of the channel and the minimum idle time of the channel within the guidance CW. In our algorithm, each station adapts its transmission probability within the guidance CW through a game-theoretic approach, the payoff function is defined as a function of both the saturation throughput and the medium access delay. Simulation results show that the proposed mechanism, especially in high-density scenarios, can effectively increase the overall throughput (increased on average 37% compared to the standard EDCA) and decrease both the data drop rate due to exceeding of retransmissions limit (decreased on average 77% compared to the standard EDCA) and the mean average delay particularly in the services that are sensitive to the data loss and delay.

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