A New Adaptive Frame Aggregation Method for Downlink WLAN MU-MIMO Channels

Lem Lem Kassa
School of Information and Software Engineering, University of Electronic Science and Technology, China

Mark Davis
Technological University Dublin, mark.davis@tudublin.ie

Jingye Cai
University of Electronic Science and Technology, China

See next page for additional authors

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Authors
Lem Lem Kassa, Mark Davis, Jingye Cai, and Jianhua Deng

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Lemlem Kassa[1], Mark Davis[2], Jingye Cai[1], and Jianhua Deng[1]
[1]School of Information and Software Engineering, University of Electronic Science and Technology China (UESTC), Chengdu, 610054, China
[2] Communication Network Research Institute (CNRI), Technological University Dublin, D08 NF82, Ireland
Email: d19125339@mytudublin.ie; mark.davis@TUDublin.ie; jycai@uestc.edu.cn; jianhua.deng@uestc.edu.cn

Abstract —Accommodating the heterogeneous traffic demand among streams in the downlink MU-MIMO channel is among the challenges that affect the transmission efficiency since users in the channel do not always have the same traffic demand. Consequently, it is feasible to adjust the frame size to maximize the system throughput. The existing adaptive aggregation solutions do not consider the effects of different traffic scenarios and they use a Poison traffic model which is inadequate to represent the real network traffic scenarios, thus leading to suboptimal solutions. In this study, we propose some adaptive aggregation strategies which employ a novel dynamic adaptive aggregation policy selection algorithm in addressing the challenges of heterogenous traffic demand in the downlink MU-MIMO channel. Different traffic models are proposed to emulate real world traffic scenarios in the network and to analyze the proposed aggregation polices with respect to various traffic models. Finally, through simulation, we demonstrate the performance of our adaptive algorithm over the baseline FIFO aggregation approach in terms of system throughput performance and channel utilization in achieving the optimal frame size of the system.

Index Terms—Channel utilization, downlink MU-MIMO, heterogeneous traffic, frame aggregation, frame size optimization, transmission efficiency, WLAN.

I. Introduction

As one of the most widely deployed wireless technologies, IEEE 802.11 Wireless Local Area Network (WLAN) has experienced tremendous growth to fulfill the promise of increasing IEEE 802.11 performance and effectively supporting more client devices on a network. The IEEE 802.11 working group introduced the IEEE 802.11ac also known as Very High Throughput (VHT) [1],[2]. The IEEE 802.11ac standard improves the achieved throughput compared to previous standards by introducing improvements and new features in the PHY and MAC layers. The PHY layer has been enhanced by employing modulation and coding rates (256 QAM 5/6 modulation), wider bandwidth channels (up to 160 MHz) and MU-MIMO channel with 4 spatial streams that enable higher spectral efficiency in allowing the AP to support simultaneous transmission to multiple users [1],[2].

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Corresponding author email: d19125339@mytudublin.ie,
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On the other hand, the IEEE 802.11ac standard specifies the use of different frame aggregation mechanisms which was first introduced in IEEE 802.11n at the MAC layer level to increase channel utilization and MAC efficiency [3]. Channel Utilization is the ratio of the time that the channel is used for effective packet transmission over the total channel time used [3]. These aggregation schemes are, the A-MSDU only aggregation, the A-MPDU only aggregation, and a two-level aggregation that combines both A-MSDU and A-MPDU followed by a single acknowledgement frame, denoted Block Ack [4], [5]. IEEE 802.11ac includes many of the improvements that were first introduced by IEEE 802.11n and also uses these three aggregation schemes but enables larger frame sizes.

Aggregation schemes also benefit from amortizing the control overhead over multiple packets. However, when traffic loads to individual STAs are different, it is possible to incur a wastage of space and time resources on downlink MU-MIMO channel transmission. The longer the aggregate frame is the better the channel utilization and the smaller the space channel time wastage. Space channel time is the consequence of heterogeneous traffic patterns and it occurs when data transmission duration among streams is variable while sharing the common transmission medium in the downlink Multiple User-Multiple Input Multiple Out (MU-MIMO) channel of WLAN [6].

In this study, the efficiency of MAC layer aggregation is examined on the performance of downlink MU-MIMO channel in focusing on the challenges of heterogeneous traffic demand among spatial streams. MU-MIMO allows an Access Point (AP) to simultaneously transmit multiple data streams as Aggregated Multi-Protocol Data Units (A-MPDUs) to a group of multiple stations (STAs) over the same channel using MU-MIMO. In the non-MU-MIMO system, frames are transmitted one after another, unlike the MU-MIMO channel which can transmit a group of streams simultaneously [7]. These communication technologies enable the IEEE 802.11ac protocol to use spectrum more efficiently compared to the previous standards [7]. However, MU-MIMO wastes the unused part of the channel interval when short and long data streams are grouped together. To tackle this problem, we have proposed a dynamic adaptive aggregation selection algorithm to enhance system throughput and channel utilization performance of the downlink MIMO channel in WLANs

A system model must be developed that can capture the characteristics of the actual traffic load. Numerous traffic models have been proposed to understand and analyse the traffic characteristics of the networks in the past years. However, there is no single traffic model that can efficiently capture the traffic characteristics of all types of networks, under every possible scenario [8]-[10]. Different models are used to describe different types of traffic. Traffic sources such as variable- bit- rate (VBR) video are better represented by self-similar traffic models [10]. Self-similarity (or "burstiness") refers to the distributions that exhibit the same characteristics at all scales [8],[11]. Voice traffic is commonly described using the on-off source, therefore traffic models that reflect the bursty nature of voice data are the best to describe this traffic [11]. Models that are characterized as a self-similar and heavy-tailed process, such as *Pareto*, *fractional Brownian Motion (fBM)* and *Weibull* distribution are among the best fitting traffic models by different studies to emulate the basic traffic features of self-similarity and long-range dependence (LRD) for VoIP and Video data traffic, unlike the Poisson traffic model which is memoryless and insufficient to characterise the actual internet traffic [8]-[13].

In this study, different traffic models are proposed to characterize the actual network traffic scenario and analysed the performance of the proposed algorithm with regard to various traffic models under ideal channel conditions, where transmission errors are not present. Finally, through simulation the proposed scheme will be evaluated in comparison with the baseline FIFO aggregation approach and we will demonstrate that it increases the system throughput performance and achieves better channel utilization.

The rest of this paper is organized as follows. In Section II, we discuss previous works on the performance of frame aggregation strategies in WLAN in downlink MU-MIMO channel to enhance the system throughput performance and channel utilization. In Section III, our proposed adaptive aggregation approach and traffic models will be discussed. In Section IV, we evaluate the performance of the proposed approach under ideal channel conditions and compare its performance with the baseline FIFO aggregation approach. Then, the details of the experimental simulation scenarios will be explained followed by the results and a discussion. Finally, conclusions are given in Section V.

II. Related Work

In this section, previous works are reviewed on the performance of frame aggregation in WLAN downlink MU-MIMO channels to enhance system throughput performance and channel utilization. Unlike conventional single-user transmission, the performance of frame aggregation in MU-MIMO transmission is affected due to variable demands of traffic load individual users has in the system. Thus, several works have addressed the challenges of various frame aggregation approaches in downlink MU-MIMO channel.

A frame duration-based frame aggregation scheme is proposed by [14] employing a criteria for selecting a receiving Mobile Terminal (MT). This approach provides high priority to the MT expecting high throughput in the next MU-MIMO transmission and having large amount of data while reducing signaling overhead. By equalizing the transmission time of all spatial streams in all MTs according to their MCS level, they achieved maximum performance of system throughput and minimize space channel time in WLAN the downlink MU-MIMO channel. However, the experiment considered a Poisson traffic model which is inadequate to represent the real network traffic scenarios and they did not examine the performance of their approach under the effects of different traffic scenarios.

Aggregated MPDU using fragmented MPDUs with a compressed Block ACK mechanism for use in IEEE 802.11ac MU-MIMO transmission is proposed by [15]. The main concept of this study is fragmented MPDU instead of A-MPDU pads can be added to fill the length of A-MPDU boundary in Enhanced Distributed Channel Access (EDCA) Transmission Opportunity (TXOP) sharing mode. This mechanism eliminates the overhead caused by MPDU padding which in turn increases the system throughput and enhances channel utilization in eliminating frame pads, called padding bits. However, the proposed approach does not elaborate on the traffic model adopted.

The authors in [16] proposed a solution to reduce wasting a portion of an A-MPDU of a short data stream in a group of unequal streams by concatenating longer data streams in consecutive groups. The main concept is to propose an average policy where the frame aggregation size is set to the average of transmission queue lengths for spatial streams. These policies improve channel utilization by decreasing the wastage in space and time resources. However, average aggregation policy cannot always be effective while traffic models in downlink MU-MIMO channel is heterogenous among spatial streams, thus this leads to suboptimal solution.

According to [17], they have presented a coordinated MAC protocol to improve Channel Utilization in both the Time and Spatial domain (CUTS), i.e., the channel access time and the antenna usage. Thus, they emphasized that the channel utilization in MU-MIMO should consider both time and spatial domains. To address this issue, a new MAC-PHY architecture design, CUTS, is proposed to allow distributed nodes effectively contend for the channel and utilize the channel in both maximum channel utilization and antenna usage. However, this work particularly focuses on channel utilization and antenna usage and traffic model used is not elaborated.

Focusing on the padding problem of downlink MU-MIMO [18] and [19] enhances the transmission efficiency of MU-MIMO in IEEE 802.11ac networks by considering both the channel and heterogeneous frame lengths of streams mainly to increase the transmission efficiency of multiuser (MU) frames. They have proposed a scheme which replaces padding bits with a data frame from other stations. However, these phenomena increase the complexity of both transmission and reception processes of communication since to allow multiple destinations within a spatial stream or equivalently changing a set of multiplexed users frames and accompanied modulation and coding schemes in the middle of multi-user (MU) frame requires modification of the standard. However, according to the results, transmission efficiency and channel utilization are enhanced.

To control the frame aggregation size in downlink MU-MIMO channel, [20] has proposed a minimum policy when the traffic variation is small and average policy when the traffic variation is large in response to the traffic variation among spatial streams in considering both channel utilization and delay data frames suffer from transmission queues. According to their results they have achieved efficient channel utilization in keeping the transmission delay to a relatively small value. However, this study does not elaborate the traffic model they have used, thus this leads to suboptimal performance in different network scenarios.

In an effort to reduce the space channel time in the downlink MU-MIMO channel, [21] proposed a frame size-based aggregation scheme. The basic frame aggregation principle of this approach is to use a uniform data frame size in each spatial stream by aggregating equal number of frames under constant data rate. However, this work has considered a Poison traffic model which is not adequate to represent the network traffic in real system. In addition to this, uniform data frame size aggregation policy cannot always achieve better performance due to the heterogenous traffic nature among spatial streams, thus the algorithm is not suitable for variable network scenarios.

In analysing the impact of different overhead components in multi-user transmission of WLAN, a data frame construction scheme called DFSC is proposed by [22] to optimize the length of frame size transmission in both downlink and uplink transmission of WLAN. The main contribution of this scheme is to maximize transmission efficiency in both uplink and downlink multiuser transmission taking into account the buffer statuses and transmission rate of the stations. However, this work particularly focuses on transmission efficiency considering a Poisson traffic generation model for the packet arrival distribution.

According to the literature, the existing adaptive aggregation solutions are based on the assumption of a specific Poisson traffic model or they do not elaborate the traffic model they have used. However, it is feasible to control the effects of different networks traffic scenarios on frame aggregation size determination in downlink MU-MIMO channel to enhance system throughput performance.

III. PROPOSED ADAPTIVE AGGRIGATION APPROUCH

In this section, we describe the proposed adaptive aggregation algorithm which has been developed to achieve the goal of realizing a maximum system throughput performance of WLAN in downlink MU-MIMO channel. The adaptive aggregation policy employed determines the optimal frame size of the system according to the traffic load among STAs. The following diagram illustrates the structure of the proposed approach.

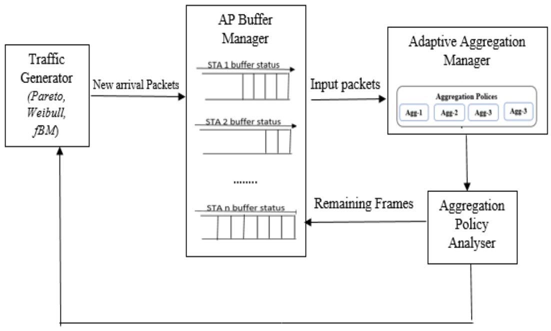

Fig. 1. The structure of the proposed adaptive model

As Fig. 1 shows, the algorithm is essentially a feedback-based system which encompasses four main operations. It operates in such a way so as to predict the optimal frame size of the system which maximizes the system throughput employing adaptive aggregation polices. The traffic models employed are used to emulate the real traffic scenario to efficiently capture the traffic characteristics of all types of networks under every possible circumstance. The function of each element is discussed as follow:

(i) Traffic Generator: The Traffic generator is the first element to generate the traffic data according to the specified traffic generation model employed in the system such as Pareto, Weibull or Fractional Brownian Motion (fBM). The description of each traffic models is discussed in section A.

(ii) AP Buffer Manager: The buffer manager accepts the new arrival packets generated by the traffic generator and stations in the network could have variable buffer capacity as shown in the Figure. The AP stores all packets as long as it has buffer space to accommodate them. If the buffer is full the AP denies accepting new traffic data and continue the aggregation process. It also stores remaining packets received from *Aggregation Policy Analyser* and arrange them for next transmission.

(iii) Adaptive Aggregation Manager: The adaptive aggregation manager is an algorithm used to aggregate the traffic data received from the buffer manager employing the aggregation models proposed. Different aggregation strategies do not always achieve the same

performance under heterogenous traffic conditions in downlink MU-MIMO channel. These aggregation strategies are specified as (Agg1, Agg2, Agg3, Agg4) in the figure and they are briefly discussed in section *B.*

(iv) Aggregation Policy Analyser: The aggregation policy analyser is used to selects optimal aggregation strategy which produces the optimal fame size that maximize the system throughput. If more than one aggregation polices archived the same performance, the AP always prioritize the one that promotes more frames transmission at a time. For instance, if *All Agg FA (Baseline approach)* and *Avg Num MPDUs* have similar performance, *All Agg FA (Baseline Approach)* will be selected as the optimal aggregation strategy. The characteristics of each aggregation polices are discussed in section B. The optimal frame size and the corresponding throughput are recorded at every simulation run. Finally, the performance of our adaptive aggregation compare with the baseline FIFO aggregation approach in terms of system throughput performance and channel utilization under ideal channel condition. Remaining frames which are not selected due to the adaptive aggregation procedure is buffered back to the AP for the next transmission. This process continues throughout the simulation time.

A. *Traffic Model*

Voice traffic data type is the main focus of this study to characterize the traffic load on a network addressing the challenges of heterogeneous traffic pattern on the system performance of downlink MU-MIMO WLAN, we will use the following mathematical traffic models: *Pareto*, *Weibull*, and *fractional Brownian motion (fBM).*

TABLE I: SIMULATION PARAMETERS

Parameters	Symbol	Values
#Antenna at AP	N_{Ant}	4
#Stations with a single antenna	Num_{STA}	2-4
Traffic Type		VoIP
Average Data frame length	L_{data}	100 Byte
Traffic rate		20Kbps
Data rate		260Mbps per user
Basic Rate for control frames		6Mbps
Average A-MSDU length		11454 Byte
Max Number of MPDU Frames Aggregated		64
Max A-MPDU length		1.0 Mbyte
AP Buffer size	LBuf	50MB

We focus on the busy traffic scenarios in all distribution models. The generation interval of frames depends on the average frame size and traffic rate considered for VoIP as specified in Table I. Once data frames are generated, all data are buffered at the AP whose maximum length is *LBuf.* An ideal channel condition is considered in this study with no transmission errors. The successful transmission is followed by an acknowledgement from the stations.

1) *Pareto distribution model*

Pareto distribution is a skewed, heavy-tailed distribution applied to model self-similar arrival in packet traffic [8], [9] which is feasible to emulate the real bursty traffic scenario. The parameters such as shape parameter λ and scale parameter k are used to characterize the behaviour of random Pareto distribution. Other important characteristics of the model are, the Pareto distribution has an infinite variance, when $\lambda \geq 2$ and achieves infinite mean when $\lambda \leq 1$. Mathematically this is formulated as follows. For $X \sim Pareto\ (\lambda, \kappa)$, the *pdf* and expected value E is defined by the following expressions [9].

$$f(x) = \frac{k\lambda^k}{x^{k+1}} \qquad if\ \lambda > 1 \tag{1}$$

$$E(x) = k\lambda/\lambda - 1 \tag{2}$$

X is a random variable generated from Pareto distribution. Given input parameters such as average packet size, average packet arrival rate, shape parameters and average burst time, the interval between packet arrivals and burst length can be computed as shown below.

$$Interval\ = \frac{packet\ size \times 8}{rate} \tag{3}$$

$$BurstLength = \frac{burstTime}{Interval} \tag{4}$$

Then, to generate the Pareto traffic the burst length can be denoted as the following expression [23].

$$BurstLength = E(x) = k\ \times \frac{\lambda}{\lambda - 1} \tag{5}$$

Then, the scale parameter k can be derived as follow:

$$k = BurstLength \times \frac{(\lambda - 1)}{\lambda} \tag{6}$$

Finally, the Pareto random number generator generates the next random scale parameter p using scale k and shape parameters λ using inverse transform sampling, given a random variate U drawn from the uniform distribution on the unit interval (0, 1] using the following expression.

$$U \sim uniform(0,1)$$
$$p = k/U^{1/\lambda} \tag{7}$$

Different values for the shape parameter λ for each station are considered to allow different traffic patterns. Whereas the scale parameter is randomly generated using (7) to determine the traffic rate depending on the average frame size and traffic rate considered. In general, the shape and scale are the main parameters which affect the behaviour of the distribution given a constant traffic rate and frame size values.

2) *Weibull distribution model*

Weibull distribution is one of the most widely used lifetime distributions in reliability engineering. However, it is also adaptable to characterise bursty network traffic distribution in ON/OFF bases [8], [9] based on the value of the *shape* and *scale* parameter. Therefore, we have also adopted a Weibull distribution to generate network traffic. Then the *pdf* of two-parameter Weibull distribution *f* and expected value of random variable x denoted by *E(x)* is defined by the following expression [9].

$$f(x;\alpha,\beta) = \begin{cases} \frac{\alpha}{\beta}\left(\frac{x}{\beta}\right)^{\alpha-1} e^{-\left(\frac{x}{\beta}\right)^{\alpha}}, & x > 0, \alpha, \beta > 0; \\ 0, & \text{Otherwise.} \end{cases} \quad (8)$$

$$E(x) = \beta\gamma\left(1+\frac{1}{\alpha}\right) \quad (9)$$

where:

- α is the shape parameter
- β is the scale parameter
- μ is the location parameter.
- γ is gamma. A gamma function at parameter a can be evaluates as $\gamma(a) = (a-1)!$ [9].

Following the same procedure as Pareto, given the input parameters such as average packet size, average packet arrival rate, shape parameters and average burst time, the interval between packet arrivals and burst length are derived using formulas specified in (3) and (4).

Then, to generate the Weibull traffic, we apply the same procedure as of Pareto, then the burst length i.e., the expected value of Weibull distribution denoted by the following equation.

$$BurstLength = E(x) == \beta\gamma\left(1+\frac{1}{\alpha}\right) \quad (10)$$

So that the scale parameter β can be derived from the formula in (10) as follows.

$$\beta = \frac{Burstlen}{\gamma\left(1+\frac{1}{\alpha}\right)} \quad (11)$$

Finally, the Weibull random number generator generates the next random scale parameter given the scale value β and shape parameters α using inverse transform sampling method with a given a random variate U drawn from the uniform distribution on the unit interval (0, 1].

Therefore, for X ~ Weibull (β, α), the random variable W which is the scale value represents the traffic rate in our case is generated randomly according to the following expression.

$$U \sim uniform(0,1)$$

$$W = -\beta\,[\ln(1-U)]1/\alpha \quad (12)$$

Similarly, a different *shape* value is assigned to vary the traffic pattern generated for each station. Whereas the *scale* parameter is randomly generated using (12) to determine the traffic rate depending on the average frame size and traffic rate considered. Therefore, to change the behaviour of the distribution, the shape and scale parameters can be adjusted. Fig. 2 demonstrates an example of the bursty traffic scenario generated using Weibull distribution model for a single user case.

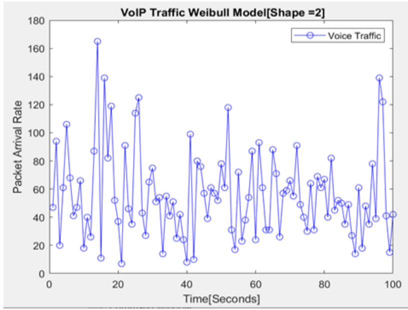

Fig. 2. Sample traffic generated using Weibull traffic model for a single user case.

3) *Fractional Brownian Motion (fBM) traffic model*

According to the authors [8], [12], [13], fBm is a continuous-time Gaussian process defined for all positive time values, with mean centred at 0. Gaussian distribution appears when a large number of independent, random variables are summed together. It is also characterises the important feature of self-similarity and long-range dependence of traffic behaviour depends on the Hurst parameter *H*, where $0 < H < 1$. According to the value of H, the fBM exhibits for $H > 0.5$ Long-range dependence, and $H < 0.5$ Short-range dependents. We consider $H > 0.5$ in this study. Fractional Brownian traffic is defined as a process of the form defined in (13). We adopt this analytical approach to generate fBM traffic for the experiment [13].

$$A(t) = M \times t + \sqrt{a \times M} \times B_H(t) \quad (13)$$

Then, we use MATLAB programming function 'wfbm' to generate the fBM signal given the inputs Hurst parameter H and sample size S using the following syntax.

$$B_H(t) = f = wfbm\,(H,S) \quad (14)$$

where:

- A(t) is the amount of traffic that enters the network in the time interval [0, T]
- *M*, $M > 0$ is the average traffic intensity
- *a*, $a > 0$ is a constant for variance coefficient called the peakness parameter
- $B_H(t)$ is a normalized fBM and a continuous-time Gaussian process $B_H(t)$ on $[0, T]$.

B. Aggregation Models

In this section, our aggregation models are discussed to tackle the challenges of bursty traffic on the performance of the downlink MU-MIMO channel aiming to maximize the system throughput performance. Due to the heterogeneity of the traffic patterns among streams in the network it is not easy to determine the optimal aggregation policy which could achieve the best performance. In this regard, it is difficult for one aggregation policy to always achieve the goal of good performance. In addressing this issue, we have proposed the following aggregation schemes to employ adaptive aggregation policy which determines the optimal frame size that produces the maximum throughput as per the traffic condition in the system.

(i) Maximum Size Aggregation Policy (All Agg FA):- This strategy follows a FIFO aggregation policy which suggests using a larger frame size aggregation as large as the maximum aggregation frames length that is allowed per transmission. This strategy promotes all frames in the AP buffer to be transmitted to the receivers rather than dropping some of them in the buffer for the next transmission. However, if the frame size is large and the channel is noisy, many frames could be lost. So that the frame success rate will be decreased, thus the throughput is degraded. In addition to this, longer frame size would take longer transmission times and will affect the throughput performance. We use this aggregation policy as a baseline approach to assess the performance of our proposed approach.

(ii) Equal Length of Frame Size Aggregation Policy (Equal Frame Size FA):- This approach emphasizes equalizing the number of frames aggregated for all streams. Since the aggregated frame length is equalized in all streams, this approach enhances channel utilization and eliminate channel time wastage. However, channel overhead could be a problem with short frames aggregated. If the length of the frames transmitted is short, a better throughput can be achieved due to shorter data transmission time on air. However, when the traffic is bursty the number of frames left in the AP buffer will be increased due to the frame length equalization policy, and this allows more frames to remain in the buffer for the next transmission and consumes memory space.

(iii) Equal Number Of MPDUs Aggregation Policy (Equal Num MPDUs FA):- Under this aggregation policy, an equal number of MPDUs are aggregated on each stream. In the case of less bursty traffic among stations, this approach could perform better than Equal Frame Size FA as it allows more frames transmitted as a form of MPDU aggregated frame. When the network traffic is more bursty, the station with many MPDUs could be affected as more frames would be left in the buffer for the next transmission. This approach has a better performance in terms of space channel time utilization enhancing the channel utilization better than All Agg FA approach.

(iv) Average Number of MPDUs Aggregation Policy (Avg Num MPDUs FA):- In this approach, the average number of MPDUs are computed to determine the length of data frame transmitted on each stream. Therefore, the number of MPDUs equal to the average value will be selected for each stream and aggregated for transmission. This approach enhances transmission of more frames especially when the traffic rate variation is bigger among streams. The performance of channel utilization and space channel time is better than *All Agg FA* mechanism. However, it has poor performance of space channel time as compared to aggregation approaches *Equal Frame Size FA* and *Equal Num MPDUs FA* but is better in minimizing the number of frames waiting in the buffer before transmission than *Equal Frame Size FA* and *Equal Num MPDUs FA*.

Finally, each of the aggregation policies perform the following operation to construct the wireless frame setting for A-MSDU and A-MPDU derived from the mathematical model [1], [14]. The total length of L_{MSDU} is constructed by aggregating the number of MSDUs of MAC data frames of length L_{Data}[Bits] and can be calculated as shown in (15). The maximum length of A-MSDU frame (L_{MSDU}) is 11454 Byte according to IEEE802.11ac. In this scheme the MSDU size is kept constant at 100Byte for VoIP traffic data.

$$L_{MSDU} = MAC_{Hdr} + (N_{MSDUs} + L_{Data}) \tag{15}$$

From this equation, we can derive the maximum number of MSDUs *(N_{MSDUs})* that can be aggregated into a single A-MSDU data frame as shown the following expression. The function *floor(x)* is used to get the largest integer less than *x*.

$$N_{MSDUs} = floor\left(\frac{L_{MSDU} - MAC_{Hdr}}{L_{Data}}\right) \tag{16}$$

After we have obtained the maximum number of MSDUs *(N_{MSDUs})*, the AP can construct the A-MSDU frames for each receiving STAs. The number of A-MSDUs which is used to construct A-MPDU can also be formulated as follow:

$$N_{MPDUs} = ceil\left(\frac{Total_{NMSDUs}}{L_{Data}}\right) \tag{17}$$

where the function *ceil(x)* is used to get the smallest integer number greater than *x*. Therefore, the A-MPDU frame is set as a wireless frame transmitted for all receiving STAs. This aggregation procedure is carried out for all receiving stations by the AP. The 1 MByte is the maximum A-MPDU size considered in this study which is approximately 1048575 Bytes according to IEEE 802.11ac and the maximum number of MPDUs that can be aggregated is 64.

The two-layer aggregations such as A-MSDU and A-MPDU are applied to achieve our adaptive aggregation models. These aggregation models are used to adaptively adjust the optimal frame size of the system that maximizes the system throughput as per the condition of the traffic pattern among the streams. This approach is feasible since a particular aggregation strategy cannot always contribute to the achievement of the maximum system throughput while the real situation of the traffic pattern in downlink MU-MIMO channel is influenced by heterogeneous traffic patterns.

IV. Performance Evaluation

The performance of the proposed approach is evaluated in this section under the assumption of an ideal channel condition (i.e., BER=0) which means there is no error transmission and no penalty for large frame size. Therefore, the aggregate frame size will be as large as possible, e.g., 1 MByte according to the limitation defined in the IEEE 802.11ac standard [1] for the A-MPDU frame. Weibull, Pareto and Fractional Brownian Motion (fBM) analytical traffic generation models are used to emulate real network traffic data and the adaptive aggregation approach proposed are the main simulation scenarios. We developed the MATLAB program to simulate the algorithm. Simulation parameters are chosen for IEEE 802.11ac [1] standard and the detailed simulation parameters are shown in Table I. The simulation operates at a data rate of 260Mbps per-user. Each simulation result is performed ten times to obtain an average result. The proposed approach will be compared with the baseline FIFO aggregation approach. The AP can communicate with up to $STAs \leq N_{ANT}$ under the assumptions of ideal spatial channel separation and ideal channel orthogonality between the antennas at the AP [14]. In this section, we will perform the following experiments: (i) the performance of system throughput under variable numbers of STAs. (ii) performance of system throughput with increasing traffic load. System throughput is the ratio of the sum of the successful frame size of the system over total channel transmission time which involves data transmission time, DIFS and Backoff times, and block acknowledgement time. (iii) the performance of channel utilization with increasing traffic load. Channel utilization is the ratio of the time that the channel is used for effective packet transmission over the total channel time. Analytically it is formulated as follows:

$$Channel\ time(CT)_i = \sum_{i=1}^{4} TXData_i \tag{18}$$

$$SPTime = \sum_{i=4}^{4} (Max(TXData) - TXData_i) \tag{19}$$

Then, the channel utilization ratio *(ChUtil)* of the system in percentage is formulated as:

$$ChUtil(\%) = \frac{\sum_{i=1}^{4}\left(\frac{TXData_i}{TXData_i + SPTime_i}\times 100\right)}{NumSTA} \tag{20}$$

where

- i counts the number of stations
- $SPTime_i$ is the space channel time. It is an idle channel time when no data is transmitted for STA_i
- $TxData_i$ is the data transmission time of STA_i.
- *NumSTAs:* the total number of STAs

Then, (iv) the performance of transmission efficiency of the system is examined. Transmission efficiency is computed as the ratio of the total number of successful payloads bite over the total bits transmitted (i.e., payload bits plus the MAC overhead bits). Analytically it is expressed as shown in (22).

$$frm = \sum_{i=1}^{4}\left(\frac{Succ\_Payload_i}{Succ\_Payload_i + MAC\_Overhead_i} \times 100\right) \tag{21}$$

$$Transmission\ Efficiency(\%) = \frac{frm}{NumSTA} \tag{22}$$

Were,

- *Succ-Payload*: the payload frames that is successfully delivered to the receiver
- *MAC-Overhead:* it involves the overhead frame add at each MPDU and PSDU frames.
- *NumSTAs:* the total number of STAs
- *frm*: the ratio of the sum of the system successful frames transmitted in percentage

Finally, (v) the performance of individual user's throughput is simulated under the traffic load offered.

The experiments are conducted with a fixed frame size of 100Byte VoIP traffic with a data rate of 20kbps. Variable Hurst parameter H = 0.5,0.7,0.9 and 1 is considered for each STAs respectively for the case of fBM traffic model. Average traffic burst time (10^6, 10^5, 10^4 and 10^6 microseconds), and shape parameter (2,3,4 and 5) are used for each STA respectively for Weibull and Pareto traffic generation models.

A. Performance of System Throughput under a Variable Number of STAs

Fig. 3 demonstrates the performance of the system throughout under the effect of variable number of STAs using fBM traffic model. As the number of stations increases the amount of data traffic transmitted increases, this in turn increases the system throughput. As the simulation result shows, different aggregation approaches perform different performance for each number of station. However, the proposed approach exhibits better performance due to its adaptive aggregation strategy employed to be adjusted as per the traffic condition of the system at each number of STAs.

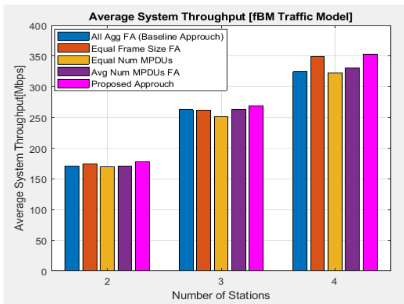

Fig. 3. Performance of average system throughput as the number of STAs varies from 2 to 4 using fBM traffic model

B. Performance of Average System Throughput with Increasing Traffic Offered Load

In this section Weibull, Pareto, and fBM traffic models are considered to examine the effects of different traffic scenarios and analyze the performance of different aggregation polices on the performance of system throughput.

Fig. 4 shows the performance of system throughput using Weibull traffic model. It can be seen that as the traffic load increases, the system throughput performance of each aggregation policy increases. However, our approach exhibits a better performance of 427Mbps than the *All Agg FA (Baseline approach)* as it adaptively adjusts the optimal aggregation strategy according to the traffic pattern that contributed to the optimal frame size and maximizes the system throughput. As the result shows, *All Agg FA(Baseline approach)*, *Avg Num MPDUs FA*, and *Equal Num MPDUs FA* exhibits the same performance initially, however, the performance of the proposed approach increased after the traffic load of 0.2Mbps. *Avg Num MPDUs FA* aggregation policy contributed for the maximum performance in this traffic model whereas *Equal Frame Size FA* is the worst performance aggregation policy. This result exhibits that a particular aggregation approach cannot always achieve the maximum performance due to the bursty traffic nature in the downlink MU-MIMO wireless channel.

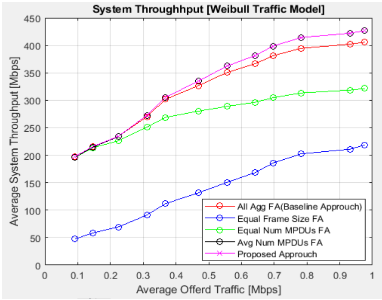

Fig. 4. Performance of average system throughput with increasing offered traffic load using Weibull traffic model.

The result in Fig. 5 shows the performance of system throughput using Pareto traffic model. Similarly, the system throughput performance of each aggregation policy increases as the traffic load increases. *Avg Num MPDUs FA* aggregation policy contributed for the optimal aggregation strategy in this traffic model throughout the simulation time. As the result shows the proposed approach exhibits better performance of 384Mbps than *All Agg FA (Baseline approach)*. Whereas *Equal Frame Size FA* has the worst performance aggregation policy with 303Mbps.

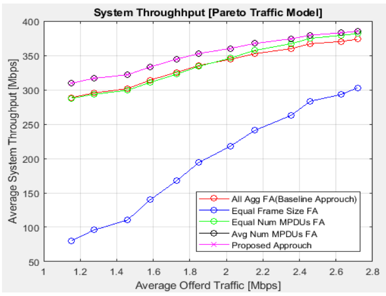

Fig. 5. Performance of average system throughput with increasing offered traffic load using Pareto traffic model.

Fig. 6 shows the performance under fBM traffic model as the traffic load increases. Initially all aggregation policies perform the same performance however, as the simulation result shows the proposed approach broadly increases after 0.3Mbps traffic load. *Equal Frame size FA* aggregation policy contributed to the optimal aggregation strategy in this traffic model and therefore, the proposed approach exhibits the performance of 606Mbps maximum performance better than *All Agg FA (Baseline approach)*.

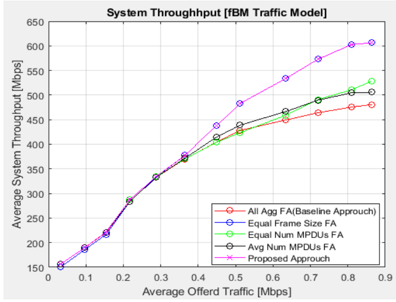

Fig. 6. Performance of average system throughput with increasing offered traffic load using fBM traffic model.

In general, according to the simulation results shown, adaptive aggregation policy is a feasible approach to manipulate the challenges of different traffic scenarios and achieve the maximum system throughput in downlink MU-MIMO channel.

C. Performance of Channel Utilization with Increasing Traffic Load

In this section the performance of the channel utilization is examined using Weibull, Pareto, and fBM traffic models. Using these traffic models the effects of different traffic scenarios are examined on the performance of different aggregation polices to achieve better performance of channel utilization.

As the simulation result shows in Fig. 7, using Weibull traffic model the performance of channel utilization decreases from 54%, however, when the traffic load increases after 0.3Mbps the proposed approach exhibits better performance of 54% than the *All Agg FA (Baseline approach)* which has the worst performance of 50% due to the adaptive aggregation approach employed. Whereas *Equal Frame Size FA policy* enforced the length of aggregated A-MPDU frames to have equal length setting. This in turn allowed *Equal Frame Size FA policy* to achieve 100% channel utilization performance as the result shows.

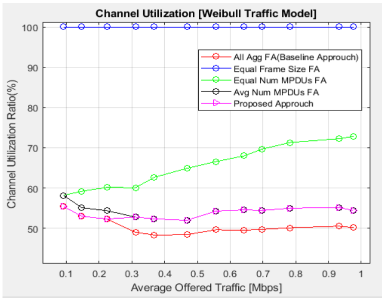

Fig. 7. Performance of channel utilization with increasing offered traffic load using Weibull traffic model

The simulation result in Fig. 8 shows the performance of channel utilization using Pareto traffic model. As the result shows, when the traffic load increases the performance of *Equal Frame Size FA* and *Equal Num MPDUs* aggregation policies exhibit better performance since both approaches encourage equal frame size aggregation policy which enhance channel utilization performance. The maximum 100% channel utilization performance is achieved by *Equal Frame Size FA*. Since the proposed approach follows adaptive aggregation strategy, the performance of channel utilization influenced by the selected optimal aggregation policy. In this traffic model *Avg Num MPDUs FA* contributed for the optimal aggregation policy. Therefore, as the result shows, the proposed approach performs better performance with a maximum 40% channel utilization as compared with the *All Agg FA (Baseline approach)* which performs the least 39%.

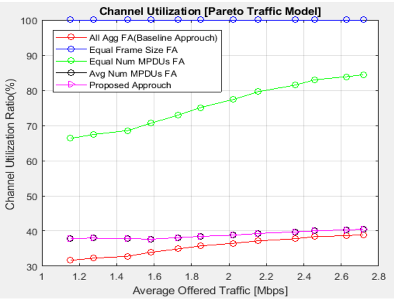

Fig. 8. Performance of channel utilization with increasing offered traffic Load using Pareto traffic model

Fig. 9 shows the performance of channel utilization using fBM traffic model. As the result shows channel utilization performance of the proposed approach extensively increased after the traffic load 0.1Mbps. This result shows that channel utilization performance influenced by the adaptive aggregation approach employed in the system. Initially *All Agg FA (Baseline Approach*, *Equal Num MPDUs FA*, and *Avg Num MPDUs FA* achieved similar performance, however, after 0.3Mbps the channel utilization performance of the proposed approach increased with 100% following *Equal Frame size FA* which is contributed for the optimal aggregation strategy better than *All Agg FA (Baseline Approach)* which contributed the worst performance throughout the simulation.

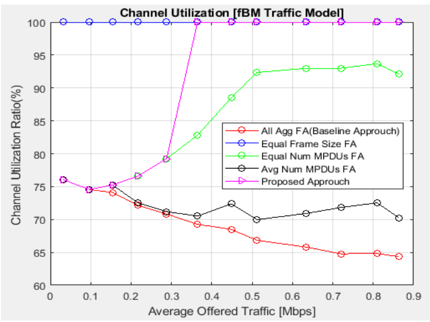

Fig. 9. Performance of channel utilization with increasing offered traffic Load using Pareto traffic model

D. Performance of Transmission Efficiency with Increasing Traffic Load

In this section Weibull, Pareto, and fBM traffic models are used to examine the effects of different traffic scenarios on the performance of different aggregation polices to achieve better performance of average system transmission efficiency.

The simulation result in Fig. 10 shows the performance of transmission efficiency when the traffic load increases using Weibull traffic model. Transmission efficiency increases if the number of A-MSDUs frames aggregated per A-MPDUs is large in minimizing the MAC layer overhead. The size of MAC overhead will be larger when the size of the actual payload is small in the aggregation. As the result shows, *Equal Frame Size FA* aggregation approach achieved the worst performance since it allows a smaller number of frames to be aggregated due to equal number of frames aggregation policy employed for it. However, our proposed adaptive approach achieved better performance increasing from 94% up to the maximum 99% as the traffic load increases which is similar performance with *All Agg FA(Baseline Approach), Equal Num MPDUs, and Avg Num MPDUs FA.*

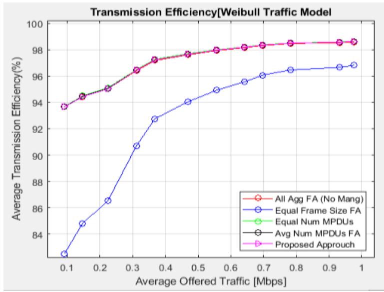

Fig. 10. Performance of channel utilization with increasing offered traffic Load using Pareto traffic model using Weibull traffic model.

Fig. 11 shows the performance of traffic efficiency using Pareto traffic model. *All Agg FA(Baseline Approach), Equal Num MPDUs FA*, and *Avg Num MPDUs FA* aggregation approaches achieve the maximum performance as the traffic load increases. In this experiment, the performance of the proposed approach increased from 97% to 99% as load increases. Whereas *Equal Frame Size FA* achieves the poorest performance again.

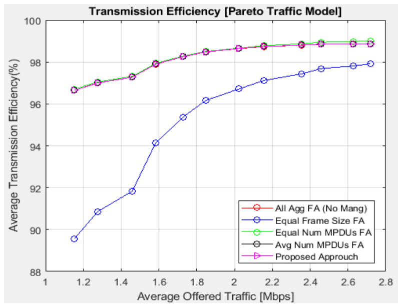

Fig. 11. Performance of system transmission efficiency with increasing offered traffic load using Pareto traffic model

Similarly, Fig. 12 shows the performance of transmission efficiency under fBM traffic model. The performance of the proposed approach increases from 95.8% to 99% as the traffic load increases. However, it decreases slightly between 0.4 and 0.9Mbps traffic load due to the adaptive aggregation approach employed following *Equal Frame Size FA* aggregation policy which achieved the worst performance.

In general, according to all the simulation results of Weibull, Pareto and fBM traffic models, *Equal Frame Size FA* aggregation policy is the worst performance since it enforces the length of aggregated A-MPDU frames to have equal length setting as compared to the other aggregation approaches.

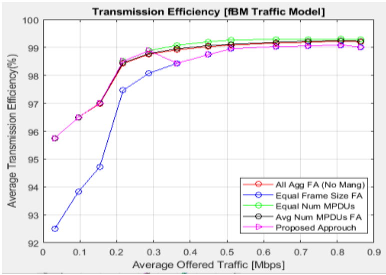

Fig. 12. Performance of system transmission efficiency with increasing offered traffic load using fBM traffic model.

E. Performance of Individual STAs Throughout with Increasing Traffic Load

In this experiment the performance of individual STAs throughout is examined using Weibull, Pareto, and fBM traffic models. The traffic models are used to capture the characteristics of different traffic scenarios and analyze the performance of different aggregation polices on the performance of individual STAs throughout. Average individual throughput is computed as the ratio of the sum of individual users throughout over the total number of STAs. These experiments demonstrate the throughput performance from individual users' point of view.

The simulation result in Fig. 13 shows the performance of average individual users' throughput as the traffic load increases in the system using Weibull traffic model. As the result shows, different aggregation approaches exhibit different results. However, our proposed approach achieved the maximum individual throughput performance of 142Mbps improved from 60Mbps as the traffic load increases. It is better than the *Equal Num MPDUs* and *Equal Frame Size FA* approaches which is the worst performance with maximum 55Mbps. As the result shows the *All Agg FA (Baseline approach)* is the optimal aggregation strategy to predict the optimal frame size which maximized the average individual users' throughput performance. This result indicates that our adaptive aggregation approach can achieve better performance in both system throughput and individual user's throughput.

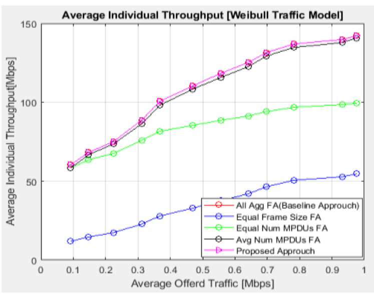

Fig. 13. Performance of average individual user's throughput with increasing offered traffic load using Weibull traffic model.

The result in Fig. 14 shows the performance of individuals user's throughput using Pareto traffic model. The performance of all aggregation approaches increased as the traffic load increases. As the result shows the performance of the proposed approach increased from 128Mbps to 173Mbps. However, the worst performance of 76Mbps is exhibited by *Equal Frame Size FA*. Pareto traffic model achieved the maximum performance than Weibull traffic model in Fig. 13 since the traffic load generated in pareto is bigger than Weibull as the result shows. This indicates that the more the traffic load in the system the maximum the performance of individual user's throughput exhibited.

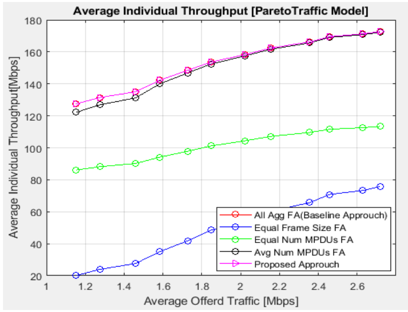

Fig. 14. Performance of average individual users' throughput with increasing offered traffic load using Pareto traffic model.

Fig. 15 shows the performance of individual user's throughout using fBM traffic model. The performance our proposed approach increased from 50Mbps to 174Mbps as the traffic load increases. As the result shows, *All Agg AF (Baseline Approach)* and *Avg Num MPDUs FA* aggregation policy contributed for the maximum performance. Since traffic load generated at the earlier simulation time is smaller, poor performance of 50Mbps is exhibited as compared to both Pareto and Weibull traffic models. However, as the traffic load increases the maximum performance of 174Mbps is achieved.

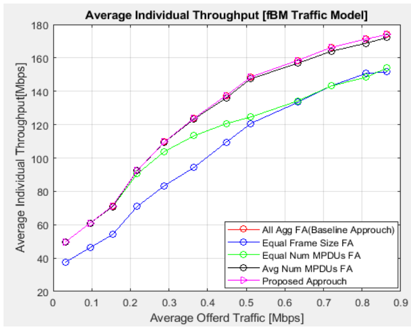

Fig. 15. Performance of average individual user's throughput with increasing offered traffic load using Pareto traffic model.

In general, according to the results in Fig. 13, Fig. 14, and Fig. 15, all the *Agg FA (Baseline approach)* and *Avg Num MPDUs FA* aggregation policies contributed more to the maximum performance for individual users' throughput which support more frame aggregation per transmission. Therefore, our adaptive approach is feasible in providing a good performance from an individual users' point of view.

V. Conclusion

In this paper, we have studied the performance of frame aggregation in a downlink MU-MIMO channel. An adaptive aggregation approach is proposed to address the trade-off between frame aggregation policies and heterogeneous traffic patterns to predict the optimal aggregation frame size which enhances system throughput performance under ideal channel condition. We have demonstrated simulation experiments employing Weibull, Pareto and fractional Brownian motion (fBM) traffic models to emulate real world traffic scenarios in the network and to analyze the proposed aggregation polices with respect to various traffic models. The performance of the algorithm is tested under the effect of increasing traffic offered load in the system, increasing number of stations, the performance of system throughput, channel utilization, transmission efficacy, and individual users' throughput in comparing its performance with the baseline approach. Based upon on the simulation results, our approach produces batter performance than the baseline approach in terms of channel utilization time and system throughput. Future work will extend our algorithm to examine its performance on a noisy wireless channel, the issue of delay and buffer management, including the uplink MU-MIMO transmission in IEEE 802.11ax networks.

Conflict of Interest

The authors declared that there is no conflict of interests regarding the publication of this paper.

Author Contributions

All authors conducted the research; contributed to the idea, design and implementation of the research, to the analysis of the results and all authors discussed the results and contributed to the final manuscript.

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Lemlem Kassa has been a senior lecturer in Addis Ababa Science and Technology university in Addis Ababa, Ethiopia since February 2013. She is currently pursuing her PhD study in School of Information and Software Engineering in University of Electronic Science and Technology of China (UESTC) in China. She received the B.S. degree from Micro link Information Technology college in Addis Ababa Ethiopia in 2006 in software engineering and M.S. degree from University Putra Malaysia (UPM), Malaysia in 2009. Her research interests are in the area of wireless communications, artificial intelligence, mobile computing, and software designing.

Prof. Mark Davis received his BE, MEngSc, and PhD degrees from University College Dublin in 1986, 1989 and 1992 respectively. He is currently the director of the Communications Network Research Institute at Technological University Dublin (TU Dublin). His research interests are in the area of radio resource management techniques for wireless networks, specifically IEEE 802.11 WLANs.

Prof. Jingye Cai is Professor and Associate Dean at University of Electronic Science and Technology of China (UESTC). He received BS from Sichuan University in 1983 with a major in radio electronics and Phd from the University of Electronic Science and Technology of China in 1990, with major in signal and information processing. His research interests are in the area of intelligent computing, information engineering, digital Information Processing, and signal processing.

Dr. Jianhua Deng graduated in information security from the University of Electronic Science and Technology of China (UESTC), China, in 2006. After graduated, he joined the School of Computer Science and Engineering at UESTC as a staff. From 2009 to 2014, he was a Ph.D. student in Dublin Institute of Technology (DIT) in Ireland and received Ph.D. degree in electrical engineering from DIT in 2014. Now, he is a vice professor in the School of Information and Software Engineering at UESTC. His research interests are in the area of wireless communication, statistical machine learning, artificial intelligence, deep learning. He is the reviewer of some SCI journals (e.g. wireless personal communications).