Cognitive Rate Adaptation for High Throughput IEEE 802.11n WLANs

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***Abstract*—Rate adaptation (RA) is responsible for dynamically adjusting transmission rates based on channel quality changes. Finding the best suited transmission rate for time varying channel conditions with RA is challenging issue in wireless communications since it has great impact to the network performance in terms of throughput and efficiency. The existing RA approaches for IEEE 802.11n (e.g., RAMAS, MHT and ARC) use inefficient mechanisms for exploring the optimal rates that lead to stuck in suboptimal rates. In this paper, we propose a cognitive rate adaptation (CRA) algorithm for high throughput IEEE 802.11n WLANs. The proposed RA employs cognitive probing, cognitive modulation and coding scheme (MCS) upgrading/downgrading mechanisms that allow discovering the optimal rates efficiently. Our case study showed that the proposed CRA outperforms the existing well-known RA algorithms under various channel conditions.**

Keywords— IEEE 802.11n; rate adaptation; cognitive; MCS

I. INTRODUCTION

Rate adaptation (RA) is responsible for dynamic transmission rate selection based on channel quality changes and is considered as an important feature of WLAN because of its great impact on resource utilization and network throughput [1]. RA of 802.11n WLANs has more complicated task compared with simply adjusting monotonic related rates based on runtime channel quality as in legacy WLANs. Due to the new physical layer (PHY) features proposed in IEEE 802.11n standard such as Multiple-Input Multiple-Output (MIMO), different guard intervals (GI), and channel widths, the range of rate options dramatically increased and monotonic relationship between the rates was abolished [3].

Existing off-the-shelf RA algorithms for 802.11n such as *ath9k rate control* (ARC) [4] and *minstrel high throughput* (MHT) [4] are based on random probing of the rates including the ones that do not show any performance. This kind of random probing mechanisms yields poor efficiency in network resource utilization and fails to discover the optimal rates. Moreover, other existing proposals in literature try to avoid above shortcomings using the mechanisms with adaptive probing [1-2] or without any probing at all [5], but those mechanisms waste the resources for exploring the other rates and eventually lead to significant inefficiency. In this paper, we propose a novel, *cognitive rate adaptation* (CRA) algorithm for high throughput IEEE 802.11n WLANs. CRA employs *cognitive probing* and *cognitive modulation and coding scheme (MCS) upgrading/downgrading* mechanisms that fasten the optimal rate exploring process. CRA differentiates the candidate probing rates based on the performance statistics they are showing and makes the transmissions more robust against sudden channel changes through adjusting the rate within the same MCS group. Our experiment results discovered that CRA can show significant throughput improvement over MHT, ARC, and RAMAS [5] under various channel quality conditions.

The rest of this paper is organized as follows. Section II briefly reviews the background and related work. Discussions regarding new features proposed in IEEE 802.11n, RA approaching methods and details of specific RAs are briefly explained. Section III explains the proposed *cognitive rate adaptation* (CRA) algorithm in detail. Section IV is dedicated to the performance evaluation of CRA compared to other RA schemes. Finally section V concludes this paper.

II. RELATED WORK

A. IEEE 802.11n Standard

IEEE 802.11n standard introduced enhancements and new features in both physical (PHY) and media access control (MAC) layers [3]. The greatest PHY improvement is MIMO technology that increased the transmission rate dramatically in 802.11n WLANs. Moreover, 802.11n PHY supports both 20 MHz and 40 MHz channel width, and short and long guard intervals (SGI, LGI). All above mentioned enhancements increased the transmission rate from 54 Mbps in IEEE 802.11g up to 600 Mbps. In order to exploit physical layer enhancements efficiently, aggregation of MAC service data unit (A-MSDU), MAC protocol data unit (A-MPDU), and block acknowledgement (Block ACK) mechanisms were proposed for MAC layer of 802.11n [6].

Similar to legacy 802.11a/b/g, 802.11n also specifies modulation and coding schemes (MCSs), but in 802.11n case each MCS represents the number of spatial streams, channel width and GI types in addition to modulation type and coding rate. More specifically, 3x3 MIMO enables wireless LAN card to offer up to 24 MCSs and that means 96 different rates due to the different channel widths and GIs. Thus 802.11n has more

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bit rates and unlike legacy WLANs, there is no monotonicity between the rates due to the presence of MIMO.

B. RA Methodologies and Existing Works

We can classify the existing RA approaches into two groups: (i) *closed-loop*, and (ii) *open-loop RA approaches* [7]. *Closed-loop RA approaches* are receiver based approaches. Sender acquires information about channel quality through explicit means, i.e., receiver periodically sends channel quality information using control frames. The sender can obtain perfect knowledge on channel quality; however, this approach requires changes in IEEE 802.11n standard since the standard does not consider the control frames for channel status information. Moreover, it can cause significant communication overhead under time varying channel conditions since frequent changes in channel quality require more transmissions of control packets carrying channel state information.

On the other hand, *open-loop RA approaches* are based on sender itself. The sender decides solely about the selection of optimal rate based on transmission statistics such as packet error ratio (PER) per rate. It is simple, requires no communication overhead and no change in the proposed standard.

Both *open-loop* and *closed-loop RA approaches* have their own advantages and disadvantages. But, we will demonstrate that one can use *open-loop RA approach* to design effective RA, and packet error rate(PER) and block ACK statistics per rate are enough for exploring optimal transmission rate. Therefore, we shrink the scope of our study to existing open-loop approach based RA methods (Table I).

ARF [8], AARF [9], SampleRate [10], and ONOE [11] are some examples of *open-loop RA approaches* for legacy WLANs. These and other existing works for 802.11a/b/g are based on either successive transmission counters or random probing.

ARC is the default RA module in *ath9k* driver [4]. It creates its own rate table that does not include all of the available offered rates by hardware(e.g., 3x3 MIMO 802.11n wireless LAN card supports 96 rates, but ARC employs only 72 of them) and does not differentiate the rates based on spatial stream number, hence fails keeping the monotonicity between the rates. Moreover, it handles packet error rate (PER) for the rates using EWMA mechanism where it gives much higher weighting (87.5%) to older PER than current one. It also periodically probes the higher rates even if they are not showing any performance.

Another RA algorithm included in *ath9k* driver is MHT. It is an extension of *minstrel* [12] for 802.11n and based on probing of all available rates while current optimal rate is working fine; however, most of the probed higher rates always fail because they are multiple spatial stream rates and they have high modulation and coding rates. It limits the number of lower rates(lower than the current optimal rate) to be probed up to 3 times per update interval (50msec). But there are lower rates that has multiple spatial streams and high modulation and coding rates and hence they always tend to fail.

L3S [1] and MiRA [2] are RA proposals for limited configurations of 802.11n. They have many similar features. Both works consider only two spatial streams, 40MHz channel width, and 800ns GI combinations; therefore lead to very limited number of rates and both schemes employ similar intra- and inter-mode adaptive probing mechanisms. L3S maintains PER of the rates, ignores them if they have less than 11% and calculates the throughput using PER. Unlike L3S, MiRA estimates the throughput statistics using EWMA. The common drawback of both schemes is that they waste resource to explore the inter-mode rates even if current mode is working fine.

RAMAS [5] avoids probing mechanisms; instead it divides the RA task into two groups, namely, *modulation group* and *enhancement groups*. *Modulation group* includes the modulation and coding rate combinations, while *enhancement group* includes streams, channel widths, and GIs. RAMAS tries to adapt these two groups concurrently and maps back their indices to the MCS index. But, as we observed throughout our experiments, RAMAS adapts the *enhancement group* parameters much faster than the *modulation group*. It always tends to transmit using higher spatial stream rates even the spatial structure of the link does not support it. As a result, under low RSSI values it cannot discover the optimal rates properly, and gets stuck in sub-optimal high spatial stream rates.

TABLE I. COMPARISON OF EXISTING OPEN-LOOP RA ALGORITHMS

RA algorithm	Probing feature	Included major mechanisms	Target Wi-Fi platform configuration	Number of supported rates
MHT [2]	Yes	Probing of all of the rates	Up to 3 spatial streams, LGI/SGI, 40/20MHz	96
ARC [2]	Yes	Probing of higher rates	Up to 3 spatial streams, LGI/SGI, 40/20MHz	96
RAMAS [5]	No	Modulation and Enhancement group concurrent adaptation	Up to 3 spatial streams, LGI/SGI, 40/20MHz	96
L3S [1]	Yes	Adaptive probing of candidate rates	Up to 2 spatial streams, LGI, 40MHz	16
MiRA [2]	Yes	Adaptive probing; Zigzagging between streams	Up to 3 spatial streams, LGI, 40MHz	16

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III. COGNITIVE RATE ADAPTATION (CRA)

Summing up the shortcomings of RA algorithms mentioned in previous section, we can conclude that we need some cognitive feature in probing mechanism; in other word, only the promising higher rates should be probed. Frequently probing the rates which are showing poor performance (usually $P_{success} = 0$) worsens the resource utilization because probing frame failure requires the retransmission of failed frame at current optimal rate and retransmission doubles the contention window size hence increasing the overhead for single frame; in some cases the wasted time for erroneous probing frame transmissions can be enough to transmit large aggregate frame at optimal rate. Also, we need some mechanism that provides the RA with robustness against sudden channel changes because the decision about optimal rate selection is made at the beginning of update interval (50 msec) in existing RAs and they cannot react against frequent and short lasting channel changes. Also CRA, statistics are updated at the beginning of every round and one round lasts for 50 msec. Based on the estimated throughput of the rates, the highest throughput rate is selected as an optimal rate for a new round. Throughput and success probability estimations are based on the method used in MHT, i.e., using exponentially weighted moving average (EWMA) where we denote 75% weighting to the older PER statistics and the rest 25% to the recent ones. Using EWMA has a smoothing effect; recent results have a reasonable influence on the selected rate.

In [1] and [4-5], the available rates are divided into MCS groups based on their spatial stream number, channel width and GI types. This kind of grouping makes RA task easier by keeping partial monotonicity between the rates of the same MCS group. CRA also includes the same differentiation for rates since its *cognitive MCS upgrading/downgrading* mechanism can efficiently exploit the partial monotonicity feature to adjust the rates within the same MCS group. Since our target platform supports up to three spatial streams, 20/40 channel widths and 800/400ns GIs, CRA has 96 rates distributed into 12 MCS groups (Table II). Table III depicts the detailed information for the MCS groups; because of space limitations we included MCS group 0, 1, and 11.

Our proposed CRA algorithm is based on *cognitive probing* and *cognitive MCS upgrading/downgrading* mechanisms. Thanks to the new advanced mechanisms employed, RA usually probes the potentially good higher rates, and adapts the rate more effectively under sudden channel changes.

TABLE II. MCS GROUPS FOR 3X3 MIMO, 20/40MHZ AND LGI/SGI

MCS group	Spatial stream number	Channel width (MHz)	GI (ns)
0	1	20	800
1	2		
2	3		
3	1	20	400
4	2		
5	3		
6	1	40	800
7	2		
8	3		
9	1	40	400
10	2		
11	3		

TABLE III. RATE INFORMATION OF MCS GROUPS

MCS group	Rate index	Spatial stream number	Modulation & coding type	Channel width (MHz)	GI (ns)	Data rate (Mbps)
0	0	1	BPSK 1/2	20	800	6.5
	1		QPSK 1/2			13
	2		QPSK 3/4			19.5
	3		16-QAM 1/2			26
	4		16-QAM 3/4			39
	5		64-QAM 2/3			52
	6		64-QAM 3/4			58.5
	7		64-QAM 5/6			65
1	8	2	BPSK 1/2	20	800	13
	9		QPSK 1/2			26
	10		QPSK 3/4			39
	11		16-QAM 1/2			52
	12		16-QAM 3/4			78
	13		64-QAM 2/3			104
	14		64-QAM 3/4			117
	15		64-QAM 5/6			130
…	…	…	…	…	…	…
11	88	3	BPSK 1/2	40	400	45
	89		QPSK 1/2			90
	90		QPSK 3/4			135
	91		16-QAM 1/2			180
	92		16-QAM 3/4			270
	93		64-QAM 2/3			360
	94		64-QAM 3/4			405
	95		64-QAM 5/6			450

A. Cognitive Probing Mechanism

Cognitive probing allows to improve probing efficiency by differentiating the candidate rates based on their performance (Algorithm 1). In our algorithm, there is one probing frame after 64 user data frames. Candidate probing rate is selected randomly among higher rates only and final decision of

Algorithm 1 Cognitive probing mechanism

probe(rate, P_{probe});// probes the rate with given probability
get_probe_rate();// selects the probing rate from the probing list
get_succ_prob();// returns the success probability of the given rate

if (*probing_frame*) **then**
  probe_rate = get_probe_rate();
  $P_{success}$ *= get_succ_prob(probe_rate);*
end if
if ($P_{success} \geq 0.5$) **then**
  probe(probe_rate, 1);
else if ($0.1 \leq P_{success} < 0.5$) **then**
  probe(probe_rate, 0.5);
else
  probe(probe_rate, 0.1);
end if

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probing is made according to the success probability of the selected rate, as follows:

- If the selected candidate probing rate has $P_{success} \geq 0.5$, then it will be probed.
- If the candidate probing rate has $P_{success} \in [0.1, 0.5)$ it will be probed with probability $P_{probe} = 0.5$.
- Finally, if the candidate probing rate has $P_{success} \in [0, 0.1)$, then it will be probed with probability $P_{probe} = 0.1$.

Algorithm 2 Cognitive MCS upgrading/downgrading mechanism

p;// poor delivery counter
h;// high delivery counter
poor_delivery_ratio = 0.8;// threshold for poor delivery ratio
high_delivery_ratio = 0.9;// threshold for high delivery ratio
downgrade_thresh = 3;// threshold for downgrading the MCS
upgrade_thresh = 5;// threshold for upgrading the MCS
cur_rate;// current optimal transmission rate
get_this_prob(rate);// returns the succ/att for this round

if ($\frac{ampdu\_ack\_len}{ampdu\_len} \leq poor\_delivery\_ratio$) **then**
  p++;
  h = 0;
else if ($\frac{ampdu\_ack\_len}{ampdu\_len} \geq high\_delivery\_ratio$) **then**
  p = 0;
  h++;
else
  p = h = 0;
end if
if (*p == downgrade_thresh*) **then**
  cur_rate--;
  p = h = 0;
end if
if ($h \geq upgrade\_thresh$) **then**
  if (*get_this_prob(cur_rate+1)≥0.9*) **then**
    cur_rate++;
    p = h = 0;
  end if
end if

B. Cognitive MCS Upgrading/Downgrading Mechanism

Another feature of CRA, *cognitive MCS upgrading/downgrading* mechanism (Algorithm 2), which supports CRA with increased robustness and reactivity against sudden and short lasting changes in channel quality. It exploits the partial monotonicity between the rates of the same MCS group; when there is sudden change in channel quality it upgrades or downgrades the MCS within same MCS group. For doing so, this mechanism continuously checks A-MPDU delivery level, i.e., $\frac{ampdu\_ack\_len}{ampdu\_len}$ of the current rate; *ampdu_ack_len* is the number of positively acknowledged MPDUs of the transmitted AMPDU and *ampdu_len* is the number of MPDUs included in the transmitted A-MPDU. If the A-MPDU delivery level becomes less or equal to poor delivery ratio, the delivery counter *p* will be incremented.

The *cognitive MCS upgrading/downgrading* mechanism works as follows:

- If the A-MPDU delivery level becomes less or equal to *poor_delivery_ratio* (0.8), then the poor delivery counter *p* will be incremented. When *p* reaches the threshold value i.e., so called *downgrade_thresh* (3), MCS of current rate will be degraded to the next lower rate of the same MCS group.
- Else if, the A-MPDU delivery level is greater than or equal to *high_delivery_ratio* (0.9), then the high delivery counter *h* will be incremented. If the *h* reaches the threshold value of *upgrade_thresh* (5), then MCS of current rate will be upgraded to the next higher MCS if the next higher rate of the same MCS group was successfully probed lately, i.e., within current update interval.
- Else, the A-MPDU delivery level of current rate is between *poor_delivery_ratio* and *high_delivery_ratio*, so the delivery counters *h* and *p* will be reset to 0.

IV. PERFORMANCE EVALUATION

A. Configuration of Test-bed

Our experiments were conducted on TL-WDN4800 wireless cards that use Atheros AR9380 chipsets. This card can operate in both 2.4 and 5 GHz bands and supports up to 3x3 MIMO configuration, 20/40 MHz channel width and SGI/LGI.

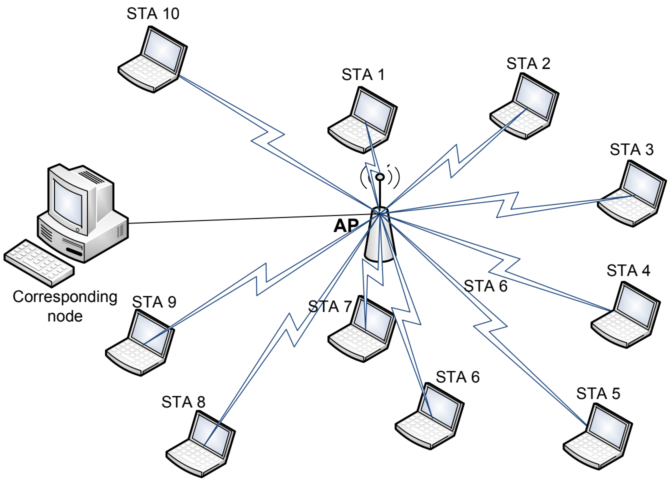

Fig. 1. Experiment test-bed topology

We compared the performance of CRA with RAMAS, MHT and ARC. Since the scope of L3S and MiRA is limited to 40MHz channel width, LGI (800ns), and two spatial stream (2x2 MIMO) cards only, their extension for our test-bed can have different approaches; so we decided not to include them in performance evaluation.

We conducted our experiments in 5GHz band in order to create the same channel condition for all evaluated RAs. In the experiments, we used 10 stations (STA) and access point

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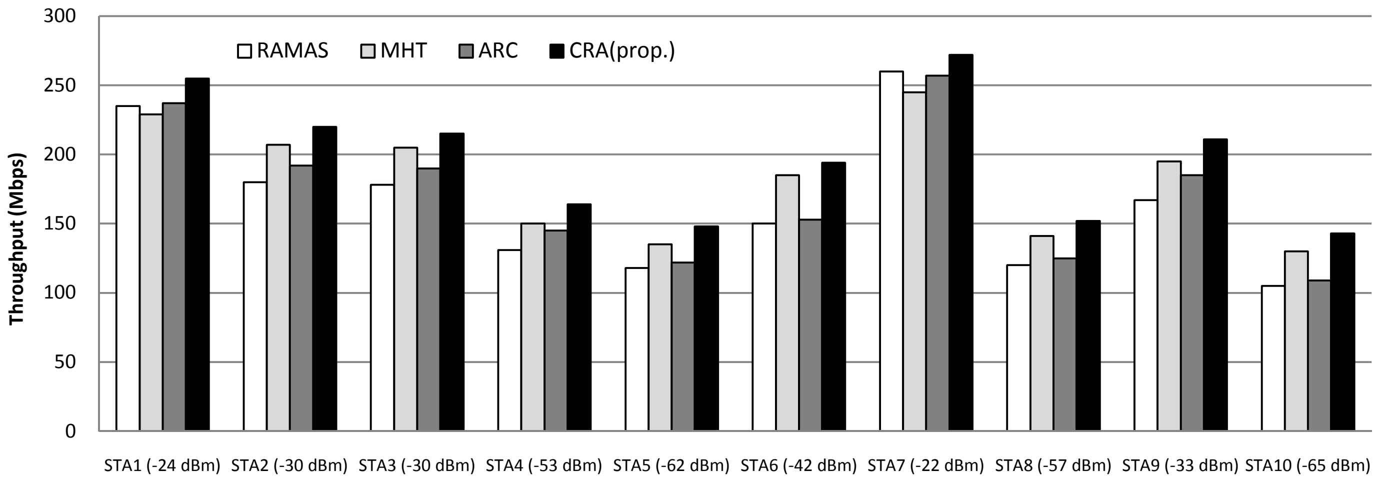

Fig. 2. Average throughput in single station scenario

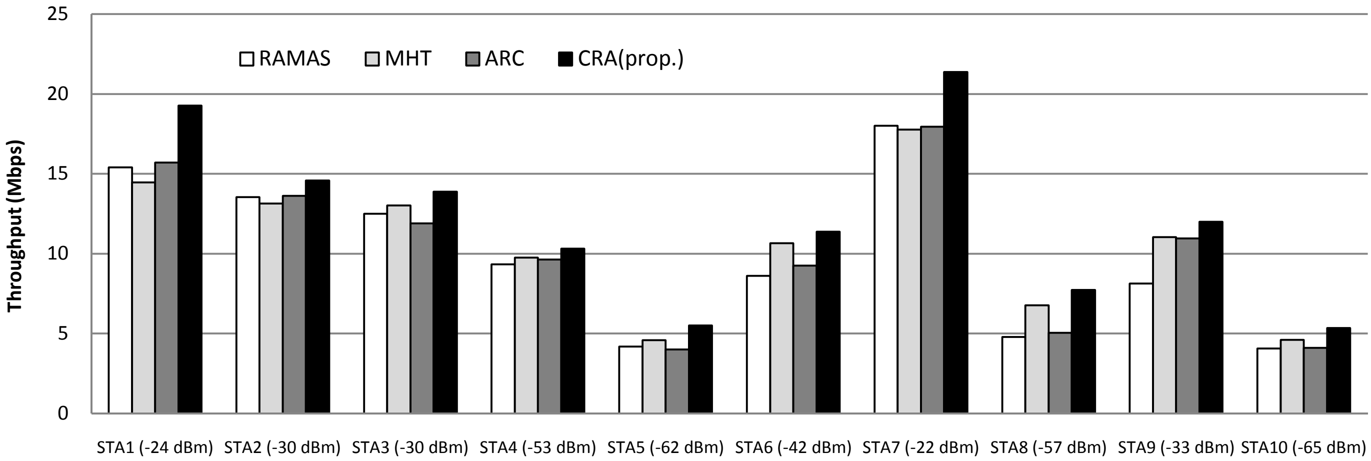

Fig. 3. Average throughput in multi-station scenario

(AP); the STAs are located at different distances from AP, so the received signal strength indicator (RSSI) values at AP are different, i.e., the STAs have different channel conditions (Fig. 1). Uplink UDP traffic was generated and measured in all experiments using Iperf [12].

B. Single Station Scenario

First we conducted the experiments in single station scenario. We measured the maximum achievable throughput per RA algorithm at each STA (Fig. 2). The performance of RAMAS is quite poorer than other RA algorithms if the RSSI values are low, i.e., at STA 2, 3, 4, and 9. Because RAMAS adapts an enhancement group faster than modulation group; therefore it always tends to transmit at high spatial stream rates even if the link quality does not support it. But under even lower RSSI values at STA 5, 8, and 10 RAMAS and ARC show almost same performance. Under high RSSI values like at STA 1 and 7, RAMAS show high performance and outperforms MHT but cannot reach the performance of CRA. MHT shows better performance than ARC and RAMAS in most of the cases because it keeps the partial monotonicity between the rates by dividing them into MCS groups based on stream numbers, channel width, and GI. But it always probes all of the higher rates even the ones that are not showing any performance. Moreover it spends more time and wastes resources on probing of lower rates as well. In result, as RSSI increases, ARC and RAMAS exceed the performance of MHT.

ARC shows the similar performance to RAMAS under the lowest and highest RSSI values. This is due to the fact that ARC creates own table of rates that does not include all of the offered rates by hardware and sorts these rates in increasing order in spite of spatial stream numbers, channel width, and GI. Moreover, it periodically probes the higher rates even if they are not showing any reasonable performance. But under high RSSI values the number of candidate probing rates becomes less and it does not waste much resource on probing as in STA 5, 8, and 10; therefore ARC outperforms the MHT.

Finally, CRA shows the best throughput in all conditions. More specifically, CRA outperforms RAMAS, ARC, and MHT with 8~36%, 6~35% and 5~11% throughput improvement respectively. This is because it explores the

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optimal rate in more advanced ways; *cognitive probing* feature probes the most promising rates by differentiating them based on their performance statistics; in presence of sudden channel errors, *cognitive MCS upgrading/downgrading* feature efficiently adjusts the transmission rate within current MCS group. Due to the fact that these two mechanisms together avoid the rates with high PERs, CRA does not waste the medium resources on retransmissions as RAMAS, ARC and MHT do.

C. Multi-station Scenario

We conducted the second series of experiments in multi-station scenario where we run all four STAs simultaneously in order to create the contention in the network. This scenario helps us better understand the impact of RA algorithm on overall network performance.

Selection of improper rate as an optimal one and probing wrong rates yield poor efficiency in network resource utilization. High PER is one of the major reasons for inefficiency in multi-station scenario since it requires many retransmissions leading to poor resource utilization. Since CRA avoids high PERs efficiently using its *cognitive probing* and *cognitive MCS upgrading/downgrading* features it shows highest performance in this scenario also. More specifically, under different channel conditions, CRA provides around 7~61%, 7~53% and 6~33% throughput improvement over RAMAS, ARC, and MHT respectively.

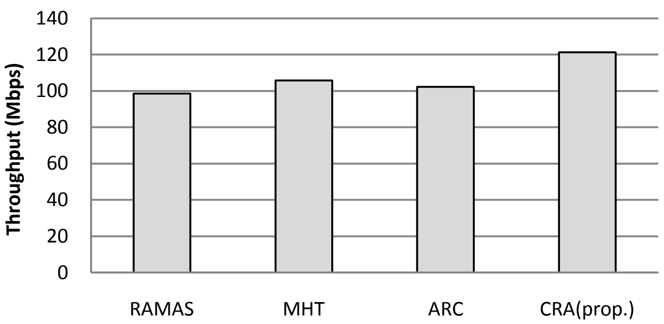

Fig. 4. Average aggregated throughput in multi-station scenario

Moreover, the aggregated throughput, i.e., the overall network performance in multi-station scenario shows reasonable throughput per RA algorithms (Fig. 4); CRA has throughput improvement of around 14~23% over other RA schemes.

V. CONCLUSION

Adaptive rate selection is a challenging problem in 802.11n WLANs due to the wide range of rate options and the presence of novel PHY and MAC features that makes it different than legacy RAs. Existing RA methods provide poor performance due to their inefficiency in exploring the optimal rates. In this paper, we presented a *cognitive rate adaptation* (CRA) for IEEE 802.11n WLANs that is simple and an open-loop approach based rate adaptation algorithm. Performance statistics – based *cognitive probing* and *cognitive MCS upgrading/downgrading* mechanisms provide CRA high efficiency in exploring the optimal rates and making the transmissions robust against sudden channel changes. Our experimental evaluations show that CRA outperforms well-known RA algorithms such as RAMAS, ARC, and MHT with around 8~36%, 6~35% and 5~11% throughput improvements in single station scenario, and 7~61%, 7~53% and 6~33% improvements in multi-station scenario respectively.

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