2023 Spring, Introduction to Wireless and Mobile Networking Final Project - DLMA experiments

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***Abstract*— In the paper [1], the DLMA framework is proposed for adapting to heterogeneous networks. We utilize the same DLMA framework to explore its behavior when coexisting with different types of networks and design various simulation scenarios to observe the efficiency and effectiveness of overall environment throughput analysis.**

I. Introduction

To achieve the desired results, we designed a series of experiments using the DQN model to simulate different environments[1].

Based on different scenarios, we further analyzed the throughput obtained by the adapted DQN, we conducted the following networks for analysis:

1) **Single DLMA + Single non-DLMA**: The network consists of just two nodes: one being the DLMA node, while the other is not.
2) **Hybrid**: This network consists of over 2 nodes, with at least one being a DLMA node.
3) **Muti-DLMA**: This is a pure DLMA-network.
4) **Heterogeneous network with queue**: This network can be any of the 3 types mentioned above. Moreover, the bit arrival rates and the queues are considered to simulate a more practical scenario. In this context, a FIFO queue is applied.

Afterward, we observe the overall variation in system throughput and analyze the characteristics of DLMA

By analyzing the changes in the overall system, we sum up the specific characteristics of DLMA, determining the environments in which it is most suitable. Based on these findings, we can design a protocol that leverages DLMA to tackle the problem of low throughput in nodes effectively.

II. The Protocols

A. Introduction to the DLMA Protocol

DLMA is an RL-based protocol proposed by [1], which strives to outperform traditional protocols by adapting to heterogeneous network. It takes actions based on the previous environmental state. It then collects rewards and the environmental state transitions. These transitions are stored in DLMA's memory, enabling it to optimize its strategies through the training of historical data and updating its decision model. Consequently, DLMA adapts to the presence of coexisting networks.

Moreover, to avoid extreme suppression of the throughput of non-DLMA nodes, the **α-fairness** technique is introduced. To apply α-fairness, DLMA also collects the rewards of all other nodes in the environmental state. DLMA then chooses its action based on the output of α-function. Essentially, α-value measures the fairness, i.e.

- $\alpha = 0$: Maximize total throughput.
- $\alpha = 1$: Proportional fairness in ideal. This implies that every node ideally receives at least $\frac{1}{n}$ of the total throughput among the n nodes.
- $\alpha = \infty$: Maximize the minimum throughput.

In the following experiments, we'll quickly find it impractical to achieve a maximum total throughput; therefore, unless stated otherwise, $\alpha = 1$ in default.

In this context, we aim to avoid delving into the specific RL intricacies of DLMA, including Q-learning, the ϵ-greedy algorithm, and so on. If you're interested in gaining further insights into the workings of DLMA, we recommend referring to [1].

B. Coexisting Protocols

In this report, besides DLMA, there are 3 traditional protocols are considered.

1) **TDMA**: Repeat the transmission of X fixed time slots within 10 time slots. $X = 2$ unless stated otherwise.
2) **Exponential backoff ALOHA (EB-ALOHA)**: The initial window size is W. After the backoff countdown ends, transmission takes place. If successful, the window size reverts back to W. In the event of a collision, the window size doubles. $W = 2$ and $max.count = 2$ unless stated otherwise.
3) **q-ALOHA**: There is a probability of transmitting q at any given time slot. $q = 0.2$ unless stated otherwise.

III. Experiment-1: Single DLMA + Single non-DLMA

A. TDMA

For the case of 1 DLMA + 1 TDMA, please refer to Fig. 2. In this experiment, different numbers of occupied time slots $X = 2,\ 5,\ 8$ are considered and α is set to 0. Because TDMA occupies fixed X time slots among all, DLMA can easily predict the empty time slots and achieve a full total throughput.

We have also discovered that DLMA is capable of stabilizing the overall throughput, as illustrated in Fig. 1. Despite the extreme alteration of TDMA's behavior, the total throughput remains consistently at maximum.

[1]For the following experiments, please refer to basic_main.py and sim_tool/ in https://github.com/Xuan-Yi/IWMN-Final-Project-DLMA.git.

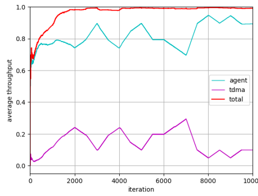
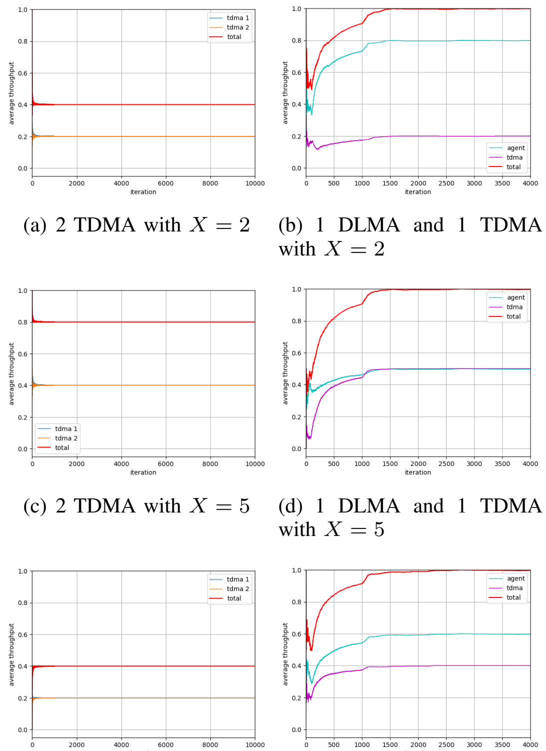


Fig. 1: 1 DLMA coexists with 1 TDMA, which alters $X \in [0, 10]$ randomly every 500 iterations.



(a) 2 TDMA with $X = 2$

(b) 1 DLMA and 1 TDMA with $X = 2$

(c) 2 TDMA with $X = 5$

(d) 1 DLMA and 1 TDMA with $X = 5$

(e) 2 TDMA with $X = 8$

(f) 1 DLMA and 1 TDMA with $X = 8$

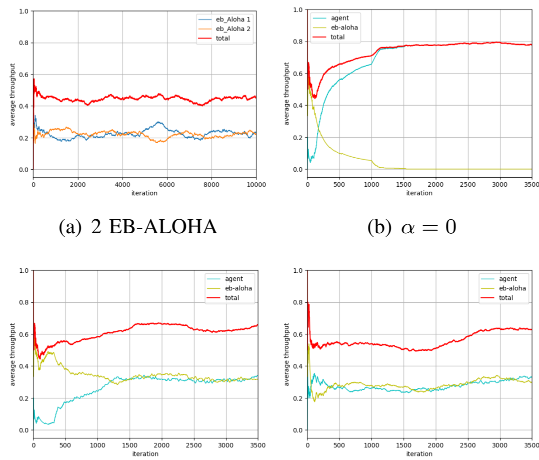
Fig. 2: Compare with the pure TDMA networks (left figures), the networks composed of 1 DLMA + 1 TDMA (right figures) can achieve full total throughput for $X = 2,\ 5,\ 8$.

B. EB-ALOHA

Regarding the case of 1 DLMA + 1 EB-ALOHA, please refer to Fig. 3. In Fig. 3(a), these 2 EB-ALOHA nodes perform well. However, when EB-ALOHA coexists with DLMA, which aims to maximize the total throughput as shown in Fig. 3(b), the throughput of EB-ALOHA decreases to 0, even though the total throughput is maximized.

To address this, we set $\alpha = 1$ in order to make DLMA promote proportional fairness. As illustrated in Fig. 3(c), both DLMA and EB-ALOHA achieve a fair division of total throughput. Moreover, compared with a pure EB-ALOHA network, regardless of the value of α, the total throughput gets boosted. This indicates that DLMA is effective to enhance the performance of EB-ALOHA.

Returning to the phenomenon depicted in Fig. 3(b), we infer that DLMA does its best to prevent the transmission of EB-ALOHA in order to minimize the likelihood of collisions because EB-ALOHA operates based on a semi-random rule. To reach this goal, DLMA continually transmits, thereby increasing the backoff time for EB-ALOHA. Then the guaranteed successful transmission is maximized.



(a) 2 EB-ALOHA

(b) $\alpha = 0$

(c) $\alpha = 1$

(d) $\alpha = \infty$

Fig. 3: Pure EB-ALOHA network (a) and the networks (b) (c) (d) compose of 1 DLMA + 1 EB-ALOHA with different fairness.

C. q-ALOHA

Please refer to Fig. 4 for the case of 1 DLMA + 1 q-ALOHA. Initially, let's consider $\alpha = 0$. By examining Fig.4(a) and Fig.4(c), we observe that q-ALOHA is suppressed when $q < 0.5$, while DLMA compromises when $q > 0.5$. Interestingly, they function jointly when $q = 0.5$, as demonstrated in Fig. 4(e). Consequently, we can infer that the strategy of DLMA can be summarized as "If DLMA can't win, it concedes." Then considering $\alpha = 1$, it is obvious from Fig.4(b) and Fig.4(d) that both DLMA and q-ALOHA achieve non-zero throughputs.

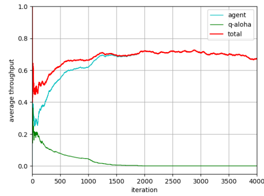
IV. Experiment-2: Hybrid

A. Participation of DLMA

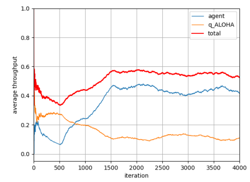
By observing Fig. 1, Fig.3, and Fig.4, we are inspired by the potential of DLMA to regulate an existing network.

At first, we considered a network that consisted of 1 TDMA, 1 EB-ALOHA, and 1 q-ALOHA in Fig.5(a). After the participation of a DLMA as shown in Fig.5(b), we observed that the total throughput didn't have a significant decrease. This is abnormal compared to traditional protocols, as more nodes typically lead to a higher probability of collision. Furthermore, Fig. 5(b) demonstrates the effective regulatory capability of DLMA, which is due to the application of α-fairness.

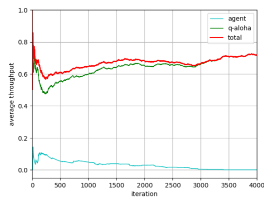
Additionally, we single out EB-ALOHA and examine its behavior, as depicted in Fig. 5(c) and Fig. 5(d). It is evident that there is a notable increase in the variance of EB-ALOHA



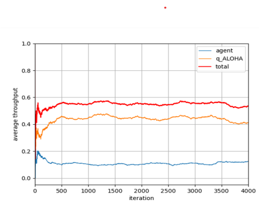
(a) 1 DLMA + 1 q-ALOHA with $q = 0.3$ and $\alpha = 0$



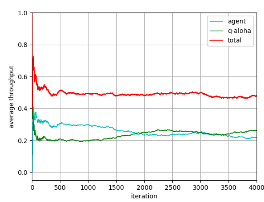
(b) 1 DLMA + 1 q-ALOHA with $q = 0.3$ and $\alpha = 1$



(c) 1 DLMA + 1 q-ALOHA with $q = 0.7$ and $\alpha = 0$



(d) 1 DLMA + 1 q-ALOHA with $q = 0.7$ and $\alpha = 1$



(e) 1 DLMA + 1 q-ALOHA with $q = 0.5$ and $\alpha = 0$

Fig. 4: The networks compose of 1 DLMA + 1 q-ALOHA with different fairness for $q = 0.3,\ 0.7$. Also, $q = 0.5$ for $\alpha = 0$.

after DLMA's participation. Therefore, there actually exists a trade-off between the overall enhancement of throughput and the amplified variance of EB-ALOHA.

B. *Replacement of DLMA*

How good DLMA is may become one of the primary topics that interest people. To answer this question, we gradually replace traditional nodes with DLMA and observe the change in behavior as in Fig. 6 and Fig. 7.

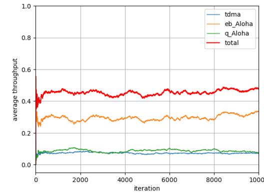
In the case of EB-ALOHA shown in Fig.6, the total throughput improves as the network has a higher proportion of DLMA. However, similar to the previous finding in Fig.5, the network's variance also increases.

Regarding the q-ALOHA case depicted in Fig. 7, we observe that the total throughput doesn't have a significant increase. However, we noticed a phenomenon wherein DLMA attempts to mimic the behavior of q-ALOHA when they share the same q value.

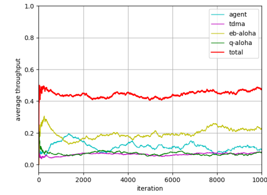
V. Experiment-3: Consider More Practical Scenarios

A. *Pure DLMA Networks*

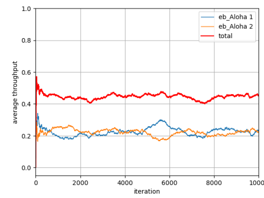
We have considered several heterogeneous and proven some good characteristics of the network coexisting with DLMA so far. As a result, we anticipate even better performance for a pure DLMA network, as we expect it to exhibit collaborative behavior by establishing its own rules. However, the gap between ideal and reality is shown in Fig. 8. Although the total throughput reaches approximately 80% and 70% of media usage for Fig. 8(a) and Fig. 8(b), respectively, both the total and individual throughput are unstable. Therefore, a pure DLMA network is a bit impractical.



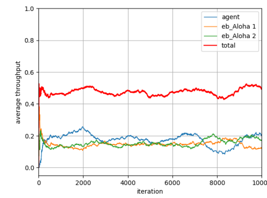
(a) 1 TDMA + 1 EB-ALOHA + 1 q-ALOHA



(b) 1 DLMA + 1 TDMA + 1 EB-ALOHA + 1 q-ALOHA

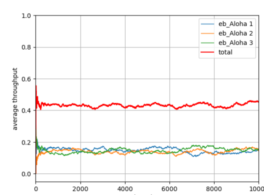


(c) 2 EB-Aloha

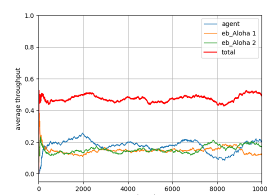


(d) 1 agent + 2 EB-Aloha

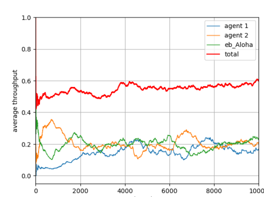
Fig. 5: Building upon the findings from Fig. 1, we'd like to discuss the regulatory of DLMA on the existing network. First, we examine a network comprising TDMA, EB-ALOHA, and q-ALOHA in (a) and (b), finding that EB-ALOHA is the most significantly impacted protocol. Therefore, we dig deeper into the scenario of the EB-ALOHA network in (c) and (d).



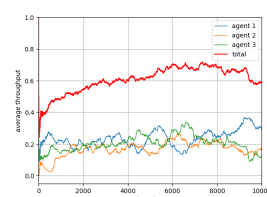
(a) 3 EB-Aloha



(b) 1 DLMA + 2 EB-Aloha

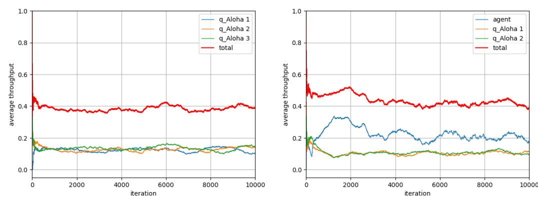


(c) 2 DLMA + 1 EB-Aloha



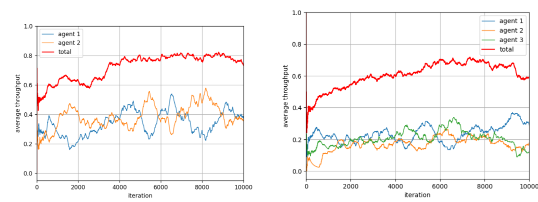
(d) 3 DLMA

Fig. 6: We are interested in how DLMA can enhance the total throughput of EB-ALOHA and the potential trade-off.



(a) 3 q-ALOHA (b) 1 DLMA + 2 q-ALOHA

Fig. 7: We also want to understand how DLMA coexists with q-ALOHA.

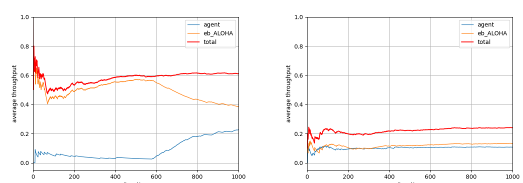


(a) 2 DLMA (b) 3 DLMA

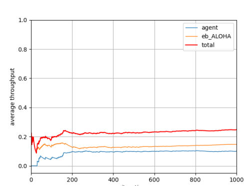
Fig. 8: We consider the behavior of pure DLMA networks.

B. Heterogeneous Network With Queue

In our previous experiments, we simulated a scenario where the MAC protocols constantly had data to transmit. However, this doesn't always accurately reflect real-world situations, as the arrival rate of data can vary over time and with varying degrees. To address this, we have incorporated simulations of different types of data arrivals into our code[2]. An example of the simulation result can be seen in Fig. 9.



(a) no queue (b) constant bit rate



(c) Poison packet arrival

Fig. 9: We consider the behavior of pure DLMA networks.

VI. Discussion

From the above simulation experiments, we can deduce that the interaction of DLMA in the environment can be roughly summarized into three points of discussion.

A. Effectiveness

From the evaluation of effectiveness based on the total throughput in the environment, we can observe that the participation of DLMA almost always enhances overall performance.

The best performance is observed when DLMA interacts with TDMA. When only DLMA and TDMA are present in the environment, DLMA is able to effectively and fast learn the transmission pattern of TDMA. When TDMA consistently changes the transmission parameter X, DLMA demonstrates the ability to rapidly adapt and maintain the overall system's throughput stability.

Under the EB-ALOHA scenario, DLMA improves the overall throughput. However, in the case of q-ALOHA, we have observed that DLMA learns the transmission pattern of q-ALOHA. We hypothesize that this is because DLMA cannot predict the future random variations of q-ALOHA and can only learn its transmission mode. Nevertheless, this learning process helps ensure the enhancement of overall throughput.

In a Hybrid environment, the participation of DLMA does not reduce the overall throughput, and in fact, it can even improve it. This is a favorable outcome because it signifies that despite more users contending for resources, there is a reduced occurrence of collisions. As a result, it becomes possible to lower the complexity of the transmission protocol while increasing its effectiveness.

B. Regulation

In our previous experiments, we utilized the properties of DLMA α-fairness and found that by integrating a DLMA into an existing network, we could achieve maximum fairness. As shown in Fig. 5, we can reduce the throughput of EB-ALOHA, which originally consumed a higher amount of resources. Thus DLMA may have the capability to maintain network fairness, which in practice can be utilized to regulate resource allocation among different protocols in heterogeneous networks, thereby enhancing the overall QoS.

However, we may not achieve real proportional fairness. This is because DLMA relies on penalizing protocols that consume excessive resources, such as causing collisions with EB-ALOHA to reduce its transmission opportunities. Additionally, if a protocol itself has a fixed transmission capacity, such as TDMA or q-ALOHA, DLMA cannot adjust its throughput either. Therefore, although DLMA is capable of regulating network throughput, it still has its limitations.

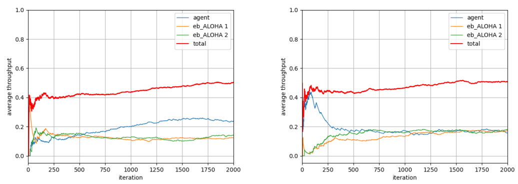
C. Adaptability

Using the DQN architecture for learning does not require significant resource consumption. Therefore, we believe DLMA can be trained on edge devices. Additionally, DLMA exhibits a relatively fast convergence speed, which is advantageous for conducting incremental or episodic training.

We provide a scenario of using an adapted DLMA strategy to improve the performance of low throughput nodes.

[2]For the experiments considering queue, please refer to general_main.py in https://github.com/Xuan-Yi/IWMN-Final-Project-DLMA.git.

From our simulation in Fig. 10, it can be observed that the pre-trained DQN model in Fig. 10 (b) exhibits better convergence speed and performance than Fig. 10(a).



(a) without pre-trained

(b) pre-trained with 1 DLMA + 2 q-ALOHA for 50000 iterations

Fig. 10: pre-trained experiment

In this experiment, we apply a pre-trained model (q-ALOHA) to another totally different network (EB-ALOHA) to simulate the effect of deployment. Therefore, when the transmission level of a particular node falls below a certain threshold, we can utilize a DQN model to train a DLMA that best suits the current environment and save the weight as a pre-trained model.

VII. Conclusion

We observed the interaction between the DLMA and different environments through the designed simulations. DLMA demonstrates the ability to adapt well to the environment and, under the influence of α-fairness, ensures system stability and fairness.

However, the experiments are basic simulations, and interactions with complicated protocols with RTS/CTS require considering additional factors for network behavior and performance analysis. Although DLMA has not yet been a mature protocol, we still believe that DLMA has great potential to revolutionize the world of wireless networks.

VIII. Future Work

We aspire to handle continuous transmission and train DQN models that can interact with MACA or CSMA/CA. This approach would enable DLMA to be more practically aligned with real-world scenarios.

References

[1] Y. Yu, T. Wang and S. C. Liew, "Deep-Reinforcement Learning Multiple Access for Heterogeneous Wireless Networks," in IEEE Journal on Selected Areas in Communications, vol. 37, no. 6, pp. 1277-1290, June 2019, doi: 10.1109/JSAC.2019.2904329. Simulation codes: https://github.com/YidingYu/DLMA.git