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MACHINE LEARNING BASED PERFORMANCE ANOMALY AVOIDANCE SCHEME FOR MEDICAL IOT APPLICATIONS

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ABSTRACT

The Restricted access window (RAW) method, which is part of the IEEE 802.11ah standard for the Internet of Things (IoT), reduces the effect of collisions on the network while increasing the overall performance of the network. However, in multi-rate IoT networks based on IEEE 802.11ah, performance anomaly degrades the network performance. The Machine Learning based Performance anomaly avoidance with cluster-based grouping (MLPA-CBG) scheme proposed in this article is intended to address this issue. The proposed scheme makes use of the self-organizing map neural network for the purpose of categorizing devices as per bit rate. Then, each group is assigned a time slot that allows them to access the channels. CBG outperforms the default uniform grouping scheme in terms of throughput, delay and energy consumption.

Keywords: *CBG, SOM, IoT, anomaly, Machine Learning.*

1. INTRODUCTION

With the fast advancement of telecommunications technology, the Internet of Things (IoT) is becoming more popular in many areas of human existence. IEEE802.11ah has recently been announced as a potential standard for Internet of Things (IoT) applications [1]. This standard makes use of a variety of MCS in order to accommodate a wide range of data rates. The network nodes use rate adaptation methods to determine the most effective MCS depending on the observed channel quality. Because of the restricted access window (RAW) method, which is implemented at the medium access control (MAC) layer, power usage is minimized in case of dense Internet of Things networks. When the RAW mechanism is activated, it controls the MAC layer by specifying limited periods for channel access, which are referred to as RAW slots. When it comes to RAW slots, it enables each group of nodes to compete with one another by utilizing CSMA/CA, to get a channel in a RAW slot.

According to the typical IEEE802.11 multi-rate networks, the channel is primarily used by the nodes with the lowest data rates rather than the nodes with the highest data rates, resulting in performance anomaly. A performance anomaly is defined as a reduction in the throughput of higher rate nodes to the point where it falls below the throughput of lower rate nodes. Similar to the legacy 802.11, it has been found that the performance of the RAW mechanism in conjunction with the UG scheme has been significantly reduced as a result of a performance issue. One easy solution to this issue is to provide the same amount of channel time to all of the nodes. The authors achieved time-based fairness by taking advantage of the transmission opportunities provided by the nodes. In addition, the authors tuned MAC parameters such as arbitration inter frame spacing (AIFS), contention window (W_0), and packet size in accordance with the data rate provided by nodes [2–7].

The majority of existing solutions to the performance anomaly are based on adjusting the MAC settings, which results in extra MAC overhead being introduced. Due to the fact that grouping is an important component, we suggest a Machine Learning based Performance anomaly avoidance with cluster-based grouping (MLPA-CBG) method to prevent the performance anomaly while maintaining the default network configuration. The proposed CBG system divides nodes into categories depending on the data rates that may be achieved. Also discussed is the development of an analytical model that can be used to determine the proposed CBG system.

This work avoids performance anomalies to prevent them from occurring by using the CBG method. The remainder of the paper is organized as follows. Section **2** provides an overview of the RAW method. Section **3** provides a proposal for the CBG system, while Section **4** presents throughput, energy and delay model. Section **5** of the paper contains the results and discussion, and Section **6** of the article concludes the study. The following are the most significant contributions made by this article.

- We propose a CBG method for categorizing nodes based on the maximum data rates they are capable of achieving.
- In this paper, we provide a simple analytical model for evaluating the throughput, delay and energy consumption of the proposed method in the context of Internet of Things networks.
- According to the suggested CBG system, the performance of CBG scheme is superior than the default UG scheme.

The results of the simulation utilizing ns-3. support the conclusions reached by the analytical results.

2. RAW MECHANISM

The RAW mechanism, which is implemented in IEEE 802.11ah with the goal of reducing channel congestion [8]. The RAW mechanism organizes the nodes into groups and gives a RAW slot to each group. Then, using the following equation, each node determines which RAW slot has been assigned to it.

$$\Phi_{slot} = (Association\ Identifier + offset)\ mod\ N_r, \quad (1)$$

In this instance, offset is utilised to guarantee validity, and N_r is the access

point's number of RAW slots(AP). As illustrated in Fig. 1, the network time is divided into RAW and contention-access periods (CAP). The AP configures the RAW mechanism in this instance, and the beacon message is used to communicate elements of the RAW parameter set to the system (RPS- IE). The RPS-IE contains the AIDs of the sensors, as well as the length of the RAW slot. Every RAW slot's nodes access the channel in accordance with the EDCA [9].

3. MACHINE LEARNING BASED PERFORMANCE ANOMALY AVOIDANCE WITH CLUSTER BASED GROUPING

As discussed in the previous section, we present a CBG method that makes use of SOM to categorize nodes based on the data rates they transmit. Once the network has been created, the access point (AP) transmits beacon frames containing a variety of components on a periodic basis. Each node calculates the maximum data rate that may be achieved depending on the observed SNR, as shown in Fig. 2. Then, before starting the association process with the AP, each node adjusts the rate information in accordance with the channel condition on which it is connected. As soon as all of the nodes are connected with the AP, the AP uses the CBG algorithm to categorise the nodes based on their rate capabilities.

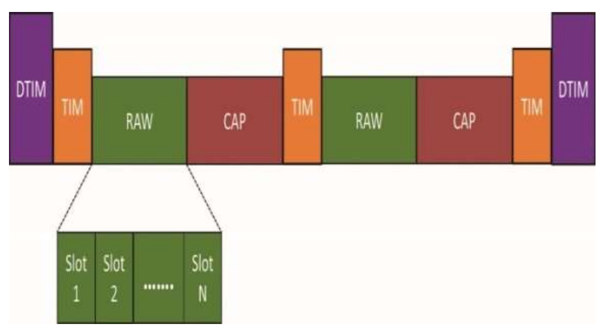

Figure 1: Channel Timing

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Algorithm 1: CBG

```
Inputs:
counter = 1000;
learning_rate = 0.5; \\ Learning rate
P = [ ];
for N_d do
    S(n) = datarate, n ∈ [1,G];
end for
\\ Classify S with SOM neural network
W_ij = rand(i,j), i = 1,j = d;
for counter do
    for N_d do
        for N_r do
            p_j = (S(n) − w_ij)^2, j ∈ [1,d];
            P = [P p_j];
        end for
        [V alue Index] = min(P);
            W_ij(new) = W_ij(old) + learning_rate(S(n) − w_ij(old));
        learning_rate = 0.5 learning_rate;
    end for
end for
```

Initialization involves decapsulating the rate bits and storing the decapsulated data in an array S(n) as shown in Algorithm 1. After starting with a $learning_{rate}$ = 0.5, the SOM iterates thousands of times before categorising N_d nodes into D_r groups. At the end of the process, the CBG algorithm guarantees that all G nodes are categorised into D_r groups. A unique association identifier (AID) is assigned to each node by the access point, which broadcasts the RPS-IE after grouping the nodes. Then, using Eq. (1), each node determines the RAW slot it has been assigned and begins competing for the channel by using the DCF method.

4. SYSTEM MODEL

Throughput, delay and energy consumption analysis is presented here. An access point (AP) and N_d number of restricted mobility nodes are used in this article to illustrate the network situation. At the PHY layer, the AP employs D_r different rates, each of which is determined by the distance between the node and the AP. as shown in Fig. According to Fig. 2, the AP is located in the middle of D_r zones, each of which has a length of L_d. By using rate adaptation methods, each node selects a certain MCS S based on the maximum data rate that can be achieved. According to the research given in [10], the node communicates with rate of R_j. the data rates of the nodes that are present in the different zones are $R_j \in [0.6, 79]$ Mbps for $L_d \in [100,400]$m..

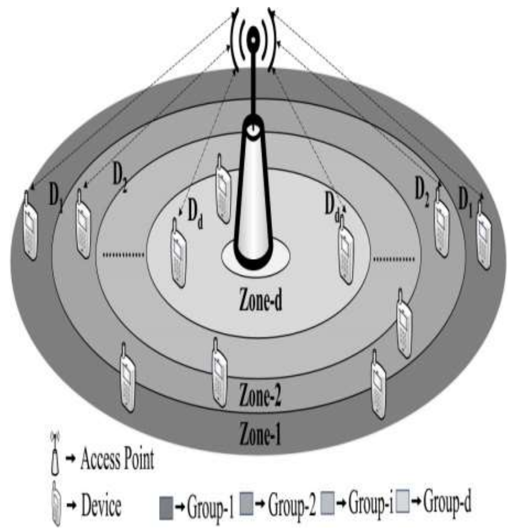

Figure 2. : Network Scenario

Let t_s is slotted time. The IoT network divided into D_r with $g_j \left(\sum_{j=1}^{d} g_j = G\right)$ devices and the RAW (Δ_{RAW}) has D_r units of time $\Delta s,j \left(\sum_{j=1}^{d} \Delta s, j = \Delta_{RAW}\right)$. Let $\Delta_L^{(r_j)}$ be the duration of a node transmission, $\Delta_L^{(r_j)} = \Delta_{E[P]}^{(R_j)} + \Delta_{sifs+\ ACK+2t_p}$ where $\Delta_{E[P]}^{(R_j)}$ is payload time, Δ_{sifs} is SIFS, δ_{ACK} , t_p is the propagation and acknowledgement time . Let $\Delta_h = \Delta_L^{(r_j)} + t_d + t_g - t_s$ is defined for no crossing case with a RAW slot of $\Delta'_s = \Delta_s - \Delta_h$. Each node competes for communication links in Δ' that used the DCF method, which would be based upon CSMA/CA and binary exponential back-off and has an early contention frame specified as W_0. Thus, the transmission and collision probability [11] are given by,

$$p_{t,i}^{(R_j)} = \frac{2\left(1 - 2p_{c,i}^{(R_j)}\right) p_q}{\left(1 - 2p_{c,i}^{(R_j)}\right)\left[p_q(W_0 + 1) + 2(1 - p_q)(1 - p_{c,i}^{(R_j)})\right]},$$

$$+p_q\left(1 - \left(2p_{c,i}^{(R_j)}\right) m_b\right) W_0\, p_{c,i}^{(R_j)}$$

$$p_{c,i}^{(R_j)} = 1 - \left(1 - \tau_i^{(R_j)}\right) g^{(R_j)-1} \prod_{p=1,p\neq j}^{d} \left(1 - \tau_i^{(D_p)}\right) g_i^{(D_p)} \quad (1 - k), \tag{2}$$

The packet arrival probability at a rate Π is $P_q = 1 - e^{-\Pi E[\Delta_{avg}]}$, where $E[\Delta_{avg}]$[1] [11] and is given by,

$$E[\Delta_{avg}] = 1 - p_{tr,i}^{(R_j)} t_s + p_{tr,i}^{(R_j)} p_{s,i}^{(R_j)} (\Delta_L^{(r_j)} + t_d) + p_{tr,i}^{(R_j)} (1 - p_{s,i}^{(R_j)}) (\Delta_L^{(r_j)} - \delta_{ack} - t_p + t_d \quad (3)$$

Here, the success probability and the probability of have a transaction are given by,

$$p_{s,i}^{(R_j)} = \frac{1}{p_{tr,i}^{(R_j)}} \Big[g_i^{(R_j)} \tau_i^{(R_j)} \Big(1 - \tau_i^{(R_j)}\Big) g_i^{(R_j)} - 1 \times \prod_{p=1,p\neq j}^{d} (1 - \tau_i^{(D_p)}) g_i^{(D_p)} (1 - k) \Big], \quad (4)$$

$$p_{tr,i}^{(R_j)} = 1 - \prod_{p=1}^{d} (1 - \tau_i^{(D_p)})\, g_i^{(D_p)} \quad (5)$$

Therefore, the average throughput of the nodes $g_i^{(R_j)}$ with data rate R_j, j ∈ [1,d] is given by,

$$T_i^{(R_j)} = \frac{d\, E[P]\, P_{s,i}^{(r_j)}}{\Delta_{RAW}} \sum_{\pi=1}^{G\Delta_L} \pi P_{Q,i(\pi)}, \quad (6)$$

where,

$$p_{Q,i}(\pi) = \sum_{j=\pi}^{\Delta-(\pi-1)\Delta_L(R_j)-t_d-t_s} Prob\{\textstyle\sum_{i=1}^{\pi} x_{b,i} = j\} \quad (7)$$

The energy consumption per bit (η_j) [10] is given by,

$$n_j \approx \frac{E_T}{E[Payload]} \quad (8)$$

where E_T is the total energy consumption.

The average delay (R_j) experienced by a node is equal to the time taken for successful transmission of a packet.

$$D_j = E[B]_\rho + N_t(\xi - \Delta_{ACK}) + \xi' \quad (9)$$

5. RESULTS AND DISCUSSIONS

[1]We describe the analytical findings and simulation results obtained using ns-3 [12] in this section. We begin by assuming that all nodes are classified into four categories. The AP is located in the centre of zone-4, as shown in Figure 2. Zone-1 nodes have the longest propagation delays due to their proximity other AP, while zone-4 nodes have the fastest data rates due to their proximity to the AP. Table 1 contains a list of the parameters utilized in the analysis. Fig. 3b illustrates the proposed CBG system. In this section, we'll examine a network of 1024 nodes that are evenly distributed around the AP, as shown in Fig. 3a. The CBG algorithm divides nodes into four categories. It demonstrates clearly how the SOM effectively classifies the nodes into different zones and guarantees that all nodes in each zone have comparable data rates.

5.1 Analysis Of PA

The research analyses various 512 and1024-bit networks that have been adequately categorized into four groups. Scenario-1 focuses only on the nodes with the slowest data transmission rate *(0.6Mbps).* Alternatively, scenario-2 considers a set of nodes running at different data speeds. In scenario-2, the constant throughput is because of the nodes have varying data rates, the nodes with the highest data rates are penalized by the nodes with the lowest data rates due to the channel's prolonged usage. As a consequence, the average throughput of the nodes with the greatest data rates is lowered to that of the nodes with the lowest data rates. This is much more pronounced in dense networks

[1] here π = 100 packets/s, mb = 5, and W_0 = 32

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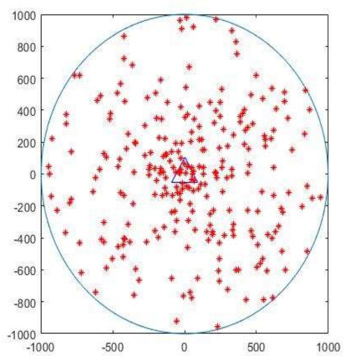
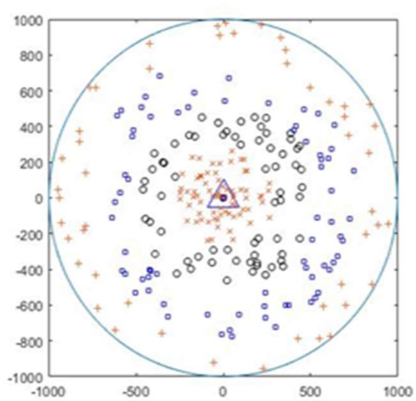
Table 1: Analytical and simulation parameters

Parameter	Value
Payload	256 bytes
MAC Header	14 bytes
PHY Header	156 bits
ACK	14 bytes
tp	1 μs
Δ_{RAW}	500 ms
ts	52 μs
Δ_{sifs}, t_d	160 μs, 264 μs



(a)



(b)

Figure 3: Node classification using the CBG method. The triangle denotes the access point, while the other symbols denote the nodes. (a) Illustrates a network setup with 1024 nodes. (b) Demonstrates the classification of 1024 nodes into four categories using the CBG method

5.2 Performance Of The Proposed CBG Scheme

Figure 4 compares the proposed system's performance to that of the UG scheme. The average throughput is determined in Fig. 4 by changing the network size. The graphic shows the

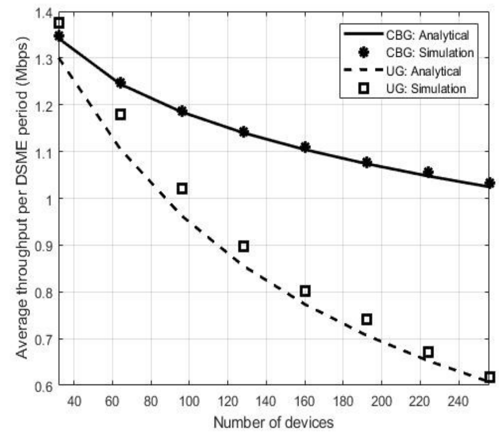


Figure 4: Average throughput Vs. network size.

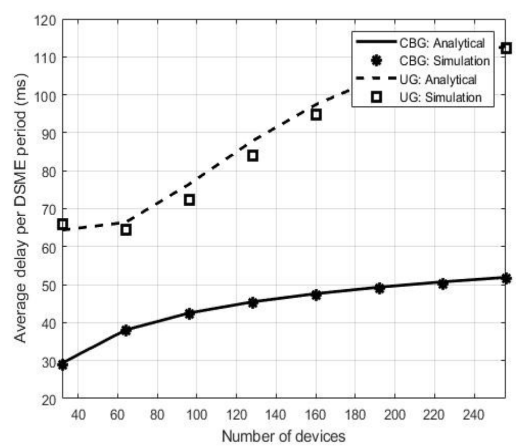


Figure 5: Average delay Vs. network size.

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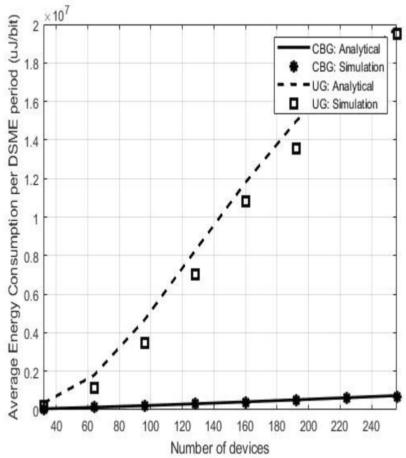

Figure 6: Average energy consumption Vs. network size.

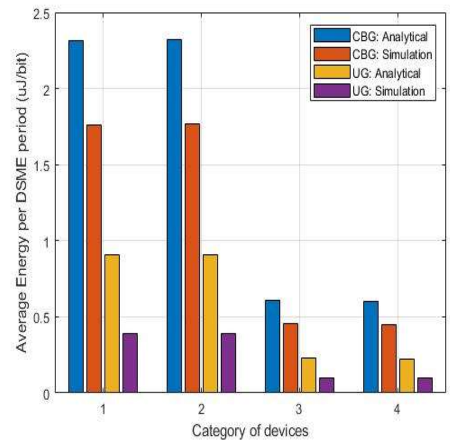

Figure 9: Average energy consumption Vs. group size.

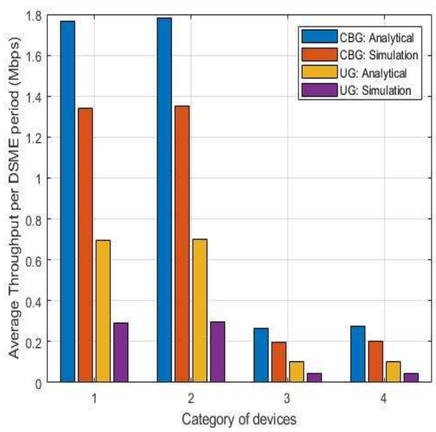

Figure 7: Average throughput Vs. group size.

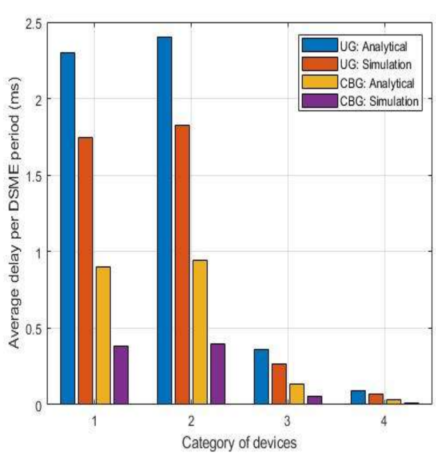

Figure 8: Average delay Vs. group size.

reduction in throughput associated with increasing the network size. Because as the network grows in size, conflict rises proportionately, lowering the network's average throughput. Additionally, it is found that the CBG system has a considerably greater throughput than the UG scheme. This is because, in the case of the UG scheme, the performance anomaly has a significant impact on the network's performance. Whereas the proposed CBG system guarantees that each group has nodes with comparable data rates. As a result, performance is improved since the performance anomaly has no effect on the network. Similarly, Fig. 5 and 6 show the performance improved of delay and energy consumption using CBG scheme

Figure 7 analyses a network with a size of G = 1024 that has been grouped into four categories by using CBG technique in this section. The UG scheme, on the other hand, splits nodes into four workgroups, each one includes nodes with different data rates. When a result, as the index of the RAW slots rises, the plot in Fig. 7 diminishes. This is because the first RAW space is allocated for the nodes with the greatest data rate, while the last RAW slot is reserved for the nodes with the lowest data rate. The graphs for the UG scheme, on the other hand, are same regardless of the slot index, since the average throughput for each RAW slot remains constant due to the various data rate nodes. Thus, in both approaches, the network with G = 2048 nodes has a lower throughput than the network with G = 1024 nodes. Finally, as shown in Figure 7, the CBG approach significantly improves network throughput by removing the performance anomaly associated

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with IoT networks. Similarly, 8 and 9 illustrate how the CBG scheme improves performance in terms of latency and energy usage.

6 CONCLUSIONS

We found a significant decrease in the throughput performance of IoT networks utilizing the default UG scheme in our study owing to a performance anomaly. By addressing the performance anomaly in IEEE 802.11ah multi-rate IoT networks, we suggested CBG scheme. We have provided an analytical model for the purpose of doing a throughput analysis. The findings clearly indicate that the suggested CBG system outperforms the UG scheme. Finally, comprehensive simulation studies are used to validate all analytical findings.

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