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PERFORMANCE ANALYSIS OF SCHEDULING ALGORITHMS FOR CONSTANT BIT RATE (CBR) TRAFFIC IN VEHICLE-TO-NETWORK (V2N) APPLICATION

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Abstract

To achieve a sustainable Quality of Service (QoS) and optimised network performance, scheduling is a crucial aspect in Radio Resource Management (RRM). With 5G NR technology and increased network users, the network scheduler plays a vital role in controlling congestion and ensuring satisfactory service delivery. In an emergency, poor network resource management can cause harm or loss. This study evaluates the performance of three scheduling algorithms - MAX C/I, DRR, and BF Allocation - in NR 5G uplink transmission for an urban scenario. The algorithms are evaluated based on throughput, packet delay, and frame delay variation using the Simu5G framework on OMNET++ simulator. The results show that MAX C/I achieves 80% higher throughput and 30% lower CBR frame delay time, while DRR displays the lowest average MAC delay with 25% less delay time. The study provides a benchmark for scheduling algorithms in C-V2X for 5G under high mobility and loads.

Keywords: 5G, Best fit, CBR, DRR, MAX C/I, New radio, Resource allocation, Scheduling, V2N.

1. Introduction

Wireless network environments face challenges in securing stable network traffic for users due to the growing number of devices with internet communication capabilities, such as smartphones, tablets, and the internet-of-things (IoT) [1]. To address this issue, 5G New Radio mobile networks have been developed, which offers 10 times better data transmission than previous technologies [2].

In 2017, The 3rd Generation Partnership Project (3GPP) launched a new technology for V2X based on cellular network known as cellular-vehicle-to-everything (C-V2X). This technology integrated the capabilities of cellular networks which provide high bandwidth and low latency with the V2X communication technology, thereby enhancing the reliability and efficiency of communication between vehicles and other entities. C-V2X enables direct communication between vehicles, pedestrians, and roadside infrastructure without the need for a dedicated short-range communication (DSRC) network, which was the primary V2X technology before C-V2X [3]. C-V2X was known to have higher coverage, allow higher vehicles mobility and serve larger number of vehicles with lower error rate [4]. This technology also supports a wide range of use cases, such as collision avoidance, traffic management, and cooperative driving, among others. As such, C-V2X is becoming increasingly popular and is expected to be widely adopted in the future, particularly with the development of autonomous driving technology.

However, as a new technology as compared to the more established DSRC, there are several issues that need to be addressed and resolved pertaining to the implementation of C-V2X. Using cellular network as its basis, C-V2X is competing against a huge number of devices to secure a resource. Unlike DSRC which provided dedicated and exclusive technology to V2X, cellular networks serve multitude of applications with different requirements and traffic characteristics. In the instance where network demand is massive, congestion level of the network will escalate and give effect to the QoS of the system [5]. This is more critical to C-V2X technology environment which features connection between many different entities with distinctive characteristics through V2V, V2I, V2P and V2N communications. The effect could be more fatal as vehicles move at high mobility and causes frequent changes in topologies [6]. With the expected spike in the number of vehicles and devices with 5G capabilities, managing network resources is crucial to ensure a suitable level of network performance, especially considering the inadequacy of available spectrum resources [7]. Resource management is therefore essential to ensure a suitable level of network QoS performance.

Effective scheduling is crucial for allocating resources in 5G networks, ensuring that the appropriate resources are provided to users when needed [8]. This aids in avoiding congestion and enhancing overall network performance. Failure to effectively allocate the limited resources may badly affect the QoS received by the users. This is especially true for delay-sensitive resources such as videos and images where compromised data may lead to misinformation and interruptions. Prospectively, the QoS could be improved by strategically distributing the available resources based on the needs and requirements of the service. By scheduling resources according to QoS demands, networks can ensure that the most important services are given priority access to resources. This helps to ensure that users receive the best possible performance.

Hence, this paper intends to examine the performance of image data transmission in an urban area with varying density for 5G New Radio wireless networks based on C-V2X (V2N) environment. This study examines three different classical algorithms (from the previous generation) which are known to have contradictory tendency towards each other: Deficit Round Robin (DRR) which known to be highly strict in fairness (fair-inclined), Maximum Carrier to Interference Ratio (Max C/I) known to incline towards channel's quality (quality-inclined) and Best Fit (BF) algorithm which preferred efficiency of resource distribution (efficiency-inclined). At the end of this study, the performance of each scheduling scheme will be analysed due to data transmission on image or video based on constant bit rate (CBR) encoding by means of MAC throughput, MAC delays and CBR frame delay experienced by the network.

The rest of the paper is organised as follows. Section II will provide a brief insight on scheduling algorithms used in the study (DRR, MAX C/I and BF), features of the algorithm along with the pseudocode of each algorithm. The section also discussed some notable research which are relevant to the study. Section III will detail the simulation model which includes the modelling of channel and traffic, plus the QoS requirements based on NR network. Results of the scheduling algorithm will be presented and discussed thoroughly in Section IV which entails the performance of each algorithm in terms of MAC throughput, MAC delay and CBR delay.

2. Scheduling Algorithm

Scheduling plays a key role in resource allocation for 5G networks by securing the right resources to the right users at the right times [8]. This helps to prevent congestion and optimize performance. For example, when multiple users are transmitting data, the network can use scheduling algorithms to decide which users should be given priority access to the resources. Through a strategic distribution of resources, the network can enhance its overall QoS. Prioritizing resource allocation based on QoS demand ensures that critical services have priority access, leading to improved overall performance for users.

Various scheduling algorithms have been established and developed to improve data transmission for different scenarios and purposes. In this section, DRR, MAX C/I and BF allocation scheduling algorithms are explored.

2.1. Deficit round robin (DRR)

DRR is a fair queuing algorithm, known as one of the oldest algorithms existed [9] which aimed to prevent node starvation by providing network resources fairly without any bias on the channel quality [10]. Uniquely, it uses a quantum value and deficit counter to measure past inequality and allocates resources based on non-served time [11]. The algorithm is well known for its incomplexity which achieves O(1) work of process per packet and near-perfect throughput fairness [12]. This is proven by an extensive analysis by Shreedhar and Varghese [13] which satisfy the definition of fairness by Golestani [14]. However, DRR is known to have critical issue with latency - its latency is worse compared to most timestamp-based schedulers [15]. This was analysed and revealed in [16] which concluded that it is not tolerant towards framework with very low delay constraints [16, 17]. Pseudocode for DRR algorithms shown in Algorithm 1.

2.2. Maximum carrier to interference ratio (MAX C/I)

MAX C/I scheduling algorithm on the other hand is more selective in terms of channel quality. Channel quality is prioritizes over fairness by allocating resources based on carrier-to-interference ratio rank [18]. Consequently, the available resources are distributed to the deserving ones (with good channel quality) while marginally ignoring those with bad quality.

Performance of MAX C/I is known to be prominent in crowded environments with multiuser diversity [19], resulting in higher successful transmission rates and reduced packet loss [20]. Result in [21] shows that MAX C/I exhibits positive correlation between the average throughput and number of users. Additionally, its performance could reach up to 100% improvement as the number of relay station (RS) was increased. MAX C/I exhibits higher cell throughput compared to other algorithms but sacrifices fairness as the number of loads increases [22]. As a result, clients with good connectivity enjoy better QoS since more resources are allocated to them, while those with bad connectivity may experience poor reception. Pseudocode algorithm for MAX C/I is shown in Algorithm 2.

2.3. Best fit (BF) allocation

The Best Fit (BF) algorithm is a heuristic solution for the bin packing problem (BPP) that aims to efficiently manage available resources [23]. It assigns the user to the resource block with the smallest partition, minimizing the maximum number of resource blocks used [24]. If no resource block is available, a new one is assigned [25]. In contrast to DRR which prioritizes fairness or MAX C/I which prefers quality, the main objective of BF is to efficiently manage the available resources, hence efficiency-inclined. BF has shown to perform well in wireless LTE and NR network resource allocation with a competitive ratio of up to 3.0 for any bin packing problem [26]. In spectrum sharing scenario, for D2D scenarios, BF has been found to produce better throughput than Proportional Fair (PF) [23]. Pseudocode algorithm for BF allocation is shown in Algorithm 3.

Algorithm 1 Deficit Round-Robin

```
Input: quantum_size, scheduled_packet, UE
Output: deficit_counter, transferred_packet
Set quantum_size
Set deficit_counter = 0 for each user
for all UE, i = 1, 2, 3, … n
    deficit_counter = deficit_counter + quantum_size
    if deficit_counter > scheduled_packet
        transfer packet to base station
        deficit_counter = deficit_counter - scheduled packet
    else
        deficit_counter = deficit_counter + quantum_size
    move to the next UE
end for
```

Algorithm 2 Maximum Carrier to Interference Ratio (MAX C/I)

```
Input:UE, SNR_value (SNR = Signal-to-Noise Ratio)
Output: UE_score
for each UE, i = 1, 2, 3, … n
    Calculate SNR_value
end for
```

```
Each UE is assigned a UE_score based on the SNR_value
Find minimum and maximum SNR_value from each i
Calculate $\Delta SNR = ( SNR_{max} - SNR_{min} )/(i-1)$
for each SNR > ΔSNR
    Transmit data with the highest UE_score
end for
```

Algorithm 3 Best Fit Allocation

```
Input: UE, RB, packet_size, RB_size
Output: remaining_capacity
for all UE, i = 1,2,3, ..., n
    find packet_size
    for all RBs, j = 1,2,3, …, n
        find RB_size
        if packet_size fits in RB_size then
            calculate the remaining_capacity after added
        end if
    end for
    Allocate user i in RBs j where j is now with remaining_capacity
    Allocate user i which means the user "fits best"
    If no RBs available, extend the RBs and allocate user i
end for
```

In summary, three prominent classical scheduling algorithms, each with its own unique characteristics employed for network resource allocation studied in this section. The fair-inclined DRR, the quality-inclined MAX C/I, and the efficiency-inclined BF. Each of these algorithms will be tested in this study to determine which policy will benefit the most towards image or video transmission based on CBR-type data.

3. Simulation Model

The performance of DRR, MAX C/I and BF was evaluated based on an Objective Modular Network Testbed in C++ (OMNET++) version 6.0 which is a simulation library and framework to build a virtual network [27]. To achieve a simulation where both vehicular traffic and network traffic can co-exist and be derived in one platform, Eclipse SUMO (Simulation of Urban Mobility) is integrated into the software. SUMO is an open-source software which enable microscopic vehicular traffic simulation and allows multi-modal replication of real-time traffics [28]. For synchronicity between OMNET which is simulated on event-based for wireless network, and SUMO which simulate time-discrete vehicular traffic flow, Veins (Vehicles in Network Simulation) framework is adopted [29]. Veins provide a structural network model which fully details IEEE 802.1p standards, specifically designed for wireless network environments for vehicles. Modelling of 5G networks in the algorithms is done by incorporating Simu5G networks simulator into OMNET. Simu5G is an evolved framework based on 3GPP 38.901 release 16 specifications for frequencies from 0.5 to 100 GHz. It was designed based on its successful predecessor, SimuLTE for 4G LTE network simulations. Network environment in Simu5G allows the simulation of 5G networks in both standalone and non-standalone deployments [30].

3.1. Channel model

Attenuation of 5G simulation was made based on specification in a documented 3GPP technical record 38.901 version 16.1.0 [31]. The scenario is based on urban micro (Umi) where the formation of channel model is based on the relationship between 2D and 3D distances (d_{2D} and d_{3D}) as shown in Fig. 1. The relationship of d_{2D} and d_{3D} could be described as follows:

$$d_{3D-out} + d_{3D-in} = \sqrt{(d_{2D-out})^2 + (h_{BS} - h_{UE})^2} \tag{1}$$

where h_{BS} and h_{UE} represent the height of base station and user equipment (UE) transceivers respectively.

Path loss plays a crucial role in the large-scale fading model and closely related to the distances [32-34]. The path loss equation for Umi is given by the following model [31]:

$$PL = \begin{cases} 218.42 + 21\log_{10}(d_{3D}) \; for \; 10\,m \le d_{2D} \le d'_{BP} \\ 170.8 + 4\log_{10}(d_{3D}) \; for \; d'_{BP} \le d_{2D} \le 5\,km \end{cases} \tag{2}$$

which derived based on centre frequency, f_c = 2 GHz, h_{UE} = 1.5 m and h_{BS} = 25 m.

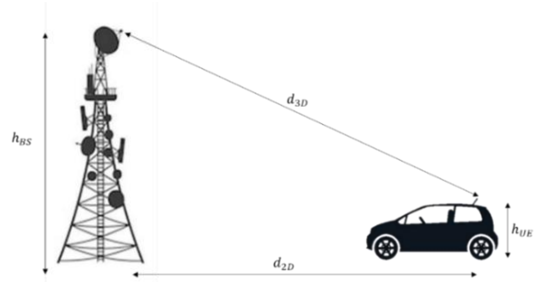


Fig. 1. Geometric relationship between d_{3D} and d_{2D} based on the height of base station and UE.

Line of sight (LOS) probability shows the probability of successful signal transmission from transmitter to receiver when both parties are within line-of-sight. The signal strength and reliability are highly dependent on LOS probability. LOS probability is determined based on 2D distances between the transceiver and receiver as shown in the following equation:

$$Pr_{LOS} = \begin{cases} 1 & , \; d_{2D} \le 18\,m \\ \frac{18}{d_{2D}} + e^{\left(-\frac{d_{2D}}{63}\right)} \cdot \left(1 - \frac{18}{d_{2D}}\right), & 18\,m < d_{2D} \end{cases} \tag{3}$$

The dynamic nature of signal transmission from UEs should consider the effect of fading as the distance of UEs gets farther from the receiver. Fading effect of the simulation is modelled based on Jakes model considering that the model take into account the mobility of the receiving vehicles, while the effect of shadowing is modelled according to a log-normal distribution with standard deviation $\sigma_{LOS} = 4\,dB$ for line-in-sight condition [35].

3.2. Traffic model and QoS requirements

The scheduling algorithm's performance for CBR traffic is evaluated in the Simu5G framework, using OMNET++ network simulator. CBR provides a uniform load, making algorithm comparison more distinct and intelligible. It is particularly useful in sending a media type data such as video streaming and images [36]. The simulation models vehicular traffic in a moderately congested urban area, with a gNodeB base station and UEs transmitting at a fixed rate of 125 kb/s using OFDMA modulation format [20]. The simulation tests the scheduling performance with 0 to 200 UEs, with UE0 located 1.3 km away from the base station moving towards it at 10 m/s and passing it, while the other UEs (UE1 - UE100) move randomly at 1 m/s. See Fig. 2 for the traffic model.

A background noise source is simulated as an antenna tower located approximately 2 km away from the base station. The BackgroundTrafficGenerator is used to generate inter-cell interference by serving 10 background UEs [35]. The tower has a transmission power of 20 dBm at 12.5 kb/s rate, and a target block error ratio (BLER) of 0.01 with a BLER shift of 5 [37]. See Table 1 for simulation parameters of the base station, UEs, and background antenna tower.

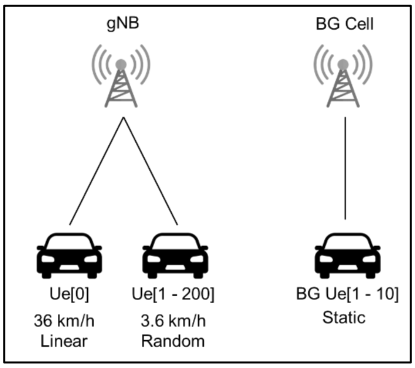


Fig. 2. Traffic model for simulation based on urban minor scenario.

The simulation of network traffic through the integration of OMNET, Simu5G and SUMO aims to replicate the realistic environment of C-V2X in 5G networks. The urban micro (Umi) model based on 3GPP technical record was implemented to further enhance the practicality of signal attenuation. Background Traffic Generator was employed to produce background noises similar to a condition in a moderate urban environment. Dynamic connectivity was established between base station and a variable number of UEs ranging from 0 to 200, effectively simulating diverse levels of network congestion. In essence, this study strives to provide an accurate representation of a network dynamics within urban environments for C-V2X-enabled 5G networks.

Table 1. Main network parameters for 5G Network used for simulation [9].

Parameter	Value
gNodeB	
Carrier Frequency	2 GHz
Cell Radius	2000 m
System Bandwidth	20 MHz
gNodeB Tx Power	40 dBm
gNodeB Antenna Gain	8 dB
gNodeB Antenna Height	25 m
UEs	
UE Tx Power	20 dBm (100 mW)
Number of UEs	0 to 200 (increment by 20)
Mobility Model	UE[0] - 10 m per second (36 km per hour) UE[1] - UE[200] - 1 m per second (3.6 km per hour)

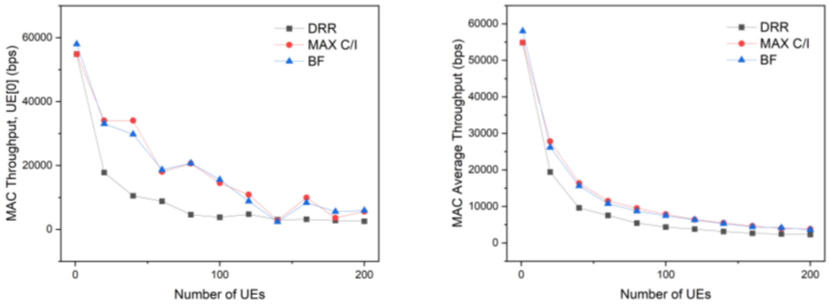
Mobility Type	Linear
Schedulers	DRR, MAX C/I and BF
UE Antenna Height	1.5 m
Background Cell	
Carrier Frequency	2 GHz
Cell Radius	2000 m
System Bandwidth	20 MHz
Background Tx Power	20 dBm
Target BLER	0.01
BLER Shift	5

4. Performance Evaluation

4.1. Average MAC throughput

MAC throughput is the measure of data transmitted successfully from the medium access control (MAC) layer. It represents the actual throughput submitted by UEs. Average MAC throughput is the average throughput value transmitted by the MAC layer for all loads over the number of loads present.

Figure 3 illustrates the average cell throughput for DRR, MAX C/I and BF algorithm based on 20 MHz system bandwidth across different number of loads (L). Each scheduling algorithm displays a similar pattern such that the value keeps decreasing over increasing number of loads which is represented by the number of UEs. MAX C/I and BF algorithms show similar throughput across increasing loads shown by UE0. Observation on the average throughput gives an indication that it does happen to the other available UEs as well. However, numerical comparison of both schemes shows that MAX C/I is superior in terms of MAC average throughput performance by up to 8.87% higher than BF scheme. In contrast, DRR scheme displays the worst performance in throughput. DRR tries to act fairly towards all available users. Nodes with poor quality which have a higher chance of packet drop and packet loss will also be served as long as it is within the radar. Consequently, the amount of successful transmission is also reduced. The effect is more prominent as the number of load increases. The throughput of MAX C/I reached up to 80% higher as compared to DRR scheme. However, as the number reaches 140 nodes, the throughput converges towards a similar range which indicates the saturation of performance in the network. This relates to the limit of the bandwidth available which must be shared among the clients. As the number of clients increases, the overall throughput will eventually reach a value which is the maximum throughput allowed by the network due to its limited bandwidth.



(a) (b)

Fig. 3. Average MAC throughput for DRR, MAX C/I and BF algorithm on (a) UE0 and (b) all UEs.

Simulation results were compared to Modified Largest Weighted Delay First (MLWDF) and Exponential Proportional Fair (EXP PF) by Biernacki and Tutschku [38] as shown in Fig. 4. The work by [38] reveals superior performance under condition of lower user count, likely attributed to the utilization of a video bit-rate of 242 kbps, almost double that employed in current study. However, as the number of users escalate, the average throughput exhibited a sharp decline, indicating its vulnerability towards high traffic. Beyond approximately 50 users, the trend observed in MLWDF and EXP PF are very similar to the current study while showing lower value as compared to ours.

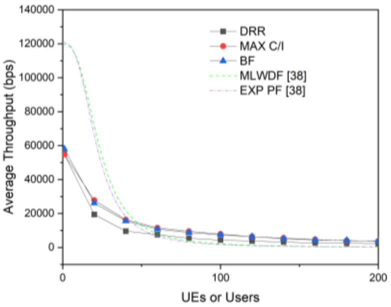
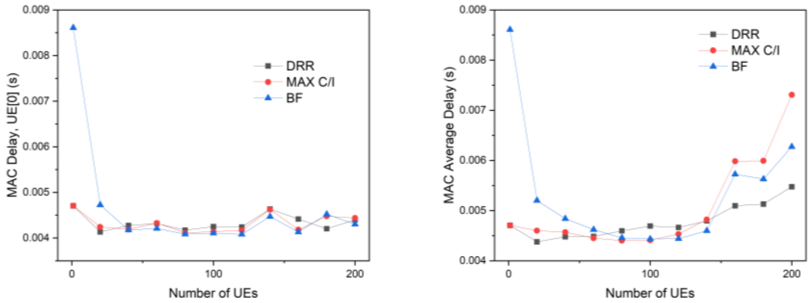


Fig. 4. Average throughput comparison.

4.2. Average MAC delay

MAC delay represents the time interval as the time reaches the MAC layer until it is transmitted towards the receiving node. Average MAC delay in this scenario measures the average time lag occurring from UEs to the base station. For a better QoS performance, lesser MAC delay is favoured.

Graph in Fig. 5 denotes the performance of the three scheduling algorithms in terms of MAC delay. Highest delay shown by BF algorithm at a small number of loads. To fit a scheduled packet to the available resources, require the base station to scan through the entire list of nodes available in the area. This process takes a considerable amount of time for the system, hence significantly increasing the total delay. The lowest and most stagnant performance shown by DRR scheme with up to 25% and 12.7% lower delay time compared to MAX C/I and BF respectively. This is in contrast to what numerically discussed by Boyer et al. [16] and Tabatabaee and Boudec [17] which emphasized on the latency issue in the scheme. This is due to the type of data CBR which is transmitted periodically at fixed size. DRR divides the transmission time for each queue into fixed-size timeslots, hence each scheduling task receives the same amount of time for data transmission. The fixed time allocation causes each task to be treated equally, hence the time delay experience by each user is also similar. Further observation shows that MAX C/I depicts the largest average delay value particularly at high number of UEs. At high number of loads, traffic competing for the same resources increases as well. Consequently, the chance for traffic collision also increases, resulting in higher delays when the amount of traffic is at its peak. This is in contrast to DRR scheme which is based on round-robin manner, which reduces the number of collisions. Similarly, BF algorithm reduces the probability of collisions by assigning each user a different set of resources.



(a) **(b)**

Fig. 5. Average MAC delay for DRR, MAX C/I and BF algorithms on (a) UE0 and (b) All UEs.

Figure 6 illustrates a comparison of average delay with reference to [38]. At lower load level, our study and that of [38] exhibit a similar starting point. However, as the load increases, [38] demonstrates a rapid surge in its average delay value. In contrast to our scheduling algorithm, MLWDF and EXP PF exhibit inferior performance. Notably, MLWDF and EXP PF are known for their sensitivity to variation in user speed and channel quality [39], whereas our current study demonstrates a more stable performance.

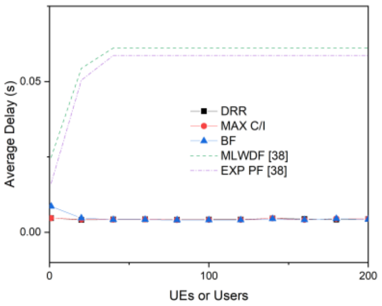
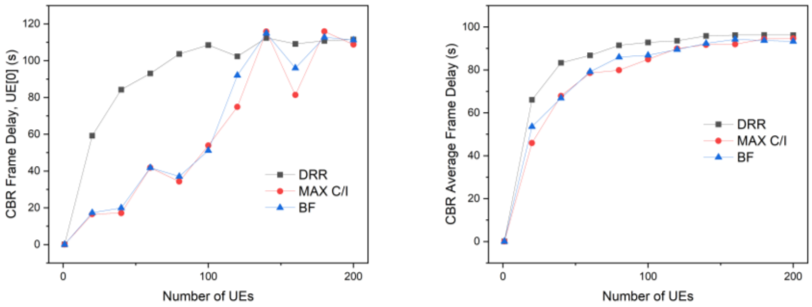


Fig. 6. Average delay comparison.

4.3. CBR frame delay

CBR frame delay is the amount of time it takes for a data frame to travel from one point in a network to another. This delay is a result of the limited bandwidth of the network and the data’s need to compete with other data for network resources. CBR frame delay can have a significant impact on network performance, as it can cause delays in the transmission of data.

Figure 7 depicts the CBR frame delay for the three scheduling algorithms. Among them, DRR exhibits the highest CBR frame delay. Since resources are fairly distributed, the scheduler will also consider UEs from far distances and with high interference [15]. Consequently, the time taken to upload resources to the base station will increase considerably. Even though DRR shows lower average MAC delay as in Fig. 5, the frame delay shows contra result partly due to unsuccessful transmission and excessive delay from nodes of lower quality. Due to the fair policy of DRR, UEs who are near to the base station and subjected to lesser signal interference will experience significant delays while waiting for the completion of jobs scheduled for previous UEs.



(a) **(b)**

Fig. 7. CBR frame delay for DRR, MAX C/I and BF algorithms on (a) UE0 and (b) All UEs.

The effect is more obvious on UE0. The frame delay of UE0 reaches a maximum frame delay of 112.75 s surpassing the average CBR frame delay of 94.21 s. Starting at a distance from the base station, UE0 encounters higher delay from transmitter to receiver compared to other UEs near the base station. Although delay are expected to reduce as UE0 approaches the base station, the time-slot limitation imposed by the scheduling scheme which limits the occupancy on a given time-slot restricts its potential to transmit data with low delay. Additionally, to adhere to its policy, DRR has to serve UEs at farther area as well, and UE0 still needs to wait for its appointed time to have its service. Consequently, UE0 experiences a significant increase in frame delay, and even as UE0 approaches the base station, the QoS improvement will remains marginal at best.

This is contrary to MAX C/I and BF schemes which acknowledge higher quality nodes and select suitable match up of the resources respectively. Compared to DRR and BF, MAX C/I performed up to 30% better in CBR frame delay particularly at low loads. MAX C/I shows better performance in terms of CBR frame delay due to its nature which avoided channels with high Signal-to-Interference-plus-Noise Ratio (SINR) value and high chance of transmission. There will be less tendency for the data packet to be disrupted, hence the transmission will require lesser transmission time.

5. Conclusions

This study evaluates the performance of DRR, MAX C/I, and BF scheduling algorithms in a 5G network simulation. MAX C/I showed the highest throughput (up to 80%) and the lowest CBR frame delay (with up to 25% lesser delay time), while DRR showed the lowest MAC delay (about 30% lesser) due to its fairness nature.

Based on the findings, MAX C/I is the most optimal scheduling algorithm for high mobility and high loads. The results could serve as a benchmark for further studies on scheduling algorithms in C-V2X. Additionally, the MAX C/I and DRR algorithms could potentially be hybridized to form a hybrid MAX C/I-DRR algorithm which may generate better QoS performance than its singular form.

Through fairness approach, DRR could ensure each node is considered in the network traffic which will consequently reduce the effect of CBR delay. Integration with MAX C/I algorithm would improve the transmission process by eliminating the traffic with critical delay or throughput issue.

In practical term, the potential of hybridization of MAX C/I and DRR algorithms, holds promise for real-world 5G C-V2X networks by addressing both high mobility and traffic fairness. Implementing such hybrid may not only enhance QoS but also mitigate the impact of delay, thereby contributing to the efficient and equitable management of network traffic in dynamic and diverse environments.

A similar study could also be extended to a heterogenous network encompassing diverse applications and services. In this context, the impact of scheduling algorithm on the performance of CBR traffic would be particularly noteworthy, as it could serve as a baseline for addressing the ever-changing nature inherent in heterogenous network. The application of CBR traffic and the proposed hybrid approach would reflect a step towards bridging the simulation results and real-life scenarios, offering a valuable strategy for scheduling optimization in the context of C-V2X and heterogenous networks.

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