# A Dual-Objective Bandit-Based Opportunistic Band Selection Strategy for Hybrid-Band V2X Metaverse Content Update

Sherief Hashima*[1], Zubair Md Fadlullah†[2], Mostafa M. Fouda‡§[3], Kohei Hatano*¶[4], Eiji Takimoto¶[5], and Mohsen Guizani‖[6]
*Computational Learning Theory Team, RIKEN-AIP, Fukuoka, Japan.
†Department of Computer Science, Western University, London, ON, Canada.
‡Department of Electrical and Computer Engineering, Idaho State University, Pocatello, ID, USA.
§Center for Advanced Energy Studies (CAES), Idaho Falls, ID, USA.
¶Department of Informatics, Kyushu University, Fukuoka, Japan.
‖Machine Learning Department, Mohamed Bin Zayed University of Artificial Intelligence (MBZUAI), UAE.
Emails: {[1]Sherief.hashima, [4]kohei.hatano}@riken.jp, {[2]zfadlullah, [3]mfouda, [6]mguizani}@ieee.org, [5]eiji@inf.kyushu-u.ac.jp.

***Abstract*—As vehicular communication networks embrace metaverse beyond 5G/6G systems, the rich content update via the least interfered subchannel of the optimal frequency band in a hybrid band vehicle to everything (V2X) setting emerges as a challenging optimization problem. We model this problem as a tradeoff between multi-band VR/AR devices attempting to perform metaverse scenes and environmental updates to metaverse roadside units (MRSUs) while minimizing energy consumption. Due to the computational hardness of this optimization, we formulate an opportunistic band selection problem using a multi-armed bandit (MAB) that provides a good quality solution in real-time without computationally burdening the already stretched augmented/virtual reality (AR/VR) units acting as transmitting nodes. The opportunistic use of scheduling rich content updates at traffic signals and stand-still scenarios maps well with the formulated bandit problem. We propose a Dual-Objective Minimax Optimal Stochastic Strategy (DOMOSS) as a natural solution to this problem. Through extensive computer-based simulations, we demonstrate the effectiveness of our proposal in contrast to baselines and comparable solutions. We also verify the quality of our solution and the convergence of the proposed strategy.**

***Index Terms*—Metaverse, Content Update, Radio Frequency (RF), Visible Light Communication (VLC), Hybrid Band Allocation (HBA), MAB, and MOSS.**

## I. Introduction

As vehicle-to-vehicle/infrastructure (V2X) communications meet metaverse, optimizing the scene and environment updates requiring a large capacity while minimizing the residual energy of metaverse-enabled wireless devices on-board vehicles emerges as an interesting research problem [1], [2]. While beyond 5G (B5G) network technologies exploiting both legacy RF (radio frequency) and high spectrum bands such as mmWave (millimeter wave) and visual light communications (VLC), they are still likely to be challenged by the tremendous bandwidth requirements of metaverse services and applications. Therefore, it is crucial to efficiently perform the V2X metaverse content updates by AR/VR devices to make the best of the available high-frequency spectrum while minimizing the energy consumption of these wireless nodes onboard the vehicles as depicted in Fig. 1. In this vein, we formulate a hybrid band allocation (HBA) problem with regard to our considered V2X-assisted metaverse system setting to opportunistically make use of the best possible frequency band and its sub-channel [3], [4]. Our optimization problem aims to maximize the data rate while opportunistically switching to the best metaverse roadside unit (MRSU) band/sub-channel while waiting/stopping at traffic signals/parking within a reasonably limited time. Since solving such a problem requires complete system information along with high computational resources, we are motivated to address this problem in a distributed setting by playing a multi-armed bandit (MAB) game between the metaverse-enabled transmitting device and the receiving MRSU in the presence of variable-sized blockers which dramatically and adversely impact the propagation characteristics of high-frequency, high-capacity frequency bands and their corresponding sub-channels. Motivated by the above, the contributions in this work are summarized as follows:

- We formulate the band selection problem using MABs, where the AR/VR is the bandit player attempting to upload metaverse content to MRSU via available bands (bandit arms). The bandit reward is the upload rate content and the cost is the energy consumption upon the decided arm.
- We propose a dual-objective bandit strategy to solve this problem, referred to as dual-objective minimax optimal stochastic strategy (DOMOSS). Then, we incorporate residual energy-aware (REA) features for performance comparison.
- DOMOSS is compared with classical bandits such as upper confidence bound (UCB), Thompson sampling (TS), Minimax Optimal Stochastic Strategy (MOSS) schemes, and HBA benchmarks.
- Simulation results indicate the near-optimal band selection performance of our proposal compared to other methods in terms of upload content rate, energy-efficiency, and convergence performance.

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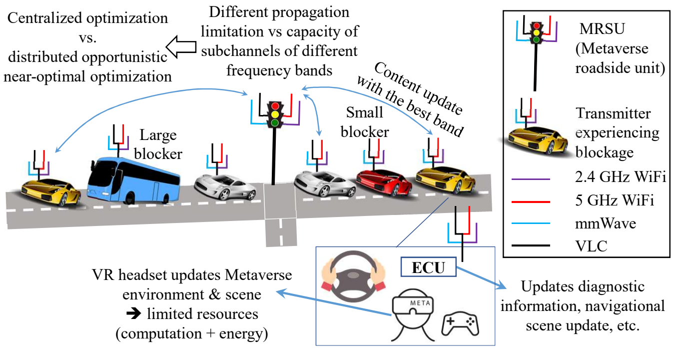


Fig. 1: Considered hybrid-band V2X metaverse content update scenario.

The remainder of this paper is structured as follows. Section II summarizes the related work of HBA systems. Section III details the hybrid-band V2X metaverse content update scenario. Section IV overviews the band optimization problem formulation. Section V discusses the proposed DOMOSS scheme after highlighting REA-UCB, REA-TS, and REA-MOSS methods. Section VI presents the performance evaluation of our proposal compared with other methodologies. Finally, Section VII highlights the concluding remarks.

## II. Related Work

Since multi-band communication in V2X-enabled metaverse is a relatively new concept, we present the relevant research work available in the literature that addresses hybrid-band/channel selection learning techniques in wireless systems [5]–[9]. In Device-to-Device (D2D)-enabled communication, the copresence of WiFi and VLC bands were considered in [10]. A hybrid neural network-driven heuristic decision-making was conceptualized to select the best possible band. However, this approach requires extensive dataset collection, preprocessing, and training. Furthermore, this approach could not be enhanced beyond indoor settings. On the other hand, a convolutional neural network (CNN) was employed to intelligently predict the best signal-to-interfernce-noise-ratio (SINR) band from a diverse frequency-bands pool in [11]. Despite its potential, that methodology suffered from the limitation of training datasets and simplistic VLC channel model assumptions. In [12]–[15] coauthors of our work addressed the HBA problem by employing distributed learning via MAB, and introduced enhanced UCB strategies. However, according to [16], there is significant room for improvement beyond considering only a single objective in the MAB formulation.

## III. System Model

In this section, we present our considered system model. As depicted in Fig. 1, both MRSU and on-vehicle AR/VR nodes, and Electronic Control Units (ECUs) are assumed to be equipped with hybrid-band radios, i.e., legacy RF, mmWave, and VLC bands with the presence of possible vehicular blockers with varying sizes that obstruct the line-of-sight between the MRSU and AR/VR/ECU nodes. In this setting, the multi-band AR/VR device is responsible for delivering the metaverse update to the MRSU via possible frequency bands, i.e., legacy RF (2.4/5.25GHz WiFi), mmWave (38GHz (also referred to as WiGig), or VLC (400-800THz). Each band is split into a number of sub-channels to upload the metaverse scene or environment-related update bits [3].

As for the legacy RF bands, we consider 2.4GHz and 5.25GHz WiFi channel models based on log-normal shadowing comprising zero means; standard deviations of 2.15dB and 6dB, reference path losses of 41.8 and 47.2; and path loss exponents of 2 and 2.32, respectively [13]. Also, the multi-band MRSU is assumed to comprise a two-dimensional directional antenna model Next, we describe the mmWave channel in the 38GHz spectrum [3], [15]. The received mmWave power at the ECU node depends on the antenna beamforming gain and the effect of the vehicular blocker [3]. For the mmWave model, we consider a zero-mean log-normal distributed path loss while allowing the RSU-ECU beamforming. Note that the system model mainly is interested in the Line-of-Sight (LoS) link between the RSU and ECU nodes owing to an approximately 20dB gain in contrast with that achieved by the non-LoS mmWave link [12]. On the other hand, for the VLC system, we consider the Light-Emitting Diode (LED) transmitters at the RSU node based on the Lamebrtian framework [3].We utilize the vehicular blocker model for the legacy RF, mmWave, and VLC bands via an empirical setup in an urban setting, obtained from the work in [17]. In our scenario, we consider no vehicular blocker, small vehicular blockers (comprising dimensions of 5.07x1.69x1.93m$^3$), as well as large vehicular blockers (with the dimensions of 7.01x2.04x2.63m$^3$). Based on the reported findings in [17], we then derive a vehicular blocker loss function with regard to the frequency and blocker types as a linear regression as follows,

$$Blockingloss[dB] = \beta_b + \alpha_b \log(1 + \frac{f_{c,n}}{1\text{GHz}}), \tag{1}$$

where $\alpha_b$ is the gradient, $\beta_b$ denotes the line intercept, and $b$ represents the size of the vehicular blocker.

Based on the co-presence of these multi-band radios at the MRSU, we assume opportunistic connectivity between the serving MRSU and each AR/VR node that attempts to perform a metaverse update of size $l$. Consider that there are $R$ vehicles with one AR/VR node on-board and $E$ MRSU in a service area. Each MRSU $e$ ($\in E$) can connect to a given AR/VR unit $r$ ($\in R$) at time $t$ over the best sub-channel of any of the three frequency bands, models of which were described earlier. Here, each AR/VR unit $r$ is assumed to have its own metaverse content update payloads. Also, we consider each transmitting and receiving nodes pair $e$ and $r$ such that $e$ can resume the remaining metaverse content update payload $(l - l')$ from $r$ and upload them with the remote metaverse server over high-speed backhaul links. Based on the system model foundations, we are now ready to formulate the research problem in the following section.

## IV. Problem Formulation

### A. Optimization Problem with Complete System Information

Herein, we first formulate the band selection problem based on the pre-described system model by considering AR/VR device $r$ and MRSU $e$. This can be considered as a linear programming problem as follows,

$$\arg\max_{i,j} \sum_{i=1}^{m}\sum_{j=1}^{n_i} \frac{BW_{ij}T_D\Gamma_{ij}(t)}{U(t)*T_{h,ij}+T_D} d_{ij} \tag{2a}$$

$w.r.t.$

$$d_{ij} \in \{0,1\}, \tag{2b}$$

$$\arg\min_{i,j} C_{VR,ij}(t) = \frac{P_{\mathrm{VR}}^{N} L_D}{BW_{ij}\Gamma_{ij}(t)}, \tag{2c}$$

$$\sum_{i=1}^{m}\sum_{j=1}^{n_i} d_{ij} = 1, \tag{2d}$$

$$\sum_{i=1}^{m} n_i \geq N, \tag{2e}$$

$$T_D \leq t+\epsilon \mid \epsilon > 0, \tag{2f}$$

$$L_D + l' <= l, \tag{2g}$$

$$E_i \geq \Xi_{th}, \tag{2h}$$

where $m$ denotes the number of frequency bands supported by the transmitting AR/VR device $r$ and the receiving MRSU $e$ while $n_i$ indicates the available sub-channels in the corresponding band $i$. Let $N$ denote the maximum number of available channels across all the considered frequency bands. The objective function describes the selection of the band $i$ and sub-channel $j$ at MRSU $r$ such that the term inside the two summation notations yield the maximum data rate at time $t$. $d_{i,j}$ refers to a decision variable for the band and sub-channel selection that can take only a binary value between 0 and 1 while the summation of all the decision variable (i.e., overall $i$ and $j$ values) is considered to be 1 as shown by the first two constraints. $C_{VR,ij}(t)$ refers to a cost function where $P_{VR}^{N}$ denotes the transmit power of the AR/VR device upon the utilized band $N$. $BW_{ij}$ denotes the bandwidth of channel $j$ that belongs to band $i$. The third constraint describes the fact that all channels over the available bands must be equal to or more than available sub-channels $N$. The next constraint articulates the data download time, $T_D$, which is considered to be not more than the current time $t$ plus $\epsilon$ where the latter parameter acts as a limited waiting time of AR/VR device $r$ at a traffic stoppage or parking for opportunistic connectivity with the best possible band/sub-channel at MRSU $e$. $L_D$ refers to the segment of the metaverse content payload to be uploaded by the device $r$ to serving MRSU $e$ such that the sum of $L_D$ and $l'$ (i.e., previously uploaded segments of the metaverse content updated to other MRSUs) are equal to or less than the size of the entire metaverse content update. $E_i$ refers to the residual energy of AR/VR device $i$ which must remain at least the same as the threshold energy level $\Xi_{th}$ so that other operations of the AR/VR device are not disrupted. The overhead time between $r$ and $e$ is denoted by $T_{h,ij}$, which is subject to the adopted band/sub-channel. $\Gamma_{ij}(t)$ refers to the spectral efficiency (bits per second per hertz) and is equal to $\log_2(1+\frac{P_{\mathrm{MRSU}}^{ij}(t)}{N_0+I(t)})$, where $P_{\mathrm{MRSU}}^{ij}(t)$ indicates the received power at MRSU $e$ at time $t$ using band $i$. $N_0$ and $I$ represent the noise and interference power, respectively.

### *B. Reformulation of the Original Problem into A Multi-Armed Bandit (MAB) Game*

Since the constrained maximization problem (2a) requires the AR/VR device $r$ to obtain the complete information of the channel state information of all the available bands/sub-channels of all the surrounding MRSUs, the solution to the problem in real time is challenging. Also, the problem becomes computationally heavy on the AR/VR devices when the number of MRSUs is significantly high leading to high values of $m$ and $n$. As such, we transform the original optimization problem into a sequential decision-making problem, referred to as a stochastic multi-armed bandit by considering the blocking phenomena of the vehicular blockers where $r$ is the MAB player and it plays its games to maximize a reward (i.e., the data rate for disseminating the metaverse content update payload to the MRSU) over a number of rounds while minimizing a penalty in terms of the communication cost for selecting the band/sub-channel. At each round $t$, which is bounded by a time horizon, the transmitting device $r$ chooses an action among a finite set of options, referred to as arms, which describe the $m$ possible bands and $n$ sub-channels. By selecting an arm (i.e., a band and its sub-channel), $r$ draw an arbitrary reward $\psi_{i,j}(t)$ from an unknown distribution that does not change with time. At the end of each round, $r$ updates the estimate of the mean reward of arm $i, j$ as follows.

$$\psi_{i,j_t} = \frac{1}{T_{i,j}(t-1)} \sum_{p=1}^{t-1} \psi_{i,j}(p)\mathcal{I}_{I_p=i,j}, \tag{3}$$

where $T_{i,j}(t-1)$ refers to the number of times arm $i, j$ was played prior to the commencement of round $t$. Next, $\mathcal{I}_{I_p=i,j}$ is an indicator function that equals 0 if the arm i,j is not played during round $t$ or equals 1, otherwise. In this manner, after playing for a finite number of rounds, the observed mean will approach the mean reward of the arm. Thus, the reformulated problem via the stochastic MAB game needs to be solved with a strategy that can allow updating these estimates at the AR/VR device after each round to select a good arm (i.e., a high SINR band/sub-channel) in the following round. In the following section, we design the solution methodology for the re-formulated problem. Therefore, the optimal dual objective arm is the lowest cost one from highly rewarded arms that attains:

$$\{i,j\}^* = \arg\max_{i,j}\ (1-\epsilon)\mu_{i,j}\ \ s.t.\ \ \arg\min_{i,j} C_{i,j}. \tag{4}$$

$$C_{\mathrm{VR},N_{MAB}^*}(t) = \frac{P_{\mathrm{VR}}^{N} L_D}{BW_{N_{MAB}^*}\Gamma_{N_{MAB}^*}(t)}, \tag{5}$$

where $MAB$ is applied MAB technique (e.g., DOMOSS, UCB, and TS), $C_{\mathrm{VR},N_{MAB}^*}(t)$ is the VR battery/energy consumption to upload data content of $D_L$ bits with a speed of $BW_{N_{MAB}^*}\Gamma_{N_{MAB}^*}(t)$ bps. In the following section, we discuss the methodology for solving this transformed problem in a distributed manner with high-quality solutions close to the optimal solution to the original problem.

## V. Proposed Baseline Methods and Envisioned Near-Optimal Solution

Herein, we present a systematic methodology to solve the aforementioned MAB problem using UCB, TS, and MOSS [18], respectively. We incorporate residual energy awareness (REA) with regard to the transmitting AR/VR device into these three strategies, referred to as REA-UCB, REA-TS, and REA-MOSS, respectively. Then, wen design a dual-objective MOSS algorithm to solve the MAB game.

### A. Designed baseline 1: REA-UCB Method

REA-UCB is a modified UCB approach where the energy-related term is subtracted from the exploration term of the basic UCB equation as follows [13], [14],

$$m^*_{REA-UCB}(t) = arg\max_i\{\bar{\psi}_i(t)+\sqrt{\frac{2log\ T_U}{\rho_{i,t}}}-\frac{x_i}{\Xi_{\mathrm{VR},i}(t)}\}, \quad (6)$$

where $\bar{\psi}_i(t)$ denotes the upload rate from AR/VR device to MRSU and $\rho_{i,t}$ reflects how many times arm $i$ was played within round/time $t$. The term $\frac{x_i}{\Xi_{VR,i}(t)}$ accounts for the VR/AR energy expense due to transmitting to MRSU over the chosen band/sub-channel (i.e., the arm) $i$ at time $t$.

### B. Designed baseline 2: REA-TS Method

REA-TS is designed by modifying the basic Thompson Sampling (TS) strategy by taking into account the VR/AR energy consumption in its exploration phase. In this vein, the term $\frac{x_i}{\Xi_{VR,i}(t)}$ is included in the basic TS formula expressed as [13], [15],

$$m^*_{REA-TS}(t) = arg\max_i\{\theta_i(t)-\frac{x_i}{\Xi_{VR,i}(t)}\}, \theta_i(t)\sim\mathcal{N}(\bar{\psi}_i(t),\frac{1}{\rho_{i,t}+1}), \quad (7)$$

where $\mathcal{N}(\bar{\psi}_i(t),\frac{1}{\rho_{i,t}+1})$ denotes a normal distribution with $\bar{\psi}_i(t)$ mean and $\frac{1}{\rho_{i,t}+1}$ variance.

### C. Designed baseline 3: REA-MOSS Method

Again we incorporate residual energy-awareness (REA) term into conventional MOSS [19]. Our customization is as follows,

$$m^*_{REA-MOSS}(t) = arg\max_i\{\bar{\psi}_i(t)+\sqrt{\frac{max\left(log\left(\frac{t}{\rho_i(t)}\right),0\right)}{\rho_i(t)}}-\frac{x_i}{\Xi_{\mathrm{VR},i}(t)}\}, \quad (8)$$

### D. Envisioned Dual-Objective MOSS (DOMOSS) Algorithm

From hereon, we describe our envisioned DOMOSS algorithm by jointly taking into consideration two objectives, namely maximizing data rate and minimizing energy consumption of AR/VR device for metaverse content update to the MRSU. For this purpose, we exploit the strengths of the classical MOSS algorithm [19] and apply it to the Explore Then Commit (ETC) algorithm [16] instead of UCB. The idea is to subsidize from the maximum rewards to pull the cheapest arm (lowest cost). This is more effective than deducting the cost in the exploration part as in the baseline methods, i.e., REA-UCB, REA-TS, and REA-MOSS. Such subtraction is not suitable in a lot of realistic application scenarios, particularly if the payoffs and costs are not the same category/type [16]. Hence, in our envisioned DOMOSS algorithm, first, the UCB and lower confidence bound (LCB) for the bandit's arms are determined using MOSS policy. Then, a feasibility set containing the arms of payoffs exceeding the maximum LCB value of entire arms is established. Finally, from the constructed feasibility set, DOMOSS elects the lowest-cost arm. Algorithm 1 outlines the main steps of our proposed DOMOSS algorithm. Its input is all existing bands $\mathcal{N}$ and $\epsilon$ tuning parameter. The output of the algorithm is the decided channel to connect with $N^*_{MAB}(t)$. At $t$=0, $\rho_{n,t}$ the counter of each band/channel $N = N_{ch}$ is decided and their attained upload data rates, $\bar{\Psi}_{N_{i_t}}$, are initiated by 0. The algorithm comprises two key stages, namely the pure exploration and selection stages. In pure exploration phase, the AR/VR attempts all bands/channels, i.e., $i^*_t = t\ mod\ J$, to notice their update rates $\Psi_{I_{i^*_t}}$. Also, $\rho_{k_{i^*_t}}$ are updated, and the average rates of the AR/VR$\bar{\Psi}_{k_{i^*_t}}$ are estimated. This is done for an investigation period of $\tau J$, where $\tau = \left(\frac{T_U}{J}\right)^{2/3}$ ( [16]). On the other hand, during the selection stage, at trial $t \in [\tau J+1, T_H]$, the UCB and LCB arms are calculated as follows:

**Algorithm 1:** Proposed DOMOSS algorithm.

```
Result: Best band N at t ∈ [T_U].
Input: t = 0, ψ̄_N(t) = 0, ρ_{n,t} = 0,
       Ξ_th, Ξ_{VR,N}(t = 1), 1 ≤ N ≤ J, 1 ≤ t ≤ T_U.
Pure Exploration Stage:
for t ∈ [τJ] do
    I_t = t mod J;
    play arm I_t and observe reward ψ_{I_t};
    ρ_i(t+1) = ρ_i(t) + 1 {I_t = i} ∀ i ∈ [J]
    update
     Ξ_{VR,i}(t) = Ξ_{VR,i}(t) − C_{VR,i}(t), {I_t = i} ∀ i ∈ [J]
end
UCB Stage:
for t ∈ [τJ + 1 : T_U] do
    μ̂_i(t) ← ψ_i(t)/ρ_i(t), β_i(t) ← sqrt( max(log(t/ρ_i(t)),0) / ρ_i(t) ),
    Update μ_i^{UCB}(t) & μ_i^{LCB}(t) using Eqs.9,10
    m_t = arg max_i μ_i^{LCB}(t);
    F(t) = {i : μ_i^{UCB}(t) − (1 − ε)μ_{m_t}^{LCB}(t) ≥ 0 ;
    I_t = arg min_{i∈F(t)} C_i;
    Play arm I_t then obtain
     reward/achievable data rate ψ_{I_t}(t);
     ρ_i(t+1) = ρ_i(t) + 1 {I_t = i} ∀ i ∈ [J]
    update Ξ_{VR,I_t}(t) = Ξ_{VR,I_t}(t) − C_{VR,I_t}(t)
end
```

$$\mu_i^{UCB}(t) \longleftarrow \min\hat{\mu}_i(t)+\beta_i(t), \quad (9)$$

$$\mu_i^{LCB}(t) \longleftarrow \max\hat{\mu}_i(t)-\beta_i(t). \quad (10)$$

Now, the feasible set of chosen arms with $F(t) = \{i : \mu_i^{UCB}(t)-(1-\varepsilon)\mu_{m_t}^{LCB}(t) \geq 0$ are established. Out of $F(t)$, the arm attributed with the minimum energy cost $C_{N_{i_t}}$ is decided to upload the metaverse update payload as follows:

$$I_t = \arg\min_{i\in F(t)} C_i. \quad (11)$$

Lastly, DMOSS parameters are updated, and residual energy levels of AR/VR sets are enumerated upon the decided band/sub-channel. The proceeding trial repeats the whole process if the AR/VR device needs to upload new metaverse content update payloads to the MRSU.

## VI. Performance Evaluation

Herein, we conduct numerical simulations and evaluate the performance of our proposed DOMOSS algorithm in contrast with the baseline methods, i.e., REA-UCB, REA-TS, REA-MOSS, and benchmark (e.g., optimum, exhaustive, and random) HBA algorithms. The optimal HBA solution is found via the simultaneous election of the best channel with the cheapest cost. The exhaustive HBA first attempts all existing bands then chooses the supreme one after significant overhead. On the other hand, the random HBA method pulls a random band/channel without any information by giving priority to the decision time. Table I lists the considered simulation parameters including vehicular blocker details.

Fig. 2 presents the performance of spectral efficiency in terms of the achieved data rate of our proposal at $\varepsilon = 0.5$ with regard to the baseline and benchmark methods. In other words, this performance measure signifies the selection of the arms that are attributed with larger than or equal to half of the maximum payoff. The results are presented over increasing separation distances by considering three vehicular blocker scenarios, i.e., no blockage (line-of-sight between AR/VR device and MRSU), small vehicular blocker, and large vehicular blocker, respectively. The obtained reward or data rate was reported to be inversely related to the vehicular blockage type as demonstrated in the plots of Figs. 2(a), 2(b), and 2(c), respectively. From the results, we notice that with the increasing distances, the metaverse content update rate drops for all the compared methods owing to the path loss effect for the selection of the respective band/sub-channel. Additionally, with the introduction of blockers with larger blockers, the drop in the data rate appears even more significant. Interestingly, the performance of our proposed DOMOSS algorithm is near-optimal, i.e., 99% with regard to the optimal benchmark solution, for all the considered separation distances between the transmitting AR/VR device in the vehicle and the destination MRSU.

Next, we evaluate the energy-efficiency of our proposal compared with other methods in Fig. 3. DOMOSS works at $\varepsilon = 0.7$ which means 70% of maximum content upload rates are grouped to decide the cheapest arm. Our proposed DOMOSS algorithm outperformed other schemes due to proper channel allocation strategy that minimizes the AR/VR device's consumed energy. With growing separation distances between the transmitter and the receiving MRSU, the energy expenditure of all the methods was found to increase as well. Interestingly, the REA-UCB, REA-TS, REA-MOSS, and DOMOSS exhibit significantly low energy consumption in the AR/VR device. In particular, DOMOSS achieves the highest energy-efficiency in terms of the residual energy of the transmitting AR/VR device. On the other hand, the brute-force HBA method results in the highest energy consumption. This is because of exhaustively searching all possible frequency bands and their respective sub-channels without paying any attention to the residual energy constraint of the transmitter.

TABLE I: Simulation parameters.

| Simulation parameter | Value |
|---|---|
| $N$ | 4, i.e. (38,5.25,2.4,$10^5$) GHz |
| $BW_1, f_{c,1}, P^1_{Tx}, T_{h,1}$ | 40MHz, 38GHz, 20mW, 0.28msec |
| $BW_2, f_{c,2}, P^2_{Tx}, T_{h,2}$ | 40MHz, 5.25GHz, 20mW, 3.6$\mu$sec |
| $BW_3, f_{c,3}, P^3_{Tx}, T_{h,3}$ | 20MHz, 2.4GHz, 20mW, 3.6$\mu$sec |
| $BW_4, f_{c,4}, P^4_{Tx}, T_{h,4}$ | 20 MHz, $10^5$GHz, 20mW, 3.6$\mu$sec |
| $\Xi_{VR,n}(t=1)$, $\Xi_{th}$ | uniform [0.01 $\rightarrow$ 1], 1% |
| $x_0$, $x$ | 5 m, [10 - 100] m |
| $T_U$, $D_L$, $T_D$ | 150, 1TB, 0.1 S |
| $\alpha_{small}, \beta_{small}$ | 2.6, 3 [17] |
| $\alpha_{large}, \beta_{large}$ | 3.6, 7.7 [17] |

Now, we evaluate the convergence of our proposal as depicted in the plot of Fig. 4 at $x = 20m$. The convergence trends of the comparable methods are also shown in the plot. As evident from these results, our proposed DOMOSS algorithm achieves 99.8% of the optimal performance during all the trials until the time horizon of 400 trials. Thus, the viability of our proposal is verified in terms of metaverse content updates while substantially improving the AR/VR device's energy budget.

Regarding the computational complexity of our proposed DOMOSS algorithm, its space complexity is $O(N)$ while the time complexity is $O(NT_U)$ based on the analysis provided in [18] where $N$ refers to the number of arms and $T_U$ denotes the time horizon.

## VII. Conclusion

The introduction of vehicular communication networks beyond 5G/6G systems into the metaverse presents a challenge in terms of optimally updating rich content via an interference-free subchannel in a hybrid-band V2X setting. To address this, we model this optimization problem as a tradeoff between multi-band AR/VR devices performing metaverse scenes and environmental updates to MRSUs while minimizing energy consumption of the transmitting AR/VR devices. Given the computational hardness of this optimization requiring detailed channel state information of all possible bands/sub-channel links for the nearby MRSUs, we formulate an opportunistic band selection problem based on MAB game. This solution effectively balances the competitive demands of both AR/VR units acting as transmitting nodes without challenging computational requirements. To exploit stand-still scenarios, e.g., at traffic signals for a brief stoppage, we proposed a DOMOSS algorithm. We evaluated the effectiveness of our proposal in comparison to three designed baselines and several benchmark solutions and verified the quality of our solution in terms of its fast convergence, near-optimal data rate, and energy-efficiency performances.

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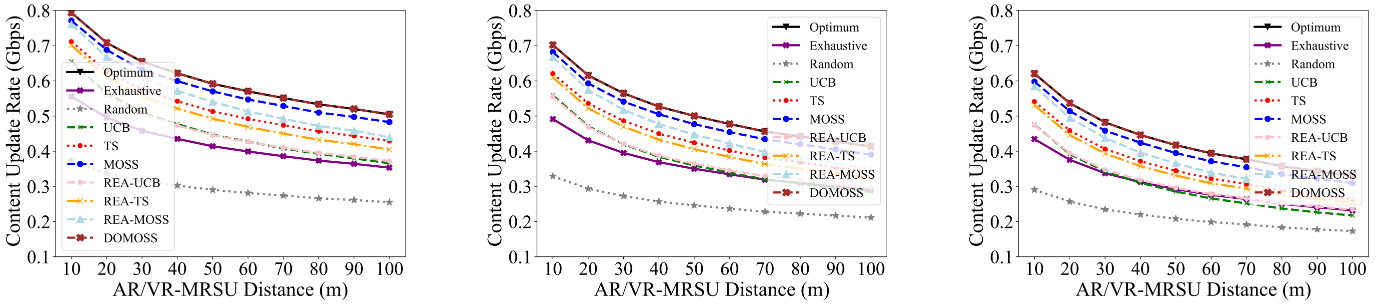
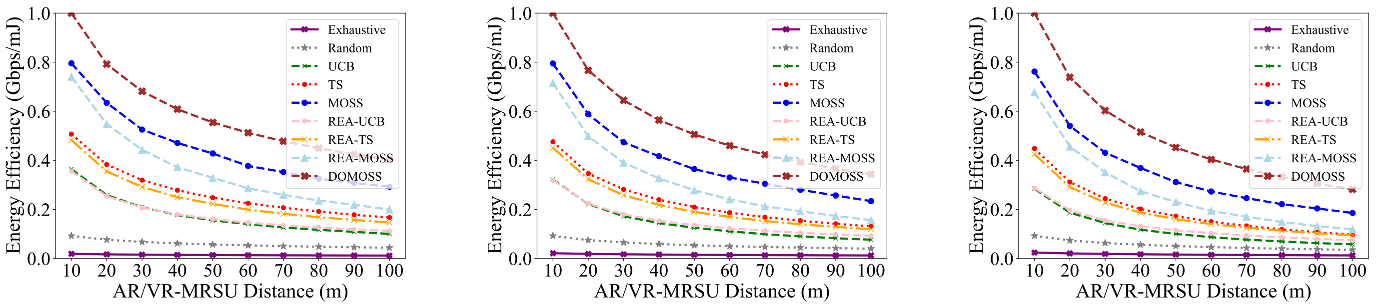



(a) No vehicle blocker. (b) Small vehicle blocker. (c) Large vehicle blocker.

Fig. 2: Metaverse content update data rate comparison of proposal and other methods over increasing V2I distances by considering various sized vehicular blockers (none, small, large types).




(a) No vehicle blocker scenario. (b) Small vehicle blocker. (c) Large Vehicle blocker

Fig. 3: EE comparison of our proposal and other methods over increasing V2I distances by considering various sized vehicular blockers (none, small, large types).

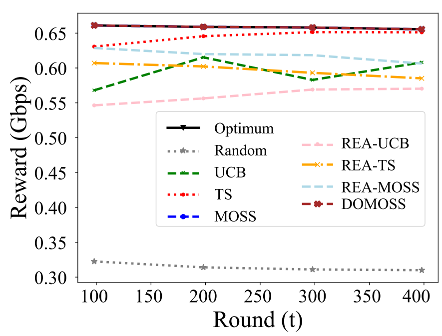



Fig. 4: Convergence rate performance of our proposed DOMOSS algorithm and other compared methods.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