IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 27 September 2023, accepted 18 October 2023, date of publication 23 October 2023, date of current version 30 October 2023.
Digital Object Identifier 10.1109/ACCESS.2023.3326842

RESEARCH ARTICLE

DL-Based Minimizing Virtual Environment Resource Usage in 6G Cellular Networks

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ABSTRACT The efficient Virtual Reality (VR) data delivery in 6G cellular networks is challenging, as it requires high throughput and ultra-reliable low-latency communication. In this work, VR based Software-Defined Network (SDN) model is proposed for efficient uplink-downlink resource management in 6G networks that guarantees low latency and high data rates. The suggested solution achieves End-to-End (E2E) management. among VR users with centralized resource management involving supervised deep learning (SDL) and unsupervised deep learning (UDL). Comparative results is demonstrated, which show the performance differences between these approaches in 6G networks that improve the transmission of VR video, enable such improvement.

INDEX TERMS Virtual reality, 6G cellular networks, software defined network, frequency searching adaptive bat algorithm, deep learning, achievable data rate, low latency.

I. INTRODUCTION

Virtual Reality (VR) is a simulated environment that users can interacted with whereas the objective of VR is to present a three-dimensional, immersive experience such that the user perceives being physically present in the environment. VR systems do this by using hardware and software together to show images and sounds that react to how the person moves or what they do. Virtual environments can vary from single scenes to multi-scene applications that let the user move around and manipulate objects in the environment. Some VR systems utilize a variety of display technologies such as Head-Mounted Displays (HMDs) for immersion i.e. projection-based VR [1]. In order to succeed, VR needs low responsive and imperceptible to the user. This calls for a high-bandwidth, low-latency network connection to transmit the VR system's video and other data back to the user. The user experience in VR depends directly on the quality of the network connection; latencies or dropped frames can cause physical discomfort and destroy the illusion of immersion. So, the goal for any successful VR distribution network must be effective management of these resources. [2]. From this prospect managing bandwidth to VR system and congestion control is addressed by effectively managing network resource and prioritizing. VR video transmission, 6G cellular networks can deliver a high data rate, low latency immersive experience to the users [3], [4].

6G Cellular networks is the forthcoming stage in the progression of mobile telecommunication technologies, this technology is expected to bear a significant improvement than the current 5G technology. 6G cellular networks is in the research and development segment now days, however it's a promising technology due to its potential to revolutionize the use of virtual environments and VR. One of primary advantages of the 6G cellular networks that it is expected to give a much higher bandwidth and lower latency compared to the current technologies [5]. This will empower VR systems to transmit massive data, for example high-resolution video with minimal latency, producing a much more immersive and responsive VR experience for individual user [6]. With the capability to support new and creative VR applications. 6G cellular networks are positioned to have a substantial role on the expansion and progress of the VR industry. Another benefit for VR and 6G cellular networks that it's expected to convey a numerous advancement in the field of mobile telecommunications [7]. This involves higher data speeds,

The associate editor coordinating the review of this manuscript and approving it for publication was Chen Chen.

greater coverage, enhanced security features and increased capacity. By all of these advantages will contribute to make 6G cellular networks a promising technology in the coming years, as it possesses the potential to revolutionize the way we communicate and interact with the world surrounds [8].

Software-Defined Networking (SDN) allows for the efficient and effective management of the connections between VR systems in the 6G cellular networks. The SDN, consist of the SDN core network and the SDN-enabled wireless network which allows for fine-grain decomposition of the wireless elements of the network and effective resource allocation and scheduling [9]. This can be accomplished using a wireless slice manager, which supervises resource allocation based on the instructions from the global scheduler in the SDN controller. With the capability to manage network resources effectively, SDN can help in the transmission of large amounts of VR data with minimal latency, enhancing the VR experience to be more immersive and responsive VR experience for users Furthermore, the utilization of SDN in a 6G cellular network will offer a more secure and efficient way of managing the network resources, assuring that the VR data is transmitted with the highest possible quality for transmitting the data [10]. Additionally, SDN allows End-to-End (E2E) management of the links between VR systems. This implies that the entire network from the VR system to the end user, can be controlled and enhanced for the VR data transmission, ensuring more seamless and consistent VR experience for users [11]. In brief, SDN plays an essential role in supporting the use of VR in 6G cellular networks. It has an efficient capability to manage network resources and links between VR systems confirms a high transmission data rate VR experience for users and offers the foundation for new and innovative VR applications [12].

II. LITERATURE REVIEW

In recent years, the field of virtual environment communications has faced numerous challenges as the demand for advanced and more efficient communication systems continues to increase. To address these challenges, a number of research works have been conducted with the aim of exploring the potential of 6G cellular networks and SDN in this area.

Previous works have shown the impact of wireless communication on VR in terms of Quality-of-Service (QoS). For instance, the authors in [13] analyze the slicing issue within a VR environment that supports both ultra-reliable low-latency communications and enhanced mobile broadband by utilizing principles of stochastic geometry. Solutions for optimizing the VR environment was provided. Similarly, in [14], the authors focus on jointly optimizing caching and computation offloading policies to minimize the mean transmission rate while ensuring QoS constraints for VR applications. The authors in [15] delve into the VR service requests offloading problem and propose a proactive computing framework and a suitable resource allocation strategy to guarantee the necessary latency and reliability constraints. An echo liquid state-based approach was employed with the goal of maximizing the reliability of the VR environment as expressed through constraints on the instantaneous VR latency [16]. The aim of work in [6] is to establish a stochastic E2E delay limit using super martingale envelopes to enable accurate VR reliability prediction based on the number of users connected to the same computing node with specific service profiles. The proposed approach's effectiveness is demonstrated through analytical predictions based on classical Markov queueing theory. These papers contribute to the ongoing efforts to provide high VR quality of experience through effective solutions to the challenges posed by ultra-reliable low latency communications and enhanced mobile broadband.

The utilization of Deep Neural Networks (DNNs) to approximate optimal resource allocation policies has been a topic of interest in several studies. In [17], the authors demonstrate that a Fully-Connected Neural Network (FNN) can accurately approximate an iterative algorithm for power control in wireless networks. In [18], Convolutional Neural Networks (CNNs) were employed to approximate the power control policy and content delivery policy, respectively. In cases where the optimal solution is not obtainable, unsupervised deep learning has been applied, as seen in [19], where the parameters of a DNN are trained to meet the Karush-Kuhn-Tucker (KKT) conditions of the optimization problem. However, it should be noted that KKT conditions do not exist for optimization problems with integer variables that are not defined over a compact set.

6G is a promising cellular network technology that support applications need high data rate and ultra-low latency. Thus, many research are developed to address solutions for VR users. In [20], The impending arrival of 6G is set to revolutionize the VR landscape. It promises faster data rates and extensive device connectivity, paving the way for ubiquitous VR services. With the surge in IoT devices, 6G networks will face unprecedented demand for VR resources. To meet these demands, the proposed Information-Centric Massive Internet of Things (IC-mIoT) in the 6G context aims to enhance efficiency and ensure high-quality VR experiences. This paper [21] discusses the attaching of RISs to Wireless VR Users in a Cellular Network. It's designed to achieve VR with high bandwidth and low latency. It provides a risk-based framework for rate optimization and resiliency. The Lyapunov optimization problem makes the problem simpler while bounding queue lengths. A policy-based Reinforcement Learning (RL) algorithm addresses the stochastic channel, combining Recurrent Neural Networks (RNNs) to efficiently model state space. The authors of [22] propose a delay traffic analysis that utilizes the Martingale theory. The paper focuses on investigating the QoS in computation offloading environments with the objective of minimizing the outage probability, or the likelihood of a task incurring a delay violation. A task allocation approach based on a unique water-filling policy is presented in the paper as a solution. In [23], An E2E delay bound in a multiloop vehicular ad hoc network was formulated, considering both access and queuing delay terms. The paper provides a theoretical analysis and discussion of the E2E delay bound for heterogeneous traffic demand under various scheduling policies (first-in first-out, static priority, and earliest deadline first). In [12], the authors investigate E2E delay bounds of delay-tolerant and delay-sensitive burst applications in a heterogeneous traffic environment. The study uses Martingale analysis to examine the E2E delay bounds of these different types of applications. In [24], the Quality of Experience (QoE) requirements for wireless VR optimized, emphasizing high data rates, reliable and low latency. Though signal attenuation remains an issue, the terahertz band's vast bandwidth provides opportunity for high data rates. This can be handled by Reconfigurable Intelligent Surfaces (RIS). Mobile Edge Caching (MEC) solves the low VR interaction latency problem. Furthermore, we propose an indoor TeraHertz (THz) VR network with RIS and MEC support, taking into account uplink viewpoint prediction, MEC computation offloading, and downlink beamforming. The authors present a combination of Long Short-Term Memory (LSTM) and Convolution Neural Networks (CNN) for uplink location prediction, and a deep reinforcement learning algorithm for downlink phase shift optimization under latency constraints. Network slicing is important for wireless communication [25], which aims to provide services based on various quality parameters such as latency, availability, reliability, throughput, etc. Mobile traffic forecasting helps optimize things. This paper predicts network slice segmentation (streaming, messaging, search, and cloud) using datasets and compares four deep learning models (MLP, Attention-based Encoder Decoder, GRU, LSTM), where LSTM gets the best results

In previous studies, SDN turned into shown to provide advantages in terms of enhancing overall network performance, encompassing tasks such as managing network traffic, and facilitating E2E control for various users located in different positions. This paper [26] introduces a hierarchical multi controller deployment strategy for SDN based 6G space air ground integrated networks to address challenges like ultra dense networks and satellite network dynamics the strategy optimizes network delay controller load and throughput drop by defining delay and load models employing a simulated annealing algorithm for controller placement and proposing a switch migration strategy for load balancing. In [27] authors propose a novel 6G system architecture using SDN to enhance control plane efficiency by separating end-user signaling functions, resulting in increased simplicity, modularity, and adaptability to diverse use cases. This study [28] addresses the need for improved communication in vehicular ad hoc networks and drones within the context of 6G it introduces an E2E oriented management architecture based on fog computing and software defined network SDN technologies enhances network performance through techniques like transport service aggregation and normalized throughput adjustment resulting improvements in packet delivery and packet loss ratios increased trustworthiness in performance metrics and optimized resource utilization for faster computation and lower power consumption. In [29], a key goal is to support different vertical services such as AR/VR, eHealth, video streaming, and automation with specific QoS and QoE requirements. This is achieved through Network Slicing, enabled by NFV and SDN, where multiple logical networks operate independently on a shared infrastructure. This study addresses slice allocation using machine learning algorithms and data sets, and demonstrates high accuracy in assigning optimal network slices to specific services.

In this paper, a VR based SDN system model has been proposed to meet the transmission requirements of VR video in 6G cellular networks. The model enables centralized administration of network resources and communication between VR users and base stations while considering the VR user's status and allowing for both low and high data rate communication to achieve efficient and effective resource management. The solution presents the use of both supervised deep learning (SDL) and unsupervised deep learning (UDL) approaches. The UDL is used for resource selection, weighting factor determination and identification matrix generation the results of the two systems reveal significant differences in performance and features. The main contributions of this paper are:

1. System Model is proposed of a VR based SDN system model for efficient resource management of VR data transmission in 6G cellular networks. Whereas, E2E links between VR users are considered.
2. Construct optimization problem to maximize achievable data rate under E2E latency constraint.
3. Utilization of both SDL and UDL approaches for VR data transmission requirements.
4. Use of UDL and SDL for optimizing the network parameters by suitable resource allocation among VR users.
5. Comparative analysis of the performance and features of the two systems.

The organization of the paper is as follows: Section II outlines the system model and Section III introduces the problem formulation. The optimization of deep learning-based resource selection is demonstrated and explained in Section IV. The results and discussion of the proposed approach are presented in Section V. Finally, the paper is concluded in Section VI. Additionally, all notations used in this work are mentioned in Table 1.

III. SYSTEM MODEL

In this section, the system model of VR based SDN in 6G cellular networks is introduced. Detailed architecture E2E VR cellular system is shown in Fig 1, which consist of two planes: control plane and data plane. Among them, control plane is responsible for controlling the network through northbound interface of SDN. A standard controller is used to centralize global network resource administration and OpenFlow (OF) protocol is employed to communicate

TABLE 1. Table of notations.

Notation	Description	Notation	Description
C	No of controllers	p_n	Transmitting power of VR user and it is assumed to be constant for all VR users in the same BS n
I	No of OpenFlow Switches	$d_{m,n}$	Distance between user m and BS n
T_J	Time interval of network slice request in backhaul	σ^2	Variance of the additive Gaussian white noise (AWGN) at the receiver
T_i	Time taken to process the data sent to switch i	$a_{i,n}$, $a_{j,n}$	Indicator of VR user m associated to BS n and act as transmitter and receiver, respectively
T_c	Time taken for the data to be processed in its corresponding tenant application	$b_{i,j}$	Indicator to the link between two VR users $l_{i,j}$
$T_{backhaul}$	Time taken in SDN network of packets to be served	$r^{ul}_{m,n}$	Uplink rate between VR user m and BS n
N	No of BSs that are served by SDN switches	$r^{dl}_{m,n}$	Downlink rate between VR user m and BS n
M	No of VR users with single antenna	$S^{ul}_{m,n}$	Amount of data sent in uplink from VR user $u_{m,n}$ to associated BS n
U_n	Set of VR users in BS n where $\{U_n: U_n \subseteq M, \sum_{\forall n} U_n = M, n = 1,2, \dots, N\}$.	$S^{ul}_{m,n}$	Amount of data sent in downlink from BS n to a served VR user $u_{m,n}$
$\mathfrak{R}$	Set of subcarriers where $\mathfrak{R} = (1, \dots, R)$	$l_{i,j}$	link between two VR users
Θ^{ul}_n	No of RBs in each slice in BS n assigned for uplink transmission	$T^{ul}_{m,n}$	Time taken to transmit data from VR user m to BS m
Θ^{dl}_n	No of RBs in each slice in BS n assigned for downlink transmission	$T^{dl}_{m,n}$	Time taken to transmit data from BS m to VR user n
$\theta^{ul}_{m,n}$	No of RBs that VR user m communicate with the associated BS n in uplink transmission	BW	Bandwidth of each uplink or downlink subcarrier for all channels
$\theta^{dl}_{m,n}$	No of RBs that VR user m communicate with the associated BS n in downlink transmission	$h_{m,n}$	channel information for the link of VR m to BS n

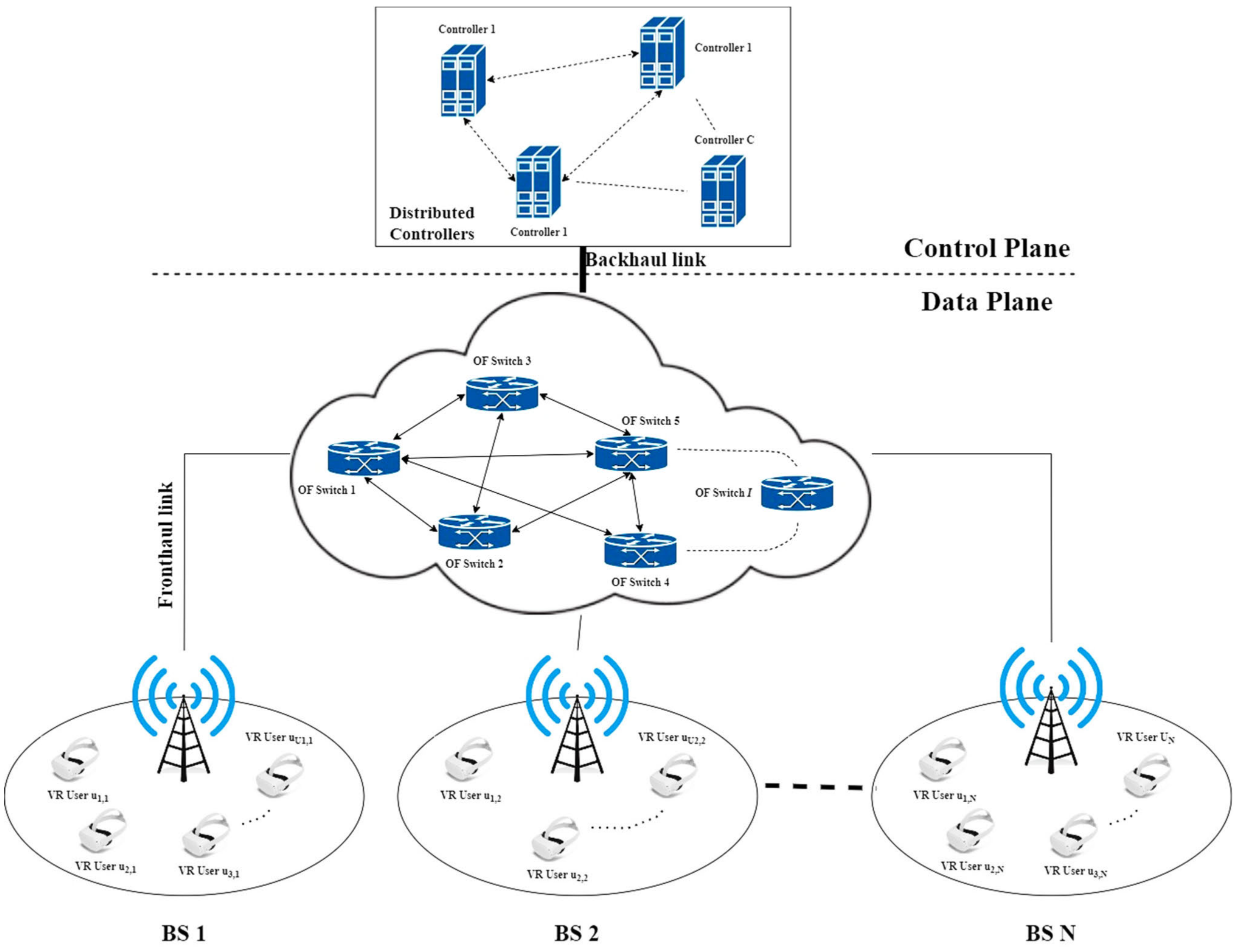


FIGURE 1. System model.

with switches and obtain network information, resulting in efficient network resource management and optimization. In SDN, set of controllers C = {1, 2, ..., C are considered physically distributed but logically centralized and connected south to OF switches mentioned as set I = {1, 2, ..., I. SDN is used to simplify the network management orchestration, ultimately providing seamless end-to-end management of proposed system model.

Fig. 1 shows the proposed architecture, which consists of N BSs that are served by SDN switches, M VR users with a single antenna. Assume SDN switch $i \in I$ either managed alone or integrated with Base Station (BS) $n \in N$. Each BS has a set of VR devices $\{U_n{:}U_n \subseteq M, \sum_{\forall n} U_n = M, n{=}\ 1, 2, \ldots, N\}$. Let the set R $=$ $(1, \ldots, R)$ denote the subcarriers (i.e. Resource Blocks (RBs)) assigned to each BS. The following assumptions are taken into account in the model: i) providing adequate orthogonal radio resources (in a multi-cell situation) is difficult due to restricted radio resources. As a result, certain BSs may share radio resources, potentially causing cell interference. To balance radio resource sharing and inter-cell interference reduction, the same set of radio resources can be assigned to multiple BSs as long as the distance between them is sufficient to reduce inter-cell interference; ii) because a BS sharing group is an area with strong overlaps between BSs, orthogonal resources are assigned to BSs within one sharing group, resulting in interference unavailability within the BS sharing group; iii) Each BS assigns a set of RBs to the end-devices it manages. The RBs assigned to each end-device should guarantee a minimal communication latency and a high rate while transmitting or receiving data through wireless transmission between the VR user and the associated BS; iv) each VR user is associated with only one BS; v) consider that the system is operating in Frequency Division Duplex (FDD) mode; vi) each BS assign a number of RBs for each slice (i.e. VR slice requires Θ_n^{ul} RBs for uplink transmission and Θ_n^{dl} for downlink transmission); vii) assume each VR user can communicate with the associated BS using a number of RBs, $\theta_{m,n}^{ul} \subseteq \Theta_n^{ul}$ for uplink and $\theta_{m,n}^{dl} \subseteq \Theta_n^{dl}$ for downlink.

VR user $u_{m,n} \in U_n$ in BS n transmit or receiving data rate through uplink or downlink $r_{m,n}^{ul}$, $r_{m,n}^{dl}$, respectively. The user can send his status according to devices attached to VR such as: Leap Motion, Virtuix Omni, Oculus Touch, Manus VR, Play Station VR Aim, VirZoom, Unlimited Hand, body sensors, etc. Hence, the amount of data sent in uplink from the VR user $u_{m,n}$ to associated BS n is $S_{m,n}^{ul}$. Also, it can receive data from virtual server in controller c or from another user in the same BS or another BS. Thus, this amount of data sent in uplink from BS n to a served VR user $u_{m,n}S_{m,n}^{dl}$. Assuming the link between two VR users is represented as $l_{i,j}$. Assuming two scenarios for VRs communication; in the first scenario, VR sender is sending sensed data whereas $S_{m,n}^{ul}$ is comparably small amount of data that needs a low data rate and hence low transmission latency. And on the other side, the receiver is visualizing this sensed data whereas $S_{m,n}^{dl}$ is much higher and needs high data rate which will impact higher latency. Oppositely, in the second scenario, the transmitter sends a larger amount of data such as video and receiver just receives action which is a low amount of data.

Let BW be the bandwidth of each uplink or downlink subcarrier for all channels. The data rate of the transmission from user m to the associated BS n [30]:

$$r_{m,n}^{ul} = \theta_{m,n}^{ul}.BW.\log_2\left(1 + \frac{p_n^{ul}\left|h_{m,n}\right| d_{m,n}^{-\zeta}}{\sigma^2}\right) \tag{1}$$

where $h_{m,n}$ is the channel information for the link of VR m to BS n. p_n is the transmitting power of VR user and it is assumed to be constant for all VR users in the same BS n. $d_{m,n}$ is the distance user m and BS n. σ^2 is the variance of the additive Gaussian white noise (AWGN) at the receiver. By similarity, the data rate from BS n to their serving user m is [30]:

$$r_{m,n}^{dl} = \theta_{m,n}^{dl}.BW.\log_2\left(1 + \frac{p_n^{dl}\left|h_{m,n}\right| d_{m,n}^{-\zeta}}{\sigma^2}\right) \tag{2}$$

Depending on whether the VR user is assigned as transmitter or receiver in a certain time slot, uplink or downlink rate is assigned respectively. The infrastructure network is defined as set of physical devices, i.e., Switches and Controller-nodes. T_J represents the time interval of network slice request in backhaul. The time taken to process the data sent to switch i can be defined as T_i. The flow is received in the backhaul controller and the data take time T_c to be processed in its corresponding tenant application. Assume this time is constant for all VR devices that need to be served by controller c. Those packets sent are received from or requested by VR user in another BS n or they may be served from a virtual environment loaded from a certain server in controller c. From the previous analysis, the time taken in SDN network of packets to be served is defined as:

$$T_{backhaul} = T_J + T_i + T_c \tag{3}$$

The transmitter and receiver latencies are shared and vary based on the amount of data to be sent or received while ensuring that the E2E latency is within the QoS range necessary for optimal VR performance. By performing the same condition of E2E latency in first scenario latency at each user experience is achieved. The required latency to improve the QoS for the VR device either in transmitting its interaction with the environment or in receiving the instantaneous variation in other VR user environment interaction is considered as [30]:

$$T_{m,n}^{ul} = \frac{S_{m,n}^{ul}}{r_{m,n}^{ul}} \tag{4}$$

$$T_{m,n}^{dl} = \frac{S_{m,n}^{dl}}{r_{n,m}^{dl}} \tag{5}$$

IV. PROBLEM FORMULATION

The aim is to maximize the achievable rate while VR users communicate with each other or interact with the environment. Also, E2E Latency is considered as major problem in VR applications whereas it needs to be minimum for latency-sensitive applications. Although rate in uplink and downlink may be vary according to the amount of data sent. Thus, the latency taken to transmit data from VR user to BS is differ from receiving data from BS. This means that the time taken from end to end for link $l_{i,j}$ can be described as [29]:

$$T_{total,i,j} = \alpha T^{ul}_{n,m} + T_{backhaul} + (1-\alpha)\, T^{dl}_{n,m} \tag{6}$$

where, α is a weighting parameter between uplink and downlink latency to satisfy transmitter and receiver QoS as mentioned in both scenarios. Thus, the overall system data rate can be calculated as [30]:

$$R_{total} = \sum\nolimits_{n=1}^{N} \sum\nolimits_{j=1}^{U_n} \sum\nolimits_{\substack{i=1 \\ i\neq j}}^{U_n} b_{i,j}(a_{j,n} r^{dl}_{j,n} + a_{i,n} r^{ul}_{i,n}) \tag{7}$$

where $a_{i,n}$ and $a_{j,n}$ is indicator of VR user m associated to BS n and act as transmitter and receiver, respectively. The matrix $A = [a_{i,n}; a_{j,n}]$ is represent users associated in BS n act as transmitter or receiver. $b_{i,j}$ is an indicator to the link between two VR users $l_{i,j}$ and can be determined by matrix $B = [b_{i,j}]_{M\times M}$. Thus, the optimization problem is formulated as:

$$\max_{\theta,\alpha} \; R_{total} \tag{8}$$

$$\text{s.t. } T_{total,i,j} \leq T^{e2e}_{th} \tag{i}$$

$$\alpha \in [0, 1] \tag{ii}$$

$$\sum\nolimits_{m=1}^{M} a_{m,n}\theta^{ul}_{m,n} \leq \Theta^{ul}_{n} \tag{iii}$$

$$\sum\nolimits_{m=1}^{M} a_{m,n}\theta^{dl}_{m,n} \leq \Theta^{dl}_{n} \tag{iv}$$

Constraint i is the major proposed point in our problem which is guaranteed E2E latency achieves a certain threshold that ensures VR performance in virtual environments. The sum of assigned RBs for each VR user must be in the range of assigned RBs for each slice in BS n, this is assured in constraints iii and iv. Matrices A and B demonstrate that each VR user must be assigned to one BS and which VR users in link $l_{i,j}$ are communicated, respectively.

V. DEEP LEARNING BASED RESOURCES SELECTION

An overview of SDL and UDL approaches is provided in this section. Following that, a full explanation of our proposed UDL used to decide resource selection, weighting factor, and identification matrices are provided. Furthermore, the detailed technique for data processing, training, and online inference are explained. After that, an explanation for SDL is discussed, and how the dataset is generated.

A. UNSUPERVISED DEEP LEARNING

Unsupervised Deep Learning is a form of machine learning that allows the system to learn patterns and correlations in data without relying on labelled examples. This approach is often used for tasks such as clustering, anomaly detection, and dimensionality reduction, and relies on collections of data tensors that capture relevant characteristics and optimization parameters [31]. Let P be the collection of tensors with characteristics gathered from different contexts, and let ρ be a tensor holding all the optimization situation's parameters in a particular state. P can be employed to refer towards the data sets especially within the context of unsupervised deep learning. Furthermore, x_{opt} is supposed to be the optimal solution when the input parameter is ρ and X denotes the collection of optimal solutions consistent to P. UDL tries to provide x_{opt} for every ρ such objective function is minimized labelless. To achieve this, the optimization problem, represented as $\mathcal{L}(\rho, x_{opt})$ can be utilized as the loss function for the UDL. By minimizing the mean of the loss values for each epoch, the UDL iteratively trains the translation from X to P, also known as f_{NN}, i.e. [31]:

$$\mathcal{L}(P; X) = \frac{1}{|P|} \sum\nolimits_{\rho\in P} \mathcal{L}\left(\rho; x_{opt}\right) \tag{9}$$

Regarding the problem in eq. (10), ρ can be constructed as $\rho = \{h_{m,n}, d_{m,n}, f^{ul}_{m,n}, f^{dl}_{m,n}, A, B$, but $h_{m,n}$ is channel condition which is estimated to real and imaginary parts whereas in UDL it is divided into two inputs real and imaginary. Such that ρ can be rewritten as $\rho = \{Re(h_{m,n}), Im(h_{m,n}), d_{m,n}, f^{ul}_{m,n}, f^{dl}_{m,n}, A, B\}$. While the x_{opt} is the optimal resource selection and weighting factor such that $x_{opt} = \{\theta^{ul}_{m,n}, \theta^{dl}_{m,n}, \alpha$. With this approach, the inputs may have a variety of data that may be used to choose the number of resources and the weighting factor. However, there are a variety of approaches to creating the UDL's inputs based on ρ, and this is also one of the most crucial processes to create f_{NN}. For instance, a typical approach to creating the inputs is to vectorize each coefficient accessible in ρ.

Our proposed UDL framework is structured to extract features and correlations of the samples using ρ. Additionally, UDL is a matter of fact viewed as an extension to Artificial Neural Networks (ANN) in which multiple hidden layers with a huge number of neurons is designed. Initially, the network input is illustrated as P which is the collection of tensors input. First, the input layer is constructed as tensors fed with all input vectors. Subsequently, all tensors are concatenated and flattened in the following flattened layer in UDL. The number of nodes is denoted as l_k for the kth layer. A UDL's performance is heavily influenced by the training process. Normally, the training procedure should be carried out offline at the console because it could use too many resources. When using a supervised learning method, it is necessary to get the labels which takes time and effort that will be discussed in the next section. In contrast, no labels are necessary for the UDL method. As discussed, the input layer will hold out P vector which contains ρ tensors. Each tensor describes the data of VR user in the network. UDL is trained to predict the number of channels assigned for each user and the weighting factor for each E2E link that satisfies the constraints in the problem described in eq (9). In particular, the loss function set for the proposed UDL is [31]:

$$\begin{aligned}\mathcal{L}\left(\rho;x_{opt}\right) = &\left(-\frac{1}{NM}R_{total} + \tau_1\left(\sum\nolimits_{m=1}^{M} a_{m,n}\theta_{m,n}^{ul} - \Theta_n^{ul}\right)\right.\\ &+\tau_2\left(\sum\nolimits_{m=1}^{M} a_{m,n}\theta_{m,n}^{dl} - \Theta_n^{dl}\right)\\ &+\varphi_1\left(\frac{1}{M}\left(\sum\nolimits_{m=1}^{M}\left[\sum\nolimits_{n=1}^{N} a_{m,n} - 1\right]\right)\right)\\ &+\varphi_1\left(\frac{1}{M}\left(\sum\nolimits_{m=1}^{M}\left[\sum\nolimits_{m=1}^{M} b_{m,m} - 1\right]\right)\right)\\ &\left.+\rho\left(\frac{1}{M}\sum\nolimits_{\forall M} T_{total,i,j} - T_{th}^{e2e}\right)\right) \end{aligned} \tag{10}$$

The UDL's weights and biases are tuned during training so that loss function is minimized. Equivalently, achievable data rate is maximized under given constraints. Data normalization plays an important role in UDL. As which E2E communication was considered in our problem, channel information and distance from base station shows a significant impact on training process. So, the optimal number of channels assigned for each VR user depends on input vectors. Moreover, each component in input data has very low values such as channel information and high values such as the amount of data sent or received. This might lead to a gradient vanishing problem. Thus, data normalization will be very useful in this particular.

Inspired by the work in [32] Generative Adversarial Networks (GAN) are used to generate the data set used in the proposed solution. But the amount of data is assumed random according to each VR user's requirements. Consequently, this dataset is divided into two data sets: training set and test & validation set. To enhance the proposed UDL architecture, the Stochastic Gradient Decent (SGD) technique with momentum is presented. Finally, the test phase is held out in terms of performance and network stability.

In Algorithm 1, UDL steps are presented in full details. It starts out by simulating a wireless atmosphere in order to formulate the channel gain (or equivalently the likelihood ratio for a given channel) and constructs a specific connection between two nodes (i.e., communication lines), which we use to generate training examples. Next, it initializes the learning_rate and loss_rate, initializes the UDL weights with the Xavier method, and sets the batch size. Its main looping process involves using SGD in order to train a UDL approximation of a task at hand. They are iteratively revised until the converging condition is met. Eventually the algorithm computes an optimal solution with respect to the UDL and returns into an array of varying types.

B. SUPERVISED DEEP LEARNING

The proposed problem is also solved using supervised deep learning. The basic SDL module, which serves as the core component of the proposed SDL, is discussed in this section. The fundamental DNN module is made up of a number of basic units, each of which is made up of a Fully Connected (FC) layer, a Batch Normalization Layer (BN), a Rectified Linear Unit (ReLU) layer, and a dropout layer. After the input vector is fed to the fully connected layer, batch normalization and ReLU. Then, dropout layer role is come applied to randomly drop c_k with a certain probability predetermined such that some of the input data is blocked to avoid overfitting of SDLs. The proposed SDL is structured as an input layer, L hidden units, and an output layer. Each kth hidden unit is constructed with l_k neuron. The difference between UDL and SDL is labeling input data whereas SDL needs to label all data input but UDL needn't. From this scope, a heuristic technique was used to generate dataset with labels x_{out} to represent the required number of channels for each VR user and the weighting factor for VR link. Hence, labels are represented as [33]:

$$x_{out} = \left\{\theta_{m,n}^{dl}, \theta_{m,n}^{ul}, \alpha\right\} \tag{11}$$

The proposed SDL is adjusted to newly exposed samples and scenarios, offline learning policy is implemented to produce the best results. Most of the channel conditions are distributed and considered in a certain region of BSs by filling out all points that VR users can exist. Hence, the heuristic technique used produces all possible conditions and the dataset generated is used to train the SDL. A huge number of inputs are created using Frequency Searching Adaptive Bat Algorithm (FSABA) [30] and the related optimal solutions are found in order to obtain enough labeled training examples. The SDL is trained using a portion of the data, and their performance is tested using a different portion of the data.

A batch of training samples is randomly chosen from among all the training samples for each training epoch in order to train the SDL. The Adam algorithm is used to optimize the parameters of W_k and b_k to minimize a loss function. The loss function used is Categorical Cross entropy and is represented as [33]:

$$\begin{aligned}\mathcal{L}\left(x_{out};\hat{x}_{pred}\right) = \frac{1}{S}\sum\nolimits_{i=1}^{S}&\left[x_{out,i}\log\hat{x}_{pred,i} + (1-x_{out,i})\right.\\ &\left.\times\log\left(1-\hat{x}_{pred,i}\right)\right]\end{aligned} \tag{12}$$

where $\hat{x}_{pred}$ represents the predicted output and S is the number of samples fed to SDL. Finally, after training and

Algorithm 1 UDL Based Training Algorithm

Input: $Re(h_{m,n})$, $Im(h_{m,n})$, $d_{m,n}$, $S_{m,n}^{ul}$, $S_{m,n}^{dl}$, A, B
Output: cache matrix $X^* = \{\theta_{m,n}^{dl*}, \theta_{m,n}^{ul*}, \alpha^*\}$
Start running environment simulator to generate the wireless channel gains
Identify E2E VR links operated by SDN network
Generate a set of training samples.
Develop the UDL framework
Initialize the learning rate, and the loss rate.
The weights of the network are initialized using Xavier method [35] and set the batch size
while error $\geq \epsilon$ or epochs = max_iter
    Train the UDL to approximate problem (10) using the provided training samples and the SGD's suggested learning mechanism.
    Update the network parameters of the UDL
    Update the weight W and the output of each layer of the UDL.
end while
Calculate x_{opt} depending on resulted UDL

Algorithm 2 SDL Based Training Algorithm

Input: $Re(h_{m,n})$, $Im(h_{m,n})$, $d_{m,n}$, $S^{ul}_{m,n}$, $S^{dl}_{m,n}$, A, B
Output: cache matrix $X^* = \theta^{dl*}_{m,n}, \theta^{ul*}_{m,n}, \alpha^*$
Start running FSABA to generate samples
Identify E2E VR links operated by 6G SDN network
Split dataset to training and test sets
Develop the SDL framework
Initialize the learning rate, and the loss rate.
The weights of the network are initialized, biases and set the batch size
while error $\geq \epsilon$ or epochs $=$ max_iter
    Train the SDL to approximate problem (10) using the provided training samples and the SGD's suggested learning mechanism.
    Update the network parameters of the SDL
    Update the weight W and the output of each layer of the SDL.
end while
Test the SDL developed and deploy the model
Calculate $\hat{x}_{pred}$ depending on input samples

testing SDL offline, deployment is ready to be used online and the network can predict upon the number of VR users available. Thus, assigning number of channels and finding the optimal weighting factor for each link is much unproblematic.

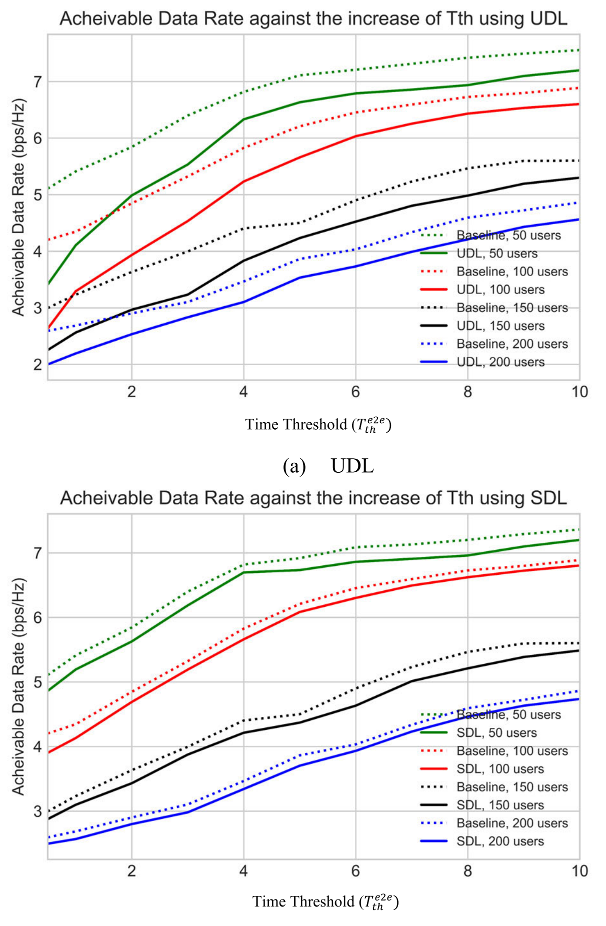
Algorithm 2 is showing the pseudo-code of how SDL operates. Firstly, samples using FSABA method are generated and then E2E VR links over an 6G SDN network are identified. The dataset is divided training and testing sets, and is used to develop an SDL framework. Initialization of learning rate and loss rate is done along with setting the weights and biases of layers in the network. The main loop of the algorithm repeatedly trains the SDL until an end of training condition is reached, such as a predetermined error threshold (ϵ) or a specified maximum number of epochs reached max_iter. During the training, the SDL approximates required optimizing by SGD. The network parameters are optimised sequentially, and when the training converges, the SDL model is evaluated and then deployed. Ultimately, the output array $\hat{x}_{pred}$ which consists of corresponding output values is calculated using input patterns.

VI. RESULTS AND DISCUSSION

In the studied scenario, 2 BSs are considered with coverage of 300 meters. Users are randomly distributed over 600 m $\times$ 150 m area. The uplink power p^{ul}_n and the downlink power p^{dl}_n are assumed to be 7 dBm and 23 dBm, respectively. Furthermore, the file size for uplink $f^{ul}_{m,n}$ and downlink $f^{dl}_{m,n}$ are ranged randomly between 1 Byte to 20 MByte. The network is structured depending on the number of VR users available, whereas results are demonstrated according VR users set available. For simplicity, VR-VR link is considered that one VR user is acting as a transmitter and the other one acting as a receiver. Furthermore, the number of channels R for VR users in each BS serving U_n users are predefined as 1024 channels for each VR slice, i.e. hard slicing used. It should be noted that SDN is used to connect VR users to requested tenant applications which the latency for transmitting and receiving the required contents is assumed to be constant for simplicity.

TABLE 2. Experimental setup.

Parameters	Value
Bandwidth (BW)	1 MHz
Noise Power (σ^2)	-174 dBm
No. of BSs	2
No. of RBs in each BS	1024
Cell Radius	300 m
Transmission power of VR users	7 dBm
Transmission power of BS	23 dBm
Time Threshold (T^{e2e}_{th})	0.125, 0.25, 0.5, 1, 2, … , 10 ms



(a) UDL

(b) SDL

FIGURE 2. Achievable data rate against the increase of time threshold.

Additionally, the parameters used in simulation is shown in Table 2.

In Fig. 2(a) and 2(b), the achievable data rate is illustrated against the increase in time threshold T^{e2e}_{th} for the designed two techniques and compared with the reference scenario. Moreover, the optimal output number of RBs assigned to VR users are compared to show the performance of UDL and SDL. The impact of time threshold T^{e2e}_{th} for E2E VR link on the achievable data rate considering UDL and SDL, respectively, is investigated by plotting the achievable data rate in four different cases. Firstly, 50 VR users are served at the same time by the network which are managed as E2E VR links. Whereas, two user groups are constructed to measure E2E latency. Those user groups use SDN network to communicate with each other through the main controller. In the second case, 100 VR users are considered to perform two user groups. Moreover, groups may consist of two users served by the same base station or in different BSs. By increasing the number of users in the following two cases to 150 and 200 users, managing the available resources will be more difficult to achieve the QoS required of VR users.

In Fig. 2(a) and 2(b), each DL model used i.e. UDL and SDL are compared to the baseline scenario (i.e. reference scenario (FSABA)). It can be seen that the baseline is the maximum achievable data rate as it is used as a reference scenario for UDL and SDL. Also, it is used as a generative model for the dataset used in SDL. In all cases, the achievable data rate is increased with the increase of T_{th}^{e2e} whereas the VR links are allowed to continuously increase their channel number allocated from the assigned channels for VR slice. It is clear that, in first case, $M = 50$, the achievable data rate reach its maximum value even at early T_{th}^{e2e}. This is because the network has the availably of channels that can be assigned to all users and reach the required T_{th}^{e2e}. Therefore the number of channels for each E2E VR are increased.

By comparing the achievable data rate for the different 4 scenarios in Fig. 2(a) and 2(b), it can be seen that SDL is outperforming UDL, especially for a small number of users. As for $M = 50$ *and* 100, the improvement of SDL compared to UDL is about 29% for smaller time thresholds. But for larger T_{th}^{e2e} at a certain point the percentage becomes smaller around 5%. Moreover, the achievements of SDL compared to UDL in scenarios 3 and 4 (i.e. 150 and 200 users) the percentage of most T_{th}^{e2e} is around 8%. This is due to the fact that SDL is trained based on samples generated using the heuristic technique (i.e. baseline model) which reaches accuracy near to its results. Thus, the percentage of error will be much smaller than UDL that reaching the maximum achievable data rate in each case. In contrary, UDL is reaching the maximum achievable data rate according to the unsupervised search of minimum loss.

The study opted for a time threshold of 0.5 ms to assess how well the network performs for ultra-low latency applications like real-time trading and scientific simulations when utilizing SDL. The goal of the study was to improve network performance for latency-sensitive applications by identifying techniques to achieve the lowest possible latency for different user loads. On the other hand, if UDL is employed without any dataset, a time threshold of 7 ms provides satisfactory performance. Therefore, for low-latency applications, SDL is recommended, while UDL is a better choice when latency is not critical. The results shown describe the performance of the network depends on various factors, such as the number of users served and the size of the files being transmitted, and that different strategies may be needed to optimize the network for different applications and scenarios. Since it is recognized that SDN networks are used to allocate resources and manage the entire network, SDL and UDL are used to predict appropriate RBs for individual users and which as a result, the time required for E2E connections to send data across the link. Accordingly, this meets the required standards, because SDN effectively controls the RB allocation throughout the network, ensure the absolute delay time, which is held as a constant value in the proposed solution. OF provides a standardized and programmable framework for managing network traffic flows whereas making it a natural fit for the proposed approach. For applying OF configurations to our work, define flow rules that align with the RBs allocation strategy generated by our solution mechanisms. These rules indicate how network traffic should be preserved based on users' demands and resource availability. For instance, OF rules set to prioritize RBs allocations for latency-sensitive applications by dynamically allocate resources based on changing VR user demands. By configuring OF in this manner, our research not only optimizes RBs allocation but also ensures that network resources are efficiently utilized to meet end-to-end connectivity requirements.

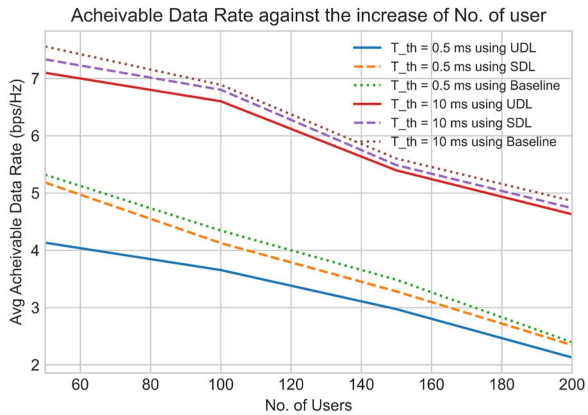


FIGURE 3. **Achievable data rate against the increase of number of users.**

The impact of the number of users on the achievable rate of a network was investigated in this research as shown in Fig. 3. The results indicate that when serving a small number of users (50 users), SDL outperforms UDL. However, for a larger number of users (200 users), both SDL and UDL exhibit similar performance. This observation suggests that UDL can achieve a minimum loss function and assign a similar number of channels as SDL as the number of users increases.

These findings are supported by the results presented in Table 3, which compare the performance of SDL and UDL to a reference value. The table reveals that for SDL, a time threshold of 0.5 ms yields good performance, with a loss function of only 7%. Conversely, UDL performs best with a time threshold of 7 ms, with a loss function of 6%. These results validate the assertion that UDL can achieve comparable performance to SDL when serving a larger number of users. Therefore, the choice of network architecture between

TABLE 3. SDL and UDL comparing according to change number of users against T_{th}^{e2e}.

	0.25 ms	0.5 ms	0.75 ms	1 ms	2 ms	3 ms	4 ms	5 ms	6 ms	7 ms	8 ms	9 ms	10 ms
SDL for 50 Users	8.20%	5.00%	4.82%	4.02%	3.70%	2.82%	2.75%	2.68%	3.19%	3.12%	3.35%	2.64%	2.18%
UDL for 50 Users	41.68%	37.62%	33.19%	24.10%	14.67%	13.53%	7.11%	5.56%	5.58%	5.23%	5.05%	5.38%	4.89%
SDL for 100 Users	9.84%	7.85%	5.29%	4.93%	3.24%	2.46%	2.85%	2.82%	2.45%	3.67%	2.60%	2.48%	2.44%
UDL for 100 Users	39.87%	35.72%	28.77%	24.22%	18.86%	14.82%	10.19%	8.85%	6.51%	5.13%	4.38%	3.88%	3.46%
SDL for 150 Users	8.88%	7.95%	6.63%	4.15%	5.56%	3.03%	4.31%	2.89%	5.45%	4.18%	4.66%	3.76%	2.03%
UDL for 150 Users	35.54%	30.72%	24.78%	20.70%	18.35%	14.10%	8.63%	7.71%	7.69%	4.80%	4.74%	4.36%	3.05%
SDL for 200 Users	8.77%	7.87%	6.31%	4.42%	3.53%	3.94%	3.58%	4.14%	2.48%	2.42%	2.83%	1.93%	2.61%
UDL for 200 Users	33.12%	25.23%	22.90%	18.35%	12.68%	8.71%	10.50%	8.55%	5.35%	3.38%	3.73%	2.52%	3.04%

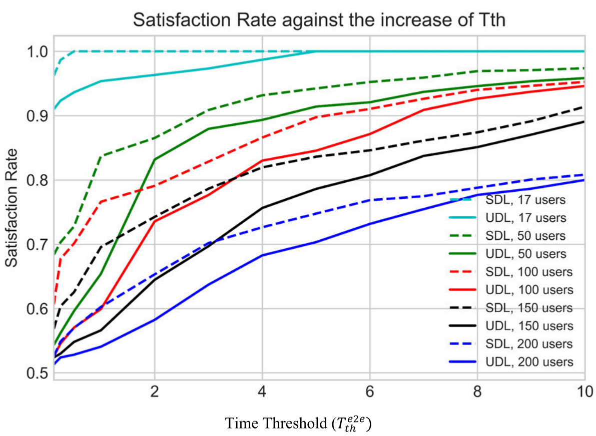


FIGURE 4. Satisfaction Rate against the increase of Time threshold using UDL and SDL.

SDL and UDL should consider the number of users to be served, and the desired trade-off between achievable rate and time threshold.

The study analysed the impact of patch unit size on the achievable data rate for various VR users in the network with respect to SDL and UDL compared to the baseline scenario. Two scenarios were considered, UDL with a time threshold of $T_{th}^{e2e} = 7$ ms and the other with $T_{th}^{e2e} = 0.5$ ms, as shown in Fig. 4(a) and 4(b) respectively. The study found that the achievable data rate decreased as the patch unit size increased for all cases. Larger patch unit sizes increased the probability of users with larger channels (i.e. hungry channel users) having larger patch unit sizes, which, in turn, decreased the number of channels assigned to users with smaller patch unit sizes. This result was expected since the ratio factor α of VR link latency is impacted when channels cannot be allocated to hungry channel users to send or receive the required patch unit size.

Fig. 4(a) in UDL demonstrates that for a large number of users (i.e. 200 users) and an increase in patch unit size, the achievable data rate is at its worst scenario. This is due to the fact that all channels assigned for VR slice are not sufficient to achieve the required E2E latency. However, for a small number of users (i.e. 50 users) and a large patch unit size, the achievable data rate only slightly decreased because there are an abundance of channels available to serve this small number of users even if they request a large patch unit size. Fig. 4(b) shows the use of SDL to maximize achievable data rate against patch unit size. It is evident from the figure that SDL results for 50 and 100 users only slightly decreased because the minimum loss function can still be achieved.

Due to the usage of the probability of satisfying or not in outage probability, the satisfaction ratio is used to determine the percentage of E2E links that satisfy the latency threshold. It can be calculated for each link as [34]:

$$\mu_m = \frac{1}{1+e^{-\delta(\frac{T_{th}^{e2e}}{T_{total,i,j}})}} \tag{13}$$

But for all users

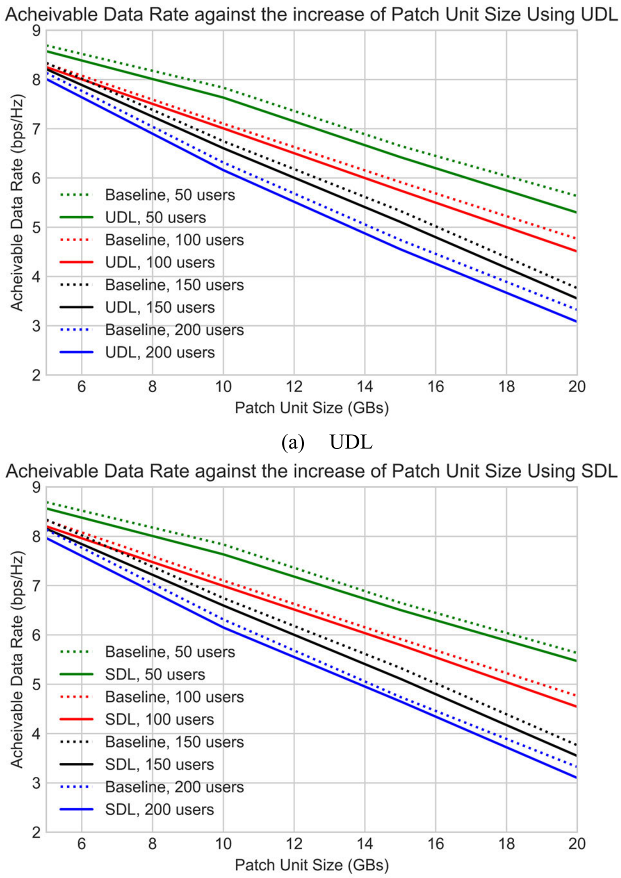
$$\mu = \frac{\mu_m}{U_n} \tag{14}$$

It can be found that the normal sigmoid function is used to determine the satisfaction rate, which is more suitable to show the rate between [1, 0]. The satisfaction rate is measured for UDL and SDL against the time threshold in Fig. 5. It can be concluded that in low latency requirements, many users in UDL can't satisfy the E2E VR latency constraint. Thus, the number of satisfied VR users with high virtual experience are affected. On the other hand, VR users that satisfy sufficient data rate and appropriate latency increased for low time threshold. It can be seen that convinced users of E2E latency in higher time threshold using UDL and SDL become closer. This is because VR users using all channels assigned with mostly equal distribution. From previous analysis, it can be determined that using UDL and SDL have similar effect on the network performance for higher time threshold (around > 7ms) especially for large numbers of users served in the same time. Furthermore, UDL need not labeled data set whereas if output can't be predetermined due to certain conditions, UDL will be the better scenario to be used. Oppositely, SDL to be trained must have labelled dataset which in some network scenarios this is not available.

The results presented in Table 4 are obtained from comparing SDL and UDL in terms of user satisfaction ratio at different time thresholds. It is evident that the two models have minimal differences in terms of the small number of VR users served in the proposed solution. However, as the number of users increases at low time threshold, UDL struggles to

TABLE 4. Comparative analysis of satisfied ratio users for UDL vs. SDL in terms of changing T_{th}^{e2e}.

	0.125 ms	0.25 ms	0.5 ms	1.0 ms	2.0 ms	3.0 ms	4.0 ms	5.0 ms	6.0 ms	7.0 ms	8.0 ms	9.0 ms	10.0 ms
17 Users	6.71%	6.53%	6.37%	4.64%	3.67%	2.67%	1.30%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
50 Users	14.47%	14.10%	13.17%	9.49%	4.47%	4.17%	3.83%	3.34%	2.68%	1.81%	1.67%	0.75%	0.30%
100 Users	16.49%	13.16%	13.08%	12.92%	5.53%	5.19%	3.59%	5.20%	3.91%	1.73%	1.37%	0.91%	0.64%
150 Users	11.62%	10.23%	11.14%	12.95%	9.78%	8.94%	6.31%	5.01%	3.87%	2.38%	1.81%	1.14%	0.88%
200 Users	8.78%	9.75%	8.97%	8.56%	7.07%	6.47%	4.37%	4.44%	3.69%	2.01%	1.12%	1.42%	0.82%



(b) SDL

FIGURE 5. Achievable data rate against the increase of patch unit size.

maintain low latency for all users to meet the required performance standards. However, as the time threshold for E2E link increases, eventually both SDL and UDL converge, providing required performance and low latency for almost all VR users as the difference in service offered in terms overall satisfied users ratio between UDL and SDL is about 5%.

VII. CONCLUSION

The proposed VR-based SDN system model for cellular networks in the future is aimed to optimize the allocation of network resources for VR video transmission by taking into account important factors such as VR user status and data transmission. The study offers valuable insights for future research and its centralized architecture, crucial to efficient resource allocation and scheduling, is composed of multiple components working together. The study focuses on comparing the performance of two DL models, UDL and SDL, in serving VR users in a network. The DL models are evaluated against the increase in time threshold T_{th}^{e2e} and the number of VR users served. The results show that SDL outperforms UDL for a smaller number of users, with an improvement of around 29% for T_{th}^{e2e} less than a certain value. However, as the number of users served by the network increases, the improvement of SDL compared to UDL decreases and the two models perform similarly. Additionally, the achievable data rate decreases with the increase of the patch unit size for both UDL and SDL. The results suggest that the performance of the DL models is affected by both the number of users and the patch unit size transmitted or received by the VR users.

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