An Optical-Fog assisted EEG-based virtual reality framework for enhancing E-learning through educational games

Sandeep K. Sood | Kiran D. Singh

Department of Computer Science & Engineering, Guru Nanak Dev University, Gurdaspur, Punjab, India

Correspondence
Kiran D. Singh, Department of Computer Science & Engineering, Guru Nanak Dev University, Amritsar, Punjab, India.
Email: kdkirandeep@gmail.com

Abstract
Virtual reality (VR) combined with cloud computing has become the pioneer to provide e-learning for making education accessible across the globe. To enhance e-learning experience, electroencephalography (EEG) based educational games are widely used to improve the cognitive and learning skills of students. This method records the electrical activities of the brain of participating students to enhance prevailed knowledge and experience by using a virtual environment. In the present cloud computing paradigm, VR faces many challenges to adapt EEG-based educational games for e-learning due to their intensive demands of low-delay, optimum bandwidth, and minimum energy consumption. In this paper, an Optical-Fog assisted EEG-based virtual reality framework is proposed that uses the resources of the optical network to enhance the e-learning experience. An EEG-based VR framework is designed with six modules those are deployed at both Edge-Fog layer and Optical-Fog layer in the Optical-Fog network. In addition, a Software Defined Network (SDN) is used to reduce the delay that improves the Quality of experience (QoE). For simulating the experiment, IFogSim is used to implement both Optical-Fog-based and cloud-based deployment scenarios for playing games. Subsequently, a novel algorithm is proposed for implementing Optical-Fog-based module placement strategy. The performance of the framework is evaluated by computing average delay, network usage, and energy consumption. The results show the significant advantages of the optical network for playing EEG-based games.

KEYWORDS
E-learning, electroencephalography (EEG), fog computing, optical fog network, software defined network, virtual reality

1 | INTRODUCTION
In the 21st century, the new pedagogy and teaching practices in higher education are continually evolving with the integration of various digitals and communications technologies. The present education trend is moving toward e-learning by using more inter-operable networks, high bandwidths, and virtual services with the latest educational technologies [36]. The educational technologies include virtual reality/augmented reality (VR/AR), brain-computer interaction, cloud computing, and information sharing through social media to enhance the e-learning experience. In the recent years, VR/AR has been adopted in many verticals like education, enterprise, entertainment, manufacturing, media, medical,
etc. [14,32,33]. Virtual Reality (VR) represents a promising area with high potential to enhance and modify the learning experience where a rich, interactive, engaging educational context and empirical virtual learning environment is provided to students [35,48,54]. In fact, VR is an artificial environment created with the help of software and presented to the person as a legitimate environment. In order to present VR/AR to human brain with the perspective to be perceived as real, the made-up information can be presented to senses with the perception of reality [34]. VR/AR needs accurate sensory feedback stimulated through integrated hardware and software such as head mounted displays (HMD), special gloves or hand accessories, and hand controls, etc.

The VR/AR has a great potential to enhance the educational landscape by making e-learning environment customizable, actively engaging, and self-paced [44]. The educators are still exploring the new ways to utilize the massive explosion of VR/AR technologies to stimulate e-learning and promote innovations in higher education. It has a great impact on providing education and training to students through e-learning paradigm [37]. It allows the education system to deal with accessible information and knowledge with computer-generated virtual imagery information to be overlaid onto the real-world environment which makes learning more interesting and exciting [57]. In higher education, the theoretical framework categorizes different VR/AR experiences those help architects in the evaluation of their buildings in new ways, astronomy students in building 3D solar systems to support more understanding of astronomical concepts as well as medical students for examining the human body in three dimensions [9,21,30]. The simulation of training regarding dangerous, expensive or inaccessible places and events are made possible using VR simulation. Thus, embedding VR/AR in a higher educational system encourages educators to design VR/AR ready content in such a way that it creates more interest and improves quality of education by developing effective e-learning materials.

In recent decades, the EEG-based educational games have captured a great attention to provide a promising solution for improving learning skills of students [20]. Students can experience learning with a lot of fun by applying their thoughts by playing games through wearable EEG headsets. The EEG-based educational games also help in the evaluation of students’ performance in their problem-solving skills [12]. The EEG technology captures brain signals in the form of brainwaves to be processed for determining the learning style of the students effectively. A better understanding and monitoring of such brainwaves helps to analyze the cognitive skills of students [45]. It has a decisive impact on the improvement, efficiency, and effectiveness of teaching and learning processes [29]. The brain-computer interface models are making their contribution to the higher education by developing educational games. An EEG-based gaming technology develops affordable, scalable, and highly portable learning games. There are a number of serious games based on EEG technology those have been developed for analyzing and improving the learning behavior of students [47].

The present cloud/fog computing technology has a primary contribution to support e-learning in higher education. It helps in making innovative e-learning applications to put education level to a new milestone [23]. It possesses the potential to shift static stand-alone VR/AR applications in the dynamic shared environments that can be accessed online [6]. In addition, it enhances the VR/AR experiences by providing virtual contents those can be updated at any time/anywhere by the teachers. Figure 1 shows three approaches to realize the VR applications with cloud/fog based deployment. Figure 1a represents the rendering process of VR content at the cloud data-center. The primary advantage of this approach is that it allows students to experience VR/AR from anywhere, anytime, and with any device [55]. In contrast, many VR applications need ultra-low delay along with minimum network congestion. The rendering at remote edge server is an alternative and depicted solution is shown in Figure 1b where edge servers are located at the network gateways but those need remote migration support of VR applications between edge servers that increases an additional migration delay. Finally, the third approach is depicted in Figure 1c which allows rendering process at local fog nodes those are located within the physical space like classrooms, laboratories, and building, etc. This approach is better for delay-sensitive VR applications as compared to previous approaches but it has limited mobility which makes it less suitable for EEG-based VR applications [1].

The EEG based gaming applications are mainly characterized by their high level of interaction and speed. Since rendering process of gaming applications requires optimum bandwidth with low delay, the main challenge is to cope with
the dynamic variability of available hardware as well as the bandwidth [31]. Consequently, the VR/AR technology enabled delay-critical EEG-based gaming applications face following challenges in present cloud/fog based deployment: (i) to handle a huge volume of real-time data generated by EEG headsets; (ii) to handle scalability issues due to bandwidth congestion; (iii) to reduce unbearable transmission delay that degrade learning experience; and (iv) balancing energy consumption of mobile devices, fog nodes and cloud data-centers. In order to address aforementioned challenges, an Optical-Fog assisted EEG-based virtual reality framework is proposed that enhances the learning experience by providing an e-learning environment which is more immersive and adaptive.

The optical network technology has emerged as fast and reliable backbone network with the capability to extend fog and cloud computing concepts by using its fundamental processing elements laying across the network. The passive optical network (PON) can provide a most promising solution for the heterogeneous computing environment. It supports the on-demand capability, multi-layer oriented network management and optimization of computing resources of underlying network [17]. For delivering cloud-based services (Infrastructure, Platform, and Software), PONs are considered as most effective and cost-efficient cloud-ready network due to their elasticity and on-demand bandwidth availability. Presently, they are more widely used by mobile 3/4/5G wireless networks to access cloud-based applications with minimum delay and less network congestion. In the rapidly growing use of cloud-based applications, fourth-generation, fifth-generation, future-ready sixth-generation and seventh-generation wireless technologies will play a tremendous role to provide heterogeneous connectivity, device-to-device, and machine-to-machine communication, etc. [13].

The proposed framework uses an Edge-Fog layer and Optical-Fog layer [46] of the optical network for providing effective solutions to run an EEG-based gaming applications. The rendering of gaming application is performed at the optical fog nodes without adding network congestion and any additional network delay. The rich immersive environment is experienced by the students because the delay-sensitive tasks are processed on local fog nodes (such as routers, switches, Optical Network Units, etc.) rather than being transmitted to cloud data-centers. The framework is adaptive in the sense that the games with immediate feedback are able to respond students’ experience, knowledge, and their thoughts to optimize their learning experience and improve the efficiency of the gaming applications. In addition, the proposed framework efficiently manages resources to play EEG-based real-time educational games running at diverse geo-locations. Our framework provides a true online, real-time experience with fast processing and minimum delay in response. The acronyms used in this paper are defined in Table 1.

The following sections of this paper are organized as follows. Section 2 introduces the related work. In order to enhance e-learning, an Optical-Fog assisted EEG-based virtual reality framework is proposed in section 3. The performance evaluation is explained in section 4. Finally, section 5 concludes the paper.

2 | RELATED WORK

There is no research work available in Scopus database for enhancing e-learning experience using EEG-Based Virtual Reality in fog/cloud environment. Besides, none of the researcher has addressed the minimum delay and low energy consumption of fog/cloud data-centers those are overbearing for real-time applications. Therefore, in this section, the contribution of virtual reality in education and the impact of gaming application in e-learning is presented.

2.1 | Virtual reality in education

Hashemipour et al. [25] presented a Virtual Learning System (VLS) which consists of a comprehensive and conducive environment to be incorporated in the field of mechanical and manufacturing engineering. They also implemented a tutorial monitoring application for evaluating learning process through VLS. Hwang and Hu [27] proposed a collaborative, VR enabled interactive future ready mathematics classroom to facilitate the solving of the three-dimensional geometric problem. It has integrated representational tools, virtual manipulators, and a whiteboard those help students to synchronously review and manipulate 3-D objects. Flanders and Kavanagh [19] developed a tool called “Build-A-Robot” by using Virtual Reality Modeling Language (VRML), MATLAB, and the Simulink 3D Animation Toolbox. It allowed robotics students to study the forward kinematics of serial robot arms according to the Denavit–Hartenberg convention. Barata et al. [5] used virtual reality for engineering students to provide training with the more concrete representation of power substations or generating

<table>
<thead>
<tr>
<th>TABLE 1 List of acronyms</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>PON</strong></td>
</tr>
<tr>
<td>OLT</td>
</tr>
<tr>
<td>ONU</td>
</tr>
<tr>
<td>QoE</td>
</tr>
<tr>
<td>SDN</td>
</tr>
<tr>
<td>RFC</td>
</tr>
<tr>
<td>MPCP</td>
</tr>
<tr>
<td>MAC</td>
</tr>
</tbody>
</table>
plant. It promotes students to achieve an understanding regarding their operations. They also developed a VR-based authoring tool that provided visualization of an electric and installed transformer in an electric power substation where students are allowed to perform virtual maintenance and operating procedures on it. Violante and Vezzetti [51] demonstrated a web-based interactive learning application explicitly designed to train the bio-medical engineering students. A virtual 3D electroencephalogram and Kano's quality model are used to measure the satisfaction level of the learning application. Alhalabi [2] applied VR for engineering students to compare major VR enabled educational systems with the traditional education methods. An effective comparison was presented between the Corner Cave System (CCS) and the Head Mounted Display (HMD) system for tracking the movements of students in the virtual environment. They evaluated its impact on the students’ achievements in engineering colleges along with favorable results.

Passig et al. [42] combined 3D IVR (immersive virtual reality) with the applied mediation strategies to enhance unique characteristics of students. They found that the increasing evidence using 3D IVR is able to cultivate the cognitive learning style of students with the dynamic assessment. The findings indicated that teaching practices used in 3D IVR environment are better. Takala et al. [49] implemented 16 different VR applications to instruct 45 students during their curriculum that augmented the learning experience. The learning method prompted students to meet their particular learning goals with effective VR teaching applications. Huang et al. [26] evaluated the learner’s acceptance in the VR learning environment. They developed a prototype for a 3D VR learning system to evaluate real-time performance of students. In order to investigate learner's attitude toward learning via VR applications, they distributed a questionnaire survey to the students from 167 different universities. Experimental results show the VR has a positive impact on the behavioral intention of the learners.

Parmar et al. [41] evaluated the effects of an interactive 3D simulation to train electrical students on psychophysical skills education. They compared an immersive head-mounted display (HMD) with a limited desktop-based virtual reality (DVR) using a spatial user interface. Their results revealed a significant benefit of using HMD in learning with high-level concepts. In addition, students experienced better task performance using HMD viewing as compared to DVR viewing. Ip et al. [28] depicted a virtual reality-based model to enhance emotional and social adaptation skills of students. They considered learning scenarios those focused on the emotion control, relaxation strategies, and simulating different social situations for the students. The learning scenarios were presented by using immersive virtual reality environment along with non-intrusive motion tracking. Results show the significant improvements in the measures of their emotional expression, regulation, and social-emotional behavior.

### 2.2 Learning through educational games

Merchant et al. [39] presented instructional design principles for games, simulation and virtual worlds in the context of virtual reality technology to enhance the learning. They experimented quasi-experimental research designs for evaluating the effects of the virtual reality-based instruction on the three categories of students. A total of 13 studies with 3,081 students in the category of games, 29 studies with 2,553 students in the category of simulation, and 27 studies with 2,798 students in the category of virtual worlds were meta-analyzed. The results suggested the educational games were more effective than simulations in virtual worlds for improving learning outcome gains. Chumerin et al. [15] introduced an EEG-based game to analyze the steady-state visual evoked potential (SSVEP) responses. The parameter values were derived through experiments those provided an acceptable trade-off between accuracy of game control and interactivity. Wehbe et al. [53] highlighted the importance of watching a game-play video before playing the actual EEG-based game. They compared two game-play situations: playing an EEG-based game before watching a game-play video and playing an EEG-based game after watching a game-play video. Their results indicated that presentation order of the video game matters and players are more aroused when watching a game-play video before playing.

Martinez et al. [38] developed a vibrotactile prototyping toolkit that facilitates the prototype and tests new vibrotactile interaction techniques for enhancing the sensation of immersion in VR based games. The player was provided the capability to involve virtual objects those augmented the impression of reality as well as improved the performance of the game. Cowley and Ravaja [16] studied the impact of the electroencephalogram based gaming applications along with associated psychophysiology. Forty-five players were selected for playing the Peacemaker (Impact Games 2007) game and their electroencephalography and other physiological signals were measured during the game. They extended the analysis of the physiological signals and their relationship to the learning scores of students.

Braghirolli et al. [10] presented the statistical evaluation of students’ academics in engineering education by introducing educational games in their first year of undergraduate degree programs. Their proposal motivated students to participate and to understand the course content effectively. Falcao et al. [18] highlighted the engagement of students toward learning in the educational world permeated with digital technologies. They analyzed the engagement of high school students’ in devising educational games with the aims to provide an alternative to the traditional educational system.
Activity theory was used to analyze participant observation, questionnaires, and social network interaction. For the same, they identified four groups of students with similar needs and motivations. Each group was engaged at different levels granting to the nature of their tasks, interaction with peers and educators, and personal expectations. Calvo [11] presented an empirical study for measuring the effect of the educational game in the context of acquisition and perceived learning gains. He showed that students those had access to the gaming content, performed statistically better. Students found the gaming material more appealing and helped to expand their learning skills.

Walter et al. [52] demonstrated an EEG-based learning environment to cultivate the learning skills of students. They used a prediction model to estimate the learner’s workload to get an inconspicuous workload measure. Their results authenticated the use of EEG as an inconspicuous measure for the cognitive workload to adapt the learning content. Ghergulescu and Muntean [22] presented a game-based e-learning solution that influences participation, progression, and possession of students to maximize their learning outcomes using engagement modeling. They also identified an important metric referred as TimeOnTask for computing the spell of time required by the player to accomplish a task through engagement modeling. The result showed that the threshold value for generic engagement metric with 76.2% of the variance in engagement change.

3 | PROPOSED MODEL

3.1 | Optical Fog network for EEG based VR gaming applications

In order to provide ultra-low delay and optimum bandwidth for an EEG-Based Virtual Reality Framework, SDN-based Optical-Fog network is proposed as shown in Figure 2. It uses the computing resources of the optical network rather than the cloud resources. The first fog layer is called Edge-Fog layer and the second layer is referred as Optical-Fog layer.

Optical-Fog layer utilizes PONs, optical line terminals (OLTs), and especially optical network units (ONUs) in the middle-ware of the cloud computing environment. In an optical network, PON is connected to multiple OLTs and each OLT is connected to several ONUs those vary from 16 to 256. These ONUs have their own processing, storage, and interconnection capabilities those are used to design Optical-Fog layer.

To ensure high gaming experience and offer the quality of experience (QoE) to the students for EEG based VR gaming applications, the Edge-Fog layer and Optical-Fog layer are utilized. The game logic is executed at the Optical-Fog layer, and VR scenes are encoded and streamed to the Edge-Fog layer. Since the games can be played across the distributed geo-locations, Software Defined Network (SDN) controller is used to execute the game logic that improves the QoE by minimizing the delay [3].

The SDN-based controller optimizes the flow distribution among the various redundant paths inside the optical fog network that reduces the delay experienced by the players. In the optical fog network, each received packet is matched with the flow table of each fog device. If no entry is found, the packet is sent to the SDN controller, which finds the optimum path and forward the packet in the network. Once the path is chosen, a new entry is added in the flow table of fog device for future packets. The traditional SDN controller uses different criteria like least delay, less hop-count, etc. to find the optimum path [4]. In contrast, the proposed SDN controller identifies the shortest path with least congestion among all possible paths from the requesting Core Fog nodes to the Top of Rack (ToR) Fog nodes in the optical network.

It employs congestion aware direct routing by using open loop congestion control mechanism on the basis of buffer availability and historical knowledge of the connection [43]. All nodes in the SDN maintain an estimate for the cost to deliver packets to each destination node c. The estimation $C_n^c(t)$ helps in finding the shortest path with least congestion on the basis of historical knowledge of the connection to node c and waiting time of packets to c in the node n's queue. All nodes in the SDN broadcast a Request For Cost (RFC) frequently to their neighbors. All neighboring nodes update their cost table on the based of received RFC.

In order to model the shortest route with least congestion, the SDN controller select the node with minimum delivery cost. The work flow of SDN controller is shown in Figure 3. The delivery cost is computed with following convoluted parameters referred as Proximity Measure $\Theta_n^c(t)$ and Net Destination Queue Waiting Time $\Omega_n^c(t)$

Proximity Measure:

$$\Theta_n^c(t) = \frac{Q_n^c(t)}{T_n^c(t)}$$
The value of $\Theta^c_n(t)$ lies between 0 and 1. The value 1 indicates the connection between $n$ and $c$ whereas 0 shows that they were never connected. Here, $T^c_n(t)$ is the time increment and $Q^c_n(t)$ is the time duration while $c$ and $n$ remains connected.

Net destination Queue Waiting Time:

$$\Omega^c_n(t) = \sum_{i=0}^{N} \left( \tau - a^c_{n,i} \right)$$

Here $\tau$ is the present time and $a^c_{n,i}$ is the arrival time of packets $i$. Since the queue waiting time is used to predict the congestion, delivery cost can be considered as an exponentially increasing function. Hence, the delivery cost to $c$ via $n$ is computed as:

$$C^c_n(t) = \Omega^c_n(t) \cdot [1 - \Theta^c_n(t)] + C^c_n(t-1) \quad (1)$$

By this way, both Proximity Measure and Net destination Queue Waiting Time not only find the shortest but also least congested path by pulling packets toward the neighbors those have smallest queue. It helps to set the threshold value for which decision is to be made by the SDN controller whether choose or avoid the selected path.

### 3.2 Proposed framework for EEG based virtual reality gaming applications

The architecture of the proposed framework is shown in Figure 4. It has two fog layers named Edge-Fog layer and Optical-Fog layer in the middle of cloud data-centers and remotely participating students. Both fog layers are managed by the fog manager which is responsible to provide ultra-low delay, optimum bandwidth, and ubiquitous computation at the edge rather than cloud data-centers. Each participating student wears an EEG-based VR headset to play the educational multi-player game. The real-time data streaming synchronization among multiple distributed players is provided by the fog manager.

#### 3.2.1 Edge-Fog layer

Edge-Fog layer consists of Data Acquisition module, a Controller module and Publisher module those are embedded in the EEG-based VR headset. Data Acquisition module collects the brain wave signals sensed by the EEG sensors and sends the streamed data to the controller module. The controller module filters the noisy signals and forwards the consistent signals to the Optical-Fog layer. It also updates publisher module with the processing game logic that is to be displayed on the screen of VR headset.

#### 3.2.2 Optical-Fog layer

The major task of the Optical-Fog layer is to process the game logic on optical fog nodes rather than cloud data-centers. This layer has Machine-learning module associated with State
Assessment module and Geo-locator module. The consistent brain wave signals received by the Machine-learning module are the neuronal activity in the brain, diffused through the scalp. Different types of features are extracted from the diffused signal with their amplitude ranges from about 1 to 100 \( \mu V \) in a normal adult. Further, the EEG signals are classified on the basis of the rhythmic activity, which is divided among delta, theta, alpha, beta, and gamma rhythms frequency bands [50]. Table 2 shows the different designations of rhythmic activities distributed for certain biological significance. For example, our brain uses high alpha or low beta frequency band designated as “normal” for thinking and intelligence. Now the classified data are used by the State-Assessment module which assesses the students’ brain state as per game logic. The Geo-locator module gathers the current running state of the game from all participating students. The final game logic is shared with the controller module along with top performing player’s score that increases the impact of multi-player gaming applications. In parallel, a VR/AR Content Manager is accessed by the teachers where they can upload VR/AR ready content in the form for educational gaming applications. This module store VR/AR content on the cloud data-centers that is further synchronized with the EEG enabled VR headset of gaming applications.

3.2.3 Optical-Fog-based gaming modules placement strategy

For deploying gaming modules in the Optical-Fog network, an algorithm is proposed that uses Edge-Fog layer and Optical-Fog layer of the optical network. The Algorithm 3.2.3 explained ahead iterates over all paths from Edge-fog layer to the cloud data-centers in the SDN topology and places gaming modules on each path. For each path, iteration starts from edge devices \( d_{\text{Edge}} \) of Edge-Fog layer to the optical devices \( d_{\text{Optical}} \) and cloud data-centers. It places modules on the devices in incremental fashion. For each fog device \( e \in d_{\text{Edge}} \cup d_{\text{Optical}} \) in the path, the modules those can be placed on it are identified by computing the processing requirement of modules against available processing capability of fog devices.

<table>
<thead>
<tr>
<th>Algorithm 3.2.3: Optical-Fog-based gaming modules placement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data: ( M )</td>
</tr>
<tr>
<td>while ( P ) is less all SDN path do</td>
</tr>
<tr>
<td>List Placed Modules;</td>
</tr>
<tr>
<td>while Fog devices ( (d_{\text{Edge}} \cup d_{\text{Optical}}) ) ( P ) do</td>
</tr>
<tr>
<td>List ModulesToPlace;</td>
</tr>
<tr>
<td>while module ( g ) ( G)amingApp do</td>
</tr>
<tr>
<td>if ( \text{All predecessors of } g \in \text{Placed Modules} ) then</td>
</tr>
<tr>
<td>Add ( g ) to ModulesToPlace;</td>
</tr>
<tr>
<td>end</td>
</tr>
<tr>
<td>end</td>
</tr>
<tr>
<td>while Module ( M ) ( G)ModsToPlace do</td>
</tr>
<tr>
<td>if ( (CPU_M^e &lt; CPU_{\text{Optimal}}^e) ) then</td>
</tr>
<tr>
<td>Allocate ( M ) on ( d_{\text{Edge}} );</td>
</tr>
<tr>
<td>if ( (CPU_M^o &lt; CPU_{\text{Optimal}}^o) ) then</td>
</tr>
<tr>
<td>Migrate ( M ) on ( d_{\text{Optical}} );</td>
</tr>
<tr>
<td>end</td>
</tr>
<tr>
<td>else</td>
</tr>
<tr>
<td>if ( (CPU_M^c &lt; CPU_{\text{Optimal}}^c) ) then</td>
</tr>
<tr>
<td>Choose ( M ) such that ( (M' &gt; M \text{ AND } M' = \text{Low-Delay-Sensitive}) ) if ( (\text{NULL}) ) then</td>
</tr>
<tr>
<td>Allocate ( M' ) on cloud data-centers;</td>
</tr>
<tr>
<td>Allocate ( M ) on ( d_{\text{Edge}} );</td>
</tr>
<tr>
<td>end</td>
</tr>
<tr>
<td>Allocate ( M ) on cloud data-centers;</td>
</tr>
<tr>
<td>end</td>
</tr>
<tr>
<td>end</td>
</tr>
<tr>
<td>end</td>
</tr>
</tbody>
</table>

A module \( M \) can be placed on a fog device \( d_{\text{Edge}} \) or \( d_{\text{Optical}} \) only if all other modules that can be placed toward Edge-Fog layer are already placed in the bottom-up path. The algorithm tries to place the identified modules on to the fog devices one-by-one. Let a module \( M \) is being placed on fog device. Initially, it is checked if any instance of \( M \) is already placed on \( d_{\text{Edge}} \) even it can be part of some other bottom-up path. If so, those instances are collected and placed on \( d_{\text{Edge}} \) only if it can accommodate the collected instances. In contrast, the devices toward Optical-Fog layer are searched to place the collected instances in same manner. However, if none of the fog device has an instance of \( M \), the module is placed on the cloud data-center.

### Table 2: Different designations of rhythmic activities

<table>
<thead>
<tr>
<th>Brain state</th>
<th>Frequency range</th>
<th>Frequency band</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deep, dreamless sleep</td>
<td>1–3 Hz</td>
<td>Delta</td>
</tr>
<tr>
<td>Intuitive, imaginary, sleepy</td>
<td>4–7 Hz</td>
<td>Theta</td>
</tr>
<tr>
<td>Relaxed, but not drowsy</td>
<td>8–9 Hz</td>
<td>Alpha1</td>
</tr>
<tr>
<td>Normal, relaxed yet focused</td>
<td>10–12 Hz</td>
<td>Alpha2</td>
</tr>
<tr>
<td>Normal, relaxed yet focused</td>
<td>13–17 Hz</td>
<td>Beta1</td>
</tr>
<tr>
<td>Active thinking, alertness</td>
<td>18–30 Hz</td>
<td>Beta2</td>
</tr>
<tr>
<td>Higher mental activity</td>
<td>31–40 Hz</td>
<td>Gamma1</td>
</tr>
<tr>
<td>Higher mental activity</td>
<td>41–64 Hz</td>
<td>Gamma2</td>
</tr>
</tbody>
</table>

4 PERFORMANCE ANALYSIS

The EEG-based gaming applications to be played among remotely located students require optimum bandwidth and ultra-low delay. The proposed Optical-Fog network solves
this problem by processing the game logic near to students. In addition, the QoE is improved by evaluating the energy consumption, bandwidth usage, and delay measure for the optical fog network used in the cloud as well as fog computing.

4.1 Delay measure

Delay measure in the context of delay is considered as the most concerning issue to improve QoE performance. A Multi-Point Control Protocol (MPCP) is used for ONU-OLT communication [40]. MPCP is a frame-based protocol that uses five MAC control messages called REGISTER_REQ, REGISTER, REGISTER_ACK, GATE, and REPORT [7].

Our proposed framework reduces the delay especially when Optical-Fog layer is being utilized by the game logic. In the standard communication scenario, GATE and REPORT messages are exchanged between OLT and ONU. Therefore, the delay is defined for a request as the time between the arrival of its last bit at ONU and the arrival of its last bit at OLT in the optical fog network. In other words, it is the time duration when respective REPORT message completely arrives at OLT (or equivalent queue status update). Thus, the delay $t_D(i)$ for request’s frame can be computed by adding three basic components shown in the following equation:

$$t_D(i) = \Gamma_i + t_p + t_R$$  \hspace{1cm} (2)

where $\Gamma_i$ is the one-way propagation time of ONU, $t_p$ is the time between the request arriving at ONU and the start of next REPORT message, and $t_R$ is the time duration of REPORT message [8]. The Optical-Fog layer processes more cloud-based applications those involve low-delay performance and achieve efficient QoS requirements.

4.2 Bandwidth measure

EEG-based gaming applications produce the extraordinarily huge volume data to be processed. Thus, the system poses a substantial burden on communication bandwidth that can increase unbearable transmission delay and degrades QoE to the playing students. Optical Fog network effectively ease the bandwidth burden and reduce transmission delay. Here, the heterogeneous network has different bandwidth constraints for both Edge-Fog layer and Optical-Fog layer over a vast geographical area. For simplicity, the bandwidth availability at Optical Fog layer is much higher than the Edge-Fog layer due to the usage of PON Network. In order to measure the communication bandwidth constraint, the traffic rate $\lambda_{ij}$ is assumed to be dispatched from the fog node $i$ located at Edge-Fog layer to the server $j$ located at cloud data-center through the transmission path. There is a limitation $\lambda_{ij}^{\max}$ on the bandwidth capacity of each path. Thus, the bandwidth constraint is computed as

$$0 \leq \lambda_{ij} \leq \lambda_{ij}^{\max}, \forall i \in N_{fog} \text{ and } \forall j \in M_{cloud}$$  \hspace{1cm} (3)

Here, $N_{fog}$ and $M_{cloud}$ are the set of fog devices and set of servers of cloud data-centers, respectively. The optical fog network is more powerful and energy-efficient than the traditional cloud/fog network. It significantly improves the QoE by using computation resources near to the participating student that leads to optimum bandwidth and reduce communication delay.

4.3 Energy consumption analysis

The energy consumption of the proposed framework is evaluated for the heterogeneous computing environment by computing the energy consumed by all the edge devices located at the Edge-Fog layer. Whereas energy consumption of PON, OLTs, and ONUs are considered at the Optical-Fog layer. The total energy consumption by the proposed framework is shown by the following equation:

$$\Delta E = E_{Edge-Fog} + E_{Optical-Fog} + E_{Cloud}$$  \hspace{1cm} (4)

- $E_{Edge-Fog} = \Sigma(E_{Edge-devices})$ is the energy consumed by all edge devices at Edge-Fog layer.
- $E_{Optical-Fog} = \Sigma(E_{ONU} + E_{OLT} + E_{PON})$ is the energy consumed by the optical elements at Optical-Fog layer.
- $E_{Cloud}$ is the energy consumed by the cloud data-centers.

The computations those are performed only on cloud data-centers increases the overall energy consumption. On the other hand, in our proposed framework most of the computations are performed at Edge-Fog layer and Optical-Fog layer that leads to less overhead on the cloud and improves the QoE.

4.4 Experimental setup

An experimental setup is simulated for evaluating the efficiency of the proposed framework in terms of delay, bandwidth usage, and energy consumption. The IFOgSim toolkit [24] is used to model and measure the impact of EEG-based gaming application in Optical-Fog environment. It supports the customize configuration for implementing hierarchical composition of edge devices, fog nodes, and cloud data-centers, etc. The toolkit is configured with two deployment strategies namely cloud-based deployment and Optical-fog-based deployment.

The cloud-based deployment uses the rendering of all gaming applications modules onto the cloud data-centers.
On the other hand, Optical-Fog-based deployment runs the application modules at both Edge-Fog layer and Optical-Fog layer those are close to the edge of the network. However, devices located at the Edge-Fog layer are not computationally powerful enough to host all modules of the gaming application. Therefore, the devices of Optical-Fog layer are used to run the remaining modules. The proposed Algorithm 1 is utilized to demonstrate the interplay of the game among the Edge-fog layer, Optical-Fog layer, and the cloud data-centers. The performance is computed for comparing the results of two distinct scenarios. In contrast to cloud-based deployment scenario, the Optical-Fog based deployment is implemented by configuring the node with higher computing capability along with optimum bandwidth.

In our experiment, the playing environment of an EEG-based game is simulated [56]. Each EEG headset is a Bluetooth enabled device which is connected to the smartphone of the student. The internet connectivity is provided by configuring local WiFi gateways those are connected to the back-end ISP. In order to increase the workload, WiFi gateways are increased in a linear manner during the experiment. Since the delay between interconnected devices influences the performance, the delay between source and destination devices are fixed for simulation as listed in Table 3. In this game, the participating students have to make concentration on the objects. The student who has a better concentration on an object can attract more objects to his/her side and win the game. Here, The Optical-Fog network facilitates the fast processing and ultra-low response time to improve a real-time gaming experience.

4.5 Results and discussion

In EEG based games, the delay of response is a major concern because severe delay affects the gaming experience. Therefore, real-time processing is required, which is responsible for shifting the value of student’s brain-state as game state and display on the screen of the mobile device. The average delay of response is illustrated in Figure 5a which shows that the proposed framework experience drastically less delay as compared to cloud-based deployment.

Figure 5b shows the bandwidth usage of the proposed framework. In cloud-based deployment, the increasing numbers of connected devices lead to network congestion that degrades the performance of the game. On the other hand, when fog devices are taken into consideration, the issue of delay is resolved because the data are preprocessed near to the source. Energy consumed by fog devices, mobile devices, and cloud data-centers during the simulation is depicted in Figure 6. Here, two deployment scenarios, that is, Optical-Fog-based and Cloud-based deployments are taken into consideration for analyzing the trade-off between energy consumed by the mobile devices in both cases. In Optical-Fog-based deployment, only the controller is deployed on Edge-Fog layer while state-assessment, machine learning, and Geo-locator modules are deployed on the Optical-Fog layer. Since the most of the processing of modules are processed by the fog devices, the energy consumed by cloud data-centers are less. It is assumed that the data acquisition and publisher modules consume a very less amount of energy as compared to other modules. Therefore, they are not taken into consideration.

Whereas, in the traditional Cloud-based deployment, all processing modules are deployed only at the cloud data-centers. In this scenario, the fog devices are used only for the routing purpose those consume negligible energy and most of the processing is done at cloud data-centers. Here, the mobile devices of students experience more delay and network congestion that leads to increase in the energy consumption and fast battery drainage.

4.6 Findings

Optical network and cloud computing are emerging as an attractive solutions to enhance the gaming experience for the EEG-based virtual reality framework. Rather than outsourcing all gaming modules to the cloud data-centers, the proposed framework uses devices on the Edge-Fog layer as well as Optical-Fog layer of the optical network. The substantial amount of interaction takes place among the gaming module. The devices of Optical-Fog layer have enough processing capability to process them at the edge of the network, thus reducing delay and network

<table>
<thead>
<tr>
<th>Source device</th>
<th>Destination device</th>
<th>Delay in milliseconds</th>
</tr>
</thead>
<tbody>
<tr>
<td>EEG headset</td>
<td>Mobile device</td>
<td>4</td>
</tr>
<tr>
<td>Mobile device</td>
<td>Local WiFi gateway</td>
<td>2</td>
</tr>
<tr>
<td>Local WiFi gateway</td>
<td>ISP gateway</td>
<td>3</td>
</tr>
<tr>
<td>ISP gateway</td>
<td>Cloud data-center</td>
<td>120</td>
</tr>
</tbody>
</table>
congestion. Results show that the Optical-Fog network reduces the delay as well as safeguards the system from the key issue of scalability. Whereas in cloud-based deployment, these modules reside at the cloud data-centers those are interconnected by noticeable delay link. This situation scenario leads to more network usage. However, the total energy consumption in Optical-Fog-based deployment is also less than the energy consumed in the cloud-based deployment.

5 | CONCLUSION

Optical-Fog network provides several benefits to the EEG-based virtual reality framework like high scalability, optimum bandwidth capacity, cost-effective services, and relatively low energy consumption. The proposed framework effectively enhances the QoE while playing EEG-based games from distributed geographical locations. The Optical-Fog-based module placement algorithm and concurrent inter-connection among the gaming modules enhance the QoE and make learning through games more entertaining. The SDN controller efficiently identify the less congested shortest path which reduces the delay. The performance evaluation section effectively interprets the measure of delay, network usage, and energy consumption of the proposed framework in both Optical-Fog based and cloud-based deployment scenarios. The results highlight that Optical-Fog-based deployment provides better gaming platform with ultra-low delay, optimum bandwidth requirement, and minimum energy consumption to enhance QoE. Our future work will involve the integration of large-scale 5G, optical network, and educational technologies to ensure robust and resilient e-learning through educational games.

ORCID

Kiran D. Singh http://orcid.org/0000-0002-8154-0986

REFERENCES


34. M. Lorenz et al., I’m there! the influence of virtual reality and mixed reality environments combined with two different navigation methods on presence, Virtual Reality (VR), 2015 IEEE, IEEE, Arles, France, 2015, pp. 223–224.


---

S. K. Sood did his PhD in Computer Science & Engineering from IIT Roorkee, India. He completed his M Tech, in Computer Science & Engineering, from G.J.U., Hisar, India. He is currently working as an associate dean (A.A. & S.W.), head & professor of Computer Science & Engineering Department, G.N.D.U. Regional Campus, Gurdaspur. He has 16 years of teaching and 8 years of research experience. He has more than 60 research publications. His work is published and cited in highly reputed journals such as JNCA, Elsevier, and Security and Communication Networks, Wiley. He completed a major research project in cloud computing. His citation number according to Google Scholar is 694 with h-index equal to 13 and i10-index equal to 17. His research areas are network & information security, cloud computing, big data, and internet of things.

K. D. Singh is pursuing his doctoral degree in Computer Science and Engineering from Guru Nanak Dev University, Amritsar. He received his M. E. degree in Software Engineering from Thapar University, Patiala. His current working research areas include Internet of Things (IoT), big data, and cloud computing.

How to cite this article: Sood SK, Singh KD. An Optical-Fog assisted EEG-based virtual reality framework for enhancing E-learning through educational games. Comput Appl Eng Educ. 2018;1–12. https://doi.org/10.1002/cae.21965