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AN INTELLIGENT ROUTING APPROACH FOR MULTIMEDIA TRAFFIC TRANSMISSION OVER SDN

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Abstract—Multimedia applications such as video streaming services have become popular, especially with the rapid growth of users, devices, increased availability and diversity of these services over the internet. In this case, service providers and network administrators have difficulties ensuring end-user satisfaction because the traffic generated by such services is more exposed to multiple network quality of service impairments, including bandwidth, delay, jitter, and loss ratio. This paper proposes an intelligent-based multimedia traffic routing framework that exploits the integration of a reinforcement learning technique with software-defined networking to explore, learn and find potential routes for video streaming traffic. Simulation results through a realistic network and under various traffic loads, demonstrate the proposed scheme's effectiveness in providing improved end-user viewing quality, higher throughput and lower video quality switches when compared to the existing techniques.

Index Terms—multimedia traffic, QoE, QoS, SDN, reinforcement learning

I. INTRODUCTION

With large-scale video traffic and various mobile devices; guaranteeing the quality of experience (QoE) for all customers becomes a challenging task even faced by 5G/future networks. According to the Cisco's Annual Internet Report (2018–2023), the total number of global mobile subscribers will expand from 66% of the population in 2018 to 71% by 2023 [1]. Video streaming services take the lead in most bandwidth-hungry applications since they contribute to most Internet traffic. Therefore, an intelligent video streaming traffic transmission is needed to allow Quality of Service (QoS) provisioning and to improve users' satisfaction with the media services. In this regard, innovative solutions and emerging technologies are researched to meet the increasing demand for exceptional service expectations, such as Software Defined Networking (SDN), Network Function Virtualisation (NFV), Multi-access Edge Computing (MEC), and Cloud/Fog Computing (C/FoC) [2]–[5].

SDN is an innovative networking technology, drawing expert committees' attention to study its application further and address potential benefits [6]. It is noteworthy that dynamic traffic routing systems reinforce several protocols and allow controlling traffic flows on the fly by monitoring network and flow conditions. Thus, leading to a fast adaptation to the dynamic traffic changes and unrestricted support to various QoS demands. Machine learning (ML) techniques are exploited to

acknowledge a dynamic routing approach for multimedia transmission over softwarised networks. A significant branch of ML, reinforcement learning (RL), can learn from experience by realising interaction between its agent and the environment. This has the potential of achieving effective solutions for the intelligent routing optimisation problems that the SDN network needs to solve.

This paper presents a new framework-based multimedia traffic transmission approach; leveraging the RL method with SDN. The scheme allows for the exploration, learning, and exploitation of possible multimedia traffic routes by considering link-state factors and network information. The proposed framework aims to improve end-user satisfaction toward Dynamic Adaptive Streaming over HTTP (DASH)-based video flows. It is operated on a realistic SDN-enabled network and built using an emulated test-bed with actual video content broadcast via a multimedia server. It is also compared to other available solutions concerning throughput, video quality switches, video multimethod assessment fusion (VMAF), and structural similarity index measure (SSIM).

The remainder of this paper is organised as follows. Section II provides the related work in the area of applying RL for multimedia traffic transmission over SDN. Section III presents the architecture of RL-based multimedia traffic routing. Section IV highlights the problem definition and the proposed solution. Section V discusses the simulation setup and evaluation. Results and discussions are outlined in Section VI before concluding our work in Section VII.

II. RELATED WORK

Due to the widespread deployment of multimedia applications and the development of softwarised networks, the study of QoS/QoE provisioning has become crucial. Several studies discussed integrating ML techniques with the SDN environment, the work in [7] introduced a novel RL-based approach for determining the ideal time for adjusting the video bitrate and redirecting traffic flows to decrease packet loss. They stated that the proposed scheme performs better than standard routing and greedy-based methods; however, they only focused on small-scale topological cases. Sendra et al [8] developed a route optimisation solution based on the RL method for SDN to achieve better QoS characteristics, compared to previous studies. Three factors; latency, loss ratio, and bandwidth are taken into account by their approach, which uses the RL-agent to find the best routes at the lowest possible cost. Moreover, the study in [9] suggested LearnQoS, an intelligent QoS control system for multimedia traffic over SDN-enabled networks. In order to assure QoS compliance for multimedia traffic, their architecture employs RL method to enhance the functioning of a policy-based network management system.

Furthermore, the work reported in [10] offered a deep RLbased adaptive technique for managing multimedia traffic flow in SDN. Their technology implements a flow control strategy straight from experience and realises bandwidth allocation for maximising the overall QoE of their clients. Jawad et al. [11], [12] proposed a novel framework that employs the RL technique to select the best method from a range of existing routing algorithms on multimedia traffic flows to enhance QoS provisioning. Additionally, in [13], authors presented a new RL-based multimedia traffic transmission approach over SDN-enabled networks that aims to optimise end-user QoE. Their proposed scheme uses the link-state parameters (i.e., available bandwidth, latency, jitter and loss ratio) as RL-agent features to transmit multimedia flows.

III. MODELING AND NOTATIONS

In this section, the SDN model description is explained. It is important since it enables SDN planes' capabilities to exploit further the promise of the softwarised networking in performing QoS provisioning and optimising end-user QoE.

A. Network Architecture

Fig. 1 shows the architecture of the proposed RL-based solution in SDN to improve network QoS with the objective to optimise end-user QoE. It is made up of four elements, which are listed below.

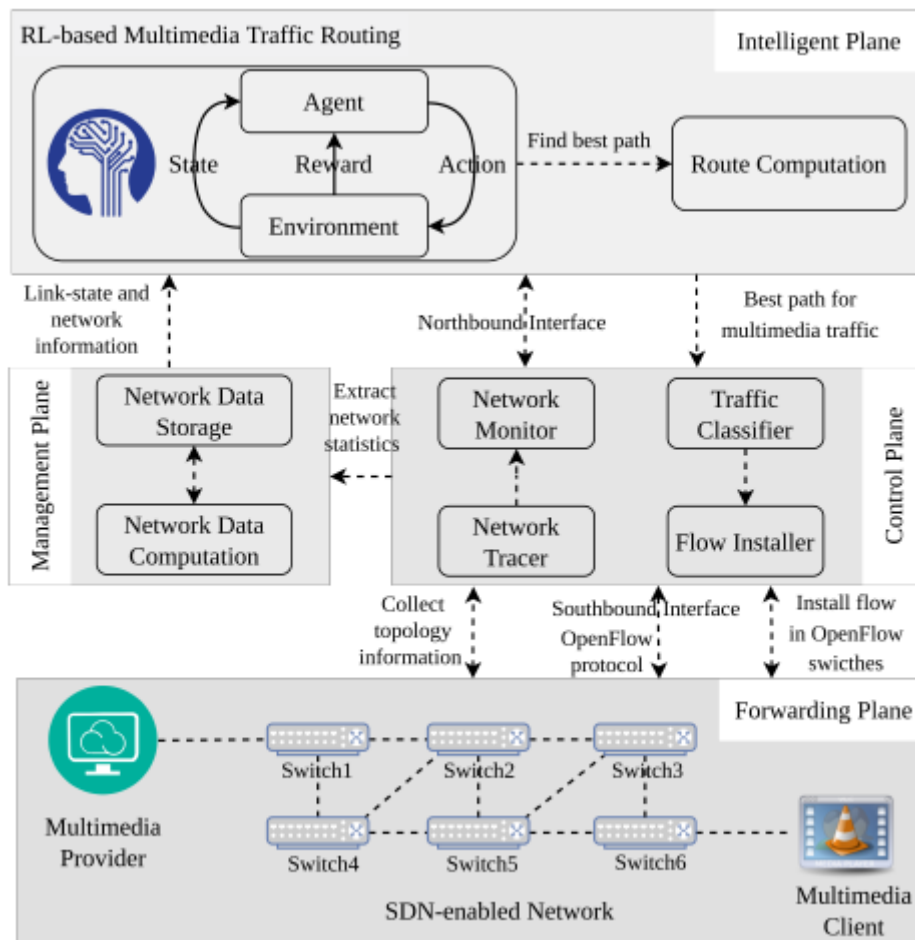


FIGURE 1 THE ARCHITECTURE OF RL-BASED MULTIMEDIA TRAFFIC ROUTING IN SDN.

1) Forwarding Plane: There are three main parts to this plane. 1 Multimedia provider; stores the DASH video content, which consists of video chunks compressed at various bitrates. 2 SDN-enabled network; it is made up of the forwarding OpenFlow switches and links connecting them. A centralised controller is in charge of these components. Incoming packets may be forwarded to one or more ports using OpenFlow switches, or they may be dropped entirely. The live stream traffic is forwarded, relying on the path information established in these switches' flow tables. The switches place emphasis on the other planes to populate and build their routing table while having no knowledge of the network. 3 Clients; are in charge of responding to video services' about their satisfaction as feedback; which echos the end-user QoE. The forwarding plane also exhibits the RL environment, which regularly responds to requests from the centralised controller by providing information related to system topology.

2) Control Plane: The plane communicates with the lower networking elements at the forwarding plane over the southbound interface. It maintains a consistent global network view since it utilised the centralised controller to collect information about network topology which represents the state of the environment. It also includes four main modules. 1 Network tracer; converts the network diagram's physical form into a graphical prototype and reserves its information for other modules. 2 Network monitor; preserves the state of the flow inside the network topology by collecting statistical

information on all flows at regular intervals. 3 Traffic classifier; checks the packet type on-the-fly and decide which path should be utilised for a multimedia traffic flow. 4 Flow installer; performs reactively, meaning that the SDN switches in the forwarding plane behave re-actively to create flow entries on the arrival of packets.

3) Management Plane: The plane includes two modules 1 Network data computation; communicates with the Network statistics module in order to get network information and periodically calculates the link-state parameters: bandwidth, delay, jitter and loss ratio. 2 Network data storage; keeps track of the parameters that the network data computation module processed. It also contains records, highlighting the source and the destination nodes along with the associated tuples of link-state factors.

4) Intelligent Plane: The plane hosts the RL-agent, where it gathers knowledge about the network features from the environment and then utilises intelligence regarding route computation. It interacts with the control and management planes over the northbound interface; acquiring the QoS metrics and network information, finding the optimal path between the client and the multimedia provider.

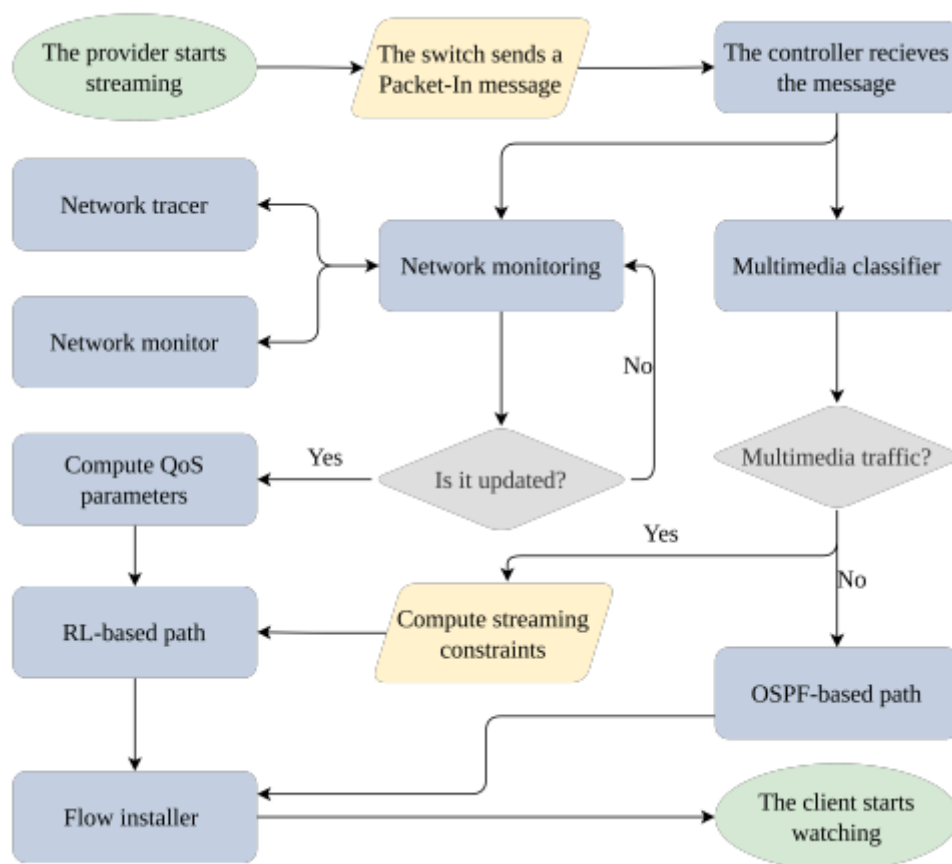


FIGURE 2 THE COMMUNICATION PROCESS OF THE PROPOSED RL-BASED SOLUTION.

B. Communication Process

Fig. 2 illustrates the flow diagram of the communication process. When a client starts to request a video from the multimedia provider over an SDN-enabled network, the OpenFlow switch informs the controller by sending a packet-In message. At this point, the control plane uses the network tracer and the network monitor modules to monitor the network topology at the forwarding plane. The controller checks 'on the fly' which route to choose for a flow according to the packet types. Multiple scheduled events run periodically to keep an overall view of the network topology and collect the required network information. Every 10 seconds, the monitoring event is updated, and it includes two modules;

the network tracer; operates every 5 seconds and the network monitor; runs within the monitoring event. A python-based application, acting every 8 seconds, is developed to compute link delay. This application is executed during the monitoring event of the network topology. At this stage, QoS metrics represented by available bandwidth, latency, jitter and loss rate are measured by utilising the management plane modules. These are then used to facilitate decision-making on the intelligent plane. Finally, the intelligent plane receives these metrics along with the network information, allowing it to apply intelligence to obtain the best route of video streaming traffic between the service provider and the end-user.

IV. RL-BASED MULTIMEDIA TRAFFIC ROUTING

A. Problem Definition

Let the forwarding plane be modeled as an undirected graph structure $G(V, E)$, where V indicates the OpenFlow switches and E is the links that connect the switches. Each link $l \in E$ in the network topology is correlated with a limited capacity C_l that denotes the maximum possible flow f that is permitted to pass across the link. Two different types of flows are corresponded to each traffic flow $F = (F_v \cup F_b)$, in which F_v represents DASH video flows and F_b represents the background flows. A flow in a network is typically described as a sequence of packets transmitted between two endpoints. It is often characterised by the properties of a 5-tuple (source IP, destination IP, source port, destination port, protocol field).

The end-users send requests to a multimedia server to view a video over the SDN network. The objective is to create a viable video flow routing path. If P is the set of possible paths, the routing technique can find a feasible path $p \in P$, which is defined by a group of links $p = l_1, \dots, l_n$ that connect the nodes between the client and the media provider. When multiple traffic flows compete over the link capacity of the network, the link becomes overloaded and congested because the link is handling the traffic flows in excess of its capacity. As a result, traffic flows are more prone to experiencing increased data loss and delay, thereby impacting network QoS and user QoE. In this case, this work proposes an optimisation approach that handles this issue by taking into account a network monitoring, in which the network status is checked on a regular basis, and path decisions are made based on the current condition of network links. Thus, RL-agent responds promptly to increased network traffic and recommends another route for video transmission. As an outcome, the proposed method should offer the clients a better watching experience.

The intention is to allow the agent to learn the next path, hop-by-hop, in order to transmit multimedia traffic flows in a network through links with large available bandwidth while avoiding links with high latency, delay variation and data loss ratio. Data loss ratio and bandwidth of each link in the network topology are measured using OpenFlow port counters. The SDN controller collects the switch port statistics by sending the *OFPortStatsRequest* message. Then, OpenFlow switches send back to the centralised controller, the *OFPortStatsReply* message, which includes the received byte count and other requested statistics. The measurement of delay and jitter of each link follows the method described in [14].

B. RL-based Solution

The presented work aims to enhance the transmission of multimedia traffic by considering integrating the RL technique with SDN to optimise network QoS and user satisfaction with the service represented by QoE. The RL-agent is employed to continue learning a method by interacting periodically with its environment, observing the current state, and then executing an action. After that, the agent will observe a new state, and a reward will be received accordingly. To address the optimisation problem, the agent uses the Q-learning algorithm. Q-learning is a model-free RL method utilised to obtain the optimal action-selection policy by learning the optimal Q-values of each state in which all possible state-action combinations are visited for predefined iterations. [15]. In the

following parts, the detail of the RL-agent and the RL-based video streaming traffic routing method are described.

1) RL-agent: The RL-agent is placed in the intelligent plane and operated by receiving network information and link-state metrics from the management plane. The RL-agent keeps learning based on the prizes it receives until the algorithm converges. Similar to the unsupervised learning, RL does not require labeling data as the supervised learning and generally correlates with four essential terms, which are explained below.

- **State space:** In the proposed scheme, the state space refers to the OpenFlow switches in the forwarding plane. The change from one state to the next reflects the links that connect the SDN switches. The network tracer module creates a topology map with OpenFlow switches representing states in the state space, which it subsequently sends to the agent via the management plane.
- **Action space:** In the proposed scheme, the action selects which neighbouring switch will serve as the next forwarder in order to transmit multimedia packets to a recipient. The actions space also maintains the best multimedia traffic strategy. When designating a route for multimedia flows, the RL-agent learns to find links with low latency, jitter, and packet loss while prioritising links with large bandwidth. The RL-agent traverses all states and takes various actions to estimate the ideal Q-function in Q-learning. Then it modifies and stores the Q-value after each episode in a Q-table, which the RL-agent uses to choose the optimal routing path for a source-destination pair. The Q-value indicates the measurement of the total anticipated prize in the event that the RL-agent is in state S and executes action A . The RL-agent's learning phase consists of a succession of stages known as episodes (0, 1, ..., n , ...). In the n th episode, at time t , the agent executes an action A on a multimedia packet at an existing state S and receives a reward R while proceeding to the subsequent state, S' .

The Q-learning algorithm must be modified to take into account the minimisation criteria in order to solve the optimal video streaming traffic routing problem. To update the Q-value for optimum path routing, the RL-agent uses the modified Q-learning equation shown below.

$$Q(S, A) = \overbrace{Q(S, A)}^{\text{Current Q-value}} + \alpha \left[\underbrace{R(S, A)}_{\text{Reward}} + \overbrace{\min_A Q'\{S', A'\}}^{\substack{\text{Minimum predicted} \\ \text{reward, given new} \\ \text{state} \\ \text{and all possible} \\ \text{actions}}} - Q(S, A) \right] \quad (1)$$

Where α is the learning rate that determines the amount to which newly acquired knowledge overrides old information. $\alpha \in [0, 1]$, a value of 0 forbids the RL-agent from learning from new actions. If the setting is 1, the agent disregards old knowledge and solely values newly learnt information, taking into account the immediate reward for the state-action pair.

- **Exploration-exploitation strategy:** This study selects the ϵ -greedy approach as the Q-learning action policy in order to balance between exploration and exploitation. The ϵ -greedy strategy means that the RL-agent has the probability of ϵ to randomly select the next action and the probability of $1-\epsilon$ to select the action with the highest quality of the current Q-table as the next action. Equation (2) depicts the computation of the ϵ -greedy strategy. This equation is used by the RL-agent to determine the next action to take in a given state. The action with the lowest Q-value is chosen in the suggested RL-based solution; this implies that, instead of finding the path with the largest reward, the solution finds the path with the lowest costs by greedily selecting actions with the lowest rewards.

$$A' = \underset{a \in A}{\operatorname{argmin}} Q'(S, A) \quad (2)$$

where $\underset{a \in A}{\operatorname{argmin}}$ indicates the exploitation of $Q(S, A)$ in regards to action A . The continued greedy exploration maximises the instant reward.

- Reward function: Equation (3) represents the reward in the proposed scheme, which is aimed to determine the optimum multimedia traffic route based on the four QoS parameters: link available bandwidth, latency, jitter, and packet loss ratio denoted by B_l , D_l , J_l , L_l , respectively. The task is to find a path with the least amount of links latency, jitter, and data loss while prioritising links with high available bandwidth to improve end-user QoE. It is worth noting that several influence factors (IFs) might have an impact on the level of satisfaction with streaming media. This study focuses on network-related IFs, which correspond to QoS factors, as it has been identified that such variables have a significant effects on QoE [16].

$$R = w_1 * \frac{1}{B_l} + w_2 * D_l + w_3 * L_l + w_4 * J_l \quad (3)$$

It is important to note that these measures have various units (e.g., available bandwidth in bits per second and latency in milliseconds), which affect quality of learning. As a result, each metric value is normalised to common ranges and scales [17]. The tuning weights w_1 , w_2 , w_3 , and $w_4 \in [0, 1]$ are applied to a specified metric during the reward computation, where $w_1 + w_2 + w_3 + w_4 = 1$. It should be noted that the tuning weights of QoS parameters are given in accordance with the quality standard boundaries and their respective relevance degree, which are presented in [18] in this manner, L_l 58.9%, J_l 15.1%, D_l 14.9% and B_l 11.1%.

2) RL-based video streaming traffic routing method: The proposed routing method is enforced to find the optimal route from the multimedia provider to the end-user in the forwarding plane. Algorithm 1 accepts the topology information, the QoS metrics, learning rate, ϵ -greedy parameter and the learning episodes number as input. The algorithm assigns the Q-values of the Q-table to zeros when media packets are sent over the SDN-enabled network from a specified server to the intended client. As a result, the first learning episode for a particular multimedia packet starts with initialising the state of a multimedia packet at the source SDN switch. Following this, the state begins choosing one action A from the current state S by utilising the ϵ -greedy exploration-exploitation strategy. Then, the algorithm uses the QoS parameters and the state S for reward calculation according to Equation (3) belonging to the action A and finds the new state S' . The next step is to utilise Equation (1) to obtain the Q-function and set the forthcoming state S' as the present state S . The state transition loop persists as this episode finishes, and a new episode begins until S is equal to the desired state (i.e., the multimedia packet reaches the recipient node). In the end, the RL-agent acquires the best route to deliver multimedia packets between the source and destination pairs in which the route fulfils the lowest Q-values determined from the Q-table. After the main objective is achieved, the flow installation module receives the path and installs it to the OpenFlow switches' routing table.

V. EXPERIMENTAL WORK AND EVALUATION

This section describes the experimental setup used to evaluate the effectiveness of the proposed scheme. The following parts include the detail explanation of simulation setup, the learning parameters settings and the evaluation scenario.

Algorithm 1: Q-Learning-based Multimedia Traffic Routing

Input: SDN-enabled network topology: $G(V,E)$
QoS metrics: B_i, D_i, J_i, L_i
Learning rate: α
 ϵ -greedy parameter: ϵ
Training episodes number: n

Output: The optimal path between the multimedia server and the client had the lowest Q-values attained from the Q-table

foreach *Multimedia transmission over* $(v_{src}, v_{dst}) \in V$
do

- Initialise Q : $Q(S,A) = 0, \forall S \in S, \forall A \in A$
- for *episode* $\leftarrow 1$ to n **do**
 - Initialise state $S = v_{src} \in S$
 - while** S' is not v_{dst} **do**
 - Choose an action A from S using ϵ -greedy policy, Equation (2) derived from Q ;
 - $R' \leftarrow R(S,A)$ //The RL-agent earns the prize based on Equation (3); then it observes new state S' ;
 - $Q(S,A) = Q(S,A) + \alpha[R(S,A) + \min_A Q'(S',A') - Q(S,A)]$
 - $S \leftarrow S'$ // Move to the next state;
 - end**
- end**

end

A. Simulation Setup

The architecture is built on Ubuntu, with the Mininet emulator [19] running the forwarding plane. The RYU Controller [20] is used to simulate the control plane, which gathers topology information and transfers it to the management plane to be used by the RL-agent in the intelligent plane, which denotes the environment state that the agent interacts with. The network topology used in the proposed approach is NSFNET network (National Science Foundation's Network) with 14 nodes. The SDN switches replaced the nodes of the utilised topology. Each switch contains a host that forwards and receives various multimedia traffic. A client with streaming capabilities is deployed in the network and acts as a multimedia provider to transmit real-time DASH-based video flows. Due to the emulator limitations, the network topology links capacities have been scaled to 10 Mbps for all links to meet the experimental environment requirements.

B. Learning Parameters Settings

It is important to specify the learning rate α and exploration probability ϵ values before executing the proposed RL-based solution. The agent was able to locate more efficient paths to broadcast the multimedia flows throughout the series of episodes in the occurrence of a likelihood of exploration value of around one with a high value of learning rate. The following parameters are specified after multiple experiments: $\alpha = 0.9$, $\epsilon = 0.8$, and 300 training episodes.

C. Evaluation Scenario

In order to evaluate the proposed solution, multiple testing scenarios are implemented. They highlight the significance of QoS factors and their influence on customer perceptions of video streaming quality. We compare the Open Shortest Path First (OSPF) protocol to our approach in order to evaluate end-users satisfaction with the streaming service. Each testing scenario involves distorting

and capturing the reference video to create the processed video with degradation. During video transmissions, the received video chunks are monitored using Wireshark as the client device’s video traffic monitoring software. This allows for analysing network performance and conducting an objective assessment to measure the perceived video quality in terms of VMAF and SSIM [21], [22]. Both techniques have a high correlation with human vision and enable for efficient computing. The mapping of objective parameters to the nominal Mean Opinion Score (MOS) is shown in Table I. MOS is a 5-point scale known as the most widely used method to evaluate the end-user QoE subjectively [23].

TABLE 1 SSIM AND VMAF TO MOS MAPPING

MOS	VMAF	SSIM
5 (Excellent)	80-100	>0.99
4 (Good)	60-79	≥ 0.95 & < 0.99
3 (Fair)	40-59	≥ 0.88 & < 0.95
2 (Poor)	20-39	≥ 0.5 & < 0.88
1 (Bad)	<20	<0.5

VI. RESULTS AND DISCUSSIONS

The findings of the proposed RL-based solution are presented in this section. To compare the effectiveness of the proposed technique to the OSPF protocol, the parameters, VMAF and SSIM, video quality switches, and network throughput are used. In addition, the Iperf testing tool was utilised to stress the SDN-enabled network. The proposed approach’s performance is assessed using real-time DASH-based video flows. DASH video is available at five different resolutions (1080p, 720p, 480p, 360p and 240p). Each video is split into 4-second segments and encoded into five discrete bitrates using FFmpeg with the H.264 codec to build the DASH manifest and related files. The video material transmitted by multimedia servers is the “Big Buck Bunny” animation, which has a resolution of 1920×1080 pixels and is 5 minutes long [24]. The hosts participating in the experiment have been chosen to allow traffic to flow via the whole network topology.

A. End-users QoE

VMAF and SSIM are highly associated with participant perceptions and offer an effective measurement that reflects the end-user’s QoE. Fig. 3 and Fig. 4 show that the computed VMAF and SSIM values for DASH video. As noticed, the end-users viewing experience is enhanced with the proposed RL-based solution, and the MOS indicates almost an excellent score. The average SSIM values of the DASH video chunks provided by the proposed method achieve 98% when a low traffic load is introduced in the network. Under the same traffic load, the transmission with the OSPF protocol shows a drop in customers’ QoE, reaching the range between good and fair. When the traffic load gets high, the network becomes overloaded, resulting in data loss in traffic flows. Despite this, the VMAF and SSIM results show that our proposed solution outperforms the OSPF protocol, even though the QoE of the end-user drops to good.

B. Network Throughput

Fig. 5 depicts the DASH live stream throughput while the network is under stress. As can be seen, the throughput of the OSPF-based strategy decreases as the packet loss rate increases. Despite this, both schemes exhibit nearly identical performance, ranging from 0 to 100 seconds, as shown in Fig. 5a. However, when the video streaming transmission continues, the throughput reduces and stays consistent at 2000 Kbps with the OSPF protocol due to the minimal background traffic on the network. At this point, the client encounters rebuffering events caused by the decreasing throughput problem, which lowers the perceived QoE. In contrast, the proposed solution achieves superior

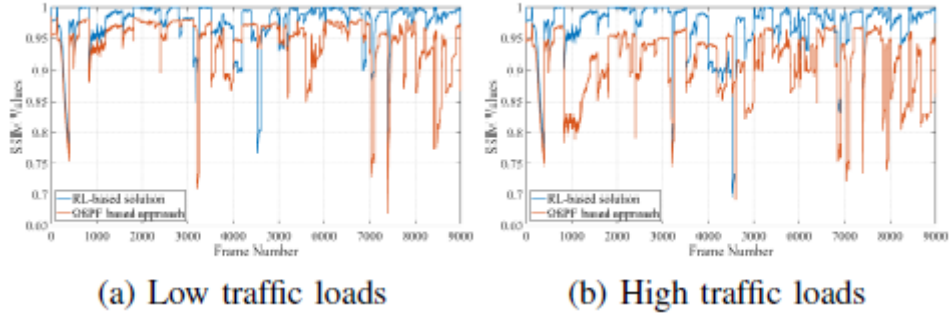


FIGURE 3 AVERAGE SSIM VALUES FOR DASH VIDEO UNDER TWO TRAFFIC LOADS.

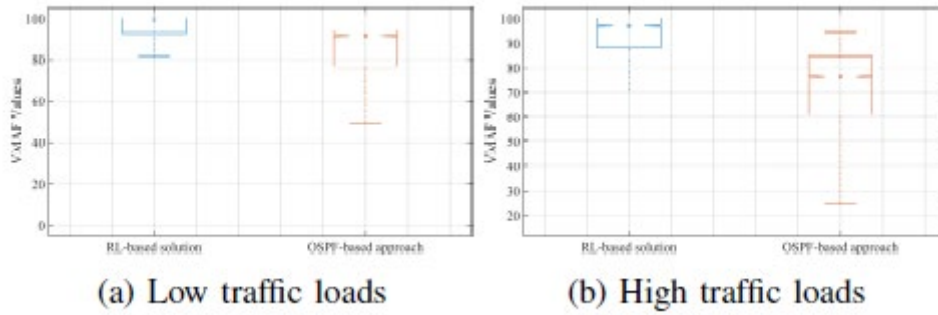


FIGURE 4 AVERAGE VMAF VALUES FOR DASH VIDEO UNDER TWO TRAFFIC LOADS.

throughput and stability at more than 3000 Kbps under low traffic loads. When the traffic intensity becomes high, the network gets congested, and according to Fig. 5b, the throughput with the OSPF protocol drops and reaches an average of 1200 Kbps. Conversely, the transmission with the proposed solution improves the network throughput, which reaches 2500 Kbps; hence the end-user maintains a better viewing experience.

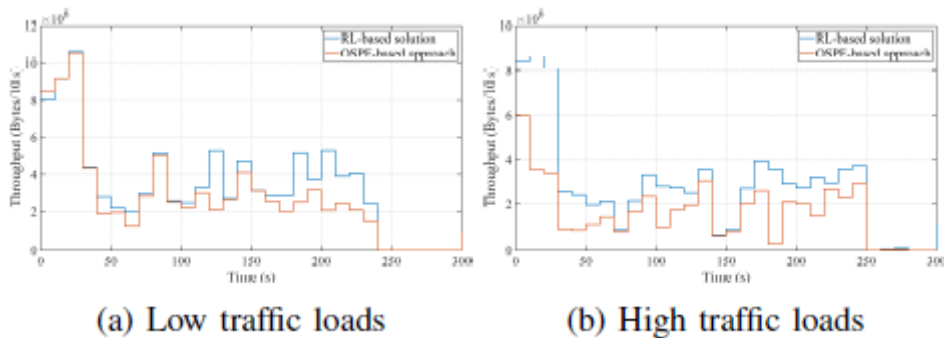


FIGURE 5 NETWORK THROUGHPUT DURING VIDEO STREAMING UNDER TWO TRAFFIC LOADS.

C. Video Quality Switches

The quality switches indicate the number of video quality switches from one bit rate to another while transmission because of the changes in network QoS parameters. Generally, plenty of quality changes negatively impact the end-user QoE, which results in bad viewing behaviour. Table. II indicates the

outcomes of quality switching during the transmission of video streaming over SDN. It can be noticed that the RL-based solution outperforms the OSPF-based approach in terms of quality switching under low and high traffic loads. The overall quality changes with the proposed scheme show 19 quality switches with 13 changes from high to low bitrate and six changes from low to high quality under low traffic loads. The overall quality switches remain the same under high traffic loads; however, nine switches from low to high bitrate occur because the network gets overloaded, and the clients start competing for bandwidth. On the other hand, the OSPF-based approach shows an overall of 27 and 25 quality changes under low and high traffic loads, respectively.

TABLE 2 VIDEO QUALITY SWITCHES UNDER TWO TRAFFIC LOADS

	Traffic Load Type	Overall Quality Switches	No. Quality Drop	No. Quality Increase
OSPF-based approach	Low	27	11	16
	High	25	14	11
RL-based approach	Low	19	6	13
	High	19	9	10

VII. CONCLUSION

This paper presents an intelligent-based multimedia traffic routing framework that exploits the integration of the RL technique with SDN. The proposed solution offers video streaming services enriched with excellent clients' viewing experience. The scheme takes advantage of SDN features to track the network topology and collect statistical information in order to obtain the optimal route. The optimal route selection involves the interaction of the RL-agent with the SDN network in which it learns to prioritise links with high available bandwidth while avoiding links with high latency, loss ratio and delay variation to improve end-user QoE. The results indicate the effectiveness of the RL-based solution during video streaming transmission, which presents excellent and good end-user QoE when executed over a realistic network topology and under two types of traffic loads. Without the optimisation technique, the QoE of DASH video streaming drastically worsened, and the MOS indicated poor watching behaviour under heavy background traffic loads.

REFERENCES

- [1] U. Cisco, "Cisco annual internet report (2018-2023) white paper," Cisco: San Jose, CA, USA, 2020.
- [2] A. Doumanoglou, N. Zioulis, D. Griffin, J. Serrano, T. K. Phan, D. Jiménez, D. Zarpalas, F. Alvarez, M. Rio, and P. Daras, "A system architecture for live immersive 3d-media transcoding over 5g networks," in *2018 IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB)*. IEEE, 2018, pp. 11-15.
- [3] N. Jawad, M. Salih, K. Ali, B. Meunier, Y. Zhang, X. Zhang, R. Zetik, C. Zarakovitis, H. Koumaras, M.-A. Kourtis et al., "Smart television services using nfv/sdn network management," *IEEE Transactions on Broadcasting*, vol. 65, no. 2, pp. 404-413, 2019.
- [4] A. A. Barakabitzte, L. Sun, I.-H. Mkwawa, and E. Ifeachor, "A novel qoe-centric sdn-based multipath routing approach for multimedia services over 5g networks," in *2018 IEEE International Conference on Communications (ICC)*, 2018, pp. 1-7.
- [5] C. Liang, Y. He, F. R. Yu, and N. Zhao, "Enhancing video rate adaptation with mobile edge computing and caching in software-defined mobile networks," *IEEE Transactions on Wireless Communications*, vol. 17, no. 10, pp. 7013-7026, 2018.

- [6] N. Anerousis, P. Chemouil, A. A. Lazar, N. Mihai, and S. B. Weinstein, "The origin and evolution of open programmable networks and sdn," *IEEE Communications Surveys & Tutorials*, 2021.
- [7] T. Uzakgider, C. Cetinkaya, and M. Sayit, "Learning-based approach for layered adaptive video streaming over sdn," *Computer Networks*, vol. 92, pp. 357-368, 2015.
- [8] S. Sendra, A. Rego, J. Lloret, J. M. Jimenez, and O. Romero, "Including artificial intelligence in a routing protocol using software defined networks," in *2017 IEEE International Conference on Communications Workshops (ICC Workshops)*. IEEE, 2017, pp. 670-674.
- [9] A. Al-Jawad, P. Shah, O. Gemikonakli, and R. Trestian, "Learnqos: A learning approach for optimizing qos over multimedia-based sdns," in *2018 IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB)*. IEEE, 2018, pp. 1-6.
- [10] X. Huang, T. Yuan, G. Qiao, and Y. Ren, "Deep reinforcement learning for multimedia traffic control in software defined networking," *IEEE Network*, vol. 32, no. 6, pp. 35-41, 2018.
- [11] A. Al-Jawad, I.-S. Comsa, P. Shah, O. Gemikonakli, and R. Trestian, "An innovative reinforcement learning-based framework for quality of service provisioning over multimedia-based sdn environments," *IEEE Transactions on Broadcasting*, vol. 67, no. 4, pp. 851-867, 2021.
- [12] A. Al-Jawad, I.-S. Comsa, P. Shah, O. Gemikonakli, and R. Trestian, "Redo: a reinforcement learning-based dynamic routing algorithm selection method for sdn," in *2021 IEEE Conference on Network Function Virtualization and Software Defined Networks (NFV-SDN)*. IEEE, 2021, pp. 54-59.
- [13] M. Al Jameel, T. Kanakis, S. Turner, A. Al-Sherbaz, and W. S. Bhaya, "A reinforcement learning-based routing for real-time multimedia traffic transmission over software-defined networking," *Electronics*, vol. 11, no. 15, p. 2441, 2022.
- [14] O. Oginni, P. Bull, and Y. Wang, "Constraint-aware software-defined network for routing real-time multimedia," *ACM SIGBED Review*, vol. 15, no. 3, pp. 37-42, 2018.
- [15] Z. Mammeri, "Reinforcement learning based routing in networks: Review and classification of approaches," *Ieee Access*, vol. 7, pp. 55 916-55 950, 2019.
- [16] P. Juluri, V. Tamarapalli, and D. Medhi, "Measurement of quality of experience of video-on-demand services: A survey," *IEEE Communications Surveys & Tutorials*, vol. 18, no. 1, pp. 401-418, 2015.
- [17] L. Al Shalabi and Z. Shaaban, "Normalization as a preprocessing engine for data mining and the approach of preference matrix," in *2006 International conference on dependability of computer systems*. IEEE, 2006, pp. 207-214.
- [18] H. J. Kim, D. G. Yun, H.-S. Kim, K. S. Cho, and S. G. Choi, "Qoe assessment model for video streaming service using qos parameters in wired-wireless network," in *2012 14th International Conference on Advanced Communication Technology (ICACT)*. IEEE, 2012, pp. 459-464.
- [19] R. L. S. de Oliveira, C. M. Schweitzer, A. A. Shinoda, and L. R. Prete, "Using mininet for emulation and prototyping software-defined networks," in *2014 IEEE Colombian Conference on Communications and Computing (COLCOM)*, 2014, pp. 1-6.
- [20] S. Asadollahi, B. Goswami, and M. Sameer, "Ryu controller's scalability experiment on software defined networks," in *2018 IEEE international conference on current trends in advanced computing (ICCTAC)*. IEEE, 2018, pp. 1-5.
- [21] Z. Li, C. Bampis, J. Novak, A. Aaron, K. Swanson, A. Moorthy, and J. Cock, "Vmaf: The journey continues," *Netflix Technology Blog*, vol. 25, 2018.
- [22] U. Sara, M. Akter, and M. S. Uddin, "Image quality assessment through fsim, ssim, mse and psnr—a comparative study," *Journal of Computer and Communications*, vol. 7, no. 3, pp. 8-18, 2019.
- [23] M. O. Elbasheer, A. Aldegheishem, J. Lloret, and N. Alrajeh, "A qos-based routing algorithm over software defined networks," *Journal of Network and Computer Applications*, vol. 194, p. 103215, 2021.
- [24] Big buck bunny. [Online]. Available: <https://peach.blender.org/>