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An Efficient RAN Slicing Strategy for a Heterogeneous Network With eMBB and V2X Services

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ABSTRACT Emerging 5G wireless technology will support services and use cases with vastly heterogeneous requirements. Network slicing, which allows composing multiple dedicated logical networks with specific functionality running on top of a common infrastructure, is introduced as a solution to cope with this heterogeneity. At the radio access network (RAN), the use of network slicing involves the assignment of radio resources to each slice in accordance with its expected requirements and functionalities. Therefore, RAN slicing will provide the required design flexibility and will be necessary for any network slicing solution. This paper investigates the RAN slicing problem for providing two generic services of 5G, namely enhanced mobile broadband (eMBB) and vehicle-to-everything (V2X). In this respect, we propose an efficient RAN slicing scheme based on an off-line reinforcement learning followed by a low-complexity heuristic algorithm, which allocates radio resources to different slices with the target of maximizing the resource utilization while ensuring the availability of resources to fulfill the requirements of the traffic of each RAN slice. A simulation-based analysis is presented to assess the performance of the proposed solution. The simulation results have shown that the proposed algorithm improves the network performance in terms of resource utilization, the latency of V2X services, achievable data rate, and outage probability.

INDEX TERMS Vehicle-to-everything (V2X), reinforcement learning, network slicing, RAN slicing.

I. INTRODUCTION

The new fifth generation (5G) network will provide a common platform to address the challenges and opportunities that come as a result of the rapid development of a wide range of use cases associated to different vertical industrial services and applications, such as high definition (HD) video, Virtual Reality (VR), online gaming, cloud services, connected car, Internet of Things, etc. New communications requirements pose challenges for existing networks in terms of technologies and business models. According to [1]–[3], the new era of 5G must meet the various demands associated to three generic service types. These services types can be concisely characterized as follows: (a) enhanced Mobile Broad Band (eMBB) supports applications to meet user demands for high data rates and focuses on services that require high bandwidth requirements such as high HD video and VR;

(b) Ultra Reliable and Low Latency Communications (URLLC) focus on supporting low-latency transmissions of small payloads with extremely high reliability for a range of active terminals, and they can cover applications such as mission critical communications or autonomous driving and Vehicle-to-Everything (V2X). (c) massive machine-type communications (mMTC) aims to meet the demands of a large number of devices belonging to the Internet of Things (IoT), which transmit small data payloads intermittently, and focus on services that include high communication density requirements, such as smart cities. In this context, the 5G system aims to provide a flexible platform to meet the diverse service requirements associated to these service types and to enable new business models resulting from the integration of vertical industries such as automotive, manufacturing, smart cities, and entertainment in the cellular networks [4].

In order to realize the above vision, network slicing is one of the key capabilities that will enable the required flexibility, as it allows multiple logical networks, referred to as

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network slices, to be created on top of a common shared physical infrastructure. Each network slice can be used to serve a particular service category (e.g., applications with different functional requirements) through the use of specific control plane (CP) and/or user plane (UP) functions [5]. The greater elasticity brought about by network slicing will help to address the cost, efficiency, and flexibility requirements a wide range of vertical services. Moreover, network slicing will help new services and new requirements to be quickly addressed, according to the needs of the industries [6], [7]. Through network slicing, resources of multi-domain infrastructure network can be efficiently allocated to multiple network slices according to the requirements of the different use cases [8], [9]. The realization of network slicing considers, in the most general case, support for specific features and resources both in the core network part, referred to as Core Network slice, and in the Radio Access Network (RAN) part, referred to as RAN slice, which is the focus of this paper. An efficient RAN slicing for 5G systems needs to face different challenges in terms of capacity, latency, reliability, and scalability. These challenges are a consequence of the increase in network size and demands for radio resources to be used for the transmissions and of the heterogeneity across applications, networks, and devices.

An efficient RAN slicing algorithm will result in different benefits, such as improving the network capacity utilization avoiding the outage of service due to the lack of resources, reducing the network traffic congestion and, ensuring a high Quality of Service (QoS), e.g., in terms of data transmission rate and latency. Based on the above, in this paper we propose an optimized RAN slicing solution for scenarios with both eMBB and V2X services sharing the same RAN infrastructure. The main focus of the proposed solution is to configure the resource split between the eMBB and V2X slices in order to satisfy their QoS requirements and maximize the system performance for both slices in terms of network metrics such as resource utilization, latency, network traffic load, and outage probability.

The proposed solution is considered to allocate resources to users of eMBB services in both UpLink (UL) and DownLink (DL) and to users of V2X services assuming Vehicle-to-Vehicle (V2V) communications. V2V communications can make use of either cellular mode (i.e. using a two-hop transmission via a base station and employing UL/DL of the Uu interface) or SideLink (SL) mode (i.e. nearby vehicles communicate directly over the PC5 interface). It is worth mentioning that, although the support for V2X sidelink communications was already standardized in 3GPP in the context of LTE [10], V2X sidelink is not yet included in the current release 15 of 5G New Radio (NR) specifications, but it is subject to study for future release 16 [11].

Based on all the above considerations, the key contributions of this paper are summarized as follows:

1- The RAN slicing problem to support an eMBB and a V2X slice on the same RAN infrastructure is formulated as an optimization problem to determine the amount of resources

assigned to each slice with the target of improving the radio resource utilization while satisfying the specific requirements for each slice. The model considers uplink, downlink and sidelink communications.

2- A novel strategy based on offline Q-learning and softmax decision-making is proposed as an enhanced solution to determine the adequate split of resources between the two slices. In this approach, the slice controller continuously interacts with a model of the environment to learn the optimal policy through an immediate reward feedback. The adopted Q-Learning algorithm tracks all possible “actions” (i.e. resource splits) the system can take through an exploration-exploitation process in order to select the appropriate action.

3- Starting from the outcome of the off-line Q-learning algorithm, a low-complexity heuristic approach is proposed for fine tuning the resource assignment and achieving further improvements in the use of resources.

4- The performance of the proposed approach is evaluated using extensive simulations to demonstrate its capability to perform an efficient allocation of resources among slices in terms of resource utilization, latency, achievable data rate and outage probability. Simulation results show the effectiveness of the proposed schemes under different system parameters.

The rest of the paper is organized as follows. Section II covers the state of art. Section III presents the system model and the problem formulation. Section IV provides the proposed solutions for RAN slicing. Section V presents the performance evaluation followed by the conclusions in Section VI.

II. STATE OF THE ART

There are different works in the literature that have proposed solutions for designing and controlling network slicing [12]–[17]. A logical architecture for network-slicing-based 5G systems and a scheme for managing mobility between different access networks is proposed in [12]. In turn, the deployment of function decomposition and network slicing as a tool to improve the Evolved Packet Core (EPC) is presented in [13]. They discussed the feasibility of designing a flexible and adaptive mobile core network based on functional decomposition and network slicing concepts. A flexible and programmable Software Defined (SD)-RAN platform is introduced in [14] with a main focus on separating the RAN control and data planes through a southbound API in order to support a flexible control plane for real-time RAN control applications and on achieving various degrees of coordination among RAN infrastructure entities. Reference [15] focuses on network slicing traffic analysis and prediction per network slice, and on admission control decisions for network slice requests. It presents the adaptive correction of the forecasted load based on measured deviations. In turn, a low complexity heuristic algorithm and slicing for joint admission control in virtual wireless networks is proposed in [16]. In [17], a model for orchestrating network slices based on the service requirements and available resources is introduced. They proposed a framework for Markov decision processes

to formulate and determine the optimal policy that manages cross-slice admission control and resource allocation for the 5G networks.

Some other research studies have been carried out in the context of managing the split of the available radio resources in the RAN among different slices to support different services (e.g., eMBB, mMTC, and URLLC) with main focus on the Packet Scheduling (PS) problem. They try to improve the utility of the network capacity and maximize the sum rates of the whole network using different approaches, such as reinforcement learning [18], auction mechanism [19], and game theory [20]. In particular, a novel radio resource slicing framework for 5G networks with haptic communications is proposed in [18] based on the virtualization of radio resources. The author adopted a reinforcement learning (RL) approach for dynamic radio resource slicing in a flexible way while accounting for the utility requirements of different vertical applications. In this respect, the slicing problem is modeled based on a Markov Decision Process (MDP) and, then, an optimal radio resource slicing strategy based on the application of Q-learning technique is introduced to solve the problem. In turn, a network slicing strategy based on a novel auction mechanism is introduced in [19] to decide the selling price of different types of network segments in order to maximize the network revenue and to optimally satisfy the resource requirements. A network slicing scheme based on game theory for managing the split of the available radio resources in a RAN among different slice types is proposed in [20] to maximize the utility of radio resources.

Similarly, novel slicing and scheduling schemes are proposed in [21] to meet requirements such as QoS, fairness, and isolation among different slices. In turn, from an implementation perspective, the scheduling of different slices has been addressed by [22]. In [23], a novel online optimizer based on genetic algorithms has been introduced in order to better support the coexistence of heterogeneous slices with highly diverse QoS requirements and allow heterogeneous utility functions of different slice types in 5G networks. An adaptive algorithm for virtual resource allocation based on Constrained Markov Decision Process is proposed in [24]. Their proposed resource allocation strategy can be dynamically adjusted to allocate power and subcarriers through continuous interaction with the external environment. An online network slicing solution based on multi-armed bandit mathematical model and properties to maximize network slicing multiplexing gains and achieving the accommodation of network slice requests in the system with an aggregated level of demands above the available capacity is proposed in [25]. They provide a novel model that addresses the dilemma of exploration versus exploitation, dubbed as Budgeted Lock-up Multi Armed Problem (BLMAP). The feasibility of the solution is proved through implementation on commercial hardware by considering three network slices such as eMBB for Guaranteed Bit Rate (GBR), eMBB for Best Effort, and Public Safety. Despite the existence of the abovementioned works in the area of network slicing, none of the above works

has considered slicing in vehicular scenarios in which the vehicles can communicate through two operational modes, either sidelink (direct-V2V) via PC5 interface or cellular mode via Uu interface. The consideration of slicing with this type of traffic is indeed one of the novelties of this paper.

Another novelty of this paper relies on the considered methodology for addressing the network slicing problem, making use of a combination of off-line Q-learning with a heuristic method for fine tuning the amount of radio resources allocated to each slice.

Some of the existing solutions in the recent literature have proposed online Q-Learning algorithms for managing the split of the available radio resources among different slices [18]. However, the on-line Q-Learning algorithm needs to keep track for a value table of all possible “actions” that the system can take, and update the values online through an exploration-exploitation process, which may have a chance of making wrong or unevaluated decisions that can degrade actual performance. Instead, to avoid this issue, in our work we focus on offline Q-Learning. This allows exploring the different actions based on a model of the system prior to modifying on-line the actual network configuration. Besides, the Q-learning approach in this paper makes use of softmax decision making for selecting the different actions, thus allowing to trade-off between exploration and exploitation, in contrast to the use of ϵ -greedy selection, which is one of the common techniques used, where ϵ is the percentage of time the agent takes to select an action randomly rather than taking the action that is most likely to increase its reward given what it knows so far. Although ϵ -greedy action selection is an effective and popular way to balance exploration and exploitation in reinforcement learning, one of the drawbacks is that when it explores it chooses equally among all actions [26], [27]. This means that the worst-appearing action is likely to be chosen as the best one.

III. SYSTEM MODEL AND PROBLEM FORMULATION

A. SYSTEM MODEL

The considered scenario assumes a cellular Next Generation Radio Access Network (NG-RAN) with a gNodeB (gNB) [28] composed by a single cell. A roadside unit (RSU) supporting V2X communications is attached to the gNB. A set of eMBB cellular users (CUs) numbered as $m = 1, \dots, M$ are distributed randomly around the gNB and a flow of several independent vehicles move along a straight highway, as illustrated in the right part of Figure 1. The highway segment is divided into sub-segments (clusters) by sectioning the road into smaller zones according to the length of the road. It is assumed that each vehicle includes a User Equipment (UE) that enables communication with the UEs in the rest of vehicles in the same cluster. Clusters are numbered as $j = 1, \dots, C$, and the vehicles in the j -th cluster are numbered as $i = 1, \dots, V(j)$.

The vehicles in the highway are assumed to enter the cell coverage following a Poisson process with arrival rate λ_a . The association between clusters and vehicles is managed

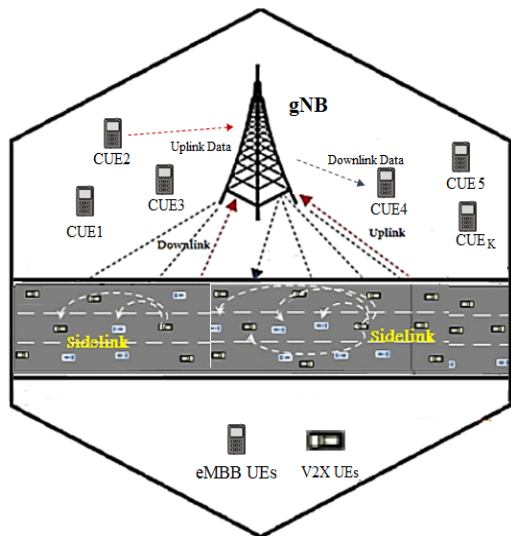


FIGURE 1. System model of the cellular network with sidelink V2V.

and maintained by the RSU based on different metrics (e.g., position, direction, speed and link quality) through a periodic exchange of status information.

Regarding V2X services, this paper assumes a V2V communication between vehicles that can be performed either in cellular or in sidelink mode. In cellular mode, each UE communicates with other UEs through the Uu interface in a two-hop transmission via the gNB, while in sidelink mode, direct V2V communications can be established over the $PC5$ interface. We assume that, when sidelink transmissions are utilized, every member vehicle can multicast the V2V messages directly to multiple member vehicles of the same cluster $1 \leq i \leq V(j)$ using one-to-many technology. The decision on when to use cellular or sidelink mode is done based on [29].

B. NETWORK MODEL FOR RADIO RESOURCE SLICING

In order to jointly support the eMBB and V2X services, and since eMBB requires a large bandwidth to support high-data-rate services, and V2X services are extremely sensitive to latency, the network is logically divided into two network slices, namely $RAN_slice_ID = 1$ for the V2X services and $RAN_slice_ID = 2$ for the eMBB services.

The whole cell bandwidth is organized in Resource Blocks (RBs) of bandwidth B . Let denote as N_{UL} the number of RBs in the UL and N_{DL} the number of RBs in the DL. The RAN slicing process should distribute the UL and DL RBs among the two slices. For this purpose, let denote $\alpha_{s,UL}$ and $\alpha_{s,DL}$ as the fraction of UL and DL resources, respectively, for the $RAN_slice_ID = s$.

Regarding sidelink communications, and since the support for sidelink has not been yet specified for 5G in current 3GPP release 15, this paper assumes the same approach as in current LTE-V2X system, in which the SL RBs are part of the total RBs of the UL. For this reason, the slice ratio $\alpha_{s,UL}$ is divided

into two slice ratios, $\bar{\alpha}_{s,UL}$, which corresponds to the fraction of UL RBs that are used for uplink transmissions, and $\alpha_{s,SL}$, which corresponds to the fraction of UL RBs used to support sidelink transmissions. The following relationships hold:

$$\sum_s \alpha_{s,DL} = 1 \tag{1}$$

$$\sum_s \alpha_{s,UL} = \sum_s (\alpha_{s,SL} + \bar{\alpha}_{s,UL}) = 1 \tag{2}$$

It is worth mentioning that, since in the considered scenario the sidelink is only used by the V2X slice, it is assumed that $\bar{\alpha}_{2,UL} = \alpha_{2,UL}$ and $\alpha_{2,SL} = 0$ for the eMBB slice ($s = 2$).

C. V2X COMMUNICATION MODEL

Each vehicle is assumed to generate packets randomly with rate λ_v packets/s according to Poisson arrival model. The length of the messages is S_m . When the vehicles operate in sidelink mode, the messages are transmitted using the SL resources allocated to the slice. Instead, when the vehicles operate in cellular mode, the messages are transmitted using the UL and DL resources. The average number of required RBs from V2X users of $RAN_slice_ID = 1$ per Transmission Time Interval (TTI) in UL, DL and SL, denoted respectively as $\Gamma_{1,UL}$, $\Gamma_{1,DL}$ and $\Gamma_{1,SL}$, can be estimated as follows:

$$\Gamma_{1,x} = \frac{\sum_{t=1}^T \sum_{j=1}^C \sum_{i=1}^{V(j)} m(j, i, t) \cdot S_m}{T \cdot SP_{eff,x} \cdot B \cdot F_d} \tag{3}$$

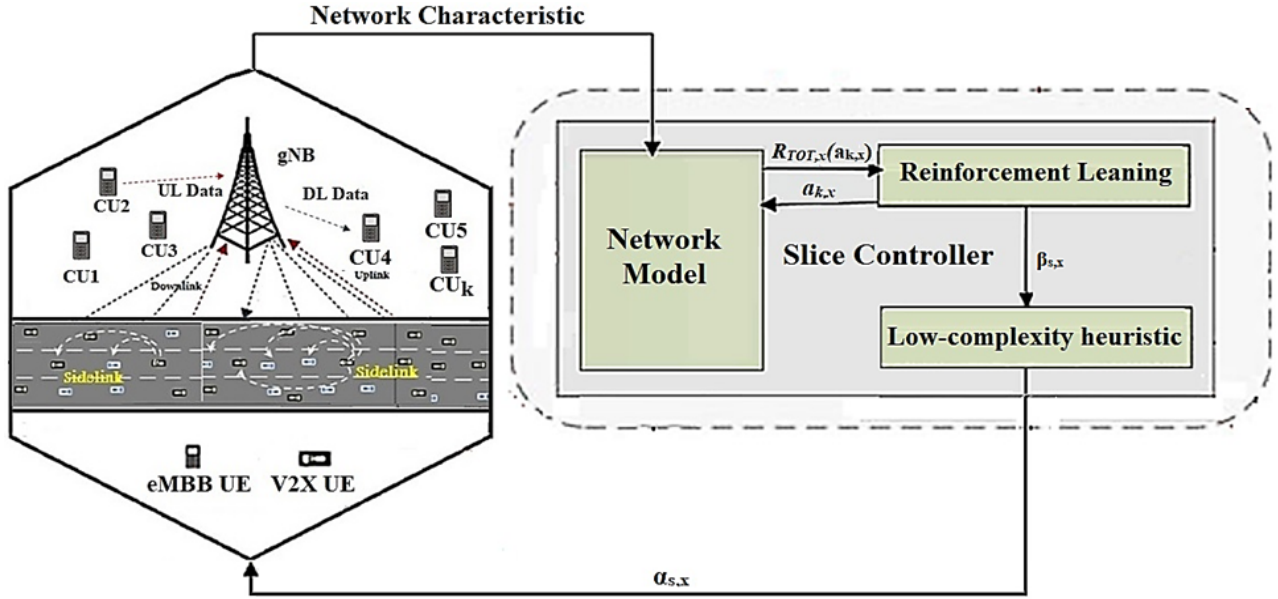
where x denotes the type of link, i.e. $x \in \{UL, DL, SL\}$, $m(j, i, t)$ is the number of transmitted messages by the vehicles of the j -th cluster in the t -th TTI and $S_{eff,x}$ is the spectral efficiency in the x link, F_d is the TTI duration and T is the number of TTIs that defines the time window used to compute the average.

D. eMBB COMMUNICATION MODEL

Each eMBB user generates sessions requiring a certain guaranteed bit rate. The session generation model follows a Poisson process with rate λ_e (sessions/s) and the session duration is exponentially distributed with average T_e . These users transmit in the uplink and downlink RBs allocated to the eMBB slice. Then, the average number of required RBs for eMBB users of $RAN_slice_ID = 2$ in UL and DL in order to support a certain guaranteed bit rate R_b is denoted as $\Gamma_{2,UL}$ and $\Gamma_{2,DL}$, respectively, and can be statistically estimated as follows:

$$\Gamma_{2,x} = \frac{\sum_{t=1}^T \sum_{m=1}^M \rho_x(m, t)}{T} \tag{4}$$

where x denotes the type of link, and $\rho_x(m, t)$ is the number of required RBs by the m -th user in the link x and in the t -th TTI in order to get the required bit rate R_b . It is given by $\rho_x(m, t) = R_b / (SP_{eff,x} \cdot B)$. The values $\Gamma_{2,UL}$, $\Gamma_{2,DL}$ are computed within a time window T TTIs. Note also that $\Gamma_{2,SL} = 0$, since the eMBB slice does not generate sidelink traffic.


FIGURE 2. RAN slicing strategy.

E. PROBLEM FORMULATION FOR RAN SLICING

The focus of this paper is to determine the optimum slicing ratios $\alpha_{s,UL}$, $\alpha_{s,DL}$ in order to maximize the overall resource utilization under the constraints of satisfying the resource requirements for the users of the two considered slices.

The total utilization of UL resources U_{UL} is given by the aggregate of the required RBs in the UL and SL for each slice, provided that the aggregate of a given slice s does not exceed the total amount of resources allocated by the RAN slicing to this slice, i.e. $\alpha_{s,UL} \cdot N_{UL}$. Otherwise, the utilization of slice s will be limited to $\alpha_{s,UL} \cdot N_{UL}$ and the slice will experience an outage situation. Based on this, the total utilization U_{UL} is defined as:

$$U_{UL} = \sum_s \min(\Gamma_{s,SL} + \Gamma_{s,UL}, \alpha_{s,UL} \cdot N_{RB}^{UL}) \quad (5)$$

Correspondingly, the optimization problem for the uplink is defined as the maximization of the UL resource utilization subject to ensuring an outage probability lower than a maximum tolerable limit p_{out} . This is formally expressed as:

$$\max_{\alpha_{s,UL}} U_{UL} \quad (6)$$

$$\text{s.t. } \Pr[\Gamma_{s,SL} + \Gamma_{s,UL} \geq \alpha_{s,UL} \cdot N_{UL}] < p_{out} \quad s=1, 2 \quad (6a)$$

$$\sum_s \alpha_{s,UL} = 1 \quad (6b)$$

Following similar considerations like in the uplink, the total resource utilization in the downlink direction U_{DL} is given by

$$U_{DL} = \sum_s \min(\Gamma_{s,DL}, \alpha_{s,DL} \cdot N_{DL}) \quad (7)$$

Similar to (6), the considered optimization problem of the downlink is formulated as:

$$\max_{\alpha_{s,DL}} U_{DL} \quad (8)$$

$$\text{s.t. } \Pr[\Gamma_{s,DL} \geq \alpha_{s,DL} \cdot N_{DL}] < p_{out} \quad s=1, 2 \quad (8a)$$

$$\sum_s \alpha_{s,DL} = 1 \quad (8b)$$

IV. PROPOSED SOLUTION FOR RAN SLICING

The problems in (6) and (8) with their constraints are non-linear optimization problems. Such an optimization problem is generally hard to solve. The complexity of solving this problem is high for a network of realistic size with fast varying channel conditions and very tight time-to-decide. For these reasons, we propose the use of an offline reinforcement learning followed by a low-complexity heuristic approach to solve the problem in a more practical way. The general approach is depicted in Figure 2. We consider a slicing controller responsible for determining the slicing ratios $\alpha_{s,UL}$, $\alpha_{s,DL}$ for each slice. The operation of the slicing controller is decomposed into two main parts. In the first part, an RL algorithm is responsible for determining some intermediate slicing ratios, denoted as $\beta_{s,UL}$, $\beta_{s,DL}$. Then, the second part is a heuristic algorithm that takes as input the results of the RL algorithm and performs a fine tuning of the slicing ratios in order to determine the final optimized values $\alpha_{s,UL}$, $\alpha_{s,DL}$. This two-step approach allows balancing the trade-off between achieving a fine granularity when setting the slicing ratios and keeping a moderate number of actions in the RL algorithm that facilitates the convergence of the algorithm in a reduced time. A detailed description of the both the RL algorithm and the heuristic algorithm is given in sections IV. A and IV. B, respectively.

A. RL-BASED SLICING STRATEGY

It is assumed that two separate RL algorithms are executed for the UL and the DL to determine respectively $\beta_{s,UL}$ and $\beta_{s,DL}$. In the general operation of RL, the optimum solutions are found based on dynamically interacting with the environment based on trying different actions $a_{k,x}$ (i.e., different slicing ratios) selected from a set of possible actions numbered as $k = 1, \dots, A_x$, where $x \in \{UL, DL\}$. As a result of the selected action, the RL process gets a reward $R_{TOT,x}(a_{k,x})$ that measures how good or bad the result of the action has been in terms of the desired optimization target. Based on this reward, the RL algorithm adjusts the decision-making process to progressively learn the actions that lead to the highest reward. The action selection is done by balancing the trade-off between exploitation (i.e., try actions with high reward) and exploration (i.e. try actions that have not been used before in order to learn from them).

In case this interaction with the environment was done in an on-line way, i.e., by configuring the slicing ratios on the real network and then measuring the obtained performance, this could lead to serious performance degradation since, during the exploration process, wrong or unevaluated decisions could be made at certain points of time due to the exploration, and affecting all the UEs of a given slice. To avoid this problem, this paper considers an off-line RL, in which the slicing controller interacts with a network model that simulates the behavior of the network and allows testing the performance of the different actions in order to learn the optimum one prior to configuring it in the real network. The network model is based on a characterization of the network in terms of traffic generation, propagation modelling, etc.

The specific RL algorithm considered in this paper is the Q-learning based on softmax decision making [26], which enables an exploration-exploitation traversing all possible actions in long-term. In turn, the reward should be defined in accordance with the optimization problem, which in this paper intends to maximize the resource utilization subject to the outage probability constraint. The details about the reward function and the detailed operation of the Q-learning algorithm are presented in the following.

1) REWARD COMPUTATION

The reward function should reflect the ability of the taken action to fulfill the targets of the optimization problems (6) and (8). Based on this, and for a given action $a_{k,x}$ with associated slicing ratios $\beta_{s,x}(k)$ the reward is computed as function of the normalized resource utilization $\Psi_{s,x}(a_{k,x})$ of slice s in link $x \in \{UL, DL\}$ defined as the ratio of used resources to the total allocated resources by the corresponding action. For the case of the V2X slice ($s = 1$), it is defined as:

$$\Psi_{1,UL}(a_{k,UL}) = \frac{\Gamma_{1,UL} + \Gamma_{1,SL}}{\beta_{1,UL}(k) \cdot N_{UL}} \quad (9)$$

$$\Psi_{1,DL}(a_{k,DL}) = \frac{\Gamma_{1,DL}}{\beta_{1,DL}(k) \cdot N_{DL}} \quad (10)$$

In turn, for the case of eMBB slice ($s = 2$), it is defined as:

$$\Psi_{2,UL}(a_{k,UL}) = \frac{\Gamma_{2,UL}}{\beta_{2,UL}(k) \cdot N_{UL}} \quad (11)$$

$$\Psi_{2,DL}(a_{k,DL}) = \frac{\Gamma_{2,DL}}{\beta_{2,DL}(k) \cdot N_{DL}} \quad (12)$$

Based on these expressions, the reward $R_{s,x}(a_{k,x})$ for the slice s in link $x \in \{UL, DL\}$ as a result of action $a_{k,x}$ is defined as

$$R_{s,x}(a_{k,x}) = \begin{cases} e^{\Psi_{s,x}(a_{k,x})} & \Psi_{s,x}(a_{k,x}) \leq 1 \\ 1/\Psi_{s,x}(a_{k,x}) & \text{otherwise} \end{cases} \quad (13)$$

In (13), whenever $\Psi_{s,x}(a_{k,x})$ is a value between 0 and 1, the reward function will increase exponentially to its peak at $\Psi_{s,x}(a_{k,x}) = 1$. Therefore, the actions that lead to a higher value of $\Psi_{s,x}(a_{k,x})$ (i.e., higher utilization) provide larger rewards and therefore this allows approaching the optimization target of (6) and (8). In contrast, if the value of $\Psi_{s,x}(a_{k,x}) > 1$, it means that the slice s will be in outage and thus the reward decreases to take into consideration constraints (6a)(8a). Consequently, the formulation of the reward function per slice in (13) takes into account the constraints of the optimization problem.

In addition, since the total reward has to account for the effect of the action on all the considered slices $s = 1, \dots, S$, it is defined in general as the geometric mean of the per-slice rewards, that is:

$$R_{TOT,x}(a_{k,x}) = \left(\prod_{s=1}^S R_{s,x}(a_{k,x}) \right)^{\frac{1}{S}} \quad (14)$$

2) COMPUTATION OF THE Q-VALUES AND PROBABILITY SELECTION CRITERION

The ultimate target of the Q-learning scheme at the slicing controller is to find the action (i.e. the slicing ratios for a given link $x \in \{UL, DL\}$) that maximizes the expected long-term reward to each slice. To achieve this, the Q-learning interacts with the network model over discrete time-steps of fixed duration and estimates the reward of the chosen action. Based on the reward, the slice controller keeps a record of its experience when taking an action $a_{k,x}$ and stores the action-value function (also referred to as the Q-value) in $Q_x(a_{k,x})$. Every time step, the $Q_{UL}(a_{k,UL})$ and $Q_{DL}(a_{k,DL})$ values are updated following a single-state Q-learning approach with a null discount rate [26] as follows:

$$Q_x(a_{k,x}) \leftarrow (1 - \alpha)Q_x(a_{k,x}) + \alpha R_{TOT,x}(a_{k,x}) \quad (15)$$

where $\alpha \in (0, 1)$ is the learning rate, and $R_{TOT,x}(a_{k,x})$ is the total reward accounting for both V2X and eMBB slices after executing an action $a_{k,x}$. At initialization, i.e. when action $a_{k,x}$ has never been used in the past, $Q_x(a_{k,x})$ is initialized to an arbitrary value.

Algorithm 1: RAN Slicing Algorithm Based on RL

1. **Inputs:**
 N_{UL}, N_{DL} : Number of RBs in UL and DL.
 S : number of slices,
Set of actions $a_{k,x}$ for link $x \in \{UL, DL\}$
2. **Initialization of Learning:**
 $t \leftarrow 0, Q_x(a_{k,x}) = 0, k = 1, \dots, A_x, x \in \{UL, DL\}$
3. **Iteration**
4. **While** learning period is active **do**
5. **for** each link $x \in \{UL, DL\}$
6. Apply softmax and compute $P_x(a_{k,x})$ for each action $a_{k,x}$ according to (16);
7. Generate a uniformly distributed random number $u \in \{0,1\}$
8. Select an action $a_{k,x}$ based on u and probabilities $P_x(a_{k,x})$
9. Apply the selected action to the network and evaluate $\Psi_{s,x}(a_{k,x})$ based on (9)-(12).
10. **If** $\Psi_{s,x}(a_{k,x}) \leq 1$ **then**
11. $R_{s,x}(a_{k,x}) = e^{\Psi_{s,x}(a_{k,x})}$
12. **else**
13. $R_{s,x}(a_{k,x}) = 1/\Psi_{s,x}(a_{k,x})$
14. **End**
15. **Compute** $R_{TOT,x}(a_{k,x})$ based on equation (14)
16. **Update** $Q_x(a_{k,x})$ based on equation (15)
17. **End**
18. **End**

3) SELECTION CRITERION

The selection of the different actions based on the $Q_x(a_{k,x})$ is made based on the softmax policy [26], in which the different actions are chosen probabilistically. Specifically, the probability $P(a_{k,x})$ of selecting action $a_{k,x}$, $k = 1, \dots, A_x$, is defined as

$$P(a_{k,x}) = \frac{e^{Q_x(a_{k,x})/\tau}}{\sum_{j=1}^{A_x} e^{Q_x(a_{j,x})/\tau}} \quad (16)$$

where τ is a positive integer called temperature parameter that controls the selection probability. With a high value of τ , the action probabilities become nearly equal. Instead, a low value of τ causes a greater difference in selection probabilities for actions with different Q-values. Softmax decision making allows an efficient trade-off between exploration and exploitation, i.e. selecting with high probability those actions that have yield high reward, but also keeping a certain probability of exploring new actions, which can yield better decisions in the future. The pseudo-code of the proposed RL-based RAN slicing algorithm is summarized in Algorithm 1. the offline RL algorithm has converged, i.e. the selection probability of one of the actions is higher than 99.99%, the slicing ratios $\beta_{s,x}$ associated to this action

Algorithm 2: Low-Complexity Heuristic Solution

1. **Input:**
Slicing ratios selected by the RL: $\beta_{s,x}$,
 $s = 1, 2, x \in \{UL, DL\}$.
2. **For each** Slice $s = \{1,2\}$
3. **Compute** the required RBs ($\Gamma_{s,x}$) from equations
4. (3) and (4)
5. **Compute** $\Psi_{s,x}(a_{x_sel})$ based on (9)-(12).
6. **End;**
7. **If** $\Psi_{1,x}(a_{x_sel}) < 1$ and $\Psi_{2,x}(a_{x_sel}) > 1$
8. $\Delta C_{2,x} = (1 - \Psi_{2,x}(a_{x_sel})) \cdot \omega$
9. $\alpha_{2,x} = \beta_{2,x} - \Delta C_{2,x}$
10. $\alpha_{1,x} = \beta_{1,x} + \Delta C_{2,x}$
11. **else if** $\Psi_{1,x}(a_{x_sel}) > 1$ and $\Psi_{2,x}(a_{x_sel}) < 1$
12. $\Delta C_{1,x} = (1 - \Psi_{1,x}(a_{x_sel})) \cdot \omega$
13. $\alpha_{1,x} = \beta_{1,x} - \Delta C_{1,x}$
14. $\alpha_{2,x} = \beta_{2,x} + \Delta C_{1,x}$
15. **else**
16. $\alpha_{1,x} = \beta_{1,x}$
17. $\alpha_{2,x} = \beta_{2,x}$
18. **End**

are passed to the low-complexity heuristic algorithm, as illustrated in Fig.2. Let's denote this selected action as a_{x_sel} .

B. LOW-COMPLEXITY HEURISTIC SOLUTION

In this section, we propose a heuristic scheme for fine tuning the initial slicing ratios $\beta_{s,UL}, \beta_{s,DL}$ chosen by the RL based on the resource requirements.

The idea of this fine tuning is that, based on the actual RB demands of each slice and the slicing ratios $\beta_{s,UL}, \beta_{s,DL}$, the algorithm assesses if one of the two slices s has more resources than actually required in the link $x \in \{UL, DL\}$, i.e. $\Psi_{s,x}(a_{x_sel}) < 1$, and at the same time the other slice s' has less resources than required, i.e. $\Psi_{s',x}(a_{x_sel}) > 1$. If this is the case, the slice s leaves some extra capacity $\Delta C_{s,x}$ that can be transferred to the other slice s' . Specifically, the extra capacity is defined as:

$$\Delta C_{s,x} = (1 - \Psi_{s,x}(a_{x_sel})) \cdot \omega \quad (17)$$

where the configuration parameter ω is a scalar in the range $[0,1]$ used to leaves some margin capacity to cope with the variations of the RBs consumption. Based on this, the slicing ratio for the slice s will be decreased in $\Delta C_{s,x}$, i.e., $\alpha_{s,x} = \beta_{s,x} - \Delta C_{s,x}$, while the slicing ratio for the other slice s' will be increased in $\Delta C_{s,x}$, i.e. $\alpha_{s',x} = \beta_{s',x} + \Delta C_{s,x}$.

The detailed steps of the proposed heuristic algorithm are shown in Algorithm 2.

V. PERFORMANCE EVALUATION

In this section, we evaluate the performance of the proposed RAN slicing solution through system level simulation performed in MATLAB.

A. SIMULATION SETUP

Our simulation model is based on a single-cell hexagonal layout configured with a gNB. The gNB supports a cell with a channel organized in 200 RBs composed by 12 subcarriers with subcarrier separation $\Delta f = 30$ kHz, which corresponds to one of the 5G NR numerologies defined in [30].

The model considers vehicular UEs communicating through cellular mode (uplink / downlink) and via sidelink (direct V2V) and using RAN_slice_ID = 1 and eMBB UEs operating in cellular mode (uplink / downlink) and using RAN_slice_ID = 2 based on the assumptions described in section 2. The eMBB UEs are randomly distributed in the cell, while the V2X user's mode along a 3-lane highway. All relevant system and simulation parameters are summarized in Table 1. As for the RAN slicing approach, the actions of the RL are defined such that action $a_{k,x}$ corresponds to $\beta_{1,x}(k) = 0.05 \cdot k$ and $\beta_{2,x}(k) = (1 - 0.05 \cdot k)$ for $k = 1, \dots, 20$, $x \in \{\text{UL}, \text{DL}\}$. The uplink slicing ratio for slice 1 $\alpha_{1,UL}$ obtained as a result of the proposed RAN slicing algorithm is split into two ratios, namely $\bar{\alpha}_{s,UL} = 0.35$ for V2X users in cellular mode and $\alpha_{1,SL} = 0.65$ for V2X in sidelink mode. The presented evaluation results intend to assess and illustrate the performance of the proposed RAN slicing solution in terms of RB utilization, throughput, outage probability and latency.

As references for comparison, we assume a simpler RAN slicing strategy denoted as ‘‘Proportional Scheme’’, in which the ratio of RBs for each slice is proportional to its total traffic rate (in Mb/s) and a reference scheme in which a fixed slicing ratio is allocated to each service for uplink (UL+SL) and downlink (70 % of PRBs for slice ID = 1 and 30 % of PRBs for slice ID = 2). In addition, in order to see the impact of the two steps in the proposed RAN slicing approach, the results analyze the performance for the case that only the RL is considered, denoted as ‘‘Proposed RL-scheme’’, and the performance for the case that both the RL and the heuristic algorithm are considered, denoted as ‘‘Proposed RL+ Heuristic’’.

B. PERFORMANCE IN TERMS OF RBs UTILIZATION

Fig. 3 and Fig. 4 present the obtained RB utilization, i.e. the number of used RBs normalized to the number of total available RBs, in UL and DL, respectively, for UL and DL, as a function of the eMBB session arrival rate (λ_e). Since SL and UL make use of the same set of RBs, the results included in Fig.3 refer to the total utilization by both links for V2X and eMBB slices.

From the presented results, we notice that our proposed model with both off-line RL and off-line RL followed by the low-complexity heuristic approach maintains high resource utilization compared to the reference models in different load scenarios. This is due to the RL-based slicing strategy that inherently tackles slice dynamics by selecting the most appropriate action. Further improvements are obtained by the off-line RL followed by a low-complexity heuristic approach by checking the unused capacity left by each slice after selecting an action and use it to serve more traffic load in the other slice.

TABLE 1. Simulation parameters.

Parameter	Values
General parameters	
Cell radius	500m
Number of RBs per cell	$N_{UL}=N_{DL}=200$ RBs
Frequency	2.6 GHz
Path loss model	The path loss and the LOS probability for cellular mode are modeled as in [31]. In sidelink mode, all V2V links are modeled based on freeway case (WINNER+B1) with hexagonal layout [ITU-R] [32].
Spectral efficiency model to map SINR.	Model in section A.1 of [33]. The maximum spectral efficiency is 8.8 b/s/Hz.
Shadowing standard deviation	3 dB in LOS and 4 dB in NLOS.
height of the gNB	10m
Base station antenna gain	5 dB
TTI duration (F_d)	1ms
Time window T	3s
V2X parameters	
Length of the highway	1Km
Number of lanes	3 in one direction (one is considered in the freeway)
Lane width	4 m
Number of clusters	4
Size of cluster	250m
Vehicular UE height	1.5m
vehicle speed	80 Km/h
Vehicle arrival rate λ_a	1 UE/s
Packet arrival rate λ_v	1 packets/s
Message size (S_m)	300 bytes
eMBB parameters	
UE arrival rate λ_m	1 UE/s
UE height	1.5m
Average session generation rate λ_e	Varied from 0.2 to 1.2 sessions/s
R_b	1 Mb/s
Average session duration	120 s
RAN slicing algorithm parameters	
Learning rate α	0.1
ω	0.85
Temperature parameter τ	0.1
Actions of the RL algorithm	20 actions, $k=1,\dots,20$ Slice 1: $\beta_{1,x}(k)=0.05 \cdot k$ Slice 2: $\beta_{2,x}(k)=(1-0.05 \cdot k)$

From Fig.3 and Fig. 4, it's clearly observed that, as the arrival rate of requests increases, the RB utilization of the system increases gradually.

For the proposed off-line RL, when the session generation rate of eMBB traffic is 1.2 sessions/s, the system utilizes around 78 % and 74 % of radio resources in uplink and

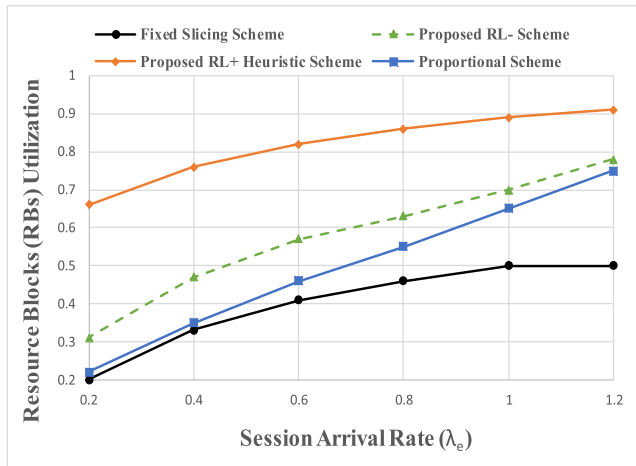


FIGURE 3. Uplink RB utilization as a function of the eMBB session generation rate λ_e (sessions/s).

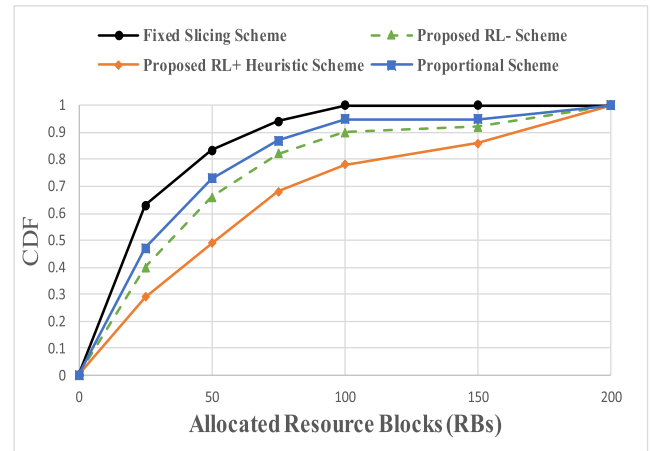


FIGURE 5. CDF of the number of utilized Resource Blocks by both slices in uplink and sidelink.

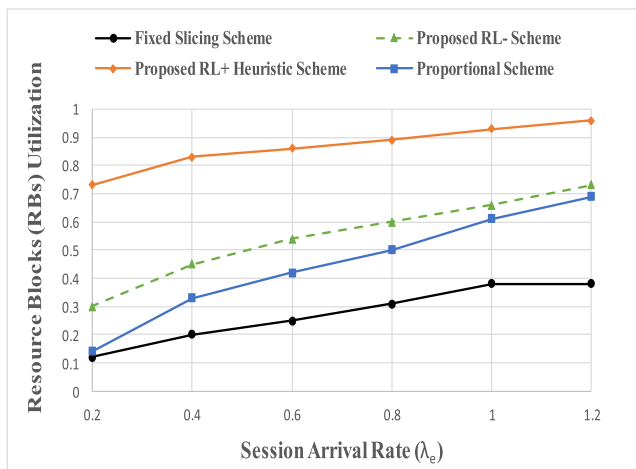


FIGURE 4. Downlink RB utilization as a function of the eMBB session generation rate λ_e (sessions/s).

downlink, respectively. Further improvements are obtained by the off-line RL followed by the heuristic approach as the system utilizes up to 91 % of radio resources in uplink and 96 % in downlink. This is due to the benefit from the unused capacity left from each slice. For the reference with proportional approach, the utilization is only about 69 % in uplink (i.e. proposed approach achieves a relative gain of 32 %) and 76 % in downlink (i.e. proposed approach achieves a relative gain of 20 %). In case of the reference with fixed slicing strategy, the utilization is only about 50 % of radio resources in uplink (i.e. proposed approach achieves a relative gain of 82 %) and 39 % in downlink (i.e. proposed approach achieves a relative gain of 146 %) when eMBB arrival rate is 1.2 sessions/s.

Fig. 5 presents the cumulative distribution function (CDF) of overall resource pool utilization for uplink and sidelink transmissions at arrival rate of 1.2 sessions/s. The results show that our proposed scheme with both approaches maintains high resource utilization and outperforms the reference with proportional and with fixed slicing schemes.

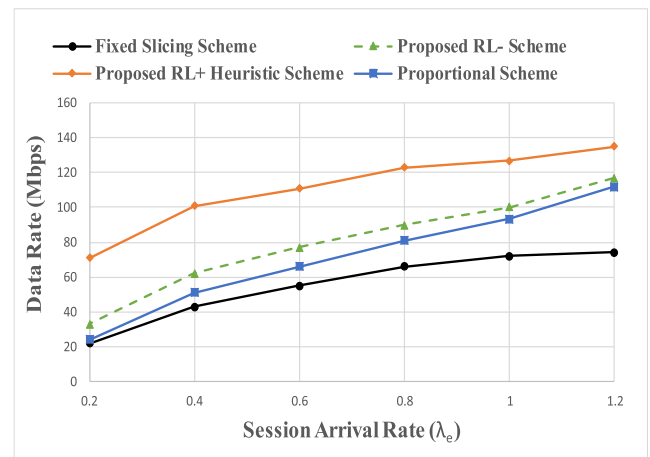


FIGURE 6. Aggregated throughput experienced by both slices in uplink (including uplink and sidelink traffic) as a function of the eMBB session generation rate λ_e (sessions/s).

C. PERFORMANCE IN TERMS OF NETWORK THROUGHPUT

Fig.6 and Fig.7 depict the aggregate throughput delivered in Mbits/sec for both eMBB and V2X slices in the uplink (including both sidelink and uplink traffic) and downlink, respectively. The figures illustrate the behavior of the proposed solutions and the reference schemes. Here, we can observe that the off-line RL and off-line RL followed by the low-complexity heuristic approach outperform the references scheme. In the case of the proposed scheme with off-line RL followed by the low-complexity heuristic algorithm, the maximum throughput for both services is about 136 Mb/s in uplink and 148 Mb/s in downlink, when the eMBB arrival rate is 1.2 sessions/s. In turn, the proposed scheme with only off-line RL achieved a maximum throughput of 118 Mb/s and 98 Mb/s in uplink and downlink respectively.

The reference with proportional approach achieved maximum throughput of 112 Mb/s in uplink (i.e. proposed approach achieves a relative gain of 21 %) and 94 Mb/s in downlink (i.e. proposed approach achieves a relative gain of 57%). Instead, in case of the reference with fixed slicing

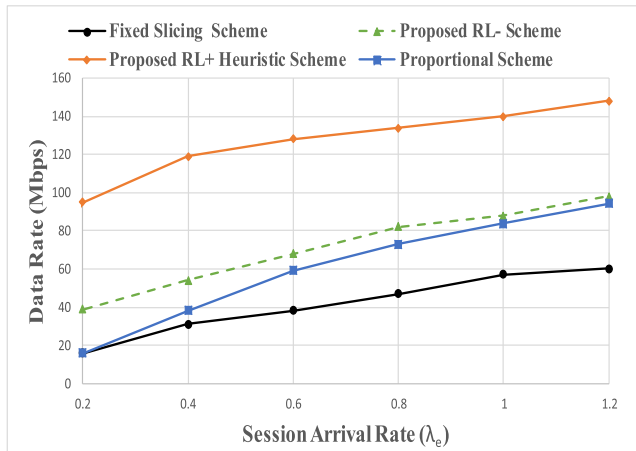


FIGURE 7. Aggregated throughput experienced by both slices in Downlink as a function of the eMBB session generation rate λ_e (sessions/s).

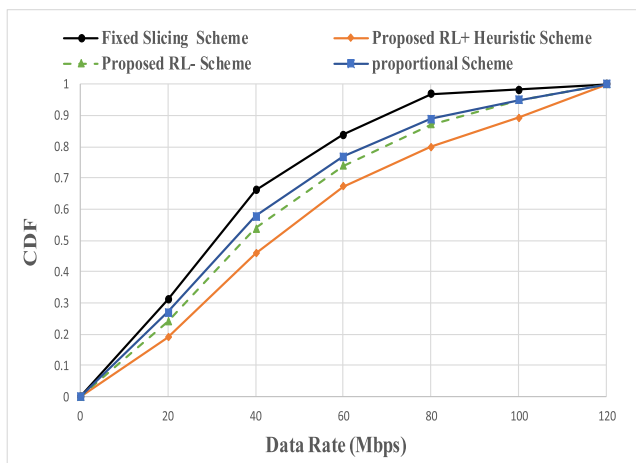


FIGURE 8. CDF of Aggregated throughput experienced by both slices in in uplink and sidelink.

model, the maximum throughput is only 74 Mb/s in uplink (i.e. proposed approach achieves a relative gain of 83 %) and 60 Mb/s in downlink (i.e. proposed approach achieves a relative gain of 146%). The reason for this behavior is that, as the number of eMBB sessions increases, requiring more radio resources, the proposed off-line RL followed by the heuristic algorithm ensures more RBs and achieves a higher utilization for radio resources than the reference schemes. Therefore, these RBs can be used to transmit data, while in the reference approaches there are no more available RBs for use by data transmissions.

Fig. 8 presents the cumulative distribution function (CDF) of the aggregate throughput achieved by the eMBB and V2X slices for both uplink and sidelink transmissions. As shown by the results, our proposed scheme with both off-line RL and off-line RL followed by the low-complexity heuristic approach maintains a higher throughput than the reference schemes. Specifically, the proposed approach achieves up to 143 Mb/s with probability of 95 % while the reference scheme with proportional approach achieves 100 Mb/s and the fixed slicing achieves only 80 Mb/s. This evaluation

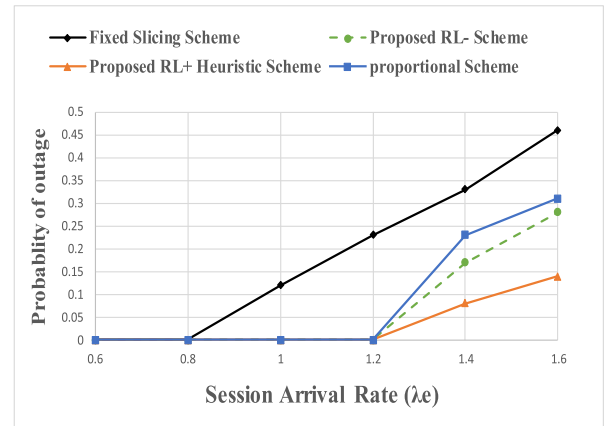


FIGURE 9. Outage probability as a function of the eMBB session generation rate λ_e (sessions/s).

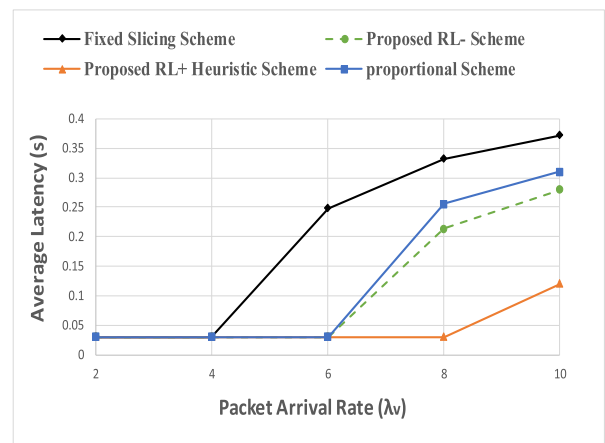


FIGURE 10. Average Latency as a function of the V2X UEs packet generation rate λ_v (packets/s).

demonstrates the capability of the proposed schemes to utilize more RBs in order to achieve high data rate.

D. PERFORMANCE IN TERMS OF OUTAGE PROBABILITY

In Fig.9, we investigate the probability of having outage due to the lack of radio resources at a certain point of time. The outage probability of the proposed and reference schemes is plotted against the eMBB session arrival rate λ_e . As shown in the figure, increasing the traffic load leads to an increase in the outage probability of service. It can be also noted that our proposed scheme can substantially reduce the outage probability compared to the two reference schemes.

E. PERFORMANCE IN TERMS OF LATENCY

Fig. 10 depicts the average latency for V2X service caused by channel access delay and the transmission delay. Latency is measured as the time spent by a packet in the system, from the time it is generated until it has been transmitted. Clearly, when packet generation rate λ_v is increased, more vehicles will use the network and request more RBs to be used for the transmissions. This causes an increase in the waiting time and therefore increases the latency. We notice that the approach proposed in this paper reduces the latency compared to the

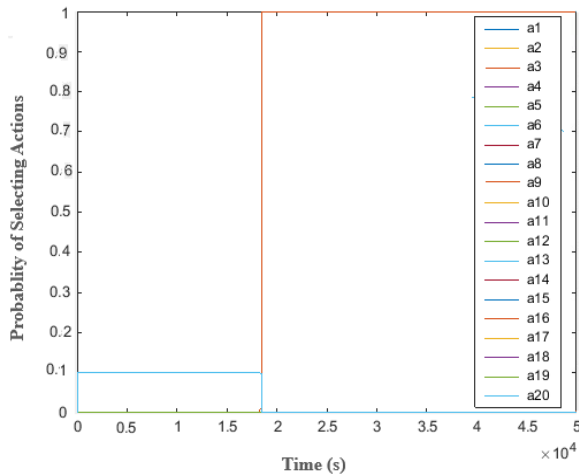


FIGURE 11. Selection probabilities $P(a_{k,UL})$ for the uplink.

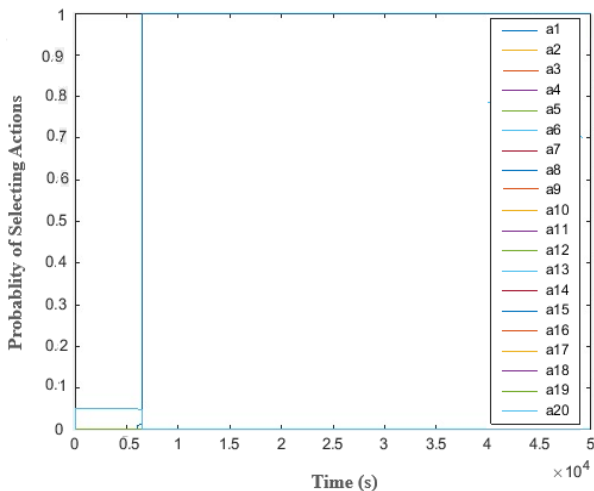


FIGURE 12. Selection probabilities $P(a_{k,DL})$ for the downlink.

two references schemes, because it makes a more efficient use of RBs and thus it increases the availability of RBs, with the corresponding reduction in waiting time. For the proposed off-line RL, when the packet arrival rate of V2X traffic is 10 packets/s, the average latency around 0.28s. Further improvements are obtained by the off-line RL followed by the heuristic approach, as the latency only about 0.13s. Instead, for the reference with proportional approach, the latency is 0.31s, while for the reference with fixed slicing strategy the latency is about 0.39s.

F. ACTION SELECTION PROBABILITY

This section intends to analyze the behavior of the Q-learning scheme when selecting the different actions. For that purpose, Fig. 11 and Fig. 12 show the evolution of the probability of selecting each action $a_{k,x}$ in uplink and downlink, respectively. In the conducted simulations, the Q-learning approach with $\tau = 0.1$ is considered to control the tradeoff between exploration and exploitation in the learning mechanism. As a result, with low values of τ , the system tends to converge

quickly toward appropriate solutions with selection probabilities close to 1.

As can be seen in Fig. 11, at the beginning of the simulation, the proposed reinforcement learning starts to check different actions in order to choose the actions that yield most long-term reward. For the uplink, action $a_{3,UL}$, corresponding to $\alpha_{1,UL} = 0.15$ and $\alpha_{2,UL} = 0.85$, begins to increase and after some iterations and at approximately time $t = 18000$ s, it is selected with probability close to 1 as the best action for determining the radio resources to each slice in uplink. Similarly, it can be seen in Fig. 12 that for the downlink, action $a_{1,DL}$, corresponding to $\alpha_{1,DL} = 0.05$ and $\alpha_{2,DL} = 0.95$, is selected as the best option. This occurs at approximately $t = 6000$ s.

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we have investigated the problem of how to split the radio resources between multiple RAN slices in a scenario with V2X and eMBB services involving uplink, downlink and sidelink communications. We have proposed a new RAN slicing strategy based on an off-line reinforcement learning followed by a low-complexity heuristic approach to determine the split of resources assigned to the eMBB and V2X slices.

Extensive simulations were conducted to validate and analyze the performance of our proposed solution, comparing it against two reference schemes and against the case with only the RL approach. Simulation results show the capability of the proposed algorithms to allocate the resources efficiently and to improve the network performance in terms of resource utilization, throughput, latency and outage probability. Specifically, from the presented results, we notice that our proposed scheme including both the off-line Q-learning and the low-complexity heuristic approach outperforms the reference based on a distribution proportional to the traffic and the reference with fixed slicing ratio in terms of the achieved Resource Block utilization with gains of up to 32% and 82%, respectively, in uplink. Results also demonstrated that bit rate improvements of up to 21% and 83% can be obtained in uplink with respect to the case with off-line Q-learning followed by a low-complexity approach compared to the reference with proportional approach and the reference with fixed slicing strategy, respectively. Besides, the proposed algorithms can reduce the latency caused by channel access delay and transmission delay for V2X communications. Specifically, latency reductions of around 0.18s and 0.26s have been obtained with the proposed approach with respect to the reference based on a distribution proportional to the traffic and the reference with fixed slicing ratio, respectively. Moreover, the proposed algorithms can also reduce the outage probability that arises when increasing the traffic and thus the demands for RBs. In this case, the proposed approach reduces the outage probability by around 0.16 and 0.32 with respect to the reference based on a distribution proportional to the traffic and the reference with fixed slicing ratio, respectively.

Based on the current work, our future work plans include, first, to introduce different options for configuring the RAN slices when considering multiple traffic classes in each slice. Second, we intend to develop new latency reduction schemes to better support the V2X traffic.

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