A Survey on Reinforcement Learning-Aided Caching in Mobile Edge Networks

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Abstract—Mobile networks are experiencing tremendous increase in data volume and user density. An efficient technique to alleviate this issue is to bring the data closer to the users by exploiting the caches of edge network nodes, such as fixed or mobile access points and even user devices. Meanwhile, the fusion of machine learning and wireless networks offers a viable way for network optimization as opposed to traditional optimization approaches which incur high complexity, or fail to provide optimal solutions. Among the various machine learning categories, reinforcement learning operates in an online and autonomous manner without relying on large sets of historical data for training. In this survey, reinforcement learning-aided mobile edge caching is presented, aiming at highlighting the achieved network gains over conventional caching approaches. Taking into account the heterogeneity of sixth generation (6G) networks in various wireless settings, such as fixed, vehicular and flying networks, learning-aided edge caching is presented, departing from traditional architectures. Furthermore, a categorization according to the desirable performance metric, such as spectral, energy and caching efficiency, average delay, and backhaul and fronthaul offloading is provided. Finally, several open issues are discussed, targeting to stimulate further interest in this important research field.

Index Terms—6G, deep learning, edge caching, machine learning, mobile edge networks, proactive caching, reinforcement learning.

I. INTRODUCTION

Currently, the wide commercial roll-out of fifth generation (5G) networks is increasingly becoming a reality, providing enhanced mobile broadband (eMBB) services to users, supporting ultra-reliable and ultra-low latency (URLLC) traffic for critical applications, as well as massive machine type communications (mMTC) for a broad range of Internet-of-Things (IoT) applications. As we move forward, the sixth generation (6G) vision is expected to materialize around 2030 and at that time, the International Telecommunication Union (ITU) predicts that the mobile data traffic volume will surpass 5 ZB per month, a 670-fold increase from 2010 [1]. Meanwhile, mobile subscriptions will more than triple, reaching 17.1 billion, as compared to 5.32 billion in 2010.

Such figures necessitate novel wireless network design approaches and the adoption of breakthroughs from the field of machine learning (ML), offering promising results. A technique facilitating the progress of 6G communications is mobile edge computing (MEC) and caching, where computation-intensive tasks take place near the place of data collection and popular contents are in close proximity to users [2]–[4]. In this way, centralized cloud-based computation is avoided, while the backhaul and fronthaul links are relieved from constant data fetching from remote web servers. This setup reduces the computational and communication delays considerably, facilitating latency-intolerant applications that they were otherwise infeasible to provide. At the same time, non-learning-based optimization techniques often fail to reach optimal solutions due to the dynamic nature of the problem that they fail to track, while their complexity might be prohibitive for online network optimization. Thus, ML-aided MEC and caching can cope with the plethora of mobile data and answer the questions of where, when and what to cache, as well as which tasks should be computed at the edge [5], [6].

As the field of online ML-aided network optimization is of tremendous importance towards 6G evolution, this survey focuses on reinforcement learning (RL)-aided edge caching and provides a holistic approach by equally presenting the different cache-aided mobile edge architectures and the corresponding RL solutions.

A. Mobile Edge Networks

Nowadays, mobile networks are struggling to satisfy the heterogeneous service requirements of coexisting users and devices. Conventional cellular architectures cannot provide throughput and delay guarantees and a radical departure is currently taking place, exploiting the cloud computing capabilities and the existence of edge network nodes [7]. Cloud computing offers abundant processing power for various tasks, including among others, baseband processing for cloud radio-access networks (C-RANs), IoT applications with a massive number of sensors and mobile big data exploitation for optimizing network parameters [8], [9]. Unfortunately, centralized cloud architectures result in increased backhaul usage and end-to-end latency that might be intolerable for critical and real-time applications. So, bringing the computation resources closer
to the network edge through the MEC paradigm has been proposed, as a remedy to the shortcomings of cloud computing [3], [10]. Also, the caching capabilities of edge nodes allow the contents to be in proximity to the users, paving the way for performance gains, in the sense of latency minimization, throughput maximization, backhaul offloading, reduced operational expenditure due to energy savings, and finally, extended lifetime for the mobile terminals and the IoT devices [4].

The MEC architecture requires from edge nodes to be equipped with storage capabilities for caching popular contents and avoiding constant fetching from remote web servers. Meanwhile, the wide range of different edge node types constitutes a challenging environment for optimizing the network performance [11]. First, fixed cellular networks based on different tiers can benefit by storing content at small base stations, considering parameters, such as user mobility and interference among cells of the same of different tiers. Moreover, novel cellular architectures, comprising fog radio-access networks (F-RANs) rely on low-complexity fog access points (F-APs) instead of conventional BSs, where only a part of baseband processing takes place at the F-APs [12].

However, caching schemes should also aim at alleviating the fronthaul capacity constraints and improve the F-RAN performance. In addition, further extensions to traditional cellular networks are offered through cooperative communication and caching. More specifically, intelligent caching schemes can exploit the caching resources at different nodes, distributing the content for increased efficiency and robustness when specific nodes experience outages due to fading. In this context, cooperation between users through device-to-device (D2D) communication improves physical-layer aspects, such as coverage and transmit diversity while using storage at the devices for offloading the BSs [13]. Finally, the introduction of highly mobile network nodes, providing wireless access and storage with increased flexibility in advanced use cases represents another fertile field of application for employing edge caching schemes. These mobile BSs include ground nodes, communicating in vehicle-to-vehicle (V2V) and vehicle-to-everything (V2X) scenarios, as well as unmanned aerial vehicles (UAVs), providing fast recovery after disasters and emergency situations, on-demand capacity provisioning and coverage in remote and rural areas [14], [15].

An illustrative edge architecture is depicted in Fig. 1, showing different cases of edge caching. More specifically, within the coverage area of a macro cell, a small cell caches content and serves users, requiring reliable and high throughput access, while a relay caches content that was transmitted from nearby users in the uplink and the macro BS in the downlink. Meanwhile, UAVs provide coverage to remote areas with limited coverage and store content that is scheduled for transmission towards the macro BS at a later moment, in order to reach the core network. Furthermore, various ad hoc communication paradigms exist, including cache-enabled devices communicating with each other, adopting D2D cooperation, as well as V2V communication in highly mobile environments.

B. Machine Learning

Research on employing machines to process large volumes of data, stemming from previously allocated tasks or simulated scenarios, towards learning to handle future tasks, has led to the tremendous growth of machine learning (ML) [16]. Machines exploit the wealth of data in various applications and interact with the environment in order to explore different actions and then, according to the observed reward, they adapt and exploit the actions yielding the highest reward for their next ventures. In mobile communication networks, a massive number of users and devices enjoy a broad range of services with different service requirements from heterogeneous network nodes, in terms of hardware capabilities. This explosive increase of wireless traffic requires highly complex network optimization solutions, posing difficulties to decision-making during resource allocation of bandwidth, power and storage. The adoption of online ML solutions in such challenging settings can lead to self-adaptive networks and accurate prediction of communication parameters, abiding to dynamic wireless conditions. In this way, network performance will be enhanced, offering improved Quality-of-Service (QoS) and resource efficiency.
ML is mainly classified into three different categories; namely, supervised learning, unsupervised learning, and reinforcement learning (RL) [17]; see, Fig. 2. In a finer categorization, one can find semi-supervised learning and more recently, federated learning [18]. In what follows, we discuss the different classes.

- **Supervised learning**: In supervised learning, the algorithms rely on datasets, providing both the input and the output. Even though supervised learning provides improved decision making, the need for labeled data might be prohibitive in practice. Algorithms in this category include classification and regression analysis which can facilitate the characterization of data traffic and content popularity.

- **Unsupervised learning**: Unsupervised learning approaches rely on training data that do not include labeled output. Clustering is a popular method to develop unsupervised learning algorithms, enabling pattern identification in datasets. In edge caching users can be clustered based on, for example, their desired contents, mobility, desire to cooperate with each other.

- **Semi-supervised learning**: An intermediate approach regarding the nature of the available data has been followed with semi-supervised learning. In this type of learning, both labeled and unlabeled data are exploited for the training.

- **Reinforcement learning**: In RL, an agent’s strategy is determined in an autonomous manner by considering the cost and reward of each action. Therefore, the main idea of this type of learning is radically different as compared to the previous mentioned ones, which exploit historical data. Instead, RL algorithms are trained by using feedback on previously taken actions, adapting their behavior to the environment. In the edge caching case, various algorithms are used, such as Q-learning for predicting content request probability or deriving the popularity distribution. While in supervised learning the model is trained with the correct answer, in RL there is no answer but the reinforcement agent makes the decision how to perform a given task. If there does not exist any training dataset, RL learns from its experience. Hence, unlike other approaches, RL is about taking suitable action to maximize a reward (e.g., best possible behavior or path) in a particular situation.

- **Deep learning**: Deep learning (DL) is closely related to the above classes of ML. It relies on multiple layers to form artificial neural network architectures for accurate decision making. In this hierarchical architecture lower-level features define higher-level ones, while feature extraction is autonomously performed. In edge caching cases, DL can provide near-optimal policies for content placement and pushing without excessive complexity, even though large volumes of training data should be available. An illustrative example of a DL architecture in the context of mobile edge networking is shown in Fig. 3. Here, the observation of the mobile edge environment leads to the formation of specific states that act as input to the deep neural network (DNN) for deciding the action that should be selected by the agent. Each action results in specific rewards, that in the long-term determine the efficiency of the DL policy.

- **Federated learning**: This approach decouples model training from requiring direct access to raw training data. In federated learning (FL) users exploit shared models trained from excessive amounts of data, without the need to centrally store it [18]. Here, devices take part as clients in a federation aiming at solving the learning task while being coordinated by a central server. Each client maintains a local training dataset that is not uploaded to the server and only computes and communicates an update to the current global model of the server. FL benefits applications where training can be based on already available data at each client, and guarantees high privacy and security levels, since attacks affect only individual devices, and not the cloud.

### C. Contributions

In recent years, the integration of ML in wireless networks has offered tremendous potential towards achieving the targets of 6G networks. In addition, edge caching has been considered an enabling technique for an overall improvement of wireless network performance, through offloading and reduced number of content fetching from remote web servers. There have been several surveys focusing on either the synergy of ML and wireless networks [5], [19] or the gains of edge caching through traditional optimization approaches [20], [21].
Meanwhile, most studies provide brief overviews on ML-aided edge caching and non-exhaustive lists of relevant works [22], [23]. Currently, only a few works offer a holistic view on ML-aided edge caching. The survey in [24] investigates ML-based proactive caching, highlighting the improvement in small cells and UAV-aided networks. However, the majority of the reviewed works are non-learning-based. Another survey studies DL for edge caching, presenting the major DL categories and the basic caching principles [25]. Still, the survey mostly focuses on describing DL operation in a more general manner while discussion of the various works often lacks the details on the networking environments and performance evaluation. The use of artificial neural networks (ANNs) for wireless network optimization is examined in [26], including the area of edge caching. However, the tutorial focuses only one part for ANN-aided edge caching and includes a small number of relevant works. Finally, the survey in [27] provides an overview of AI-based techniques for wireless caching, including supervised, unsupervised, reinforcement and transfer learning. Various challenges are highlighted, such as the dynamic environment due to mobility and fading. Still, that work does not provide a broad view of RL-based solutions, representing the main category of ML that can handle the volatility of mobile edge networks.

Considering the importance of edge caching in the context of 6G and the high interest in developing RL- and deep reinforcement learning (DRL)-aided solutions, this survey provides an exhaustive list of RL-based edge caching solutions and a spherical view on their application in mobile edge networks. Thus, it is the first survey, focusing only on RL-aided edge caching, discussing the recent contributions on this field. More specifically, our contributions include:

- Various cache-aided wireless networks are covered, from fixed cellular topologies and cooperative architectures to fog-based approaches and vehicular networks.
- RL-based edge caching schemes are discussed, presenting in detail the learning algorithms, possible caveats for their implementation and the gains they bring to the network.
- A classification of the RL solutions is conducted, according to their performance target, i.e. energy, spectral and caching efficiency, delay and Quality-of-Experience (QoE).
- Open issues are highlighted, stimulating further research on this field and discussing the interplay with other aspects of wireless networks, such as physical-layer and multiple access issues, security and network volatility.

D. Organization

The structure of this survey is as follows. In Section II, we present RL-aided edge caching in fixed cellular networks, while Section III focuses on F-RANs. Then, Section IV includes cooperative approaches, as well as local caching at mobile devices. Subsequently, highly mobile and flexible network topologies are discussed in Section V and Section VI. Open issues in RL-based edge caching are presented in Section VII and finally, conclusions are given in Section VIII.

1Deep reinforcement learning combines RL and neural network based function approximators in order to tackle the curse of dimensionality.
TABLE I

| LIST OF ABBREVIATIONS |
|------------------------|
| A3C | Asynchronous advantage actor-critic |
| AC | Actor-critic |
| AoI | Age of information |
| AP | Access point |
| BBU | Baseband unit |
| BLA | Bayesian learning automata |
| BS | Base station |
| C-RAN | Cloud radio access network |
| CDM | Content delivery market |
| CNN | Convolutional neural network |
| CPU | Central processing unit |
| CRNN | Convolutional recurrent neural network |
| D2D | Device-to-device |
| DCA | Deterministic caching algorithm |
| DDPG | Deep deterministic policy gradient |
| DDQN | Double deep Q-network |
| DL | Deep learning |
| DNN | Deep neural network |
| DQL | Deep Q-learning |
| DQN | Deep Q-network |
| DRL | Deep reinforcement learning |
| DTS | Double time-scale |
| ELSM | Echo liquid state machine |
| eMBB | Enhanced mobile broadband |
| EMQRN | External memory-based recurrent Q-network |
| F-RAN | Fog radio access network |
| FIFO | First-in first-out |
| FL | Federated learning |
| HetNet | Heterogeneous network |
| ICRP | Individual content request probability |
| IoT | Internet-of-Things |
| ITU | International telecommunication union |
| KNN | K-nearest neighbors |
| LRU | Least recently used |
| LSTM | Long-short-term memory |
| M2M | Machine-to-machine |
| MAB | Multi-armed bandit |
| MDP | Markov decision process |
| MEC | Mobile edge computing |
| MIMO | Multiple-input multiple-output |
| MINLP | Mixed integer non-linear program |
| ML | Machine learning |
| mmTC | Massive machine type communications |
| MNO | Mobile network operator |
| MVNO | Mobile virtual network operator |
| NOMA | Non-orthogonal multiple access |
| PLS | Physical-layer security |
| PPO | Proximal policy optimization |
| Q-LCCA | Q-learning collaborative cache algorithm |
| QoE | Quality-of-Experience |
| QoS | Quality-of-Service |
| RB | Radio bearer |
| RL | Reinforcement learning |
| RLNC | Random linear network coding |
| RRH | Remote radio head |
| RRM | Radio resource management |
| RSU | Road Side Unit |
| SAE | Stacked auto-encoder |
| SDDPG | Supervised deep deterministic policy gradient |
| SDN | Software-defined network |
| SNR | Signal-to-noise ratio |
| UAV | Unmanned aerial vehicle |
| UCB | Upper-confidence bound |
| URLLC | Ultra-reliable and ultra-low latency |
| V2I | Vehicle-to-infrastructure |
| V2V | Vehicle-to-vehicle |
| V2X | Vehicle-to-everything |
| VFA | Value function approximation |
| VR | Virtual reality |
| WMMSE | Weighted minimum mean square error |

II. FIXED CELLULAR NETWORKS

Cellular architectures comprising fixed base stations (BSs) represent a major field where edge caching can alleviate the burden of excessive data traffic from users residing in their coverage area. Two types of architectures will be discussed, namely, single-cell topologies and multi-cell topologies where different tiers overlap.

A. Single-cell topologies

There have been various works studying the performance of RL-aided edge caching in single-cell networks, presenting scalable solutions that can be employed to more complicated settings, after necessary modifications.

1) Energy efficiency: The paper in [28] studies resource allocation in cache-aided MEC networks to guarantee sufficient communication, caching and computing capabilities for intensive computational tasks with stringent latency constraints. Towards satisfying such constraints, the joint optimization of task offloading, as well as cache, computation and power allocation is formulated as a mixed integer non-linear program (MINLP) problem. Then, resource allocation is modeled as a Markov decision process (MDP) and a DRL framework is proposed, enabling the users and the access point (AP) to learn from historical data and increase the efficiency of resource allocation. Furthermore, DRL allows a quasi-optimal solution to be obtained with low-complexity, even under the large state space of the MDP. From the simulations, it was shown that DRL provides improved energy consumption, as the AP caching capability increases, while for increasing computation capacity, the energy consumption performance is near-optimal. Also, comparisons with other benchmark schemes without caching capabilities and different task computation strategies emphasize on the important energy gains of the MDP-based DRL algorithm.

Resource allocation for improved energy performance in cache-aided networks has also been investigated in [29], [30] where non-orthogonal multiple access (NOMA) has been employed. NOMA enables multiple users to simultaneously offload tasks to APs, operating as edge computing servers, achieving latency reduction. At the same time, the caching of computational results reduces the stress under increased computation requests, as these results can be requested at a different time by other users enjoying the same application. So, in this context, the problem of jointly optimizing task offloading, computation resource allocation and caching decisions is tackled by employing a long-short-term memory (LSTM) network. LSTM improves the exploration-exploitation trade-off when predicting task popularity. For the resource allocation procedure, a single-agent Q-learning algorithm is utilized, which is based on Bayesian learning automata (BLA) multi-agent Q-learning handles task offloading. Extensive simulations are conducted, depicting the high prediction accuracy of LSTM. Comparisons of the single-agent Q-learning algorithm with three benchmark schemes, i.e., local computation at the mobile users, computation only at the AP and computation in a non-cache-aided networks highlight important energy savings for the proposed RL algorithms, as caching and computation...
capacities are increasing. Finally, it is observed that BLA multi-agent Q-learning offers improved energy consumption performance over an algorithm that does not employ BLA for task offloading.

Focusing on optimizing the content update strategy in small BSs with limited cache capacities, the works in [31], [32] consider a more general framework characterized by random resource availability and content requests. More specifically, time-varying and stochastic costs are assumed, being associated with file fetching from the cloud, incurring scheduling, routing and transmission costs. Also, cost includes memory and energy consumption due to caching at the small BS. Two different cases are examined where in the first case, costs and content popularity follow known and stationary distributions and a dynamic programming problem is formulated and solved through value-iteration-based RL. The second and more practical case considers limited cache capacity and unknown cost distributions and an online low-complexity Q-learning solver is employed to determine the optimal content update strategy. The caching versus fetching trade-off is evaluated for both cases with varying mean values for the cost of caching and fetching. It is revealed that the online Q-learning without a priori knowledge of the statistical properties of the costs and content popularity offers almost the same average cost performance with value-iteration-based RL, while its efficiency in cache-fetch decision-making is emphasized in both stationary and non-stationary environments.

2) Caching efficiency: Targeting to improve the data offloading and cache hit rate performance, the paper in [33] presented DRL with deep deterministic policy gradient (DDPG)-based training [34] and the Wolpertinger policy [35], relying on three entities. First, an actor function, receiving as input the cache state and the content requests and providing a prototype from the set of valid actions. Then, K-nearest neighbors (KNN) mapping is employed, expanding the prototype to a set of valid actions from the action space. Finally, a critic function refining the actor in order to select the action with the highest Q-value from the expanded KNN set. Performance evaluation for centralized caching and comparisons with least recently used (LRU), least frequently used (LFU), and first-in first-out (FIFO) policies reveal that actor-critic (AC) DRL can improve the cache hit rate in the short-term and avoid cache hit rate variations in the long-term.

The issue of accurately replacing the cached content at a BS that does not know the content popularity is investigated in [36]. This problem is cast as an MDP where the BS cache status and the user requests represent the state space, while the decision of either keeping the current files or replacing them with updated versions define the action space. So, the authors propose an LSTM and external memory-based recurrent Q-network (EMQRN) algorithm to enhance the cache hit rate. The proposed algorithm is evaluated and compared with LRU and FIFO without learning capabilities and the deep Q-network (DQN) algorithm of [37]. From the results, it can be seen that EMQRN leads to higher reward and faster convergence, compared to DQN. Still, the implementation of EMQRN in more complicated topologies where multiple BSs cooperate and share their cache status for optimized content update strategies remains an open problem.

3) QoE improvement: In a network where a single caching server facilitates the transmission of short video content, a gradient-based DRL algorithm was developed in [38]. Two issues are concurrently tackled, i.e., the video quality selection and the radio bearer (RB) control transmission performance. This joint problem is modeled as an MDP for the sequence of user content requests, triggering necessary RB control actions, such as setup, reconfiguration and release. For each action, the decision is made by considering the current state while training in scenarios with different parameters enables the proposed DRL to be employed in different scenarios with the same state spaces. The performance of the gradient method-based DRL is evaluated against a greedy policy serving the content request with the highest waiting time, and transmitting it at the highest video quality, and a minimum quality policy, aiming at serving the maximum number of requests by setting the video quality at the lowest level. By considering the use of additional RBs as cost and the increased level of video quality as reward, different arrival rate cases are tested and it is observed that DRL outperforms the greedy policy for rates between 1.8 to 2.4 while for rates below 1.6 the greedy method provides better performance but at the cost of higher complexity. An open issue remaining is the generalization of the proposed gradient-based DRL for more varied communication scenarios.

Focusing on content-centric caching for improved QoE, the authors in [39] developed a DRL-based decision making model, employing DNN for Q-value estimation. Optimization considered both latency and storage costs, outlining the negatively proportional relationship of the two metrics to QoE. As there exists a conflict between these two performance metrics and the network operates in a dynamic environment, DNN might not effectively estimate the Q-value. Thus, DRL relied on fixed target network (F), experience replay buffer (E), and adaptive learning rate (L) for improved stability, leading to FEL-DRL. More specifically, fixed target network leads to stable convergence by using another neural network with fixed parameters which are periodically according to the values of the estimated network. Meanwhile, experience replay avoids temporal correlation among different training episodes, creating a dataset from the agent’s experience and randomly using data batches for network training. Comparisons using Matlab© and TensorFlow showed that FEL-DRL achieves an average QoE score of 64, while DRL provided a score of 62. Finally, the rest of the algorithms, i.e. AC-DRL, FE-DRL and RL provided QoE values below 60 which is considered as the threshold for user satisfaction.

B. Multi-cell topologies

More complicated multi-cell networks have been investigated in various works, highlighting the gains of edge caching at different nodes.

1) Age of information reduction: The authors in [40], [41] focus on the update scheduling for minimizing the age of information (AoI) of the cached content, in a two-tier heterogeneous network (HetNet) where multiple small cells act as content servers, delivering dynamic content to users.
AoI quantifies how much time has passed from the moment that the current file version has been generated [42], [43]. The content caching problem is formulated as a constrained MDP and enforced decomposition is employed to update the dynamic contents in the caches. AoI is minimized by using multiple queues to monitor user request, assuming that each request arrives prior to the desired file download time. As the state space of the different constrained MDP subproblems can be large, DRL agents are trained to derive the optimal content update policy. Performance evaluation results, using PyTorch suggest that DDPG-based DRL offers improved convergence and reduced AoI. More specifically, for the single dynamic content scenario, DDPG provides improved convergence, compared to DQN [37], while for multiple dynamic contents, the average AoI is reduced by 30% versus periodic update without considering the user request queues [44].

2) Delay reduction: The reduction of transmission delay and cache replacement cost in the long-term, in two-tier small cell networks is studied in [45]. More specifically, wireless coded caching is employed to distribute coded fractions of a file at different network nodes, thus addressing the need for large caches. As a first step to provide improved caching, historical user file requests are exploited for predicting the future ones. In the next phase, a supervised deep deterministic policy gradient (SDDPG) approach based on both supervised learning and DRL is employed to solve the wireless coded caching problem. Aiming at accelerating the learning process, supervised learning is invoked to pre-train the neural network by considering the solution to an approximate cost minimization problem at each slot. Performance evaluation results, highlight the capabilities of SDDPG in reducing the total network cost, compared to a short-term optimization cost scheme while it exhibits a small performance gap compared to the performance upper-bound of knowing the actual number of requests.

The MAB framework is adopted in [46], mapping the reward to transmission delay reduction, compared to the case without caching. Assuming unknown user preferences, the proposed collaborative caching schemes aim at minimizing the accumulated transmission delay over a finite time horizon. This paper extends the work in [47] which presented distributed and collaborative multi-agent MAB algorithms in stationary environments. Here, two stationarity cases are investigated for the file library and user preferences. For the stationary case, a fixed file set and time-invariant user preferences are considered and two high-complexity MAB algorithms are presented. Their regret performance is bounded by $O(\log T_{total})$, where $T_{total}$ denotes the total number of time-slots. Meanwhile, a lower complexity and distributed MAB solution is developed, considering that each small BS acts independently. Judging from the performance of these algorithms, an edge-based collaborative multi-agent MAB algorithm is proposed, relying on coordination graph edge-based reward assignment. Then, in the non-stationary case, the file set and user preferences dynamically vary and thus, modified multi-agent MAB algorithms are given. More specifically, the exploration duration is reduced by assigning larger initial values to the joint actions of adding new content to the varying file set in each time-slot. Also, the upper confidence bound (UCB) terms are modified to accommodate that the small BSs are unaware of the reward upper bound. Simulations for both cases show that the proposed MAB algorithms significantly reduce the delay, compared to policies, such as LRU and LFU, while narrowing the performance gap compared to an oracle greedy algorithm for a wide range of communication distance, cache size and user mobility parameters.

The delay minimization is also the focus in [48] where AC-based DRL joint user scheduling and content caching is proposed. In greater detail, the actor adopts stochastic caching, abiding to the Gibbs distribution and parameters are updated through gradient ascent by observing the environment states. The critic evaluates the actor policy and the resulting awards, in terms of delay. For this purpose, a DNN is used for value function approximation and gradient estimation. The convergence of the AC-based DRL scheme is evaluated in a two-tier network for different learning rates for the actor and the critic, highlighting that a low actor learning rate leads to improved convergence. Also, comparisons are presented with AC-based DRL without caching and AC-based DRL without scheduling. Results indicate 40% and 56% higher total rewards through the proposed joint user scheduling and caching scheme over the standalone scheduling and caching schemes, respectively.

The joint optimization of delay and blockchain-based security has been presented in [49], focusing on (machine-to-machine) M2M communication. Since blockchain systems require increased time to complete the smart contracts, delay requirements might not be met [50]. So, in this study, system performance is enhanced by developing a dueling DQN for optimal decision-making, regarding caching, computing and security. The dueling architecture allows the DDQN to efficiently learn the action value through the separate estimation of the state value and the reward of each action, including higher caching reward, reduced data computation overheads, and efficient blockchain processing. Performance comparisons against conventional DQN, greedy-based strategy and random selection for different cache and block sizes, delay constraints and a varying number of machine-type devices, showed reduced latency, and higher rewards when dueling DQN is employed.

3) Caching efficiency: An AC-based DRL policy is also employed in a network with multiple BSs, towards providing decentralized edge caching [33]. In this setting, the main goal of the learning-based approach is cache hit rate performance improvement. Comparisons with non-learning-based LRU, LFU and FIFO policies shows that AC-based DRL efficiently finds the popular contents and reduces the transmission delay by considering user location and enabling the inter-BS communication in order to avoid caching of the same content when their coverage areas overlap.

The optimization of content caching and delivery policy under non-stationary content libraries is the subject of [51]. Aiming to maximize the network utility consisting of backhaul traffic offloading, cache hit rate, as well as the content retrieving and delivery metrics, a user-assisted RL algorithm is given. This algorithm exploits the caches of the users in order to
relieve the small cells during peak hours. So, the BSs’ caches are divided in two parts where in the first part, new content from the users’ caches is stored, while using the second part for content server updates. The content caching and delivery is formulated as a MAB problem, accommodating the spatio-temporal dynamics of user requests. In this context, the content library is modeled as a system with multiple arms with unknown and stationary rewards. A central unit sequentially determines content caching, based on the trade-off of exploring possibly popular files that are rarely cached and exploiting the empirical knowledge of caching content, yielding the highest rewards up to this round. The proposed content caching and delivery algorithm operates in three phases, where in the first phase, content delivery takes place, then, in the second phase, one part of the small cell caches is updated with content from the users and finally, in the third phase, the other part of the BSs’ caches is updated from the content server.

Performance evaluation includes comparisons with benchmark schemes operating without a user-assisted phase. It is observed that the MAB-based user-assisted algorithm is more robust against the spatio-temporal variations of content requests and benefits from the exploitation of the users’ caches. Nonetheless, it is stated that providing regret performance guarantees is challenging, since this works assumes caching of multiple contents at different small cells, coordinating with each other during the last phase and possibly replacing content from the users’ caches from the second phase.

Distributed content placement was studied in [52] in a dense small cell network, aiming to alleviate the traffic load from the backhaul infrastructure. The authors showed that the problem of optimal content placement is NP-hard, independently of whether or not the small BSs know the file popularity profiles. Thus, a learning-based coded caching solution is proposed where the small BSs are employed to learn the file popularity profiles, using the content request historical data. The learning framework takes into account the connectivity of users with the small BSs and relies on combinatorial MAB. More importantly, the MAB-based learning framework is able to adapt to the dynamicity of content popularity over time, based on the trade-off among the exploration of caching new files and finding their popularity versus the exploitation of caching files with already-known high popularity. Regarding the reception of distributed cached contents, rateless coding is adopted, guaranteeing the decoding of the original file, as long as a specific fraction of the coded symbols is received. Performance evaluation depicts the advantage of MAB-based distributed caching in yielding higher rewards, compared to a local caching scheme neglecting the network connectivity status and an uncoded caching scheme.

In [53] the authors aim at improved edge caching in networks where infrastructure providers lease their physical resources, in the form of BS storage and backhaul capacity to mobile virtual network operators (MVNOs). By investigating the joint optimization of cache leasing and content popularity prediction from the MVNOs’ perspective towards maximizing their profits, a Q-learning algorithm is presented to provide DL models with optimized hyper-parameters. The generated DL models are employed to predict the parameters of content popularity, namely future cache demand and request count. Using this information, the DL models compile lists with content that should be cached at the BS. Performance evaluation focuses on the cache hit probability and backhaul usage and three different configurations for the unknown layer of the DL model, i.e., convolutional neural network (CNN), LSTM and convolutional recurrent neural network (CRNN).

The results on feature selection suggest that LSTM provides superior training and validation accuracy performance with the least amount of training time. Finally, after evaluating different configurations, the best LSTM models are compared versus the optimal and randomized caching schemes, showing that on average, the best LSTM model offers a 16% cache hit probability improvement, compared to 12% by the randomized scheme, while it reduces backhaul usage by 17%, compared to 12% by the randomized scheme.

RL-based meta-learning with enhanced searching space design and autonomous DL model generation, as presented in [53] with optimized hyper-parameters are investigated in [54]. The proposed solution comprises two parts. In the first part, a cloud-based master meta-learner provides the DL models and decides on the best-suited one. The second part involves a slave meta-learner located at each small BS, using the best DL model for popularity prediction after tuning its parameter through localized information. Simultaneously, the slave meta-learner provides feedback to the master meta-learner on the prediction accuracy, triggering the latter to explore a different model, in case of suboptimal results. Performance evaluation is conducted by implementing the RL-based meta-learning scheme, using Tensorflow [53] and Keras [56]. Comparisons show 10% and 30% cache hit rate improvement over the scheme in [53] and randomized caching, respectively.

Another work aiming to increase the net profits of mobile network operators (MNOs) through a DRL framework is presented in [57]. Here, the content is not cached at the BSs but on the contrary, it is proactively pushed and cached at the users’ devices. In order to achieve this, content pushing and recommendation for the users are investigated, resorting to RL for predicting the individual user behavior. Nonetheless, the joint problem of proactive pushing and recommendation is characterized by large action and state spaces and thus, a decomposition approach is followed. In greater detail, the recommendation subproblem focuses on increasing requests and providing revenue opportunities. Meanwhile, the pushing subproblem targets aims at minimizing the transmission delay. Considering the inter-dependency among the two subproblems, a double deep Q-network (DDQN) relying on the dueling architecture of [58] is employed. Extensive simulations are conducted to assess the performance of the dueling DDQN versus other learning algorithms, including DDPG [34], advantage AC [59] and proximal policy optimization (PPO) [60]. Results highlight that dueling DDQN converges much faster while solving the recommendation subproblem and provides the highest rewards. More specifically, even though, PPO provides almost the same reward as dueling DDQN, it requires around 43% additional training sessions, compared to the dueling DDQN. Meanwhile, the pushing policy is able to exploit the mobility pattern of the users and the propagation
characteristics, proactively pushing content under favorable channel conditions.

In [61], DRL-based network resource management for achieving better cache hit rate and computation offloading is presented. Nonetheless, in mobile edge networks, the amount of data, parameters and performance targets calls for distributed DRL agent training. Two important aspects are discussed, determining the distributed DRL architecture that should be adopted. First, maintaining a DRL agent in every network node can provide improved performance, but in practice, training will struggle due to differences in task load and network states, as well as time constraints and data unavailability. Second, the distributed DRL architecture should be able to overcome data imbalance and alleviate privacy concerns. So, FL is employed for distributed DRL agent training, reducing communication costs and offering improved privacy and security [18]. Fig. 4 shows a multi-cell topology with $K$ RANs adopting FL to optimize their operation by exploiting local model updates to improve the efficiency of the global collaborative model which is available to all the members of the federation. The proposed In-Edge AI, reduces the need to constantly uploading data in the uplink as FL relies on locally stored data and only calculate updates to the global model of the coordinating central node. Simulations compare the caching performance of DDQN with FL and centralized DDQN without FL, as well as LRU, LFU and FIFO. It is observed that DDQN with FL provides almost the same hit rate performance as centralizes DDQN and outperforms LRU, LFU, and FIFO. In addition, even though the simulated wireless topology is assumed to support the upload of the large amount of training data in the centralized DDQN approach, in practical networks, delay will severely degrade its performance while the small volume of data for FL-based training through the global model updates will be slightly affected.

In cases where user preferences and mobility patterns are unknown, the authors in [62] proposed a temporal-spatial recommendation policy addressing the issue of non-peaky local content popularity. This policy leads cellular users to request their desired files in an efficient way, i.e., during specific time-slots and through appropriate BSs. Since a limited number of user requests might hinder local popularity prediction, a Bernoulli mixture model is adopted to learn user preference and request probability. Then, the recommendation and caching policies are jointly optimized by harnessing RL algorithms. Nonetheless, this joint problem is characterized by large state and actions spaces. Thus, it is decomposed into three subproblems, related to user preference and file request probability estimation with or without recommendation, caching policy optimization, independently of recommendation, and finally, recommendation policy optimization by relying on DRL. Performance evaluation for a network with three BSs and a library of 200 files and comparisons with four baselines schemes are presented. Baselines schemes included, random recommendation, no recommendation, global recommendation, based on the estimated global file popularity and local recommendation where file recommendation in each cell is based on the aggregating the estimated local file popularity. It is shown that DRL overcomes possible user and aggregated preference estimation errors, better adapting the caching policy to user mobility through improved recommendation, compared to the other schemes.

4) Spectral efficiency: Pushing and caching popular services in a three-tier network consisting of broadcast BSs, cellular BSs and routers is studied in [63]. The broadcast BS is responsible for delivering the services and the caches of the routers are used to bring the content closer to the users. In case, a user does not receive its desired content, the router might act as a relay to establish connectivity with another router or a handover to a cellular BS takes place. Targeting the maximization of the equivalent network throughput, service scheduling is modeled as an MDP. Since the large state space entails excessive complexity, deep Q-learning (DQL) is used to find the optimal policy for each state and maximize the cumulative award. Towards addressing the large state space issue, the Q-function is approximated and modified using experience replay and target value update in several time steps, over updating in each time step. Performance comparisons with the algorithm of [64] and centralized caching with dynamic programming shows that for different Zipf factors, characterizing the content popularity, DQL provides significantly higher equivalent throughput, especially for Zipf values below 1.5.

The issue of enhanced edge caching performance through accurate content recommendation, based on personalized preferences is addressed in [65]. In greater detail, localized caching is presented, relying on the individual content request probability (ICRP) for content placement optimization and throughput maximization. This scheme is based on Bayesian learning, namely constrained Bayesian probabilistic matrix factorization, considering rating matrix imbalances towards improving the prediction accuracy of unknown content ratings. The output of this process facilitates the evaluation of personal preferences to obtain the ICRP. In the next step, RL exploits the ICRP and physical distance among caches and users for content placement, resulting in a deterministic caching algorithm (DCA). Further extensions to DCA are provided
by presenting device-to-device (D2D) cooperation for reduced transmission delay and improved ICRP estimation. DCA is compared against random caching and probabilistic caching in terms of root mean square error (RMSE) prediction performance, hit rate and system throughput. From the comparisons, it is observed that DCA offers 90% increased throughput compared to random caching, while D2D cooperation reduces the delay by 15.5% over the non-D2D case.

The work in [66] studied the issue of content placement at BSs towards maximizing the average success probability of the transmission. The authors considered a network with BSs located as a two-dimensional homogeneous Poisson point process (PPP) while the content popularity was assumed to be known and Zipf distributed. Then, by formulating the cost function using the average success probability, an online Q-learning approach was presented and evaluated for both small and large action spaces, depending on the number of cache size, content size and popularity profile set cardinality. Results indicate that for small action spaces, Q-learning converges to the optimal policy after 13 iterations while significantly more iterations are needed for convergence for large action spaces, i.e., around $2 \times 10^3$ iterations.

Aiming to alleviate the impact of tidal effects in mobile networks, i.e., increased network load in peak hours and low bandwidth utilization in idle periods, the authors in [67] propose joint pushing and caching to proactively transmit user content when the network is underutilized. This joint problem involves a transmission cost function, representing bandwidth fluctuation. The minimization of bandwidth fluctuation leads to improved bandwidth utilization and energy efficiency while avoiding duplicate data transmissions. So, the authors propose to exploit hierarchical RL for tackling joint pushing and caching and resort to decomposing the problem into two subproblems. The first subproblem is related to user cache optimization, employing Q-learning value function approximation to mitigate the impact of large state and action spaces. For the second subproblem, DRL is used to improve the performance of BS caching and tackle dimensionality issues. In order to evaluate the performance of the proposed hierarchical RL, comparisons with other policy-based schemes, such as LRU, LFU and local most popular (LMP) in three scenarios, i.e., caching at the BS, caching at the users, joint BS and user caching, are presented. It is observed that hierarchical RL outperforms the other policies in all three cases, while its advantage is significantly increased in the joint BS and user caching, since both the wired and wireless network parts are efficiently utilized.

The joint allocation of networking, caching, and computing resources for supporting smart cities applications is examined in [68]. Assuming a dynamic virtualized networking environment where MVNOs manage multiple BSs, MEC servers and content caches, an excessive number of system states exists and traditional optimization faces difficulties in deriving the optimal policy. As a result, DRL is invoked, using DQN for Q-value function approximation, determining the resource allocation of networking, caching and computing resources. The MVNO’s revenue, formulated as a function of the access link signal-to-noise ratio (SNR), the MEC server computation capability, and the cache state represents the system reward. Simulations are performed, using TensorFlow and DRL is compared to alternative versions without caching, MEC offloading or virtualization. Results suggest that the proposed DRL offers a significantly higher total utility, independently of learning rate and the number of required central processing unit (CPU) cycles per task.

5) QoE improvement: The resource allocation and user association problems in a network providing live video streaming service is the subject of [69]. As the maximization of the QoE is prioritized in such networks, DDPG-based learning algorithm is presented, as an alternative to traditional Lagrangian-based optimization. Initially, an optimization problem is formulated and found to be non-linear and NP-hard. In order to convert it to a linear problem, they focus on the binary decision variables, corresponding to caching content at a BS and receiving a user request for a specific video quality from a BS. More specifically, the DDPG-based algorithm alternatively keeps one variable fixed and then relaxes both binary variables to be continuous to find a near-optimal solution. However, it is observed that in the user association/video quality subproblem, the sub-gradient method is inefficient and in some cases, only a locally optimal value might be observed. So, the DDPG-based approach is employed where in the first step, it observes the state of resource utilization in the network and determines prices for each possible action. In the next step, the users are prompted to associate with the BSs, and request a specific video quality. In this way, the resource utilization is re-calculated based on the users’ decisions and the QoE level is acquired as reward, facilitating the DDPG agent to evaluate the action and accordingly set the NN weights. The DDPG-based learning is evaluated against sub-gradient-based pricing [70] and the approach followed in [71]. It is concluded that the proposed DDPG approach outperforms the two baselines algorithms, as it maintains higher QoE when the number of users increases, while for reduced resource availability, the baseline schemes perform more conservative allocation and provide reduced QoE.

The provision of enhanced QoE is also studied in [72], while avoiding excessive energy consumption. A software-defined network (SDN) is investigated and a mechanism monitoring and processing several parameters related to BS cache, as well as user buffer status and video transmissions parameters, among others. The problem of optimizing the QoE and energy performance is modeled as a constrained MDP that is transformed into an unconstrained MDP by adopting the $T$-period drift-plus-penalty concept, and exploiting the fact that the optimization target should be given as a time average. The unconstrained MDP problem is tackled through the asynchronous actor-critic (A3C) algorithm, employing its agents to run on a multi-core CPU with each thread processing one agent and providing a replica of the environment. Then, the globally shared parameter vector is asynchronously updated by using the cumulative gradients of multiple agents after a specific time period. A performance evaluation environment is developed using PyTorch and comparisons with DQN and traditional convex optimization are presented. It is shown that A3C exhibits faster convergence than DQN and requires half
the energy for the desired QoE. Moreover, when compared for varying numbers of BSs and users, A3C always outperforms DQN while convex optimization fails to keep up with the varying network dynamics and falls behind both learning algorithms.

An additional work, focusing on QoE improvement is presented in [73], reducing the latency for users requesting video content and the overall backhaul usage. In order to improve these metrics, a multi-agent DRL-based caching framework is developed, treating each network edge, as a cooperative learning agent and avoiding the large action spaces of centralized single-agent approaches. The proposed multi-agent collaborative caching (MaCoCache) enables each agent to consider not only its caching strategy but also, that of its neighbors, while relying on the AC algorithm. Also, to better adapt to network dynamics and exploit historical data, LSTM is integrated with MaCoCache. The proposed caching framework is evaluated through simulations and comparisons with policy-based caching (LRU, LFU) and other learning-based alternatives, such as DRL without cooperation between agents and joint-action learners (JAL), utilizing stateless Q-learning-based caching [74]. It is revealed that MaCoCache offers 73%, 50%, 21% and 14% latency and 103%, 98%, 59%, 26% backhaul cost reduction versus LFU, LRU, DRL and JAL, respectively, as well as 13% and 7% improved edge hit ratio, compared to DRL and JAL, respectively.

Table II includes the studies on RL-aided caching in fixed cellular topologies, highlighting their main performance targets and the adopted RL approach.

### III. FOG RADIO-ACCESS NETWORKS

C-RANs provide increased flexibility to network deployment by relying on cloud-based centralized baseband units (BBUs) to perform signal processing and low-complexity remote radio heads (RRHs) for wireless access. At the same time, C-RANs may stress the fronthaul due to the massive number of content requests. Thus, F-RANs have been

### Table II

| Reference | Network topology | Performance target | RL solution |
|-----------|------------------|--------------------|-------------|
| Yang et al. [28] | Single-cell | Energy consumption | DRL |
| Yang et al. [29], [30] | Single-cell | Energy consumption | BLA Q-learning |
| Sadeghi et al. [31], [32] | Single-cell | Energy, backhaul and storage costs | Value-iteration-based and Q-learning |
| Zhong et al. [33] | Single- and multi-cell | Cache hit rate | AC and KNN-based DRL |
| Wu et al. [36] | Single-cell | Cache hit rate | LSTM and external memory-based DRL |
| Wu et al. [38] | Single-cell | QoE, spectral efficiency | Gradient-based DRL |
| He et al. [39] | Single-cell | QoE | DRL |
| Ma et al. [40], [41] | Multi-cell | AoI | DDPG-based DRL |
| Zhang et al. [45] | Multi-cell | Delay, cache replacement cost | SDDPG RL |
| Xu et al. [46] | Multi-cell | Delay | Multi-agent MAB |
| Wei et al. [48] | Multi-cell | Delay | AC-based DRL |
| Li et al. [49] | Multi-cell | Delay | DQN |
| Zhang et al. [51] | Multi-cell | Cache hit rate, backhaul usage | MAB-based RL |
| Sengupta et al. [52] | Multi-cell | Cache hit rate, backhaul usage | MAB-based RL |
| Thar et al. [53] | Virtualized multi-cell | Cache hit rate, backhaul usage | Q-learning for LSTM/CNN/CRNN selection |
| Thar et al. [54] | Multi-cell | Cache hit rate, backhaul usage | Q-learning for LSTM/CNN/CRNN selection |
| Liu et al. [57] | Multi-cell | Cache hit rate | Dueling DDQN |
| Wang et al. [61] | Multi-cell | Cache hit rate | DDQN-FL |
| Guo et al. [62] | Multi-cell | Cache miss number | DRL |
| Fang et al. [63] | Multi-cell | Equivalent throughput | DQL |
| Cheng et al. [65] | Multi-cell | System throughput | Bayesian learning and RL |
| Garg et al. [66] | Multi-cell | Success rate | Q-learning |
| Qian et al. [67] | Multi-cell | Bandwidth fluctuation | Hierarchical RL |
| He et al. [68] | Multi-cell SDN | Spectral efficiency, backhaul usage | DRL |
| Chou et al. [69] | Multi-cell | QoE | DDPG-based DRL |
| Luo et al. [72] | Multi-cell SDN | QoE, energy consumption | A3C-based DRL |
| Wang et al. [73] | Multi-cell | QoE, cache hit rate, backhaul usage | AC and LSTM-based DRL |
proposed as a promising technology towards reducing the load of the fronthaul in cellular networks. The APs in F-RANs perform a part of F-RAN architecture is illustrated in Fig. 5 where F-APs are partly responsible for the baseband processing, while offering storage and computing resources at the edge. The adoption of RL for improving the caching and resource management efficiency in F-RANs represents an important research area that has attracted various contributions recently.

A. Delay reduction

In [75], a network comprising multiple cache-aided F-APs is considered. The goal of this study is to minimize the average delay without neglecting temporal channel variations, user mobility and varying user preferences. For this purpose, MDP is invoked to model the cache update content at the F-APs while dueling DQN is employed to solve the MDP problem without knowing the state transition probabilities. Dueling DQN estimates the state value and the rewards of the different actions in order to learn the state value, facilitating the replacement of the cached content with appropriate contents in each transmission period. Comparisons with policy-based caching including FIFO, LRU and LFU, shows that the dueling DQN delay-aware policy increases the average cache hit rate and reduces the average transmission delay for varying storage size and number of users. Meanwhile, it is noted that important performance gains can be harvested when a joint radio resource management (RRM) and cache update policy is developed, as this work assumes equal bandwidth allocation for all the users in the network.

Another work targeting latency minimization if F-RANs was presented in [76]. In greater detail, the authors study the joint optimization of proactive caching and power allocation in a downlink F-RAN with multiple APs and a DRL controller located at the centralized cloud. It is shown that optimizing the latency while considering the QoS of each user, the limited storage and transmit power resources of the F-APs results in a non-convex mixed-integer nonlinear fractional programming (MINLFP) problem. So, latency minimization is modeled as an MDP without a priori knowledge of the state transition probabilities and a DQN-based algorithm is developed to derive an optimal solution. In order to implement DRL, TensorFlow is employed and a network comprising 10 F-APs and 5 RRHs serving 30 users is simulated. Comparisons with other schemes relying on weighted minimum mean square error (WMMSE), Q-learning, fixed, and random resource allocation reveal that the proposed DRL algorithm achieves improved convergence while latency is reduced by 18% to 49% compared to the other schemes. Meanwhile, the cache hit rate of DRL outperforms that of LFU, LRU and FIFO since DRL achieves 89% hit rate, LFU provides 81% hit rate while LRU and FIFO provide 75% hit rate.

In an F-RAN comprising a cloud-based BBU and multiple cache-aided enhanced RRHs (eRRHs), the authors in [77] target the delivery latency minimization over X-haul links when the statistical properties of file popularity are time-varying and unknown. The proposed model-free RL-based scheme relies on linear value function approximation and adaptively activates the backhaul or the fronthaul at each transmission period. Backhaul activation updates the content at the caches of the eRRHs and reduces the latency at future transmission periods, while fronthaul activation leads to cooperative transmissions and reduces the latency at the current transmission period. Performance evaluation in a topology where the BBU is located at the center of the cell while eRRHs and users are circularly placed shows that for low eRRH cache sizes, i.e., less or equal to 4 files, fronthaul selection guarantees lower latency due to the limited potential of caching. On the contrary, for cache sizes larger than 4 files, backhaul activation is superior. Overall, RL provides the lowest latency compared to other schemes relying on only fronthaul/backhaul selection, greedy fronthaul/backhaul selection and offline caching of the most popular files.

Further results for service delay reduction, were given in [78] where the joint optimization of content caching, computation offloading, and radio resource allocation in fog-enabled IoT was studied. AC-based learning is adopted, relying on DNN for Q-value function value approximation of the critic, while the actor policy is represented by another DNN. In addition, the issue of RL divergence is mitigated by employing fixed target network and experience replay. At the same time, the Natural policy-gradient method is used, being more efficient than Standard policy-gradient and guaranteeing that convergence to the local maximum is avoided [79]. Results for a library of 1000 different contents highlight that the proposed DRL solutions offers reduced service delay, for cache sizes below 500 contents, still outperforming a conventional content popularity-based caching strategy for cache sizes larger than 500 and up to 1000 contents where identical performance is observed.

B. Caching efficiency

The improvement of the cache hit rate performance in F-RANs is the main topic of [80]. Towards this end, a distributed edge caching scheme is developed relying on Q-learning with value function approximation (VFA) for reduced complexity and improved convergence. Since content popularity is considered to be unknown, a content request model based on hidden Markov process is proposed to identify the characteristics of the varying spatio-temporal traffic requests. At the same time, the distributed learning scheme enables each F-AP to independently determining the optimal caching policy, thus avoiding network coordination overheads. Performance evaluation in a network with 20 F-APs, each having a fixed cache size of 5 files, show that the proposed Q-VFA-learning better adapts to content popularity fluctuations and dynamic user arrivals and departures from the network, compared to LRU, LFU and Q-learning without VFA.

Distributed edge caching with dynamic content recommendation is the topic of [81]. The authors aim at determining an efficient joint caching and content recommendation policy to reduce the cost of cache replacement in F-APs when user requests data sets are not available. Thus, a per-user request model is presented to characterize the fluctuation of requests.
after content recommendation. Next, a DDQN-based caching algorithm is formulated in order to reduce the large state and action spaces and guarantee faster convergence. Simulations reveal that the DDQN-based policy offers the highest net profit compared to LRU, LFU, Q-learning and DQN alternatives, for different cache sizes.

C. Spectral efficiency

The improvement of QoS provisioning to users given the fluctuations of user preferences is investigated in [82]. In order to better exploit the caching resources of F-APs, random linear network coding (RLNC) is used to divide the files into subfiles and distribute them across the F-APs. By exploiting the accumulated user requests and considering the successful transmission probability as the reward for the operation of DRL, the optimal caching strategy is derived. Simulations performed using TensorFlow, reveal that the integration of RLNC into the proposed learning solution can save significant caching resources and increase the successful transmission probability in F-RANs, compared to uncoded caching.

The reduction of the fronthaul load is the main target of the study in [83]. In order to improve the content placement process with unknown file popularity, a two-phase procedure is proposed. In the first phase, feature extraction is employed to extract the content popularity from the frequently collected user requests. In the second phase, DRL with transfer learning is adopted and exploits the predicted file popularity of the previous phase to determine the optimal content placement strategy. Performance comparisons with traditional NN-based algorithms indicate the unsupervised learning-based popularity prediction scheme improves the prediction accuracy, independently of the time-slot duration, while DRL with transfer learning outperforms both LRU and LFU, in terms of fronthaul load reduction.

In [84], the joint optimization of caching and radio resources is targeted. Following a hierarchical approach, a cloud-based cache resource manager aims at maximizing the system throughput and minimizing the storage cost at the F-APs in the long-term. Meanwhile, F-APs are responsible for RRM in the short-term, considering content placement, channel state information (CSI) and user requests. Moreover, interference mitigation is guaranteed by enabling the F-APs to form clusters and perform joint transmissions to the users. In order to achieve improved performance, multi-agent RL is employed, creating one agent per each file and F-AP pair, jointly learning the caching strategy by utilizing historical CSI and user requests data provided by the network information server. Performance evaluation shows that the efficiency of the multi-agent RL-based resource management clearly surpasses that of other schemes, relying on full caching, no caching and caching with fixed probability.

Joint user association and content placement for network payoff maximization is the topic of [85], in a two-tier network consisting of a massive multiple-input multiple-output (MIMO) macro BS and a group of F-APs. Here, network payoff is defined as the ergodic rate performance utility minus the fronthaul cost for cache replacement. In this setting, game theory is invoked, formulating a hierarchical Stackelberg game where at short time scales, users act as followers, dynamically adjusting their F-AP selection, according to content placement status, while at long time scales, the F-APs act as leaders, updating their caches, based on the user association status and the content popularity prediction of a central unit, located at the core network and storing user request data. Towards providing low-complexity and accurate popularity prediction, a stacked auto-encoder (SAE)-based scheme is adopted. Regarding content placement, a DRL-based algorithm, extending [34] is developed. The DRL architecture is based on online DQN learning where a greedy algorithm selects an action from the state space and offline deep DNN and replay memory creation, executing specific optimization and storing historical information. Performance evaluation shows that DRL offers an average prediction accuracy of 90%, while baseline DNN- and CNN-based algorithms achieve 80% and 70% accuracy, respectively. Finally, compared to LRU and LFU, DRL yields the highest reward, by better capturing the effect of user requests and the amount of data routed through the fronthaul.

### TABLE III

| Reference | Performance target | RL solution |
|-----------|--------------------|-------------|
| Guo et al. [75] | Delay | Dueling DQN |
| Rahman et al. [76] | Delay | DQN |
| Moon et al. [77] | Delay | Model-free RL |
| Wei et al. [78] | Delay | AC-based DRL |
| Lu et al. [80] | Cache hit rate | Q-VFA-learning |
| Yan et al. [81] | Cache replacement cost | DDQN |
| Zhou et al. [82] | Average success rate | DRL |
| Zhou et al. [83] | Fronthaul usage | DRL with transfer learning |
| Sun et al. [84] | System throughput, storage costs | Multi-agent RL |
| Yan et al. [85] | Ergodic rate, fronthaul usage | DRL |

## IV. COOPERATIVE NETWORKS

Cooperation among network nodes has been considered as a viable means for improving the quality of communication by improving the wireless conditions through increased diversity and intelligent transmission scheduling [86]–[88]. Furthermore, data buffering at edge nodes, in the form of dedicated relays or user devices provide reduced outages and higher data rates [89]–[92]. In the context of edge caching, cooperative schemes can be applied both in content caching in a distributed manner, as well as by employing user devices to cache content of other users.

### A. Cooperative Caching

A general network architecture comprising cache-aided BSs cooperate and share data through X2/Xn interface in order to
A simulation environment has been developed in Python and low latency of collaborative computing has to be ensured. The computation of a collaborative task. Last but not least, but also the resource allocations of multiple nodes during computing task, the workload scheduling of a single node to be addressed in this context like the uncertainty of the edge computing nodes for the management of the compute and cache resources is investigated. Several challenges have been presented in [99] and operates by allocating part of the caches in each cluster to store the most popular content in every edge BS, while the remaining parts cooperatively cache different partitions of the less popular content in different nodes. The second algorithm is the FemtoCaching strategy of [100], employing nodes with low-rate backhaul capacity but large storage to cache popular video content while non-cached files are transmitted by the cellular BS. Results suggest that the proposed strategy provides a delay reduction of at least 6% and 15%, compared to the first and second algorithm, respectively.

One of the main challenges in DRL is the need of the agent to observe enough features of the environment to ensure decision accuracy. The authors of [6] propose an AC-based DRL approach for multi-cell and single-cell cooperative networks where BSs compete with each other for wireless access and also cooperate towards reducing the average delay. In this context, the agents decide their individual caching actions while cooperating with each other, resulting in a centralized critic network and a decentralized actor network. In this framework, the agents update the actor network with their observations and the critic network with the complete state space. Compared to LRU, LFU and FIFO in a scenario with time-varying content popularity, the AC-based DRL offers the best long-term performance and each time the popularity distribution changes, it is able to converge to the previous delay performance level.

The decentralized cooperative BS caching problem to minimize the content access latency is the topic of [101]. The proposed solution relies on FL and DRL and its main novelty lies in the fact that it uses two rounds of training. During the first round, the BSs learn a shared predictive model using training parameters as the initial input of local training. In the second round, the BSs upload the near-optimal local parameters as input of the global training. They reduce the performance loss and average delay while they improve the hit rate. More specifically, they compare their proposed platform against baseline schemes like LRU, LFU, FIFO, achieving improved performance. In addition the decentralized cooperative approach performs very close to an alternative centralized DRL algorithm.

The authors of [102], [103] propose a MAB-based coope-
data caching. A roulette-based policy is presented to optimize the cache hit rate of multiple BBUs. As a third action, Q-LCCA adopts random short transmission delays, being coordinated by the SDN of BBUs. The second action exploits neighboring BBUs with a cache hit rate maximization problem and solve it through an MDP, where each small BS is considered as an agent. The caching policy aims at maximizing the cache hit rate and combines LFU and LRU policies, achieving a better performance than the standalone versions. In the simulations, they adopt the shot noise model [108] for determining the content request pattern over time, generating content requests with temporal correlation. Results show that under temporal correlation, the learning-based approach reaches a hit rate of 79%, compared to 77% and 76% for LFU and LRU. Meanwhile, delay performance is improved and the multi-agent Q-learning guarantees a delay of 1.1 time-slots, while LFU and LRU provide delays of 1.3 and 1.45 time-slots, respectively. This study is highly related to [109] which also addresses content replacement as an MDP. However, the two works aim at different objectives, since in [107] the goal is to maximize the cache hit rate while the objective of [109] is to minimize the system transmission cost. Moreover, the work in [107] adopts more realistic simulation parameters and network procedures, as multiple contents can be simultaneously replaced.

2) Caching efficiency: The authors of [6] also formulate a cache hit rate maximization problem and solve it through AC-based DRL in cooperative topologies. Performance comparisons against LRU, LFU and FIFO for different cache sizes reveal that by employing a centralized critic network, the AC-based DRL learns how the individual decisions of the agents impact the overall cache hit rate, striking a balance between the cache hit rate of each agent and that of the overall system. As a result, the cache hit rate of the learning-based framework surpasses the performance of the three conventional caching policies.

Then, in [106], the authors combine SDN and C-RAN architectures for improved cooperative edge caching. The BBUs of C-RAN are equipped MEC capabilities, resulting in intelligent BBU pools, performing signal processing and data pre-processing and improving the performance of AI applications. In order to maximize the cache hit rate and the cache capacity usage, DRL is employed, considering both global and local cache information. The proposed Q-learning-based collaborative cache algorithm (Q-LCCA) selects among three different actions, regarding cache management. The first action is to cache the most popular data in the local cache of BBUs. The second action exploits neighboring BBUs with short transmission delays, being coordinated by the SDN controller and data in the global cache, formed by the caches of multiple BBUs. As a third action, Q-LCCA adopts random data caching. A roulette-based policy is presented to optimize action selection, applying weights to each one. Performance comparisons, using Matlab©, shows improved cache hit rate, as the number of content types increases, over alternative schemes relying only on local and global caching.

Wireless content delivery and content replacement are the focus of [107]. The authors apply multi-agent Q-learning to improve content caching performance, modeling the problem as an MDP, where each small BS is considered as an agent. The caching policy aims at maximizing the cache hit rate and combines LFU and LRU policies, achieving a better performance than the standalone versions. In the simulations, they adopt the shot noise model [108] for determining the content request pattern over time, generating content requests with temporal correlation. Results show that under temporal correlation, the learning-based approach reaches a hit rate of 79%, compared to 77% and 76% for LFU and LRU. Meanwhile, delay performance is improved and the multi-agent Q-learning guarantees a delay of 1.1 time-slots, while LFU and LRU provide delays of 1.3 and 1.45 time-slots, respectively. This study is highly related to [109] which also addresses content replacement as an MDP. However, the two works aim at different objectives, since in [107] the goal is to maximize the cache hit rate while the objective of [109] is to minimize the system transmission cost. Moreover, the work in [107] adopts more realistic simulation parameters and network procedures, as multiple contents can be simultaneously replaced.

B. Device-to-Device Networks

The massive connectivity requirements of 6G networks necessitate the integration of novel communication paradigms, deviating from conventional architectures. Thus, D2D communication has been proposed as a remedy for excessive cellular traffic, enabling users to directly cooperate and exchange data or perform relaying for cell edge users. Caching at the users devices and intelligent D2D resource allocation can provide several gains to wireless networks, minimizing among others, energy consumption, delay and backhaul usage [120]–[122].

1) Energy efficiency: In [110], the authors aim at improving caching efficiency in D2D networks and minimize the energy cost by prefetching the optimal files at user’s devices and small BSs. D2D communication is used to offload part of the cellular traffic, exploiting the caching capabilities of users and their distribution. The request behaviours are modeled as the number of content types increases, over alternative caching policies and combines LFU and LRU policies, achieving a better performance than the standalone versions. In the simulations. Thus, D2D communication has been proposed as a remedy for excessive cellular traffic, enabling users to directly cooperate and exchange data or perform relaying for cell edge users. Caching at the users devices and intelligent D2D resource allocation can provide several gains to wireless networks, minimizing among others, energy consumption, delay and backhaul usage [120]–[122].

1) Energy efficiency: In [110], the authors aim at improving caching efficiency in D2D networks and minimize the energy cost by prefetching the optimal files at user’s devices and small BSs. D2D communication is used to offload part of the cellular traffic, exploiting the caching capabilities of users and their distribution. The request behaviours are modeled as an MDP and RL is applied to discover the file popularity and user preferences. Because of the different capabilities and algorithm complexities, a Q-learning algorithm is applied on users’ devices and DQN on small BSs. Comparisons against optimal caching with known popularity, random caching file selection and the case without user caching, depict that the proposed learning-based algorithm closely follows the performance of optimal caching independently of the number of files and user preferences profiles with the other two schemes significantly falling behind both in terms of energy consumption and cache hit rate.

The work in [111] focuses on both content placement and delivery strategies in cache-enabled D2D networks, aiming at
minimizing the content delivery delay and the power consumption. For this purpose, ESN-based learning is employed for predicting the content popularity and user mobility patterns, determining what and where to cache. Then, content delivery is optimized by relying on a DQN-based algorithm, exploiting CSI and content transmission delay observations to decide which actions should be taken. The DQN-based caching strategy is evaluated in a multi-user network and compared against Q-learning and random caching. It is observed that due to the larger action-state space, the reward in the DQN case is higher than that of Q-learning, while random caching provides significantly smaller rewards.

2) Delay reduction: Apart from [111], jointly tackling energy and delay performance concerns through a two-step learning process, i.e., ESN-based prediction and DQN-based content delivery, there have been various RL strategies focusing on delay reduction.

Learning-based caching strategies are proposed in [112] for D2D caching where multi-agent MAB modeling is adopted. Since the action space is too large, there is no instantaneous knowledge of the content popularity profile. More specifically, the users follow a Q-learning approach where each one learns the Q-values via their own actions, as well as considering the actions of other users. In order to reduce the action space and the overall complexity, a belief-based modified combinatorial UCB approach is adopted for regret minimization, in terms of download latency. They conduct simulation experiments to compare the performance of the proposed algorithm against conventional caching schemes, including random replacement, LRU and LFU. The proposed algorithm outperforms the baseline algorithms in average download latency and cache hit rate and its advantage increases as the cache unit size increases, while offering the best performance independently of the number of files.

3) Spectral efficiency: The authors in [113], [114] address D2D mobile edge caching for traffic offloading. They present a content delivery market formulation and their solution is based on blockchains and smart contracts. More specifically, the caching problem includes a content placement and cache sharing problem, as well as the verification that the caching actions of the peers are recorded and handled in a trustworthy manner. In this topology, there exist different subsystems performing necessary procedures, integrated by a cache and blockchain controller. First, the caching subsystem associates the peer contributions with their willingness to share data via D2D communication. In addition, the blockchain subsystem is responsible for transaction verification which should happen at low cost and latency, while ensuring system scalability. Both problems are formulated as an MDP and are addressed by a DQN algorithm. Comparisons of the proposed DQN algorithm against the DQL approach of [116], [117] and a greedy scheme, employing each node to cache the most popular content within its coverage show improved offloading performance and highlight the importance of nodes’ participation in data sharing through efficient incentive mechanisms.

Another dimension that can be exploited towards optimal resource allocation in D2D-aided mobile edge computing networks is related to social relationships among users, as presented in [115]–[117]. Here, the targeted reward is mapped to increasing the MNO’s profits through improved backhaul usage for video content delivery, considering the knowledge of the social relationships, in terms of trust among users. The social trust scheme that they present uses Bayesian inference for direct observation through past observations and Dempster-Shafer for indirect observations, combining evidence from multiple users’ belief [123]. Towards solving the resource allocation problem, a big data DQL resource allocation strategy to make optimal decisions for network resources and these decisions are based on network observations and not on any explicit control rules. Simulations are presented using TensorFlow, as well as comparisons with a scheme without indirect observation, a scheme without edge computing [124] and a scheme without D2D communications [125]. It is observed that DRL increases the backhaul usage benefiting the profits of MNOs, independently of the number of content types, while the total utility performance is better than that of the other schemes for different numbers of malicious D2D transmitters.

In D2D-aided information-centric wireless networks, collaborative caching at the users’ devices can result in improved spectral efficiency and offloading. Thus, the authors in [118] study resource allocation and power control in a small-cell MEC network with D2D communication. Initially, depending
on whether or not the cache of a user is not empty, a selection among cellular or D2D communication is performed. When D2D communication occurs, channel reuse increases and an efficient power allocation scheme should be devised. So, a policy-gradient DRL approach is presented to select the power levels, using the Gaussian distribution, as well as softmax channel selection for maximizing the spectral efficiency and minimizing the interference. Comparisons with DQN reveal improved spectral efficiency and reduced interference, since the proposed solution carries out in a continuous state space, while DQN selects among discrete power levels.

4) Caching efficiency: The work in [119] identified two challenging issues that need to be addressed in D2D networks. First, the need to make caching decisions towards maximizing the probability that the requested content will be cached in a neighboring node given the storage constraints and the plethora of available content. Second, the level of traffic offloading when multiple helper nodes are able to cache and deliver the desired content to another user. To address these issues, a caching strategy considering parameters, such as the predicted content popularity, user preferences, user activity level, and social relationships is proposed. For characterizing the offloading potential of users, the expected correlation coefficient is introduced, capturing the offloading probability and the offloading gain obtained after a D2D content delivery event. At the same time, D2D user pairs are formed by relying on an online learning algorithm, based on the combinatorial MAB framework. Comparisons with random caching, the least frequently caching and matching algorithm of [126] and the collaborative caching and auction matching algorithm of [127] are presented, using real-world traces from the Unical/SocialBlueconn dataset to model the D2D topology. Results in terms of offloading due to D2D communications indicate that the MAB-based algorithm achieves a 53% offloading ratio, contrary to 45% by collaborative caching and auction matching, 22% by least frequently caching and matching and 10% by random caching.

V. VEHICULAR NETWORKS

Edge caching provides both opportunities and challenges for vehicular networks, related to the dynamicity of the network, the computing and caching power of vehicles and road side units (RSUs), as well as the amount of data generated by participating vehicles. Different scenarios of vehicular communications, such as V2V or vehicle-to-infrastructure (V2I), either towards a macro BS or an RSU are shown in Fig. 7 where RL-aided edge caching is performed. The works presented in this section cover various aspects of these networks, aiming at energy efficiency, delay reduction and improved caching performance, as well as optimizing computation and communication-related metrics.

A. Energy efficiency

In [128] the authors propose a learning framework, allowing cross-layer offloading and cooperative multi-point caching. In cross-layer offloading, a computationally heavy task can be offloaded to the next computation layer, such as RSUs and the latter can subsequently offload it, if necessary, to BSs. Thus, a resource allocation scheme, based on the DDPG RL algorithm is proposed, maximizing the system utility which considers the energy consumption, as well as computation and caching improvement. Simulations demonstrate the effectiveness of the proposed scheme focusing on the cumulative reward of the vehicular network.

The study of [129], [130] aims at solving a two-fold problem: (a) Establishing a network for secure content caching and (b) ensuring efficient content caching in a volatile network. To address (a), the authors propose a blockchain enabled distributed content caching network providing the base stations and the vehicles to establish a secure peer-to-peer transaction environment. The base stations maintain the permissioned blockchain and the vehicles perform the content caching. To address (b), they propose an optimal content caching scheme based on DRL, taking mobility into account while they accelerate block verification by a new selection method that they propose. The reward function considers the total consumed energy for content transmission and content caching. Also, a security analysis is conducted, showing that the proposed blockchain content caching provides security and privacy protection with low-energy consumption. Performance analysis using a real dataset shows that the proposed algorithm achieves an 86% of successful content caching requests against 76% of a greedy algorithm and 5% of a random content caching algorithm.

B. Delay reduction

The topic of [131] is to minimize the content delivery in vehicular edge networks. The authors propose a framework where the RSUs collaborate with vehicles to cache popular contents. Multiple ways are provided to the vehicles to retrieve the needed content, given their limited cache: via (a) V2V links, vehicle-to-RSUs and (c) vehicle-to-macro BSs. They follow a DDPG DRL approach to model the content edge caching and delivery problem where the goal is to minimize the total content delivery latency. The performance is compared against a random edge caching and delivery scheme and a DDPG scheme without bandwidth optimization. The proposed algorithm demonstrated significant improvements against the other two approaches in terms of total content delivery latency and cumulative total reward, while exhibiting faster convergence.
The authors of [132] focus on content delivery in vehicular edge networks, optimizing the content placement and content delivery by taking into account trilateral collaborations among vehicles, macro BSs and RSUs. The problem is modeled as a double time scale MDP (DTS-MDP), considering that vehicle placement and network changes are more frequent than content changes in time. The content placement initially relies on content popularity, vehicle path and resource availability. These are also the conditions to optimize in the large timescale, while in the small timescale, vehicle scheduling and bandwidth allocation are performed, targeting the minimization of content delivery latency. In this context, a DDPG framework is adopted for obtaining a sub-optimal solution with low computational complexity. Performance evaluation is presented, taking into account content delivery latency, content hit-ratio and system cost where substantial improvements against a random caching scheme and a non-cooperative caching scheme (e.g. 135.62% and 34.33% content hit ratio increase accordingly) are shown.

The authors of [133] elaborate on the problem of vehicular edge computing in which they take into consideration RSUs able to provide computation offloading and data bandwidth. Moreover, vehicles can collaborate using V2V communications with data relays and collaborative computing. Targeting to improve the data processing performance, a penalty mechanism is introduced, dictating imposing penalties if the data processing deadline is not satisfied. To ensure the above, in [133], they propose a framework to model communication, computation and caching. Then, they propose a DQN algorithm to find the optimal strategy for a collaborative data scheduling scheme which will minimize the system-wide data processing cost with ensured application delays. They perform benchmarks where they demonstrate data processing cost reduction and help data to be processed under delay constraints.

C. Spectrum efficiency

The paper in [134] focuses on management of content caching, computing and networking at vehicular networks. They propose a DRL algorithm that uses a DQN for the approximation of a Q-value action. The proposed integrated framework orchestrates networking, caching and computing resources to meet the requirements of different applications. The reward function considers the MVNO revenue, consisting of the received SNR of the wireless access link, the task computation capability and the cache state. The authors present simulations results of their proposed approach against schemes without virtualization, MEC offloading and mobile edge caching in a setting where the system state is assumed to be static. The total reward of this work depends on computation, communication and caching. The proposed results show the superiority of the proposed approach in terms of total utility.

Another scheme focusing on maximizing the MVNO revenue is presented in [135], proposing dynamic resource allocation in vehicle networks. The reward function include the MVNO revenue, which is modeled as a function of the received SNR, the computation capability and the access link state. By relying on SDN and the principles of information-centric networking, dynamic orchestration of computing and communication resources for virtual wireless network optimization is targeted. The authors model the resource allocation strategy as an MDP, using function approximation. The high complexity of the problem is tackled using A3C-based RL. Simulation results demonstrate increased reward and good convergence speed, resulting in improved MVNO revenue compared to a conventional scheme without learning capabilities.

The authors of [136] take advantage of DRL to orchestrate edge computing and resource allocation with the goal of maximizing the MNO revenue without degrading the users’ QoE in V2V networks. More specifically, they design a DDPG model to optimize the problem of resource allocation and task assignment in a volatile vehicular environment with mobile edge caching servers. They conduct experiments based on real traffic data and they compare their proposed algorithm against a non-cooperative scheme, a computation offloading scheme and an edge caching scheme without computation offloading. They demonstrate that the MNO profits can be significantly larger when the proposed scheme is adopted, compared to the other benchmark schemes.

In [137] the goal is to maximize the reward of a vehicular network, considering the combined reward of communication, computation and data offloading, while satisfying a deadline-constrained service. In the proposed network, both vehicles and RSUs have caching storage and computing capabilities.

They collaborate and communicate via D2D communication to achieve cache hits for the vehicles when content is retrieved via nearby vehicles or RSUs. Moreover, vehicles are able to offload tasks to neighbouring vehicles, RSUs and, in the lack of available resource at those, to BSs. A Q-learning algorithm with multi-timescale network is proposed for the caching placement, computing resource allocation and assessment of the sets of possible connecting RSUs and vehicles. They use optimal parameter configuration for their proposed algorithm to validate their theoretical findings and to shown significant cost gains against a random resource allocation scheme and a scheme where caching and computing capabilities are limited to RSUs.

A similar topic with [137] is studied in [138]. The authors formulate the problem as a joint caching and computing allocation problem for cost minimization under the constraints of dynamic storage capacities of RSUs. They propose multi-time scale algorithms for caching placement, computing resource allocation and assessment of the sets of potentially connecting RSUs, contrary to connecting RSUs and vehicles, as in [137]. The developed algorithms are based on particle swarm optimization and DQL for large and small timescale models, respectively. Numerical results show significant performance gains while using optimal parameter configurations for the proposed algorithms.

VI. UAV-AIDED NETWORKS

UAVs will play a vital role towards improving the performance of 6G wireless networks. UAV-aided networks offer
flexibility in network deployment, allocating resource where and when needed, as well as fast recovery after disasters and network outages. However, the increased degrees of freedom will also pose new challenges in mobile edge networks. In this context, ML is expected to provide solutions for improving the efficiency edge caching by deploying UAVs at optimal locations and determining their trajectory and communication parameters.

### A. Delay reduction

Examining the role of cache-enabled UAVs, the paper in [139] examined proactive caching for reduced latency and backhaul load. So, multi-objective optimization is targeted for defining parameters, such as minimum number of deployed UAVs, transmit power, UAV-user association, and cache location. In order to solve the multi-objective optimization, RL is adopted for user grouping, performing local search according to the optimal UAV deployment over each group. From the results, the efficiency of the RL method is shown, effectively minimizing the number of required UAVs, compared to the case without caching, as well as their 3-D placement in the network, resulting in improved cache placement.

Aiming to optimize the performance of cache-enabled UAV-aided NOMA networks, the authors in [140] turn to RL for tackling the dynamic characteristics of UAV movement and content request variations. Initially, long-term optimization of cache placement, user scheduling and power allocation for NOMA is formulated, minimizing the long-term sum delay of ground users. Then, the optimization problem is converted into an MDP and Q-learning is invoked to reach a near-optimal solution. Still, in large-scale networks, Q-learning fails to cope with the large MDP state and action spaces and thus, function approximation-based caching and resource allocation is proposed. Performance evaluation in a multi-cell environment focuses on one cache-enabled and UAV-aided cell. Content delivery delay and cache hit ratio comparisons include the two RL solutions, a greedy algorithm obtaining the optimal delivery delay of the current state, a fixed algorithm caching the popular contents of previous states, employing round robin-based scheduling, as well as fixed power allocation and finally, random content caching and resource allocation. It is concluded that in small-scale networks, Q-learning provides a small performance gap compared to the greedy algorithm, while in large-scale networks, function approximation outperforms both random and fixed algorithms.

In a UAV-aided small cell topology, supporting virtual reality (VR) applications with stringent delay constraints, content caching and transmission are studied in [141]. Here, UAVs alleviate the burden of backhaul and access links by collecting the contents that users request and transmitting them to the cache-enabled small BSs, communicating with the VR users. The joint optimization of caching and transmission is solved by developing a DL algorithm, relying on LSM NNs and ESNs, namely echo liquid state machine (ELSM) DL, identifying the relationship among actions, selection policy of small BSs and user reliability. Compared to conventional DRL, LSM-based RL offers increased prediction accuracy, using historical data while ESNs reduce the training complexity by adjusting only its output weight matrix and avoiding the calculation of the gradients of all the neurons. Simulations are conducted, comparing ELSM with LSM, Q-learning [142] and ESN-based learning [143]. It is shown that ELSM provides a 10% and 18.4% reliability improvement against ESN and Q-learning when 35 users exist in the network. In addition, ELSM converges 11.8% faster, compared to LSM in a network with 11 SBSs.

An LTE cloud network operating in licensed and unlicensed bands is the main focus in [144], studying resource allocation for cache-enabled UAVs supporting ground users. The performance target here is to maintain queue stability, directly affecting the content transmission delay in the network. Constrained by the limited capacity of the UAV-cloud links, LSM is employed to help the UAVs perform content caching and resource management. LSM enables the cloud to efficiently learn user-centric information regarding content request distribution and to facilitate spectrum allocation by the UAVs. This method is extended in [145], where an optimization problem is formulated to maximize the number of users with stable queues. As a solution to this problem, a self-organizing, decentralized algorithm is developed and LSM is employed for joint caching and resource allocation over both licensed and unlicensed bands. Then, performance evaluation is conducted illustrating the increase in the number of users with stable queues in comparison to Q-learning with and without content caching.

### B. Energy efficiency

Improved UAV-aided network operation in the context of the Internet of Vehicles is the topic of [146]. Due to the increased mobility and dynamic environment in terms of

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### TABLE V

| Reference    | Performance target | RL solution                   |
|--------------|--------------------|--------------------------------|
| Dai et al. [128] | Energy consumption | DDPG-based                     |
| Dai et al. [129], [130] | Energy consumption | DRL and permissioned blockchain |
| Dai et al. [131] | Delay              | DDPG-based                     |
| Qiao et al. [132] | Delay              | DDPG-based                     |
| Luo et al. [133] | Computation delay  | DQN                            |
| He et al. [134]  | Backhaul usage,  | DQN                            |
| Chen et al. [135] | Backhaul usage,  | A3C-based                      |
| Ding et al. [136] | MNO revenue        | DRL                            |
| Tan et al. [137]  | Spectral efficiency, storage cost | DQL with multi-timescale network |
| Tan et al. [138]  | Spectral efficiency, storage cost | Particle swarm optimization and DQL |
content requests, content delivery becomes challenging. More specifically, vehicles request contents from the UAV in the downlink while the latter has to decide which popular contents should be cached from arriving vehicles in the uplink. As a performance metric, the maximization of the number of served vehicles over the UAV energy consumption is investigated and the problem of joint caching, UAV trajectory and RRM are tackled. However, the complex environment comprising randomly arriving vehicles makes the use of traditional optimization approaches prohibitive. On the contrary, after formulating the joint problem as an MDP, PPO-based DRL is employed to control UAV trajectory. Here its operation relies on rewarding the agent when a vehicle is served by the UAV, and penalizing the agent according to the energy consumption incurred by moving the UAV. Simulations consider a single cache-aided UAV topology and PPO is compared against stationary UAV, random UAV mobility, maximum speed selection for moving the UAV back-and-forth over the highway, as well as minimum energy selection, selecting the UAV velocity resulting in minimum energy consumption. It is revealed that the PPO balances the amount of traffic offloading and the energy consumption at the UAV, while better adapting to content requests, as shown for different content popularity values.

Another RL-based solution for improved energy efficiency in cache-enabled UAV-aided networks is presented in [147]. Focusing on an urban scenario with mobile users, the storage and energy capabilities of the UAV are considered, towards maximizing the sum achievable throughput. Since this problem is shown to be non-convex, DRL is adopted for joint content placement and trajectory design. More specifically, energy-efficient UAV control is achieved by employing a DDQN for online trajectory design, according to real-time user mobility and avoiding the over-estimation of the value function of traditional DQN. Also, during the offline content placement stage, a link-based caching strategy is developed for cache hit rate maximization through approximation and convex optimization, leading to a trade-off among file popularity and diversity. In order to illustrate the performance of caching and DDQN trajectory design, a multi-cell simulation environment using TensorFlow is developed, showing that the selection of appropriate hyperparameters, such as learning rate can increase the performance of DDQN. As a result, throughput and energy consumption gains are harvested, compared to static circular trajectory designs, as mobile users are not optimally served.

VII. OPEN ISSUES

A. Physical-layer aspects

In recent years, RL has been proposed as an alternative approach to conventional optimization when the derivation of optimal communication parameters entails excessive complexity and high network coordination overheads. In mobile edge networks where different cells might overlap, the design of RL-aided caching policies should not neglect physical-layer issues. These include intra- and inter-cell interference, fast fading due to mobility from receivers and transmitters, as well as path-loss. The RL solution should evaluate data related to signal-to-interference plus noise ratio and jointly determine the edge caching locations, BS and user association, D2D cooperation, duplexing method, as well as modulation order, coding rate, beamforming vectors and transmit power level. RL-aided solutions in the form of MAB have already shown promising performance in such physical-layer-related problems [148]–[153]. Also, in many cases, edge networks comprise nodes with limited capabilities, such as IoT devices, requiring high energy efficiency. So, the integration of wireless powered communications with RL-aided edge caching and computing should be studied [154].

Furthermore, the development of RL-aided solutions integrating high diversity data buffering techniques with edge caching represents an attractive research direction. In recent years, buffer-aided techniques in relay and D2D networks have shown tremendous gains in different communication scenarios, increasing the transmission reliability and mitigating the degrading effects of interference and fading [155]–[158]. For example, full-duplex (FD) relays can increase the flexibility in edge caching locations by operating in a hybrid fashion, establishing end-to-end communication of users with a BS, providing their desired content. However, at another instance, the FD relay, having already cached this content, can deliver it under more favorable channel conditions.

B. Non-orthogonal multiple-access

Edge caching has the potential to improve the performance of mobile networks, resulting in homogeneous QoS and better backhaul/fronthaul offloading. However, the massive number of users and devices in 6G networks calls for NOMA strategies in order to better exploit the wireless resources. Recently, the integration of NOMA in mobile edge networks has been proposed, jointly determining the task allocation, caching location and power allocation for NOMA [159]–[161]. At the same time, the benefits of NOMA in buffer-aided networks have already been shown in various works and tailor-made caching policies when users are simultaneously served on the same physical resources should be devised [162]–[165]. Still, considering the large amount of network parameters, including storage, power level, spectrum and QoS constraints,
conventional optimization will often fail in deriving optimal caching policies when NOMA is employed.

C. Radical learning paradigms

RL operation for improving the performance of edge networks with a massive number of users and IoT devices should aim at avoiding complex and resource-demanding learning solutions while still exploiting the large geographical distribution and heterogeneity of edge nodes. In this context, the incorporation of transfer and federated learning in RL-aided edge networks represents a fertile research area with only a limited number of contributions [61], [83], [101]. First, transfer learning is based on initially extracting features, such as file popularity on a base network with a generalized data set. Then, these features are used to facilitate DRL agents at the edge to converge to the optimal edge caching policy, thus minimizing the energy consumption at the edge devices. On the other hand, FL leverages the observations of multiple DRL agents at different edge nodes and trains a shared model. In addition, communication costs among edge nodes are reduced, since FL uses locally stored data, only calculating updates to the global shared model of the coordinating node.

D. Security and trust

Mobile edge networks comprise operator-owned clouds, infrastructure-based BSs and machines, as well as user devices. Caching, apart from rate and delay improvements, has the potential to improve security in such heterogeneous wireless networks, e.g., physical-layer security (PLS) [166]. While the problem has been studied extensively in different context, ranging from cellular [167] to cooperative networks [168], cooperative and low-complexity RL solutions can be implemented on a wide range of network nodes to facilitate and enhance PLS, especially when trade-offs among latency and security arise [169]. At the same time, issues of trust are raised, especially in infrastructure-less D2D-aided edge scenarios where social-awareness can be exploited [115]–[117]. RL algorithms should take into consideration the behaviour of cooperating nodes and incur penalties when malicious behavior is observed, since caching at small BSs and more importantly, at user devices can threaten user data privacy. Furthermore, in decentralized learning paradigms, such as federated learning which better suit privacy sensitive applications, it is necessary to ensure that shared models will be based on information exchange among trustworthy peers. In this area, recent works have adopted blockchains and smart contracts, highlighting their efficiency in M2M, D2D and V2V RL-aided edge caching but still, further advancements are needed [49], [113], [114], [129], [130].

E. Cooperative caching extensions

The problem of cooperative caching is examined from various perspectives and different avenues for further research are open. In [93], where the edges adaptively learn their best caching policies using a multi-agent AC DLR, the authors envision to improve their algorithms’ accuracy, scalability and efficiency in heterogeneous networks by using real-time heuristics and analytics. In a different kind of edge caching setup, like in [97], where the problem of user offloading tasks to edge computing nodes is examined and the coordination between edge computing nodes for the management of the compute and cache resources is investigated, an area of further research is the usage of competitive bidding and allocation priorities. Furthermore, since they elaborate the problem of workload scheduling but also resource allocation in collaborative tasks, user security on the edge becomes an interesting area for further research and investigation. In [6], the BS compete against each other for wireless access and also cooperate towards reducing the average delay. The authors are interested in jointly solving the content caching problem along with other problems related to power control and user scheduling.

F. Volatile networking topologies

Vehicular and UAV-aided networks represent interesting domains of edge caching where BSs, RSUs, ground and aerial vehicles collaborate for the optimal management of caching and computation resources in a highly volatile environment. Further research can be performed regarding security, resource management and mobility prediction. More specifically, the authors of [128] take into account RSUs to provide computation offloading and spectrum planning to investigate AI algorithms for efficient handover. Proactive caching and pre-allocation of network bandwidth is also the future focus of [136]. Also, the caching and computing resources orchestration for different application types, aiming at increased energy efficiency in highly mobile networks provides another interesting future direction [134].

VIII. CONCLUSIONS

Edge caching represents a major shift in network architecture design, since content is brought closer to the users in an intelligent and proactive manner. In this way, the burden in backhaul and fronthaul is relieved and repeated requests to remote web servers are avoided. Still, the optimization of edge caching performance must take into consideration several characteristics, including mobility, resource allocation, energy and storage capabilities, as well as requirements, including rate and delay. In this context, the adoption of reinforcement learning can lead to tangible performance gains at an acceptable complexity, overcoming the limitations of traditional approaches. This survey focused on reinforcement-aided edge caching in a variety of network settings, comprising fixed access points, fog-enabled paradigms, cooperative schemes, as well as aerial and ground vehicles. The discussion of the different learning solutions revealed that the fusion of learning and edge caching can result in significant benefits, independently of the complexity of the wireless environment and surpass the performance of conventional optimization solutions, while guaranteeing service requirements in an online and autonomous fashion. Finally, several open issues in the field have been highlighted, paving the way for further innovations towards realizing the 6G communications vision.
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