A critical aspect of multipath transmission is packet scheduling. A multipath scheduler must perform three main tasks: (i) path selection, (ii) packet selection, and (iii) packet/flow protection [2].

A multipath scheduler can address these tasks by using the Channel State Information (CSI) to perform optimal resource allocation on each path. Performing these tasks is more challenging in wireless networks because of the heterogeneity and time-variability of the paths, in terms of available bandwidth, delay, cost, and congestion level. This work aims to address the optimal allocation of the data streaming over multiple paths, developing a Path-Aware Dynamic Multipath scheduler (PADME) based on an AC algorithm, called AC-PADME, where the core of the scheduler is an interleaved Weighted Round Robin (WRR) mechanism to be implemented on the on-board unit of a UAV.

An AC algorithm [3] is an off-policy hybrid reinforcement learning that relies on the entities called actor and critic. The former provides the actions to the transmission system for reward optimization, while the latter estimates the goodness of the choices and sends feedback to the actor. In this work, the AC algorithm enables our scheduler to learn the optimal policy for real-time traffic allocation given the wireless path conditions and using a reward function that constitutes the End-to-End (E2E) loss, bandwidth utilization, and the packet loss rate on each path. Figure 1 shows the reference scenario we consider in this work, where a UAV transmits a multimedia stream towards a Ground Control Station (GCS) over multiple wireless paths. The AC-PADME scheduler, relying on a Real-time Transport Protocol (RTP)/User Datagram Protocol (UDP) protocol stack, determines an optimal policy to select a subset of the paths to be used and the necessary redundancy rate to increase the probability of correctly delivering all packets. The AC-based algorithm allows to find the trade-off between the amount of data replicated over the wireless paths and the amount of bandwidth usage.

Our main contributions can be summarized as follows:

• We formulate a multipath scheduling and transmission problem as an optimization problem and provide an RL based solution using an AC algorithm.

• We provide simulation results to evaluate the learning performance of our algorithm and show that our scheduler, using the AC algorithm can target very low E2E loss rate without using excessive bandwidth.
The rest of the paper is organized as follows: Section II gives an overview of the application of RL and AC to network traffic management and control. The system model is given in Section III, while in Section IV we formulate the optimization problem and provide an AC-based solution. Section V discusses the simulation results and Section VI concludes the paper and points out future research directions.

II. RELATED WORK

Following the recent advancement in the application of Machine Learning techniques in multimedia transmission, researchers have proposed RL-based frameworks for network resource management and control, particularly for traffic scheduling. In [4], a Deep-Q (DQ) RL-based scheduler is proposed for bandwidth allocation at a WiFi access point in order to meet the QoS requirements of different user applications. Wu et al. [5] have proposed Peekaboo, a RL-based multipath scheduler implemented in Multipath QUIC to target heterogeneity of both WiFi and cellular channels. In [6], an AC-based framework is proposed for dynamic wireless multichannel access; the User Equipment (UE) is trained to select a channel with favourable conditions and avoid collisions. Yang et al. [7] have coupled AC framework with a fuzzy normalized radial basis for packet scheduling in Cognitive Internet of Things systems (CIoT) in order to increase channel rate and throughput. In [8], an AC-based framework is used to reduce the end-to-end delay in Fog-based IoT systems by optimizing computing, task offloading and resource allocation.

Different from the works presented above, our approach addresses at the same time the two main challenges of multipath transmission; that is, path selection and flow protection through replicas. Our scheduler does not only find the optimal policy for selecting a subset of the available paths but also for determining the required redundancy while keeping a trade-off between flow protection and efficient bandwidth usage. Moreover, the proposed scheduler called AC-PADME is based on the AC algorithm that does not require off-line training or a priori knowledge to model the state of the communication system in order to find the optimal policy. The algorithm searches the optimal policy on a parametrized family of functions using a gradient-based approach and leveraging a feedback loop to collect CSI on the wireless paths.

The technique of using redundant packets to protect information is also used in Forward Error Correction (FEC) as described in [9]–[11] and its variants such as BCH (Bose, Chaudhuri, and Hocquenghem), Reed-Solomon and convolution codes [12], [13]. However, different from these FEC coding schemes, we employ multipath technique to distribute the redundant packets over multiple paths, thereby providing resiliency to the unavailability of one or more paths and avoiding coding/decoding overhead as well as retransmission delays. Recalling that our reference scenario is real-time multimedia delivery, we emphasize how this approach is advantageous in increasing reliability and reducing delay because the expiry time of sent packets is strictly limited.

III. SYSTEM MODELS

This paper considers a transmission system that sends $K$ information packets over a set of $m$ wireless paths by using a multipath strategy. We assume that the $K$ packets are sent through a Round Robin (RB)-based mechanism in time $T$ called cycle. Within a cycle, the packets are sent using $K$ transmission rounds. The packet transmitted during round $i$ of cycle $j$ can be replicated over a subset of the $m$ wireless paths. A path is defined by a 5 tuple of IP/Port addresses and path identifier.

We assume that the number of replicas used for each transmission round can be chosen from among predetermined values. These values are evaluated in such a way that the sequence of scheduled packets is feasible for the RB-based mechanism. Hence the sequence of replicas used in a cycle defines a scheduling class. The redundancy ratios and the scheduling class can be related by defining the vector of the redundancy ratios $r = [r_1, r_2, \ldots, r_m] \mid r_i \leq 1 \; i = 1, \ldots, m; \sum_{i=1}^{m} r_i = 1$ and by the following equation $\mathcal{F} = \sum_{i=1}^{m} r_i$, where $r_i$ is the percentage of packets replicated over $i$ paths within a cycle and $\mathcal{F}$ is the average redundancy factor.

Without loss of generality, to make the concepts introduced above clearer, let us apply them to the scenario analysed in this paper, which relies on a number of wireless paths $m = 3$. In this scenario, the left side of table I shows the predetermined seven scheduling classes from $A$ to $G$, the redundancy ratios vector for each scheduling class $r = [r_1, r_2, r_3]$, and the average redundancy factor $\mathcal{F}$. For the scheduling classes defined above, we have a total number of transmitted packets per cycle $N = \mathcal{F} K$ and the redundancy $R = N - K$. The adopted RB-based mechanism, to work correctly, must be aware of both the redundancy ratios and the number of transmitted packets per round in a cycle.

We need to evaluate the effects of the chosen scheduling class on the communication system through a reward function that consists of the E2E packet loss and the bandwidth used to transmit the packets per round. Using the CSI from the receiver feedback as provided by the RTP/Real-time Transport Control Protocol (RTCP) protocol stack, the packet loss rate per path can be computed as the ratio of the packets lost on the path.
TABLE I: AC-PADME mechanisms: (left) the scheduling classes with redundancy ratios $r_i$; (right) the interleaving policy, showing the channels rotation in the first 4 rounds.

and the total packets transmitted over the path in an interval time $t'$, as shown in the following equation:

$$PLR_i(t') = \frac{\sum_{\tau=1}^{t'} PL_i(\tau)}{\sum_{\tau=1}^{t'} PT_i(\tau)} \quad i = 1, \ldots, m$$

(1)

where $PT_i(\tau)$ and $PL_i(\tau)$ are the packets sent and the packets lost on path $i$, respectively, at time $\tau$. In our scenario $t'$ is the system RTCP report interval.

In the communication between the source (UAV) and the destination (GCS), the E2E packet loss counts the packets that are lost over all the $m$ channels in the time interval $t'$. We can define the E2E packet loss as in the following equation:

$$E2EPLR(t') = \frac{\sum_{\tau=1}^{t'} \sum_{i=1}^{m} PL_i(\tau)}{\sum_{\tau=1}^{t'} \sum_{i=1}^{m} PT_i(\tau)}$$

(2)

where the numerator and the denominator count the lost packets and the transmitted packets, respectively, over the $m$ paths until $t'$, which is again the RTCP report interval.

Finally, the used bandwidth to transmit the $K$ information packets using a given scheduling class can be defined as follows:

$$Bw = \bar{f}K$$

(3)

In the next section we formulate the optimization problem addressed through the AC approach involving the system aspects discussed in this section.

IV. PROBLEM FORMULATION

The optimization problem addressed in this work can be stated as the minimization of the E2E packet loss using the minimum bandwidth to transmit the information packets using feasible redundancy. The state of the communication system that can be observed when performing the minimization is represented by the packet loss rate of the wireless paths.

The optimization problem stated above can be formulated as a decision-making problem that can be modelled as a Markov Decision Process (MDP) [3]. An MDP is defined by the tuple $\{S, A, P(s'|s, a), r(s', s, a)\}$, where $S$ is the states space of the system, $A$ denotes the actions space that can be adopted to perform the optimization, $P(s'|s, a)$ is the transition probability over the state space conditioned by the actions, and $r(s', s, a)$ is the immediate reward due to the action $a$ that triggers the state transition from $s$ to $s'$. In the following, we define the MDP for our problem.

1) States: We define the state as the vector $s = [\ell_1, \ldots, \ell_m]$ of the packet loss rate of the wireless paths.

2) Actions: For the scheduler to minimize the E2E using the minimum bandwidth, it has to determine the redundancy factor $\bar{f}$ and the vector of weights $\omega_i$ of the WRR mechanism. The redundancy factor is computed from the redundancy ratios of the selected scheduling class as discussed in the previous section, while $\omega_i$ is the amount of packets to be transmitted over path $i$, $i = 1, \ldots, m$. Hence, in our case the action can be defined as the vector $a = [\bar{f}, \omega_1, \ldots, \omega_m]$.

3) Reward: In this work, the immediate reward $r(s', s, a)$ provides a penalty $-1$ in the following cases: when the E2E loss rate is above a given threshold $\varphi_{th}$; even if the E2E loss rate is below the threshold, the penalty is provided for increasing the used bandwidth or if the highest number of packets is not sent on the channel with the lowest packet loss rate: $\omega_u > \ldots > \omega_m > \ldots > \omega_1 > \ldots > \omega_u \Rightarrow PLR_u < \ldots < PLR_m < \ldots < PLR_1 < \ldots < PLR_e$. In the other cases the immediate reward function provides the incentive 1.

We do not need to define a model for the probability function $P(s'|s, a)$, because as stated previously, we use an AC algorithm which can approximate the probability function using the acquired observations of the states without using any apriori model. Moreover, the function policy used to select the actions can be approximated iteratively using a parametrized family of functions. We now clarify how an AC algorithm works by introducing the basic concepts presented by the authors in [3], [14].

Figure 2 shows the architecture of the AC algorithm. The main entities involved in the algorithm are the critic and the actor, which interact jointly with the system (environment) for achieving the optimization goal. The actor aims to estimate the policy function $\pi(a|s)$ used to select actions based on the state of the environment. This function belongs to a parameterized family of functions; the estimation of the parameters to fit the best one is performed with different techniques such as Neural Networks (NN). The equation used for parameter fitting involves maximizing the expected value of the total reward discounted by the parameter $\gamma$, as shown in the following.
equation:

\[ \pi^*(a|s) = \arg\max_{a} E \left[ \sum_{t=0}^{\infty} \gamma^t (r(s', s, a)) \right] \quad (4) \]

The critic evaluates the goodness of the estimated policy function and then sends the feedback to the actor to refine the parameter fitting. The critic performs this operation estimating the value of the state-action function \( Q^*(s', a) \), solving equation 5 that also, in this case, can be solved through a NN.

\[ Q^*(s', a) = E \left[ r(s', s, a) + \gamma (Q^*(s, a)) \right] \quad (5) \]

In figure 2, the architecture is based on a double critic network. Together with the critic network, there is also a target critic network which is used to estimate the time difference error in order to overcome the instability of the results obtained using the single critic network, as explained in [3], [14]. In this work, we apply the soft-update of the target critic network using the critic parameters according to the following equation:

\[ \theta_{\text{new, crit.}}^{\text{old}} = \alpha \theta_{\text{old, crit.}} + \theta_{\text{crit.}} (1 - \alpha) \quad (6) \]

where \( \theta \) is the TD error for the critic as analysed in [3], [14], and \( \alpha \) is a weighting factor that takes into account the estimate from the critic network versus the target critic.

The NNs of both the actor and the critic are designed as Deep NN (DNN) using TensorFlow-2 and Keras libraries, and ADAM algorithm as the underlying optimizer.

After the transmission of the packets using the selected action \( a \), the algorithm evaluates the reward \( r(s', s, a) \) and the triggered transition state from \( s \) to \( s' \), and observes the path loss rates \( PLR_i \), \( i = 1, \ldots, m \). The observed data \( \{s, s', a, r(s', s, a)\} \) are stored in the replay buffer of size \( B \) in order to solve the sample deficiency problem. Once the replay buffer is full, some samples are randomly drawn to update the parametrized models of both the policy and the value-state functions. The updating is based on the Temporal Difference (TD) approach that provides the following loss functions:

\[ \Delta^C = \frac{1}{B} \left( r(s', s, a) + \gamma \hat{Q}^c(s', a) - Q^c(s, a) \right)^2 \quad (7) \]

\[ \Delta^A = -\delta \ln \pi(a|s) \quad (8) \]

These functions are used to update the value-state function (critic) and policy function (actor), respectively; where \( \delta \) is the TD error for the actor as analysed in [3], [14].

V. SIMULATION RESULTS AND ANALYSIS

Simulation results are presented in this section to evaluate the performance of the proposed scheduler in terms of E2E packet loss and bandwidth utilization. The simulator is built leveraging Gstreamer and its modular plugins designed to handle multimedia streaming. The sender-side of our scheduler runs on a Jetson Nano board transmitting video to a desktop machine via three Network Interface Cards (NICs), having as reference the scenario in [10].

Fig. 3 shows the curves of the total discounted reward with different link loss rates. The learning occurs at an interval equal to the RTCP report interval, which in our case is 3s. The figure shows that within 60 iterations the algorithm reaches a stable state, except in the case with PLR 1% because in this case, the number of loss events useful for estimating models is lower than in other use cases. Note that, in the scenario with different packet loss values per path and a 3% packet loss for all the paths, convergence is achieved before 60 iterations due to the higher number of loss events available for model estimation.

In Fig.4, we show the effectiveness of our scheduler in maintaining below a threshold the E2E packet loss. The threshold is set at 0.5% to ensure an optimal QoE in our use case. The figure shows that in the scenario with packet loss 1%, the algorithm can guarantee an E2E packet loss below the threshold from iteration 20 onward, even though, the curve presents a greater variability because the number of available learning events is less than in the other use cases due to the low packet loss rate.
used reduces rapidly as the algorithm continues to learn. The average redundancy factor curve shows that the bandwidth utilization, while the E2E loss is also minimized. The figure shows the different redundancy factors selected by the algorithm during the learning process for the scenario with the paths having heterogeneous packet loss rates. The average redundancy factor curve shows that the bandwidth used reduces rapidly as the algorithm continues to learn.

Fig. 4: E2E-Packet Loss Rate (PLR) with different path loss rates. The target is $PLR_{th} = 0.5\%$.

Fig. 5 shows the capacity of the scheduler to minimize the bandwidth utilization, while the E2E loss is also minimized. The figure shows the different redundancy factors selected by the algorithm during the learning process for the scenario with the paths having heterogeneous packet loss rates. The average redundancy factor curve shows that the bandwidth used reduces rapidly as the algorithm continues to learn.

VI. Conclusions

In this work, we have proposed an Actor-Critic based scheduler called AC-PADME for multimedia delivery in a multipath environment. The results show that the AC-PADME can progressively learn the scheduling policy by observing the path loss rates and estimating in real-time the required redundancy and the optimal path weight allocation, targeting very low E2E loss, thus improving link availability and the overall QoS. These operations are performed through learning procedures that do not need apriori models or training procedures. Our future research will include the analysis of kernel basis functions for the approximation of states space analysed in this work and the possibility to introduce as feedback, the Human In the Loop (HIL), for the tuning of the policy and for improving the QoE.

Acknowledgments

This research is supported by TEACHING project funded by the EU H2020 research programme GA n. 871385

References

[1] M. Bacco, S. Chessa, M. D. Benedetto, D. Fabbri, M. Girolami, A. Gotta, D. Moroni, M. A. Pascali, and V. Pellegrini, “Uavs and uav swarms for civilian applications: communications and image processing in the sciadro project,” in International Conference on Wireless and Satellite Systems. Springer, 2017, pp. 115–124.

[2] S. Afzal, V. Testoni, C. E. Rothenberg, P. Kolan, and I. Bouazizi, “A Holistic Survey of Wireless Multipath Video Streaming,” arXiv preprint arXiv:1906.06194, 2019.

[3] V. R. Konda and J. N. Tsitsiklis, “Actor-Critic Algorithms ;” in Int. Conf. NIPS. MIT Press, 1999, pp. 1098–1104.

[4] Q. Wang, T. Nguyen, and B. Bose, “Towards adaptive packet scheduler with deep-q reinforcement learning,” in 2020 International Conference on Computing, Networking and Communications (ICNC), 2020, pp. 118–123.

[5] H. Wu, O. Alay, A. Bruinstein, S. Ferlin, and G. Caso, “Peekaboo: Learning-based multipath scheduling for dynamic heterogeneous environments,” IEEE Journal on Selected Areas in Communications, vol. 38, no. 10, pp. 2295–2310, 2020.

[6] C. Zhong, Z. Lu, M. C. Gursoy, and S. Velipasalar, “A deep actor-critic reinforcement learning framework for dynamic multichannel access,” IEEE Transactions on Cognitive Communications and Networking, vol. 5, no. 4, pp. 1125–1139, 2019.

[7] H. Yang and X. Xie, “An actor-critic deep reinforcement learning approach for transmission scheduling in cognitive internet of things systems,” IEEE Systems Journal, vol. 14, no. 1, pp. 51–60, 2019.

[8] Y. Wei, F. R. Yu, M. Song, and Z. Han, “Joint optimization of caching, computing, and radio resources for fog-enabled iot using natural actor–critic deep reinforcement learning,” IEEE Internet of Things Journal, vol. 6, no. 2, pp. 2061–2073, 2018.

[9] M. Bacco, P. Cassarà, A. Gotta, and V. Pellegrini, “Real-Time Multipath Multimedia Traffic in Cellular Networks for Command and Control Applications,” in 2019 IEEE 9th Vehicular Technology Conference (VTC2019-Fall), 2019, pp. 1–5.

[10] M. Bacco, P. Cassarà, and A. Gotta, “Air-to-ground real-time multimedia delivery: A multipath testbed,” Vehicular Communications, vol. 33, p. 100443, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2214209621001121

[11] F. Gabriel, J. Acevedo, and F. H. P. Fitzek, “Network coding on wireless multipath for tactile internet with latency and resilience requirements,” in 2018 IEEE Global Communications Conference (GLOBECOM), 2018, pp. 1–6.

[12] A. Gotta and P. Barsocchi, “Experimental video broadcasting in dvbscs2 with land mobile satellite channel: a reliability issue,” in 2008 IEEE International Workshop on Satellite and Space Communications. IEEE, 2008, pp. 234–238.

[13] A. Badr, A. Khisti, W.-T. Tan, and J. Apostolopoulos, “Perfecting protection for interactive multimedia: A survey of forward error correction for low-delay interactive applications,” IEEE Signal Processing Magazine, vol. 34, no. 2, pp. 95–113, 2017.

[14] I. Grondman, L. Busoniu, G. A. D. Lopes, and R. Babuska, “A survey of actor-critic reinforcement learning: Standard and natural policy gradients,” IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), vol. 42, no. 6, pp. 1291–1307, 2012.