# An Online Algorithm for Computation Offloading in Non-Stationary Environments

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Abstract—We consider the latency minimization problem in a task-offloading scenario, where multiple servers are available to the user equipment for outsourcing computational tasks. To account for the temporally dynamic nature of the wireless links and the availability of the computing resources, we model the server selection as a multi-armed bandit (MAB) problem. In the considered MAB framework, rewards are characterized in terms of the end-to-end latency. We propose a novel online learning algorithm based on the principle of optimism in the face of uncertainty, which outperforms the state-of-the-art algorithms by up to ~1 s. Our results highlight the significance of heavily discounting the past rewards in dynamic environments.

*Keywords*—Mobile Edge Computing, Online Learning, Computation Offloading, Multi-armed Bandit.

# I. INTRODUCTION

**T**HE future mobile networks will be characterized by ubiquitous coverage, ultra-low latency services, quasideterministic communications, and the need for extremely high data rates. In this context, a radical change consists of empowering mobile devices and base stations (BSs) with data processing and storage capabilities, thereby reducing the end-to-end latency of the mobile services. This paradigm is called multi-access edge computing (MEC) [1], also known as mobile edge computing. In MEC networks, small cells integrate computing capabilities and local cache memories to the standard radio access technique (RAT). Consequently, a user equipment (UE) can request a small cell to run a computational assignment on its behalf, resulting in a reduced effective latency and an increased UE battery-life. This procedure is called task or computation offloading [2]. Additionally, the MEC-enabled small cells can implement proactive caching strategies to satisfy the ever growing demand for downloadable multimedia content in the mobile networks, thereby limiting the load on the transport network [3]. The MEC resources are often divided into three categories: communication, computing, and caching [4].

In [5] the authors have provided a detailed overview of MEC technology and its use-cases, particularly focusing on the services requiring low-latency and highly-reliable communications. Several researchers have investigated policies to

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determine when computation offloading is more efficient than local processing. For instance, Elbamby et al. [6] have studied the task-offloading problem formulated as a matching game, subject to latency and reliability constraints. More recently, computation offloading was also extended to more realistic scenarios, where system dynamics and information uncertainty is taken into consideration. For example, Liao et al. [7] have proposed a robust two-stage task offloading algorithm that integrates contract theory with computational intelligence to minimize the long-term delay of task assignment. On the same lines, multi-armed bandit (MAB) is an online reinforcement learning (RL) framework that can be used to find an optimal policy when the reward distribution of the actions is not a priori known [8]. In particular, we focus on the case where the system characteristics, i.e., the MEC resource availability and the wireless channel are non-stationary<sup>1</sup>. It must be noted that, in non-stationary scenarios, off-the-shelf RL algorithms may indeed be sub-optimal due to the usage of outdated information. Therefore, it becomes necessary to forget past rewards and rapidly update the reward distribution based on recent information. However, selecting the policy refresh rate is challenging since the *agent* is typically not aware of the temporal behaviour of the system.

Earlier, researchers have come up with the idea of discounting the past rewards, to make the RL system adaptive to the dynamic changes and introduced the discounted variants [10], [11] of classical RL algorithms. Garivier and Moulines [11] considered a scenario where the distribution of the rewards remain constant over epochs and change at unknown time instants (i.e., abrupt changes). They analyzed the theoretical upper bounds of the regret for the discounted upper confidence bound (UCB) and sliding window UCB. Gupta et al. [12], extended this idea to Bayesian methods, and proposed the Dynamic Thompson Sampling (Dynamic TS). Hartland et al. [13] considered dynamic bandits with abrupt changes in the reward generation process, and proposed an algorithm called Adapt-EvE. Slivkins and Upfal. [14] considered a dynamic bandit setting where the reward evolves as Brownian motion or a random walk, and provided results of regret linear in time horizon. Sana et al. [15] have solved the problem of optimizing the UE-BS association by employing Deep Reinforcement Learning. Liao et al. [16] have maximized the long-term throughput for a machine type device (MTD) subject to energy and data-size constraints in a learning-based channel selection framework. The learning algorithm proposed is a variant of

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<sup>&</sup>lt;sup>1</sup>This refers to a random process whose probability distribution changes in time or space [9].

UCB. However, these works do not take into account, the abrupt changes at unknown times.

In this paper, we model the MEC server selection problem as the exploration-exploitation dilemma of a restless MAB framework with non-stationary rewards. For this problem, we propose an online learning algorithm *Sisyphus* that is modelfree and is based on the principle of optimism in the face of uncertainty. In particular, we selectively retain the knowledge of the past rewards so as to keep up with the dynamic environment. We show that Sisyphus achieves the lowest normalized regret as compared to the other algorithms proposed for the non-stationary bandit problem, namely, Thompson sampling (TS), discounted TS, discounted optimistic TS, and discounted UCB. Consequently, Sisyphus is shown to reduce the end-toend latency by up to 1 s under the considered test environment.

#### II. SYSTEM MODEL

We focus on a UE offloading its computational task to a nearby MEC server  $s_i \in S$ , where S represents the set of all servers. We assume that one task is offloaded by the UE in each time-step  $t \in \{1, 2, 3, ..., T\}$  of duration  $\delta$ . The aim of the UE is to select the MEC server which results in a minimum delay, while taking into account the task execution and signal propagation delays.

The MEC server  $s_i$  performs the task with intensity  $\kappa$ , which denotes the CPU cycles required to process a byte of task, using its available computing resources, which evolves over time [17]. Unlike the centralized architecture in [18], we consider a distributed system where each user selects an MEC server independently of the other users' decision.

Specifically, the link between the UE and the MEC server is assumed to be affected by dynamic blockages, where the probability of blockage of the server  $s_i$  is denoted by  $p_{B,i}$ . In addition, we model the MEC servers as the arms in an MAB framework, where the resource availability  $a_i(t)$ , varies with time in a *doubly-stochastic* manner. The computing resources available at time-step t is expressed as  $a_i(t)c_i$ , where  $c_i$  is the maximum computing capacity<sup>2</sup> of the server and  $a_i(t) \in (0, 1)$ is the fraction of the computing capacity available at time t. We refer to this quantity  $a_i(t)$  as *resource availability*.

We assume that the number of UEs associated with a server changes after certain number of time-steps, which in turn impacts the resource availability. This set of consecutive timesteps constitute an **epoch**. If the probability that the number of UEs connected v(t) to a server  $s_i$  changes in a single timestep is  $p = \Pr\{v(t) \neq v(t-1)\}$ , then the probability that it remains unchanged for  $\Delta$  consecutive time-steps, is given by the geometric distribution [19]:

$$\Pi_{l=1}^{\Delta}(1-p) = (1-p)^{\Delta}$$

We set  $p = \frac{1}{\Lambda_i}$  where  $\Lambda_i$  is the mean value of epoch duration. The  $j^{\text{th}}$  epoch size  $\Delta_i^j$  can then be drawn from the distribution:

$$p_{\Delta_i^j}(\Delta_i^j = \Delta; \Lambda_i) = \left(1 - \frac{1}{\Lambda_i}\right)^{\Delta},\tag{1}$$

<sup>2</sup>Computing capacity refers to the frequency of the processor clock, i.e., number of cycles per second, typically measured in GHz.

where the expected value  $\mathbb{E}\{\Delta_i^j\} = \Lambda_i$ .

The instantaneous resource availability of an MEC server  $a_i(t)$  is a function of the associated UEs. If server  $s_i$  can accept up to N users at a time, and q users offload their tasks to it, then,  $a_i(t) = 1 - \frac{q}{N}$ .

Now, we derive the probability that q UEs offload their tasks to the server at a given time-step. The considered scenario is as follows: (i) there are w UEs in communication range of the MEC server, (ii) for the  $j^{\text{th}}$  epoch, out of these w UEs,  $v_j$  are connected to the small cell hosting the server, (iii) at a given time-step t within the  $j^{\text{th}}$  epoch, out of these  $v_j$  UEs, only  $q_{t,j}$  UEs offload their computation tasks.

The probability that  $v_j$  UEs out of w are connected to the server follows a binomial distribution:

$$p_{v_j}(v_j = v) = \binom{w}{v} \psi_0^v (1 - \psi_0)^{w - v}, \tag{2}$$

where  $\psi_0$  is the probability of a single in-range UE to be connected to the server. The value  $\psi_0$  is specific for a server  $s_i$  because of the radio characteristics of the environment surrounding  $s_i$  (e.g., blockages). Out of these  $v_j$  UEs, only a fraction of the UEs offload their task to the server e.g., depending on the task computational complexity. Therefore, we denote with  $\psi_1$  the probability that a connected UE decides to offload a task. Then,  $q_{t,j}$  follows a binomial distribution:

$$p_{q_{t,j}}(q_{t,j}=q) = {\binom{v_j}{q}} \psi_1^q (1-\psi_1)^{v_j-q}.$$
 (3)

For a given server  $s_i$ , the resource availability at time-step t in the  $j^{\text{th}}$  epoch is then expressed as:  $a_i(t) = 1 - \frac{q_{t,j}}{N}$ .

Therefore, the dynamic resource availability characteristics of a server  $s_i \in S$  can be controlled through the parameters  $\{\psi_0, \psi_1, w, N, \Lambda\}_i$ .

Let us assume that the amount of uplink data related to the task to be offloaded be given by  $L_U$  bytes. The downlink data size, after the MEC server processing, is denoted as  $L_D$  and is related to the uplink data as:  $L_D = \Omega L_U, \Omega \in \mathbb{R}^+$ . Furthermore, let  $\gamma$  denote the path-loss exponent of the transmissions, which varies depending on the blockage conditions, i.e., whether the channel visibility state is in line of sight (LOS) or non line-of-sight (NLOS). Additionally, let the reference uplink signal to interference plus noise ratio (SINR) at 1 m be denoted as  $\mathcal{P}_D$ . The uplink and downlink bandwidths are denoted as  $\mathcal{P}_U$  and  $\mathcal{B}_D$  respectively. Thus, the total transmission delay  $\tau_i(t)$  when the distance between the UE and server is  $r_i$ , can be written as:

$$\tau_i(t) = \sum_{Z \in \{U,D\}} \frac{L_Z}{B_Z \log_2(1 + \mathcal{P}_Z \cdot r_i^{-\gamma})};$$
 (4)

For the processing phase, the computation delay  $\eta_i(t)$  is defined as the time taken by the MEC server  $s_i$  to process the data and generate the output, which is expressed mathematically as:

$$\eta_i(t) = \frac{\kappa L}{c_i a_i(t)}$$

Then, the total delay is the sum of transmission and com-

putation delays:  $D_i(t) = \tau_i(t) + \eta_i(t)$ . Finally, the reward associated with server  $s_i$  at time-step t is denoted by  $\rho_i(t)$ . Let  $D_{\text{max}}$  be the latency requirement of the task that the UE wants to offload; then, we can define the reward  $\rho_i(t)$  as:

$$\rho_i(t) = \mathbb{1}_{\{D_i \le D_{\max}\}}$$

which ensures that the reward is positive and bounded by 1. The UE follows a policy  $\pi$  (see Section III) to select an arm at each time-step. Let  $\rho_j(t)$  be the reward of the arm chosen at time-step t and max  $\rho_i(t)$  denote the highest reward among all arms' reward; then, the *time-normalized cumulative regret*  $R_{\alpha}(T)$  for T time-steps is defined as the cumulative sum of the difference between the rewards of the best arm and the chosen arm (according to  $\pi$ ) divided by the count of timesteps T. We refer to it as the normalized regret, given by:

$$R_{\pi}(T) = \frac{1}{T} \sum_{t=1}^{T} \left( \max_{s_i \in \mathcal{S}} (\rho_i(t)) - \rho_j(t) \right).$$
 (5)

The objective of the MAB framework is to design the policy  $\pi$  so as to minimize  $R_{\pi}(T)$ . In the next section, we propose one such policy which outperforms the state-of-the-art MAB algorithms.

# **III. PROPOSED ONLINE LEARNING ALGORITHM**

We consider an |S|-armed bandit, where the UE, at each time-step, plays the arm (i.e., selects the server) which has the highest expected reward, based on the past experiences of playing the arms. Specifically, for each server  $s_i \in S$ , the UE tracks the total number of times each arm has been played, denoted by  $k_i$  and maintains a score  $\mu_i$ , as described below.

**Definition 1.** On playing the arm  $s_i$  for the  $k_i^{\text{th}}$  time, we obtain a **reward**  $\rho_i(k_i)$ , then the **score**  $\mu_i(k_i)$  for that arm is updated as:

$$\mu_i(k_i) = \frac{1 - \alpha^{k_i - 1}}{2 - \alpha - \alpha^{k_i}} \mu_i(k_i - 1) + \frac{1 - \alpha}{2 - \alpha - \alpha^{k_i}} \rho_i(k_i), \quad (6)$$

where  $\alpha \in [0, 1)$  is the retention rate.

The parameter  $\alpha$  controls the amount of memory in the MAB framework. Two extreme states can be determined in the system, by substituting the value of  $\alpha = 0$  and  $\alpha \rightarrow 1$ . If  $\alpha$  is set to zero, the UE gives equal weight-age to the new reward compared to the weighted sum of previous rewards. For  $\alpha \rightarrow 1$ , past rewards have a larger effect on the current score and thereby influence more the UE's decision. In essence, lower the value of  $\alpha$ , the lesser memory the system has about the past rewards.

**Corollary 1.** The score assigned to arm  $s_i$  can be expressed as a weighted sum of rewards, where  $\phi_{\alpha}(k_i, m)$  denotes the **memory weight** for the reward when the arm  $s_i$  is played for the  $m^{\text{th}}$  time:

$$\mu_i(k_i) = \sum_{m=1}^{k_i} \phi_\alpha(k_i, m) \cdot \rho_i(m); \quad k_i > 0.$$
(7)

$$\phi_{\alpha}(k_i, m) = \frac{1 - \alpha}{2 - \alpha - \alpha^m} \cdot \left(\prod_{j=m+1}^{k_i} \frac{1 - \alpha^{j-1}}{2 - \alpha - \alpha^j}\right).$$
(8)



Fig. 1. Memory weight across different retention rates.

After a certain play-count  $k_i$ , the reward at the  $m^{th}$  play, becomes negligible  $(m < k_i)$ . This is bound to happen, as the recorded reward successively fades, until it no longer affects the score of that arm. This is more intuitive than resetting the previous rewards to zero at regular predefined intervals (e.g., see [20]), since smooth transitions allow to take care of abrupt changes in the reward distribution. Refreshing the score to zero at fixed intervals may either reset it too early, or too late, resulting in sub-optimal performance. In essence, the UE gives importance to the score of an arm and the number of times it has been played. This prevents us from getting biased by the performance of an arm in a few trials. This is the optimistic approach, where we expect that a poorly performing arm might perform well in the future draws owing to the uncertain behaviour of the arms. We have depicted the concept of memory weights graphically in Fig. 1. For smaller values of retention rate  $\alpha$ , the reward recorded for an arm fades quickly as it is played more number of times (k). On the other hand, for values of  $\alpha$  close to 1, the reward fades slowly in comparison.

The proposed algorithm **Sisyphus** (SSPH) is described in Algorithm 1. The scores  $\mu$  and counts k for all the arms are initialized to zero in step 1 and step 2 respectively. A time loop starts in step 3 which is terminated in step 9 within which, the following operations are performed sequentially: an expected reward  $\theta$  is drawn from the normal distribution (step 4) and the arm with the maximum expected reward is chosen to be played (step 5). The play-count of that arm (which tracks the number of times the arm has been played) is incremented by 1 (step 6). When the selected arm is played, the actual reward is revealed, after which we update the score of the chosen arm in step 7 and that of the set of the never-played arms  $S^0$  in step 8.

The algorithm is based on the principle of optimism in the face of uncertainty<sup>3</sup> [8]. We first assign the score of zero to each arm and then draw the expected reward from a normal distribution with mean equal to the score  $\mu_i(k_i)$  and variance<sup>4</sup> equal to  $\sigma^2$ . This is a Bayesian approach [21] and allows us to look for expected rewards in the neighborhood of the recorded score  $\mu_i(k_i)$ , since it is not wise to make

<sup>&</sup>lt;sup>3</sup>The optimism in the face of uncertainty principle states that the actions should be chosen assuming the environment to be as nice as plausibly possible. <sup>4</sup>The appropriate value of  $\sigma^2$  can be tuned based on empirical history.





# Algorithm 1 SISYPHUS

Retention rate  $\alpha$ 1:  $\mu_i(0) \leftarrow 0$ ;  $\forall s_i \in S$ 2:  $k_i \leftarrow 0$ ;  $\forall s_i \in S$ 3: for  $t \in 1, ..., T$  do 4:  $\theta_i \sim \mathcal{N}(\mu_i(k_i), \sigma^2)$ ;  $\forall s_i \in S$ 5:  $s_j(t) \leftarrow \arg \max_{s_i \in S} \theta_i$ 6:  $k_j \leftarrow k_j + 1$ 7:  $\mu_j(k_j) \leftarrow \frac{1 - \alpha^{k_j - 1}}{2 - \alpha - \alpha^{k_j}} \mu_j(k_j - 1) + \frac{1 - \alpha}{2 - \alpha - \alpha^{k_j}} \rho_j(k_j)$ 8:  $\mu_u(0) \leftarrow \frac{1}{|S \setminus S^0|} \sum_{s_i \in S \setminus S^0} \mu_i(k_i)$ ;  $\forall s_u \in S^0$ 9: end for

decisions by comparing the scores of the arms directly, in a non-stationary environment. This enables us to predict values which would otherwise be ignored in a greedy technique [22]. As we play, we update the score of the arms that have never been sampled as the average of the scores of the played arms. This boosts the probability of exploration of the unexploited arms. In contrast to the classical MAB algorithms, e.g., UCB, which add specific terms to facilitate exploration, the proposed scheme is a randomized algorithm in which the explorationexploitation trade-off is based on a Bayesian framework.

In the following section, we show several numerical results that compares our algorithm with other state-of-the-art algorithms.

#### **IV. SIMULATION RESULTS**

To assess the proposed online learning algorithm, we define five classes of servers  $\{s_1, s_2, s_3, s_4, s_5\} \in S$ , whose characteristics are described in Table I. In our simulations, the  $j^{\text{th}}$  server is assigned to one of these classes of servers as:  $s_j \leftarrow s_j \pmod{5}$ ; j > 5, where mod denotes the modulus operation.

Parameter	$s_1$	$s_2$	$s_3$	$s_4$	$s_5$
$\psi_0$	0.7	0.6	0.5	0.4	0.3
$\Lambda_i$	100	150	100	100	50
$r_i$ [m]	7	10	12	14	16
$p_{B,i}$	0.3	0.4	0.5	0.6	0.7
$c_i$ [GHz]	5	3.3	3.3	3.3	5

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Additional simulation parameters are:  $L_U = 20$  MB [23],  $\Omega = 1, B_D = B_U = 500$  MHz,  $\mathcal{P}_U = 20$  dBm,  $\mathcal{P}_D =$ 



Fig. 3. Normalized Latency evolution. |S| = 5.



Fig. 4. Normalized Regret vs. Retention rate. |S| = 5.

40 dBm,  $D_{\text{max}} = 1$  s,  $\kappa = 10$  cycles/byte,  $\gamma_{\text{LOS}} = 2$ ,  $\gamma_{\text{NLOS}} = 4$  w = N = 100,  $\psi_1 = 0.5 \forall s_i \in S$ , and  $\delta = 1$  s.

We compare the performance of Sisyphus (SSPH) with the following algorithms: Thompson Sampling (TS) [24], Discounted Thompson Sampling (dTS) [10], Discounted Optimistic Thompson Sampling (dOTS) [10] and Discounted UCB (D-UCB) [11]. It is important to note that the last three algorithms (dTS, dOTS, and D-UCB) are designed to tackle the issue of dynamically changing environments in the MAB framework. The value of  $\alpha$  is set to 0.6 for Sisyphus. The discounting factor of the benchmark algorithms are chosen for their best performance: dTS (0.8), dOTS (0.7) and D-UCB (0.5).

#### A. Normalized Regret

In Fig. 2, we plot the temporal evolution of the normalized regret for the different algorithms. Here, the solid lines represent the mean of the normalized regret, and the shaded region represents the variance. The proposed algorithm SSPH evidently outperforms all the other algorithms and has a much lower normalized regret ( $\sim 0.32$ ) compared to the other algorithms (> 0.37). Interestingly, we observe that SSPH also has a considerably lower variance, which indicates that it is more robust than the other contending algorithms.

# B. Latency

Naturally, the reduced normalized regret will be reflected on the latency performance with different algorithms. To validate this, we plot the variation of time-normalized latency for various algorithms in Fig. 3. We observe that as the temporal process evolves, the latency of most of the contending algorithms increases gradually and settle into a higher value > 2.5 s. On the contrary, the latency of the proposed algorithm is considerably lower ( $\sim 1.5$  s).

### C. Parameter Tuning

Indeed the performance of SSPH will depend on the agility of the environment change, and the corresponding choice of  $\alpha$ . However, the algorithm developed is model-free, and takes the rewards as input at each time-step to update its score for the respective arm. The performance can be tweaked by tuning the parameters  $\alpha$  which denotes how strongly the algorithm retains the past rewards and the variance  $\sigma^2$  which controls the degree of exploration. For a highly dynamic system, the past rewards need to be forgotten quickly and in an environment with less number of arms, the exploration factor can be kept low. In our work, for all the algorithms, the corresponding retention parameters are tweaked to obtain the best performance. In Fig. 4, we show how the normalized regret varies with varying  $\alpha$  for SSPH with 5 classes of servers. Here, the blue scattered points are observations, black solid line is mean of the observations, red lines are the standard deviation around the mean value. It can be observed that the mean of the scattered point remains reasonably flat, i.e., ranging within [0.3, 0.35] for  $\alpha \in [0.1, 0.6]$ . This indicates that a fairly robust selection of  $\alpha$  can be made for deploying SSPH in the UE.

## D. Scalability

Next, in Fig. 5, we vary the number of arms (i.e., the number of MEC servers) |S| and compare the mean normalized regret of the different algorithms. The normalized regret for TS, DTS and DOTS increases with increase in |S|. On the other hand the normalized regret of SSPH and D-UCB does not change significantly with increase in |S|. It must be noted that SSPH maintains the minimum value of mean normalized regret among the contenders.



Fig. 5. Mean Normalized Regret across various algorithms for different number of arms.

To capture these nuances of SSPH in a more concrete manner, currently we are investigating the theoretical regret bounds of the proposed algorithm and testing it for other online learning use cases.

#### V. CONCLUSION

In this paper, we proposed an online learning algorithm for the MAB framework with an objective to minimize the end-toend latency in offloading computation tasks to MEC servers. In particular, we showed that selective retention of past rewards is necessary to tackle temporally varying environments. The proposed algorithm (Sisyphus) works on the principle of optimism in the face of uncertainty, and outperforms the other state-ofthe-art algorithms for non-stationary MAB frameworks. We show that the proposed algorithm, in the test environment achieves a latency which is at least  $\sim 1$  s lower than the other benchmark algorithms.

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