Learning-Based Pricing for Privacy-Preserving Job Offloading in Mobile Edge Computing

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***Abstract*—This paper considers a scenario in which an access point (AP) is equipped with a mobile edge server (MEC) of finite computing power, and serves multiple resource-hungry mobile users by charging users a price. This price helps to regulate users' behavior in offloading computation jobs to the AP. To that end, first we introduce an economics model for MEC bearing physical layer offloading intuition. We then propose a learning based pricing mechanism, in which with no direct control and no knowledge of users' private information, the AP learns the optimal price. Under our mechanism, the AP induces self-interested users to make socially optimal offloading decisions, thus maximizing the system-wide welfare.**

***Index Terms*—Mobile edge computing, multi-user offloading, game theory, wireless network economics**

I. Introduction

With the development of internet services, a diverse variety of computing-intensive applications such as mobile shopping, face recognition, and augmented reality are emerging. These jobs typically require low latency and high power consumption, and thus are offloaded to the cloud via access points (e.g., base station) associated with mobile users. However, as the cloud is often located far away from users, they suffer from wide area network (WAN) delay [1]. As such, a trend of moving the function of cloud computing to the network edge is occurring. In cellular networks, the network edge refers to the access point (AP), which is in control of both the computing and the radio resource. Thus, a joint optimization of those resources can be performed, bringing about considerable improvement in the computing/radio resource efficiency.

Presently, researchers have been actively studying the joint optimization of the computing resource and the radio resource for different mobile edge computing (MEC) scenarios, such as the single user case [2]–[5], the multi-user case [6]–[9], the multiple APs case [10], the D2D case where mobile users share the resources among each other [11], and the complex scenario where energy harvesting is integrated [12], [13]. The above studies all formulate a centralized resource allocation problem, which involves solving a Mixed Integer Nonlinear Programming (MINP) problem. Centralized optimization requires direct control of users' offloading decisions and requires knowledge of users' profit functions of offloading, which are affected by attributes like users' battery states and distances to the AP. Generally, users are not willing to share their private information. Besides, users are selfish and may not report their true utility functions.

This paper aims to do resource allocation in a decentralized way. Along this line of research, in [14] the original centralized MINP problem is decomposed into several subproblems and solved semi-distributively. The works [15]–[19] reformulate the original problem into a game and arrive at a Nash Equilibrium of the interactive decision process among users. This equilibrium suffers from net offloading welfare loss, as selfish users do not take into consideration the negative externality of congestion they cause to others in their decision making. In light of this, we propose using pricing to regulate users' behavior, via charging users a fee for the congestion they cause. Our goal is to find a price that induces users to choose the socially optimal levels of demand, so as to maximize the net offloading welfare. Noting that existing economic works such as [20], [21] cannot be applied here since they use abstract utility functions (e.g., a simple logarithmic function), we first introduce an economics model for MEC of physical layer meanings, thus bridging the gap between economics and physical layer parameter optimizations. Based on the proposed economics model, we propose a learning-based pricing mechanism, wherein the AP iteratively updates and broadcasts prices and edge delays based on the congestion level it observes. This mechanism is privacy preserving since the AP does not need knowledge of individual utility functions. Via the proposed mechanism the AP will learn the socially optimal price, and the equilibrium point of this mechanism is the socially efficient point.

II. System Model

We consider an MEC system consisting of an access point (AP) and N mobile users. The wireless AP could be a base station, or a Wi-Fi access point. Other than being a conventional access point to the core network, it is installed with an additional edge computing server. The mobile devices might be running computation-intensive and delay-sensitive jobs, and may have insufficient computing power or limited battery energy to complete those jobs. As such, they may offload part/all of their jobs to the AP. In this section, we will introduce the offloading policy, the wireless channel model, followed by the models for computing in detail (see Fig. 1).

A. The job generation model and the offloading policy

Jobs arrive at the mobile users following a Poisson process of rate λ_a. The service time of a job is identically distributed

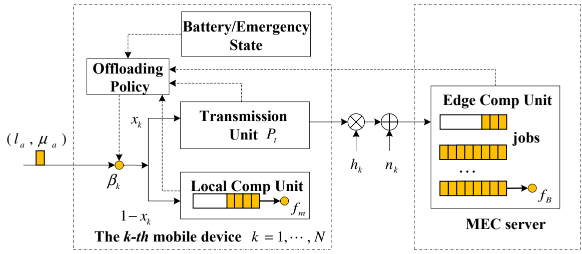

Fig. 1: An illustration of job arrival/offloading/computation.

(i.i.d.) and exponentially distributed, with an average of μ_a CPU cycles to run and $l_a\mu_a$ nats of input data to offload.

This paper considers the scenario with flat-fading channels, and assume that the user can finish offloading in a channel block. Hence, we consider the following *offloading policy*. When a job arrives, if the achievable rate is higher than a threshold β_k, the mobile user would offload its job to the AP; otherwise, the mobile user will choose local computing.

B. The radio access model

Users *access the AP in a FDMA mode*, suffering no multi-user interference. Let h_k denote the small-scale channel gain from user k to the AP. The achievable uplink data rate is,

$$R_k = \log(1 + d_k^{-\alpha}|h_k|^2 P_t/\sigma^2),\ k = 1, 2, \cdots, N, \quad (1)$$

where d_k denotes user k's distance to the AP and α represents the path loss exponent. P_t is the transmission power and σ^2 denotes the received noise power at the AP. In addition, comparing the achievable data rate R_k with the expected data rate β_k and by Shannon theorem [22]: when $R_k > \beta_k$ the mobile device can transmit its job to the AP successfully. Hence, the user k's offloading frequency (probability) is

$$x_k = \Pr(|h_k|^2 > (e^{\beta_k} - 1)\rho_k^{-1}),\ k = 1, 2, \cdots, N, \quad (2)$$

where $\rho_k \triangleq d_k^{-\alpha} P_t/\sigma^2$. A mobile user could control its offloading frequency by adjusting the threshold β_k.

C. Computation model

Based on the above radio access model and offloading policy, we discuss the total overhead/cost of local computing and edge computing. Both the processing delay and buffer delay are taken into consideration.

1) Local computing: By the Poisson arrival process and exponential job service time assumptions, we have an M/M/1 queue for local computing. Let f_m be the mobile device's computing capability (CPU cycles per second), then the expected time spent per job (including both the job execution time and the time awaiting in a local buffer) is

$$D_k^{\mathrm{LC}}(x_k) = 1/(\mu_m - \lambda_a\bar{x}_k), \quad k = 1, 2, \cdots, N. \quad (3)$$

where the local computing probability $\bar{x}_k \triangleq 1 - x_k$, and the service rate $\mu_m \triangleq f_m/\mu_a$. Next, the computational energy of local computing is

$$E_k^{\mathrm{LC}} = \kappa_m f_m^2 \mu_a,\ k = 1, 2, \cdots, N, \quad (4)$$

where $\kappa_m f_m^2$ is the power consumption the mobile device user runs one CPU cycle, and κ_m is an energy consumption coefficient that depends on the chip architecture [23].

The total weighted cost of local computing is

$$Z_k^{\mathrm{LC}}(x_k) = c_k^e E_k^{\mathrm{LC}} + c_k^t D_k^{\mathrm{LC}}(x_k),\ k = 1, 2, \cdots, N, \quad (5)$$

where $0 < c_k^e < 1$ (in units 1/Joule) and $0 < c_k^t < 1$ (in units 1/Second) are the weights of computational energy and delay. The weights allow different users to place different emphasis in decision making. For example, if the mobile device is at a low battery state, it would give energy consumption more emphasis, choosing a bigger value of c_k^e. If the user is running urgent jobs, it would give the delay cost more emphasis. Due to limitations of space, this paper studies the symmetric case where $c_k^t = c_0^t$, $c_k^e = c_0^e$, $\forall k$.

2) Edge computing: First, time taken to offload to AP is

$$D_{k,1}^{\mathrm{EC}}(x_k) = l_a\mu_a/\beta_k(x_k),\ k = 1, 2, \cdots, N. \quad (6)$$

This indicates that the energy required by offloading is

$$E_k^{\mathrm{EC}}(x_k) = P_t l_a \mu_a/\beta_k(x_k),\ k = 1, 2, \cdots, N. \quad (7)$$

Subsequently, the offloaded job will stay at the AP's buffer until it leaves after execution. By the splitting and superposition properities from queueing theory [24], the job arrival at the AP is another Poisson process with arrival rate as the sum arrival rate of $\sum_{k=1}^N \lambda_a x_k$. Hence, we get an M/M/1 queue for edge computing. Let f_B be the AP's computing capability (CPU cycles per second), then the expected time awaiting at the AP equals

$$D_2^{\mathrm{EC}}(\mathbf{x}) = 1/(\mu_B - \sum\nolimits_{k=1}^N \lambda_a x_k),\ \forall k, \quad (8)$$

where the service rate $\mu_B \triangleq f_B/\mu_a$, and $\mathbf{x} \triangleq (x_1, \cdots, x_N)$.

We neglect the energy overhead of edge computing as [12], [16], [18], since normally the AP can access to wired charing and it has no lack-of-energy issues. Combining (6) to (8) yields the total weighted cost of edge computing by user k, i.e.,

$$Z_k^{\mathrm{EC}}(\mathbf{x}) = c_k^e E_k^{\mathrm{EC}}(x_k) + c_k^t(D_{k,1}^{\mathrm{EC}}(x_k) + D_2^{\mathrm{EC}}(\mathbf{x})). \quad (9)$$

III. Proposed Economics Model for Mobile Edge Computing and Problem Formulations

By the aforementioned offloading policy, when a job arrives the mobile user will offload with probability x_k, and locally compute with probability $\bar{x}_k$. Hence, the expected total cost is

$$Z_k(\mathbf{x}) = \bar{x}_k Z_k^{\mathrm{LC}}(x_k) + x_k Z_k^{\mathrm{EC}}(\mathbf{x}). \quad (10)$$

On the other hand, when there is no such edge server providing computing power, users have to run jobs locally with average cost $Z_k^{\mathrm{LC}}(0)$. Therefore the gross profit of offloading by the k-th user under a given offloading strategy $\mathbf{x}$ is,

$$V_k(\mathbf{x}) = Z_k^{\mathrm{LC}}(0) - Z_k(\mathbf{x}),\ k = 1, \cdots, N. \quad (11)$$

The key idea of the economics model is to introduce the utility function and the cost function. Some observations are in order. Firstly, the profit each user obtains equals the cost savings from offloading, and it is a linear combination of the energy costs and the delay costs. Secondly, the coupled delay cost $D_2^{\mathrm{EC}}(\mathbf{x})$ reflects the harm/congestion each user causes to the other users. Thirdly, aside from $D_2^{\mathrm{EC}}(\mathbf{x})$, which depends on all users' offloading decisions, the other items in the profit function only depend on each user's own offloading frequency x_k. Motivated by these observations, we introduce a utility function $U_k(x_k)$ which includes the items in the profit function that only depend on the local variable x_k, i.e.,

$$\begin{aligned} U_k(x_k) =& Z_k^{\mathrm{LC}}(0) - \bar{x}_k Z_k^{\mathrm{LC}}(x_k) \\ & - x_k(c_k^e E_k^{\mathrm{EC}}(x_k) + c_k^t D_{k,1}^{\mathrm{EC}}(x_k)). \end{aligned} \tag{12}$$

This, combined with (11), indicates that

$$V_k(\mathbf{x}) = U_k(x_k) - C(\mathbf{x}),\ k = 1, \cdots, N. \tag{13}$$

where $C(\mathbf{x}) \triangleq c_k^t x_k D_2^{\mathrm{EC}}(\mathbf{x})$ denotes the delay cost due to the sharing of an MEC server at the AP.

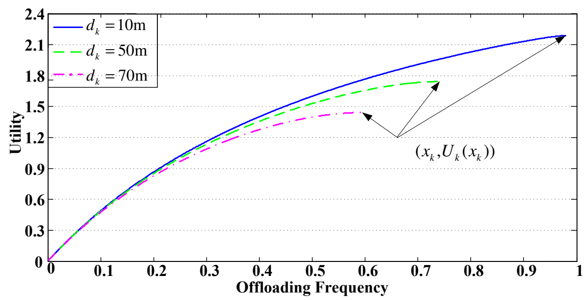

Fig. 2: The achievavble utility for varying distances to AP.

The utility function in (12) measures the welfare of offloading, while containing physical layer meaning. It is illustrated in Fig. 2, for a system with parameters set as in the numerical results section. One can see that the utility function is strictly increasing while the rate of increase, i.e., the demand, decreases as x_k increases; this is consistent with the law of diminishing marginal returns, a property of typical utility functions in economics. Moreover, the user closer to the AP has more offloading demand and can achieve a higher utility for the same offloading amount. This agrees with intuition that a user nearer the AP experiences a better wireless channel.

A. *Problem formulations*

We first consider the social-welfare offloading decision problem. Assume that the AP acts as a social planner. It would like users to choose their offloading frequency such that the net social welfare $\sum_{k=1}^N V_k(\mathbf{x})$ is maximized as follows.

Problem 1 (Social Problem):

$$\begin{aligned} \bar{x}_k^\star \triangleq & \arg\max_{x_k} \quad \sum_{k=1}^N V_k(\mathbf{x}) \\ & \text{s.t.} \quad 0 \le x_k \le 1. \end{aligned} \tag{14}$$

Intuitively, in Problem 1 each user should also be concerned with the congestion it causes to other users and should keep its offloading under an appropriate amount for other users' welfare; the difficulty lies in how to incentivise users to do so when users are selfish and will choose their offloading decisions such that its individual profit $V_k(x_k)$ is maximized.

Pricing is a useful tool in incentivising users to choose the socially optimal levels of demand. The key idea is to enforce users to pay for the congestion it causes to the other users. In the following Problem 2, we study the pricing-based scheme, which charges users an additional edge computing service fee to regulate users' behavior.

Problem 2 (Regulated Selfish Problem):

$$\begin{aligned} x_k^\star \triangleq & \arg\max_{x_k} \quad U_k(x_k) - (P + c_0^t D^{\mathrm{EC}}) x_k \\ & \text{s.t.} \quad 0 \le x_k \le 1, \end{aligned} \tag{15}$$

where P denotes the unit price for offloading.

Does there exist price P such that the individual objectives of self-interested users will be aligned with the social welfare objective? If it exists, how to design simple pricing schemes to achieve the best net welfare? In the following section, we answer the above two questions.

IV. Learning-Based Pricing to Induce Socially Optimal Offloading

In what follows, we first analyze the structural property of the formulated social and regulated selfish problems, and admit in closed form the optimal price.

A. *Optimal price for offloading under complete information*

For the Social Problem, by the first order condition, at the maximum is holds that

$$\begin{aligned} & \partial U_k(x_k)/\partial x_k - \sum_{j=1}^N \partial c_0^t x_j D_2^{\mathrm{EC}}(\mathbf{x})/\partial x_k = 0 \\ \Leftrightarrow & g_k(x_k) = c_0^t D_2^{\mathrm{EC}} + \frac{c_0^t \sum_{j=1}^N \lambda_a x_j}{(\mu_B - \sum_{j=1}^N \lambda_a x_j)^2},\ \forall k. \end{aligned} \tag{16}$$

where $g_k(x_k) \triangleq \partial U_k(x_k)/\partial x_k$ is the demand function.

By contrast, for the Regulated Selfish Problem, at the maximum it holds that

$$g_k(x_k) = c_0^t D_2^{\mathrm{EC}} + P,\ \forall k. \tag{17}$$

which, combined with (16), yields

$$P = c_0^t \sum_{j=1}^N \lambda_a x_j / (\mu_B - \sum_{j=1}^N \lambda_a x_j)^2, \tag{18}$$

which is also known as the congestion level.

Solving the equations in (16) and substituting the optimal offloading decisions, denoted by $\bar{x}_k^\star$, $k = 1, \cdots, N$, into (18), we arrive at the optimal price $P^\star$ that induces self-interested users to make socially optimal offloading decisions.

B. *Learning-based pricing inducing social-optimal offloading*

That derivation of the optimal price $P^\star$ requires solving for $\bar{x}_k^\star$ based on users' report of their individual utility functions, which include some private information such as their locations and battery states. Generally, users are not willing to share their private information. To that end, we propose an evolutional pricing algorithm, which requires no individual utility functions and learns the *correct* price.

As shown in Fig. 3, at each time slot t, the AP observes P_{true}^{t-1}, the congestion level caused by users' offloading decisions. Based on the congestion level, the AP computes and broadcasts the unit service fee P^t and delay D_{EC}^t signals to users. Noting that by comparing (8) and (18), for given P^t we have a corresponding D_{EC}^t as follows

$$D_{\text{EC}}^t = 1/(2\mu_B) + \sqrt{P^t/(c_0^t \mu_B) + 1/4\mu_B^2}. \quad (19)$$

Viewing the signals, users decide their offloading frequency x_k^t based on (17) to maximize their individual welfare. The AP will observe this new congestion level P_{true}^t. The above process iterates until convergence when the resulting congestion level equals the price set, meaning that we have learnt the optimal price and arrived at the socially optimal equilibrium.

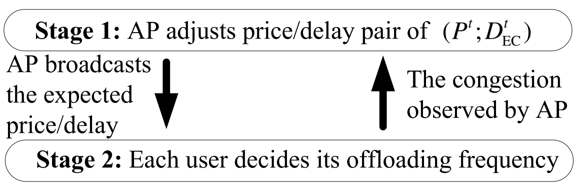

Fig. 3: Schematic view of the learning-based pricing scheme.

By definition, it can be verified that $g(x_k)$ is a monotonically deceasing function with respect to x_k. Besides, both the average edge delay and the congestion level increase as more jobs are offloaded to the AP. As such, if $P^t < P^\star$, the resulting $x_k^t > x_k^\star$, which results in a higher congestion level than P^t. Therefore, by contradiction $P^t > P_{\text{true}}^t$ indicates that $P^t > P^\star$. As such, the AP shall decrease the price if $P^t > P_{\text{true}}^t$. Otherwise, the AP shall increase the price. Please refer to Algorithm 1 for more details on the learning process.

Algorithm 1 Learning-based pricing algorithm

Initialize: $t \leftarrow 0$, $P^t \leftarrow$ rand, $D_{\text{EC}}^t \leftarrow$ by (19), $P_{\text{LB}} \leftarrow 0$
$x_k^t \leftarrow g_k^{-1}(c_0^t D_{\text{EC}}^t + P^t)$, $k = 1, 2, \cdots, N$ ▷ by (17)
$P_{\text{true}}^t \leftarrow$ by (18)
while $P^t < P_{\text{true}}^t$ **do** ▷ Learn lower/upper bounds
  $P_{\text{LB}} \leftarrow P^t$, $t \leftarrow t+1$, $P^t \leftarrow 2P_{\text{LB}}$, $D_{\text{EC}}^t \leftarrow$ by (19)
  $x_k^t \leftarrow g_k^{-1}(c_0^t D_{\text{EC}}^t + P^t)$, $k = 1, 2, \cdots, N$
  $P_{\text{true}}^t \leftarrow$ by (18)
end
$P_{\text{UB}} \leftarrow P^t$
while $P_{\text{UB}} - P_{\text{LB}} > \epsilon$ **do** ▷ Bisection search
  $t \leftarrow t+1$, $P^t \leftarrow (P_{\text{LB}} + P_{\text{UB}})/2$, $D_{\text{EC}}^t \leftarrow$ by (19)
  $x_k^t \leftarrow g_k^{-1}(c_0^t D_{\text{EC}}^t + P^t)$, $k = 1, 2, \cdots, N$
  $P_{\text{true}}^t \leftarrow$ by (18)
  if $P^t < P_{\text{true}}^t$ **then**
    $P_{\text{LB}} \leftarrow P^t$
  else
    $P_{\text{UB}} \leftarrow P^t$
  end
end ▷ The stop threshold $\epsilon = 0.01$
return $P \leftarrow P^t$ and $D^{\text{EC}} \leftarrow D_{\text{EC}}^t$

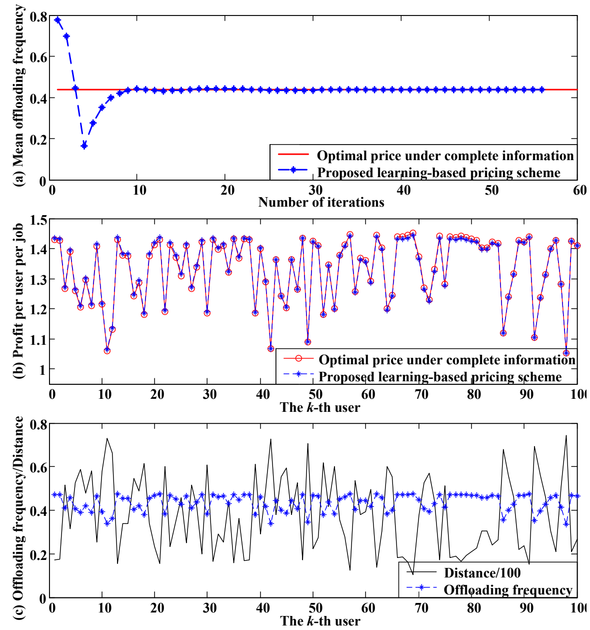

Fig. 4: (a) Convergence v.s. time; (b) Profit per user per job; (c) Offloading frequency v.s. each user's distance to the AP.

V. Numerical Results

We conduct simulations to validate Algorithm 1. Mobile users are uniformly placed at random on a ring of radius $10 \le d \le 75$ (unit: meters) and center located at AP. The AP and the mobile devices are with computing power of $f_B = 3$GHz and $f_m = 0.1$GHz, respectively. Jobs arrive at users at a rate of $\lambda_a = 0.6$, with each job requiring an average of $\mu_a =$ 100M CPU-cycles to run and $l_a \mu_a = 100$ nats to offload. The channels are assumed to be identically distributed (i.i.d.) and $|h_k|^2 \sim \exp(1)$. The path loss exponent $\alpha = 3.5$. The transmit power is $P = 100$mW and the noise power level is $\sigma^2 = -40$dBm. The weights $c_0^t = 0.9$ and $c_0^e = 0.1$.

In Fig. 4(a) we plot the convergence of the proposed learning-based pricing scheme. It can be seen that this iterative process converges after a few iterations, and learns the optimal price. In Fig. 4(b) we further plot the profit each user obtains at the equilibrium. It can be seen that by the proposed pricing-based scheme the AP induces users to achieve the social-optimal profit. In Fig. 4(c) we plot the offloading frequency versus distances to the AP. As expected, the user closer to the AP offloads more frequently.

VI. Conclusion

In this paper, we have proposed an incentive-aware offloading control mechanism for an MEC system, which consists of an access point (AP) of finite computing power, and serves multiple resource-hungry mobile users. We have introduced an economics model for MEC, based on which we then proposed a learning based pricing mechanism. With our mechanism, the AP learns the socially optimal price, without direct control and without knowledge of users' private information. This optimal price helps to align the individual objectives of selfish users with the system's social welfare objective in offloading.

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