# Resource Orchestration in UAV-assisted NOMA Wireless Networks: A Labor Economics Perspective

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# Resource Orchestration in UAV-assisted NOMA Wireless Networks: A Labor Economics Perspective

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***Abstract*—The emergence of Unmanned Aerial Vehicles (UAVs) as part of the safety-critical and traffic alleviation infrastructure in 5G and beyond wireless networks, promotes the rethinking of the conventional resource orchestration management. In this paper, we propose a novel methodology that treats the uplink power allocation problem in UAV-assisted wireless networks, operated under Non-Orthogonal Multiple Access (NOMA), based on the principles of labor economics and Contract Theory (CT). The proposed approach specifically targets the challenge of imperfect Channel State Information (CSI) due to the uncertainties of the wireless links. The users are characterized by types that depend on their experienced channel conditions, which are typically unknown to the UAVs, while the latter probabilistically estimate the users' types. The users' transmission powers are iteratively optimized and determined, while an Reinforcement Learning (RL)-empowered user-to-UAV association procedure is realized. The overall framework is evaluated via modeling and simulation regarding its proper operation, effectiveness and efficiency, under different scenarios.**

***Index Terms*—Unmanned Aerial Vehicles, Non-Orthogonal Multiple Access, Reinforcement Learning, Labor Economics, Contract Theory.**

## I. Introduction

Unmanned Aerial Vehicles (UAVs) have become an integral component of the 5G and beyond wireless networks, to further support safety-critical and increased traffic communication scenarios. The interest towards the UAV-assisted wireless communications stems from the UAVs' salient characteristics, such as mobility, fast and low-cost deployment, maneuverability and hovering ability, adaptive altitude and strong Line-of-Sight (LoS) links [1]. Building on the UAVs' attractive attributes, the improvement of their communications capabilities has been complemented with the adoption of the Non-Orthogonal Multiple Access (NOMA) combined with the Successive Interference Cancellation (SIC) technique.

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### A. Related Work & Motivation

Several research works have focused on the problem of efficient resource management in UAV-assisted wireless networks so far. In [2], a centralized two-stage heuristic algorithm is introduced, where, initially, the UAV-device association and uplink power allocation are iteratively optimized to satisfy the devices' Signal-to-Interference-plus-Noise-Ratio (SINR) requirements, while employing Orthogonal Frequency Division Multiple Access (OFDMA) technique. The UAV 3D optimal position is, then, determined aiming at minimizing the devices' total transmission power. In [3], an Internet of Things (IoT) NOMA network served by a single UAV, is considered. A coalition formation solution among the devices is proposed, capitalizing on the theories of minority games and adaptive learning, while a non-cooperative game is formulated to distributively determine the optimal uplink transmission power that maximizes each device's Quality of Service (QoS) prerequisites.

Unlike [2], [3], significant attention has also been drawn in the design of distributed Reinforcement Learning (RL)-enabled resource orchestration solutions. In [4] a deep RL approach is introduced to support the users' autonomous association with a UAV, while maximizing their long-term throughput. Studying the resource management problem from the UAVs' perspective, the work in [5] proposes an actor-critic deep RL UAV optimal deployment method that accounts for the users' mobility, towards mitigating the interference and improving the real-time network throughput. All the aforementioned research works have made the strong assumption that the UAVs have perfect knowledge of the Channel State Information (CSI) during the resource management procedure. In [6], imperfect CSI is considered between the users and the UAVs and a centralized joint user scheduling and power allocation problem is formulated using probabilistic constraints on some outage event. The original problem is converted into a non-probabilistic one and solved by decoupling it into two convex subproblems.

An alternative formal method to mathematically formulate resource allocation under imperfect CSI that promotes the users' involvement in the allocation procedure, has been introduced based on Contract Theory (CT). CT studies the interactions among a leader, offering rewards, and the followers, offering their contribution, while jointly guaranteeing the optimization of the leader's and followers' satisfaction [7]. In [8], a two-fold problem of traffic congestion prediction and employment of UAVs, which assist to the alleviation of the network traffic, is studied. CT is adopted to employ a UAV with sufficient communication capacity at a reasonable price, determined based on the predicted traffic demand. In [9], the joint problem of user-to-BS association, based on RL, and uplink power control, based on CT, in NOMA heterogeneous wireless networks under imperfect CSI, is addressed. The users are represented by discrete types that capture their communication characteristics and are probabilistically known by the BSs, which accordingly design the optimal users' contracts. The contracts jointly maximize both the BS's and the users' utilities, while the users transmit with an optimal transmission power level.

### B. Contributions & Outline

Despite the efforts made in the previous works pertaining to the resource management in UAV-assisted NOMA wireless networks, the issue of treating the problem of imperfect CSI still remains notably unexploited and open in the aforementioned framework. Especially, in the realistic scenario, where the users' channel conditions can dynamically change in a continuous and unpredictable manner, the corresponding problem and its impact thereof, becomes even more challenging. In this paper, our goal is to exactly address those issues, by introducing a labor economics-based approach to achieve the optimal resource management in UAV-assisted NOMA wireless networks, where the UAVs are characterized by imperfect CSI, and the latter can dynamically vary in a continuous manner. The key contributions of the paper are threefold as follows.

1. A multi-UAV NOMA wireless network is considered and an RL mechanism is introduced to enable the distributed and autonomous user-to-UAV association. Each user selects a UAV to be associated with, aiming at optimizing its long-term benefit, while jointly accounting for physical, networking, and QoS parameters.

2. Following the principles of labor economics, a contract-theoretic power control problem is formulated by each UAV and its communicating users, considering imperfect CSI. The users are characterized by types that depend on their experienced channel conditions. The fundamental novelty of this paper is that the users' types can have a probabilistic continuous form, given the imperfect CSI.

3. A unified framework is designed, where the uplink power allocation is iteratively optimized and determined, while an RL-based user-to-UAV association procedure is realized. Detailed numerical results, obtained via modeling and simulation, evaluate and demonstrate the proper operation and effectiveness of the proposed framework.

The remainder of this paper is organized as follows. Section II presents the system model and introduces the concepts of labor economics and RL in the resource allocation, as they are adopted in this work. Section III introduces the users' and UAVs' contract-theoretic utilities, while in Section IV the contract-theoretic resource management problem is formulated and solved. Section V presents the performance evaluation of our proposed framework and Section VI concludes the paper.

## II. System Model

A multi-UAV NOMA wireless network is considered with $|C|$ UAVs, $|U|$ users, and each UAV serves $|U_c|$ users, where their sets are $C = \{1, \dots, |C|\}$, $U = \{1, \dots, |U|\}$, and $U_c = \{1, \dots, |U_c|\}$, respectively. All the UAVs have similar coverage capabilities, they fly at the same height $h_c$ [m] following the Federal Aviation Regulations (FARs), and hover at their position [10]. It is noted that the optimal UAV positioning, though an interesting topic, it is not the focus of this paper, and it follows a state of the art approach [2], [3]. The system bandwidth $B$ [Hz] is subdivided into $|C|$ orthogonal frequency bands - each one of them of bandwidth $B_c$ - with $B = \sum_{\forall c \in C} B_c$, and each UAV uses a frequency band thus, eliminating the intercell interference.

The probability of LoS between a user $u$ and a UAV $c$ is $P_{u,c}^{LoS} = \frac{1}{1+\psi e^{-\beta(\phi_{u,c}-\psi)}}$, $P_{u,c}^{LoS} \in [0, 1]$, where $\psi, \beta \in \mathbb{R}^+$ are constants that their values depend on the carrier frequency and the type of the communications environment, e.g., rural, urban, suburban. Also, $\phi_{u,c} = \frac{180}{\pi} sin^{-1}(\frac{h_c}{d_{u,c}})$ [rad] is the elevation angle between user $u$ and UAV $c$, while $d_{u,c}$ [m] is the corresponding Euclidean distance. Therefore, the probability of Non-Line-of-Sight (NLoS) communication between user $u$ and UAV $c$ is $P_{u,c}^{NLoS} = 1 - P_{u,c}^{LoS}$. The path loss model for LoS and NLoS communication links between user $u$ and UAV $c$ are $PL_{u,c}^{LoS} = \eta_{LoS}(\frac{4\pi f_c d_{u,c}}{c})^a$ and $PL_{u,c}^{NLoS} = \eta_{NLoS}(\frac{4\pi f_c d_{u,c}}{c})^a$ , respectively, where $f_c$ [Hz] is the carrier frequency, $c$ [m/s] is the speed of light, and $a$ corresponds to the path loss exponent. Also, $\eta_{LoS}, \eta_{NLoS}$ [dB] are the excessive path loss coefficients in LoS and NLoS cases, respectively, with $\eta_{NLoS} > \eta_{LoS} > 1$. Given the links' uncertainties, the path loss is probabilistically determined as $\overline{PL}_{u,c} = PL_{u,c}^{LoS} P_{u,c}^{LoS} + PL_{u,c}^{NLoS} P_{u,c}^{NLoS}$. Thus, the user's average channel gain is $G_{u,c} = \frac{1}{\overline{PL}_{u,c}}$.

### A. Labor Economics based Power Allocation Design

Given a user-to-UAV association, each UAV $c$ classifies its serving $|U_c|$ users into different types, according to the different channel conditions that they experience. Specifically, the type of a user $u$ communicating with a UAV $c$ is defined according to the corresponding user's average channel gain, as $t_{u,c} = G_{u,c}, \forall u \in U_c$ and it holds that $t_{u,c} \in [t_L, t_H]$, where $t_L$ and $t_H$ denote the lower and higher possible values of the users' types. Hence, a user with better channel conditions is characterized by a higher type, while the latter can take any value in the interval $[t_L, t_H]$ based on the dynamic changes of the conditions of the communications environment. Owing to the uncertainties of the wireless links, the UAVs are characterized by imperfect CSI, and thus, they probabilistically estimate the users' types with probability density function $f(t_{u,c})$ and cumulative distribution function $F(t_{u,c})$.

Each user of type $t_{u,c}$ transmits its data with uplink transmission power $p_{u,c}(t_{u,c})$, which is inversely proportional to its type $t_{u,c}$, as imposed by the application of NOMA (i.e., the higher the type, the better the user's channel conditions and thus, the lower the power needed to transit its data). Following the principles of CT in the field of labor economics, the user offers a contribution $q_{u,c}(p_{u,c}(t_{u,c})) = \frac{\rho_1}{p_{u,c}(t_{u,c})}, \rho_1 \in \mathbb{R}^+$ in order to transmit its data to the UAV, which depends on its transmission power $p_{u,c}(t_{u,c})$. The physical interpretation of the user's contribution function $q_{u,c}$ formulation is that the less the user's transmission power level $p_{u,c}$ is, the more contribution $q_{u,c}$ the user brings to the system without over-increasing the interference sensed by the rest of the users served by the same UAV. Towards the users following the latter behavior, the UAV $c$ incentivizes them with a reward $r_{u,c}(q_{u,c}(p_{u,c}(t_{u,c}))) = \rho_2\, q_{u,c}(p_{u,c}(t_{u,c})), \rho_2 \in \mathbb{R}^+$ proportional to their contribution $q_{u,c}$.

### B. RL empowered User-to-UAV Association

Towards enabling the distributed and autonomous user-to-UAV association, we consider that the users act as Stochastic Learning Automata (SLA) by making autonomous decisions regarding the UAV that they will be connected to, optimizing their long-term benefit. Each user's $u$ benefit from being connected to a UAV $c$ at iteration $ite$ of the SLA user-to-UAV association algorithm is defined as $\mathcal{F}_{u,c}^{(ite)} = REW_{u,c} \cdot \sqrt{\frac{1/d_{u,c}}{\sum\limits_{\forall u \in U_c}(1/d_{u,c})}} \cdot \sqrt{\frac{B_c}{\sum\limits_{\forall c \in C} B_c}}$, where $REW_{u,c}$ is the sum of the user's rewards offered by the specific UAV $c$ over the current iteration $ite$, normalized within the range $[1,2]$, i.e., $REW_{u,c} = \sum\limits_{i=1}^{ite} r_{u,c}^{(i)}, REW_{u,c} \in [1,2]$. The physical meaning of the user's benefit function $\mathcal{F}_{u,c}^{(ite)}$ is that a user seeks to communicate with a UAV that: (a) the cumulative reward $REW_{u,c}$ that the user has received over the last iterations was high (i.e., its allocated uplink transmission power was low), (b) belongs in the user's close proximity, and (c) has high bandwidth availability $B_c$.

Based on the SLA theory, we determine the user's probability of selecting the same UAV, i.e., $Pr_{u,c}^{(ite+1)} = Pr_{u,c}^{(ite)} + b\mathcal{F}_{u,c}^{(ite)}(1 - Pr_{u,c}^{(ite)}), c^{(ite+1)} = c^{(ite)}$, or a different UAV, i.e., $Pr_{u,c}^{(ite+1)} = Pr_{u,c}^{(ite)} - b\mathcal{F}_{u,c}^{(ite)} Pr_{u,c}^{(ite)}, c^{(ite+1)} \neq c^{(ite)}$, at iteration $ite+1$. The parameter $0 < b < 1$ is the learning rate of the SLA algorithm that controls the exploration of different user-to-UAV alternatives. For large values of $b$, the SLA algorithm converges fast to a stable user-to-UAV association with low accuracy, while the exact opposite holds true for small values of $b$. The SLA algorithm converges to a stable user-to-UAV association, when for each user $u \in U$ there is a UAV selection with probability close to one, i.e., $Pr_{u,c}^{(ite)} \to 1$. In the rest of the analysis, we drop the subscripts $u, c$, wherever this is possible, for notation convenience.

## III. Utility Functions Design based on Contract Theory

In this section, the users' and the UAVs' contract-theoretic utilities are introduced. Each UAV $c$ benefits from its communicating users' $u \in U_c$ contribution $q(t)$, while it experiences a cost to provide the corresponding rewards. Thus, each UAV's $c$ probabilistic contract-theoretic utility from the $|U_c|$ users that serves is defined as $U_c(t, r(t), q(t)) = \int_{t_L}^{t_H} f(t)[q(t) - \mathcal{C}r(t)]\, dt$, where $\mathcal{C} \in \mathbb{R}^+$ is the UAV's unit cost for providing the rewards $r(t)$.

On the other hand, each user evaluates in a personalized manner its received reward through an evaluation function $e(t, r(t))$, which is strictly increasing and concave with the reward r(t) (e.g., $e(t, r(t)) = \ln(1 + tr(t))$). Also, each user experiences a personalized cost to offer its contribution $q(t)$. Thus, the user's utility function is defined as $U_u(t, r(t), q(t)) = e(t, r(t)) - \kappa_u q(t)$, where $\kappa_u \in \mathbb{R}^+$ is the user's unit cost of their contribution $q(t)$.

Our goal is to determine the optimal contract bundles $\{q^*(t), r^*(t)\}$ between each UAV and its corresponding associated users, in order all of them to optimize their utilities. The following constraints, referred to as conditions of Individual Rationality (IR) and Incentive Compatibility (IC), should hold true to guarantee that a feasible contract will be concluded for each user. In particular, according to the IR condition, the optimal contract should yield a non-negative utility for every user, i.e, $U_u \geq 0$, while based on the IC condition, the optimal contract should match each user's type $t$ in the best way, i.e., $U_u(t, r(t), q(t)) \geq U_u(t, r(\hat{t}), q(\hat{t})), \forall t, \hat{t} \in [t_L, t_H], t \neq \hat{t}$.

## IV. Labor Economics-enabled Resource Orchestration

### A. Problem Formulation

Based on the above we formulate the optimization problem to be executed by each UAV $c$ given a user-to-UAV association, in a distributed manner, as follows:

$$\max_{\{q(t), r(t)\}_{\forall t \in [t_L, t_H]}} U_c = \int_{t_L}^{t_H} f(t)[q(t) - \mathcal{C}r(t)]\, dt, \forall c \in C \quad (1a)$$

$$\textbf{s.t.} \quad e(t, r(t)) - \kappa_u q(t) \geq 0, \forall u \in U_c \text{ (IR)}, \quad (1b)$$

$$e(t, r(t)) - \kappa_u q(t) \geq e(t, r(\hat{t})) - \kappa_u q(\hat{t}), \forall t \neq \hat{t} \in [t_L, t_H] \text{ (IC)}. \quad (1c)$$

Apparently, the objective of the UAV is to maximize its personal utility, while at the same time reassuring the users' participation in the contract. Note that in general the formulated optimization problem in Eq.(1a)-(1c) is non-convex, and the procedure described in Section IV-B below is followed to derive a tractable solution.

### B. The Reduced Optimization Problem

First, we reduce the IR conditions. Provided that the IC conditions are satisfied, we get $e(t, r(t)) - \kappa_u q(t) \geq e(t, r(t_L)) - \kappa_u q(t_L) \geq e(t_L, r(t_L)) - \kappa_u q(t_L) = 0$. Hence, if the IR conditions of the user type $t_L$ are satisfied, then, all the IR conditions of higher user types will also hold. The latter equality holds true to increase each UAV's utility.

Subsequently, we prove that the IC conditions can be reduced to the following two conditions: (1) $\frac{dr(t)}{dt} \geq 0$ and (2) $\frac{\partial e(t,r(t))}{\partial r} r'(t) = \kappa_u q'(t)$ [7].

*Proof.* Given that the IC conditions hold and that $r(t)$ and $q(t)$ are differentiable, each user maximizes its utility $U_u(t, r(\hat{t}), q(\hat{t}))$ at $\hat{t} = t$. Consequently, the first and second order conditions are satisfied at $\hat{t} = t$, leading to $\kappa_u q'(\hat{t}) = \frac{\partial e(t,r(\hat{t}))}{\partial r} r'(\hat{t})$ (FOC) and $\kappa_u q''(\hat{t}) \geq \frac{\partial e(t,r(\hat{t}))}{\partial r} r''(\hat{t}) + \frac{\partial^2 e(t,r(\hat{t}))}{\partial r^2} (r'(\hat{t}))^2$ (SOC), respectively. Considering that $\hat{t} = t$ and differentiating the FOC further with respect to $t$, we get $\kappa_u q''(\hat{t}) = \frac{\partial e(t,r(\hat{t}))}{\partial r} r''(\hat{t}) + \frac{\partial^2 e(t,r(\hat{t}))}{\partial r^2} (r'(\hat{t}))^2 + \frac{\partial^2 e(t,r(\hat{t}))}{\partial r \partial t} r'(\hat{t})$. Substituting the latter to the SOC, we have $\frac{\partial^2 e(t,r(\hat{t}))}{\partial r \partial t} r'(\hat{t}) \geq 0$. But for strictly increasing and concave evaluation functions of rewards, e.g., $e(t, r(t)) = \ln(1 + tr(t))$, it holds that $\frac{\partial^2 e(t,r(\hat{t}))}{\partial r \partial t} > 0$, and thus, we conclude that $r'(\hat{t}) \geq 0$. This completes the proof of the first condition, i.e., $\frac{dr(t)}{dt} \geq 0$.

The second condition, i.e., $\frac{\partial e(t,r(t))}{\partial r} r'(t) = \kappa_u q'(t)$, is proved by contradiction. Suppose that conditions (1) and (2) hold, but the IC condition for at least one user type is violated, i.e., $e(t, r(t)) - \kappa_u q(t) < e(t, r(\hat{t})) - \kappa_u q(\hat{t})$. By integrating the latter, we get $\int_t^{\hat{t}} \frac{\partial e(t,r(x))}{\partial r} r'(x) - \kappa_u q'(x)\, dx > 0$. Integrating condition (2) in a similar manner, we obtain $\int_t^{\hat{t}} \frac{\partial e(x,r(x))}{\partial r} r'(x) - \kappa_u q'(x)\, dx = 0$. If $t < x$, then it holds that $\frac{\partial e(t,r(x))}{\partial r} < \frac{\partial e(x,r(x))}{\partial r}$, leading to $\int_t^{\hat{t}} \frac{\partial e(t,r(x))}{\partial r} r'(x) - \kappa_u q'(x)\, dx < 0$, which contradicts with our assumption that the IC conditions are violated. If $t > x$, we conclude to a similar contradiction, establishing the equivalence between the conditions (1) and (2) with the IC conditions. □

Correspondingly, we formulate the reduced optimization problem as follows:

$$\max_{\{q(t), r(t)\}_{\forall t \in [t_L, t_H]}} U_c = \int_{t_L}^{t_H} f(t)[q(t) - \mathcal{C} r(t)]\, dt, \forall c \in C \tag{2a}$$

$$\textbf{s.t.} \quad e(t_L, r(t_L)) - \kappa_u q(t_L) = 0, \tag{2b}$$

$$\frac{dr(t)}{dt} \geq 0, \tag{2c}$$

$$\frac{\partial e(t, r(t))}{\partial r} r'(t) = \kappa_u q'(t), \forall t \in [t_L, t_H]. \tag{2d}$$

To solve the optimization problem of Eq. (2a)-(2d), we first ignore the constraint of Eq. (2c) and then, check whether the solution of the reduced optimization problem of Eq. (2a), (2b) and (2d) satisfies Eq. (2c).

### C. The Implementation Problem

We define $W(t) = e(t, r(t)) - \kappa_u q(t)$, the derivative of which is $\frac{dW(t)}{dt} = \frac{\partial e(t,r(t))}{\partial t}$. Integrating by both sides the latter, we get $W(t) = \int_{t_L}^{t} \frac{\partial e(x,r(x))}{\partial t} dx + W(t_L)$. Based on Eq. (2b), it holds that $W(t_L) = 0$. Hence, $W(t) = \int_{t_L}^{t} \frac{\partial e(x,r(x))}{\partial t} dx$. Since, $q(t) = \frac{1}{\kappa_u} e(t, r(t)) - \frac{1}{\kappa_u} W(t)$, the objective function of Eq. (2a) can be rewritten as,

$$\begin{aligned} U_c = & \int_{t_L}^{t_H} f(t)[\frac{1}{\kappa_u} e(t, r(t)) - \mathcal{C} r(t)] dt \\ & - \frac{1}{\kappa_u} \int_{t_L}^{t_H} \left( \int_{t_L}^{t} \frac{\partial e(x, r(x))}{\partial t} dx \right) f(t) dt. \end{aligned} \tag{3}$$

Integrating the last term of Eq. (3) by parts, we have

$$\begin{aligned} & \int_{t_L}^{t_H} \left( \int_{t_L}^{t} \frac{\partial e(x, r(x))}{\partial t} dx \right) f(t) dt \\ & = \left[ \left( \int_{t_L}^{t} \frac{\partial e(x, r(x))}{\partial t} dx \right) F(t) \right]_{t_L}^{t_H} - \int_{t_L}^{t_H} \frac{\partial e(t, r(t))}{\partial t} F(t) dt \\ & = \int_{t_L}^{t_H} \frac{\partial e(t, r(t))}{\partial t} (1 - F(t)) dt. \end{aligned} \tag{4}$$

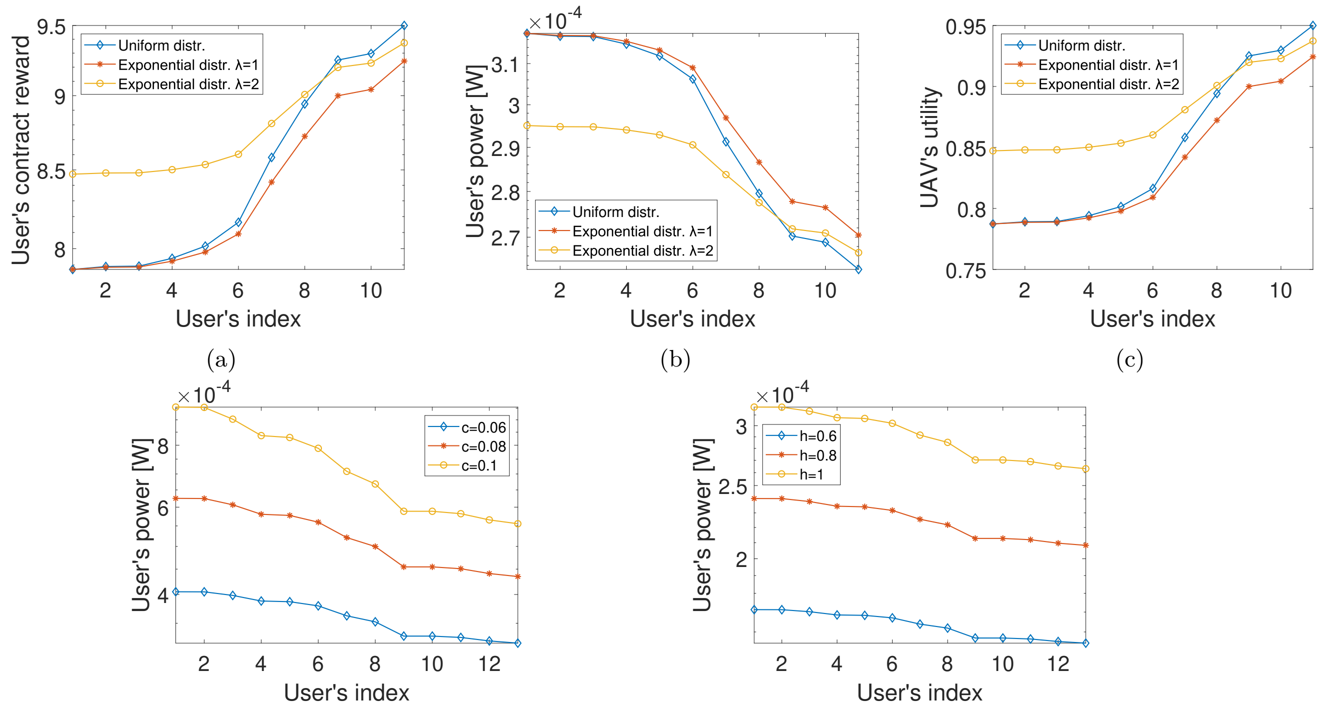
Substituting Eq. (4) to Eq. (3) and considering $e(t, r(t)) = \ln(1 + tr(t))$, the concluding optimization problem to be implemented by each UAV is summarized as follows,

$$\begin{aligned} \max_{r(t)_{\forall t \in [t_L, t_H]}} U_c = & \int_{t_L}^{t_H} f(t) \left( \frac{1}{\kappa_u} \ln(1 + tr(t)) - \mathcal{C} r(t) \right) \\ & - \frac{1}{\kappa_u} \frac{r(t)}{1 + tr(t)} (1 - F(t))\, dt, \forall c \in C. \end{aligned} \tag{5}$$

Obviously, the maximization of each UAV's utility function $U_c$ with respect to $r(t)$ indicates that the term under the integral of Eq. (5) should be maximized with respect to $r(t), \forall t \in [t_L, t_H]$. Subsequently, the optimal rewards $r^*(t), \forall t \in [t_L, t_H]$ can be obtained pointwise. If the solution $r^*(t)$ is feasible, i.e., $r^*(t) > 0$, then it can be considered as the desired optimal solution of the optimization problem. Otherwise, the region $[a, b] \subseteq [t_L, t_H]$ of infeasible solutions $r^*(t) < 0$ should be found based on the "bunching and ironing" algorithm [7] and all solutions within this region should be set equal to $r^*(t) = \mathrm{argmax}_{r(t)} \int_a^b f(t) \left( \frac{1}{\kappa_u} \ln(1 + tr(t)) - \mathcal{C} r(t) \right) - \frac{1}{\kappa_u} \frac{r(t)}{1+tr(t)} (1 - F(t))\, dt, \forall t \in [a, b]$. However, it is noted that the optimization problem of Eq. (5) has feasible solution regions for several commonly used distributions, such as the uniform, exponential, normal, etc., thus, the derived results of the previous analysis are quite general.

## V. Numerical Results

We consider a 1000x1000 square-meter densely deployed wireless system, consisting of 80 spatially uniformly and randomly distributed users served by 4 UAVs that hover at a height of 200 m above the ground. The UAVs are assumed to be of different communication capabilities, with available bandwidths $B_1 = 1.44$ MHz, $B_2 = 1.08$ MHz and $B_3 = B_4 = 0.36$ MHz. The wireless links'




(a) (b) (c)

(d) (e)

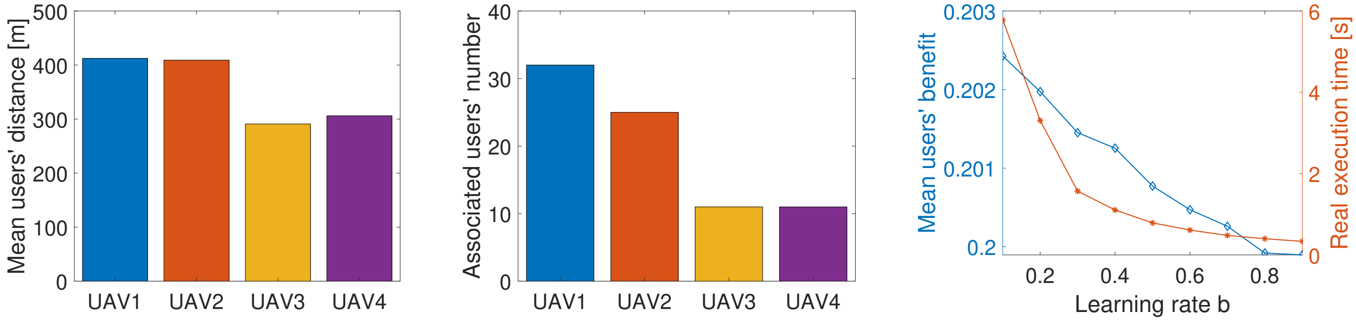
Fig. 1: Evaluation of the labor economics-based resource orchestration mechanism.

conditions between the UAVs and their communicating users are determined following the modeling in Section II, while considering the following parameters: $\psi = 11.95$ and $\beta = 0.14$ for $f_c = 2$ GHz, $a = 2$, $\eta_{LOS} = 3$ dB and $\eta_{NLOS} = 23$ dB. The user type $t_{u,c}$ representing each user is equal to the user's normalized channel gain within the interval $[1, 2]$, i.e., $t_{u,c} = G_{u,c} \in [1, 2]$, and in the general case, follows the uniform distribution. The users maximum transmission power is assumed to be 23 dBm. In the typical scenario, the contract theory related parameters are set as $\rho_1 = 0.5\,10^{-3}$, $\rho_2 = 5$, $\mathcal{C} = 0.1$ and $\kappa_u = 1$, while the SLA algorithm's learning rate is $b = 0.5$, unless otherwise explicitly stated. It is noted that both the users and the UAVs remain stationary throughout the execution of the contract theoretic power allocation and the SLA-enabled user-to-UAV association.

First, we evaluate the proper functioning and operation of the pure labor economics-based power allocation mechanism. In Fig. 1, we indicatively analyze and present the results of the allocated power levels by a specific UAV (e.g., the third UAV) to its users, under different use-case scenarios. We refer to each user associated with the UAV by the use of an index, where the higher the user index, the higher the user's type is. The results of Fig. 1 have been extracted for the optimal user-to-UAV association, as it was concluded by the convergence of the SLA algorithm.

In particular, in Fig. 1a-1c the impact of different user type distributions on the optimal solution of the optimization problem in Eq. 5 is studied, by considering the uniform and the exponential distributions with rate parameters $\lambda = 1$ and $\lambda = 2$. It should be noted that in principle the uniform distribution predicts with lower probability the existence of lower user types within the communication environment unlike the exponential, where the higher the rate parameter $\lambda$, the higher the lower user types' probability of occurrence. Predicting the different user types unevenly, leads to an inaccurate power level assignment from the UAV's behalf. Indeed, Fig. 1a presents the obtained optimal users' rewards as a function of the users' index and confirms that under the uniform and the exponential with $\lambda = 1$ distributions, the optimal users' rewards are underestimated. In turn, the underestimation of the lower user types leads to an overestimation of their allocated uplink transmission power, due to the inversely proportional relationship between the users' rewards and allocated powers, as further justified by Fig. 1b. Also, the accurate prediction of the expected user types by the UAV enables the maximization of the UAV's utility that corresponds to each user's offered contribution. The latter is corroborated by Fig. 1c, where it can be observed that following the exponential distribution with $\lambda = 2$, the UAV's utility is higher for the lower user types, compared to the other considered distributions. Finally, a general conclusion derived from Fig. 1a-1c is that as the user type increases, the users are offered a higher reward by transmitting with lower power levels.

Subsequently, we present a cost analysis, under different UAV's and user's unit costs, of providing their rewards and contributions to one another, respectively. In Fig. 1d, the optimal users' allocated power levels are presented as




(a) (b) (c)

Fig. 2: Evaluation of the SLA-enabled user-to-UAV association mechanism.

a function of the users' index, for different values of the UAV's unit cost parameter $\mathcal{C} = 0.06, 0.08, 0.1$. Obviously, when the UAV's unit cost $\mathcal{C}$ for providing rewards to its users increases, then the optimal users' rewards decrease to mitigate the expense. As a result, the optimal users' allocated power levels increase. An identical behaviour of the allocated optimal users' power levels is noted when examining different values of the users' unit cost parameter $\kappa_u = 0.6, 0.8, 1$, as depicted in Fig. 1e. As the users' unit cost $\kappa_u$ for offering their contributions to the UAV increases, they bring lower contributions to the system and thus, they transmit with higher power levels.

With reference to the performance and speed of convergence of the SLA-enabled user-to-UAV association that encompasses the power allocation procedure, indicative results are presented in Fig. 2, averaged over a number of 500 complete executions of the unified framework. Given the uniform users' spatial distribution and the different bandwidth availability of each UAV, the users achieve a greater benefit $\mathcal{F}$ when served by a UAV of their closest proximity, while at the same time the number of users associated with each UAV is analogous the UAVs' bandwidth. Actually, based on Fig. 2a, the mean associated users' distance per UAV is approximately equal among the four UAVs, and the slightly higher mean users' distance related to UAV1 and UAV2 is justified by the respective UAVs' higher bandwidth availability that encourages more users to communicate with them. The actual number of associated users per UAV is further presented in Fig. 2b. Finally, a Monte Carlo simulation over different values of the SLA algorithm's learning rate parameter $b \in [0.1, 0.9]$ is performed, and the resulting actual execution time in [s], as well as the achieved mean users' benefit $\mathcal{F}$ are derived and presented in Fig. 2c. Apparently, as the value of the parameter $b$ decreases, the exploration of the possible user-to-UAV association alternatives is becoming exhaustive, resulting in increased real execution times, yet producing slightly higher mean users' benefit, i.e., most beneficial user-to-UAV associations.

## VI. Conclusion

In this paper, the optimal uplink transmission power problem in a UAV-assisted NOMA wireless network is addressed, capitalizing on the principles of Contract Theory and following a labor economics perspective. The proposed approach is tailored to deal with the challenge of imperfect CSI from the UAVs' behalf, ensuring the seamless resource orchestration procedure. The contract-theoretic mechanism is complemented by an RL algorithm that serves the user-to-UAV association. The effectiveness and efficiency of the proposed framework under different scenarios, is evaluated and validated through modeling and simulation. In our future work, we aim at delivering an end-to-end resource orchestration methodology, accounting for both the radio access and the backhaul wireless links' uncertainties, following the labor economics paradigm.

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