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Trading in Collaborative Mobile Edge Computing Networks: A Contract Theory-based Auction Model

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***Abstract*—An effective way to accommodate the computing demands of Internet-of-Things (IoT) end-user devices without the intervention of a remote server, is to motivate the collaboration between them. The latter paradigm, termed as collaborative Mobile Edge Computing (MEC), allows an end-user device to act as service provider, by allocating excess computing resources for the computation of a service requester's task, in exchange for adequate economic incentives. In this paper, we introduce a contract theory-based one-shot auction to model the computing resource trading between a service requester and the prospective service providers. Unlike existing works, we aim to account for the different types of asymmetric information arising during and after the contracting phase between the trading parties, regarding the service providers' willingness to collaborate and their offered computing power. The service requester derives a set of optimal economic bids, having statistical knowledge of the providers' private information, and each service provider autonomously selects the bid and its computing resource allocation that maximize its utility. The economic bid comprises a two-stage payment to secure the provider's truthful collaboration both prior and after the contractual agreement. The effectiveness of the proposed model is validated by comparison against benchmark contract theory models that unilaterally account for the providers' private information either prior/during or after the contracting phase.**

***Index Terms*—Collaborative Edge Computing, Computing Resource Trading, Contract Theory, One-shot Auction, Pricing.**

I. Introduction

With the paradigm of Mobile Edge Computing (MEC) maturing over the years, more and more diverse applications and use cases of it arise that however, keep its initial philosophy of computing resource sharing unchanged. Indeed, the typical edge cloud architecture has been upgraded by the inclusion of the different end-user devices within the concept of resource sharing, giving rise to the so-called collaborative MEC [1]. Specifically, in the context of collaborative MEC, the synergy among the neighboring - usually resource-constrained - end-user devices is exploited to execute in a collaborative manner their resource-hungry computation tasks. Given their workload within a time interval, some end-user devices may play the role of computing resource providers, by outsourcing their excess computation capability to facilitate the potential neighboring service requesters. The latter, in turn, can opportunistically utilize the idle resources of the service providers to satisfy their personal Quality of Service (QoS) requirements, while at the same time improving the computing resource utilization at the end-user device computing level.

Nevertheless, the driving force for the realization of the collaborative MEC paradigm is the delivery of adequate economic incentives that settle (or even outweigh) the providers' costs. As a result, the computing resource sharing and allocation in collaborative MEC networks is majorly interwoven with the economic interplay among the computing service requesters and providers and thus, should be studied market-wisely. Well-established methods to capture a trading process in general, and especially in collaborative MEC networks, comprise game and auction theory models [2]. Another stream of research in the recent literature is contract theory [3]. The distinguishing feature of contract theory is the fact that allows the design of pricing mechanisms that motivate the truthful cooperation between the trading parties, under the existence of asymmetric information during and/or after the contracting phase.

In this paper, we aim to design an one-shot auction model based on contract theory to capture the private information from the prospective providers' behalf both during and after the contracting phase. The service requester will design a set of bids tailored to the different types of private information of the providers, while each prospective service provider will be able to autonomously select both the bid and the computing resource allocation to the requester that maximize its personal utility. The bid will comprise a two-stage payment to the provider to deal with the asymmetry of information at the various contracting phases.

A. Related Work & Motivation

Collaborative MEC exploits the social relations and interactions among the end-user devices, as well as their physical Device-to-Device (D2D) communication capability, for the accomplishment of local events without the intervention of a remote server. A survey over the specific real-life applications in Internet-of-Things (IoT) environments in terms of both collaborative computing and caching is performed in [4], while the challenging problem of task and network flow scheduling in IoT networks is formulated and addressed in [5], in order to minimize the overall application completion time. Apart from solely considering the application completion latency variability among the different available collaborative computing options, the social trust relationships among the deployed edge nodes are studied in [6], and a reinforcement learning algorithm is proposed to address the decision making problem

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of the most beneficial collaborative computing option. On top of the aforementioned aspects, the intriguing problem of mobility must be jointly taken into account, when collaborative vehicular edge computing network settings are studied, while an analytic summary of the latter's challenges is found in [7].

Placing our focus on the computing resource trading process between the service requesters and providers in collaborative MEC networks, a handful of research works, e.g., [8]–[11], exist regarding the proper service pricing that motivates their truthful cooperation. In [8], conventional optimization techniques are employed to solve the joint service provider selection, computing resource allocation, time scheduling and payment design problem, by assuming complete knowledge of the requesters' and providers' personal information, regarding their computation task and resource availability, respectively, among them. In contrast, the asymmetric information case with respect to the untruthful declaration of the requester's actual computing service request is studied in [9] via an auction, where the requester represents the bidder and the provider is the seller. Considering a similar setting, the authors in [10] introduce a double auction mechanism and a Bayes-Nash equilibrium is reached that determines the optimal auction price. Further elaborating on the idea of auctions, the work in [11] introduces an one-shot auction based on contract theory. The service requester appropriately designs the contract item that comprises the requested computing resource allocation (i.e., effort) and the offered monetary reward to the prospective provider, having only statistical knowledge about the provider's time availability and cost of effort (i.e., provider's type). Nevertheless, even the work in [11], assumes the truthful collaboration from the provider's behalf after signing the contract, with respect to the contracted effort to be provided, which is an unrealistic assumption that our work aims to reduce.

B. Contributions & Outline

Apparently, the overwhelming majority of research works in the field of computing resource trading in collaborative MEC networks has unilaterally considered the existence of asymmetric information between the trading parties, by modeling the private information only during the contracting phase. As a result, the situation of untrustworthy collaboration after reaching a contractual agreement remains notably unexplored. In this paper, we aim to exactly fill this gap and account for the scenario, where the service provider may neglect to provide the necessary effort to the requester. The main contributions of this work are summarized as follows.

- A collaborative MEC network is considered and an one-shot auction based on contract theory is proposed to facilitate the computing resource trading between a service requester and the prospective service providers, under the problems of asymmetric information during and after the contracting phase, known as Adverse Selection and Moral Hazard problems, respectively.
- The service requester aims to derive the optimal bids that are tailored to the service providers' private information, which lies both in their type and provided effort. The prospective provider autonomously selects the bid and the computing resource allocation that maximize its utility.
- A two-stage payment to the prospective provider is designed to secure the trustworthy cooperation with the requester after the contracting phase.
- Detailed numerical results for the pure operational characteristics, as well as for the comparative evaluation of the proposed trading model against benchmark cases that unilaterally account for the asymmetry of information, are obtained via modeling and simulation, to demonstrate the effectiveness of the proposed model.

The remainder of this paper is organized as follows. Section II presents the system model and introduces the service pricing and the requester's and prospective providers' utilities, under the joint Adverse Selection and Moral Hazard problem. In Section III the problem of computing resource trading is introduced, while the benchmark cases of pure Adverse Selection and pure Moral Hazard problems are described in Section IV. Section V regards the performance evaluation of the proposed trading model, and Section VI concludes the paper.

II. System Model

We consider a collaborative MEC network, consisting of a number of end-user devices that can communicate with each other either via direct D2D transmissions or indirectly via their common communicating Base Station (BS). Considering a specific time instance, a subset of the end-user devices denoted as $\mathcal{N} = \{1, \dots, N\}$ is requesting for the provisioning of a computing service from the subset of the end-user devices that play the role of providers, indicated as $\mathcal{M} = \{1, \dots, M\}$. The service requester $n \in \mathcal{N}$ has a computation task W_n [CPU cycles] that must be completed within τ_n seconds to meet the corresponding application's QoS prerequisite. A prospective provider $m \in \mathcal{M}$ is offered to allocate $f_{n,m}$ [CPU cycles/s], $0 \leq f_{n,m} \leq F_m$ from its total computing capability F_m [CPU cycles/s] for the execution of the service requester's n task W_n, based on its workload at the specific time instance. It should be noted that in this work, we aim to address the computing resource trading between a single service requester n and M prospective service providers of different private information, while the extension to the multiple-requester multiple-provider case that accounts for the competition between the different service requesters, is part of our current work.

We denote as $e_{n,m} \in [0,1]$ the provider's m effort to the service requester n that is defined as the percentage of its total computing capability F_m that is allocated to the requester, i.e., $e_{n,m} = \frac{f_{n,m}}{F_m}$. The service provider is characterized by a probability $T_m \in [0,1]$ of being able to dedicate part of its computing resources for the subsequent τ_n seconds (at most), based on its upcoming workload, as well as a computing service energy cost that is calculated as $k_m W_n F_m^2 e_{n,m}^2$ [J], where k_m is its device's effective capacitance coefficient [12]. The overall provider's m level of willingness for the provisioning of the computing service to the requester n is defined as $\theta_{n,m} = (\frac{T_m}{k_m W_n F_m^2}) / \max\{\frac{T_m}{k_m W_n F_m^2}\}, \theta_{n,m} \in [0,1]$ and is termed as the provider's type. As a result, a high probability T_m of future service availability and a low service cost $k_m W_n F_m^2$ result in higher willingness to serve the requester.

The asymmetry of information in terms of the provider's type $\theta_{n,m}$ during the contracting phase gives rise to the Adverse Selection problem, while the asymmetry of information after signing the contract regarding the provider's effort $e_{n,m}$ refers to the Moral Hazard problem. The joint Adverse Selection and Moral Hazard problem is addressed via the contract theory-based one-shot auction. Apparently, the service provider that accepts the offered bid and at the same time yields the higher utility to the requester, wins the auction.

A. Service Pricing Contract

The service requester n offers a bid to the prospective provider m to motivate the latter to truthfully leverage on its effort and type, and successfully complete the requester's task, respecting the time constraint τ_n. The bid corresponds to the service pricing contract intended to the provider, and comprises a down payment $p_{n,m} \in \mathbb{R}^+$ to be paid by the requester immediately after signing the contract with the provider, and an installment payment $q_{n,m} \in [0,1]$ paid after the successful completion of the computing task by the provider. Apparently, the successful completion of the task is determined upon its timely execution within the requested time constraint τ_n. The rationale behind this two-stage payment process is to overcome the asymmetry of information after the contracting phase and secure the successful completion of the offloaded computation task, by allowing the provider to make more revenue as its effort, i.e., computing resource allocation, increases. In the following, the bid offered by a service requester n to a service provider m is referred to as contract item and is indicated by the tuple $\{p_{n,m}, q_{n,m}\}$.

B. Service Provider's and Requester's Utility

We define the prospective service provider's m utility U_m^n for executing the service requester's n computation task W_n as the difference between its gained revenue from signing the contract $\{p_{n,m}, q_{n,m}\}$ minus its provided effort, as follows:

$$U_m^n = \theta_{n,m} e_{n,m} q_{n,m} + p_{n,m} - \frac{1}{2} c e_{n,m}^2, \quad (1)$$

where $c \in [1,2]$ is the service provider's cost of effort. The physical interpretation of Eq. (1) is that the higher the provider's willingness to share its computing resources and the higher its effort $e_{n,m}$, then the higher the installment payment to be offered by the requester n is after the completion of the task. The provider's m overall revenue is complemented by the down payment $p_{n,m}$ and certainly comes with the cost of the provided effort, where an exponential model is used to characterize the evaluation of the provider's cost of effort.

Considering the requester's behalf, in order to deal with the asymmetry of information during the contracting phase, the requester designs a set of contract items $\{p_{n,m}, q_{n,m}\}, \forall m \in \mathcal{M}$ that are tailored to different prospective providers' types. The goal is to allow the provider m to autonomously select the contract item that best fits its type $\theta_{n,m}$, which is known as the revelation principle. Without loss of generality, we consider that the different providers' types are sorted in ascending order, i.e., $\theta_{n,1} \leq \cdots \leq \theta_{n,m} \leq \cdots \leq \theta_{n,M}$. The utility of the requester n from trading with the provider m is written as:

$$U_n^m = R + \theta_{n,m} e_{n,m} (Q - q_{n,m}) - p_{n,m}. \quad (2)$$

$R \in \mathbb{R}^+$ is the requester's fixed revenue from offloading the task W_n that can map to its energy savings, while $Q \in \mathbb{R}^+$ represents the revenue that the requester n makes when its offloaded task is successfully completed, which is achieved as the provider's type $\theta_{n,m}$ and effort $e_{n,m}$ increase. Given that the requester n has statistical knowledge over the different providers' types, its total expected utility is written as follows:

$$U_n = \sum_{m=1}^{M} \lambda_{n,m} [R + \theta_{n,m} e_{n,m} (Q - q_{n,m}) - p_{n,m}], \quad (3)$$

where $\lambda_{n,m} \in [0,1]$ is the probability of the provider type $\theta_{n,m}$ to occur, such that $\sum_{m=1}^{M} \lambda_{n,m} = 1$.

III. Contract Theory-based Computing Resource Trading

In this section, the conditions that need to be satisfied in order for the different different prospective providers to accept the contract are introduced, and subsequently, their optimal contract items under the joint Adverse Selection and Moral Hazard problem are derived.

Indeed, to participate in the contract, a service provider m should obtain at least the same utility as in the case of rejecting the contract of requester n. This condition is termed as Individual Rationality (IR) and is formally expressed as:

$$\text{(IR)} \quad \theta_{n,m} e_{n,m} q_{n,m} + p_{n,m} - \frac{1}{2} c e_{n,m}^2 \geq \bar{U}. \quad (4)$$

$\bar{U} \in [0.5, 1]$ is the provider's minimum acceptable utility.

Also, the service requester n must ensure that the provider m selects the contract item that maximizes its personal utility, yielding to the Incentive Compatibility (IC) condition. From the Moral Hazard problem perspective, the provider m must be able to select the optimal effort $e_{n,m}^*$ to the requester n, which is formally written as:

$$\text{(IC.1)} \quad \max_{e_{n,m}} \theta_{n,m} e_{n,m} q_{n,m} + p_{n,m} - \frac{1}{2} c e_{n,m}^2. \quad (5)$$

As a result of solving Eq. (5) with respect to $e_{n,m}$, we obtain the optimal provider's m choice of effort, i.e., percentage of allocated computing resource, which is equal to $e_{n,m}^* = \frac{1}{c} \theta_{n,m} q_{n,m}$. Also, considering the problem of Adverse Selection, the IC condition is translated as the guarantee that the provider's m maximum utility is obtained, when choosing the contract item that best fits its type $\theta_{n,m}$, given by:

$$\begin{aligned} \text{(IC.2)} \quad & \theta_{n,m} e_{n,m} q_{n,m} + p_{n,m} - \frac{1}{2} c e_{n,m}^2 \geq \\ & \theta_{n,m} e'_{n,m} q_{n,m'} + p_{n,m'} - \frac{1}{2} c (e'_{n,m})^2, \forall m \neq m', \end{aligned} \quad (6)$$

where $e'_{n,m} = \frac{1}{c}\theta_{n,m}q_{n,m'}$ is the provider's m effort if selecting the contract item of a provider m'.

Based on the preceding analysis, the following useful propositions can be derived.

Proposition 1. *Given a feasible contract $\{p_{n,m}, q_{n,m}\}$, the following must hold: $q_{n,m} > q_{n,m'} \iff \theta_{n,m} > \theta_{n,m'}$ and $q_{n,m} = q_{n,m'} \iff \theta_{n,m} = \theta_{n,m'}$.*

Proof. In order to prove: $q_{n,m} > q_{n,m'} \iff \theta_{n,m} > \theta_{n,m'}$, we substitute $e^*_{n,m} = \frac{1}{c}\theta_{n,m}q_{n,m}$ to Eq. (6) and obtain the following two IC.2 conditions: $\frac{1}{2c}\theta^2_{n,m}q^2_{n,m} + p_{n,m} \geq \frac{1}{2c}\theta^2_{n,m}q^2_{n,m'} + p_{n,m'}$ and $\frac{1}{2c}\theta^2_{n,m'}q^2_{n,m'} + p_{n,m'} \geq \frac{1}{2c}\theta^2_{n,m'}q^2_{n,m} + p_{n,m}$. By adding these two IC.2 conditions by parts we conclude to $(\theta^2_{n,m} - \theta^2_{n,m'})(q^2_{n,m} - q^2_{n,m'}) \geq 0$. Given that $\theta_{n,m} > \theta_{n,m'}$ we get $q_{n,m} > q_{n,m'}$. Following similar steps, it can be also proved that $q_{n,m} = q_{n,m'} \iff \theta_{n,m} = \theta_{n,m'}$ holds true. □

Proposition 2. *A higher-type provider, i.e., $\theta_{n,1} < \cdots < \theta_{n,m} < \cdots < \theta_{n,M}$, will get higher installment payment, i.e., $q_{n,1} < \cdots < q_{n,m} < \cdots < q_{n,M}$, by providing higher effort, i.e., $e_{n,1} < \cdots < e_{n,m} < \cdots < e_{n,M}$.*

Proof. The proof is immediate based on Proposition 1. □

Proposition 3. *A higher-type provider, i.e., $\theta_{n,1} < \cdots < \theta_{n,m} < \cdots < \theta_{n,M}$, will achieve greater utility, i.e., $U^n_1 < \cdots < U^n_m < \cdots < U^n_M$ to be motivated by the requester n.*

Proof. Given the service providers $m, m' \in \mathcal{M}$, $m \neq m'$ of types $\theta_{n,m} > \theta_{n,m'}$, the simplified IC.2 condition yields: $\frac{1}{2c}\theta^2_{n,m}q^2_{n,m} + p_{n,m} \geq \frac{1}{2c}\theta^2_{n,m}q^2_{n,m'} + p_{n,m'} > \frac{1}{2c}\theta^2_{n,m'}q^2_{n,m'} + p_{n,m'}$, and hence, $U^n_m > U^n_{m'}$, concluding the proof. □

Consequently, the objective of the service requester n is to design the optimal contract items $\{p^*_{n,m}, q^*_{n,m}\}, \forall m \in \mathcal{M}$ that correspond to the two-stage payment process of the different service providers' types, and then, allow the prospective service provider m to autonomously select the one contract item that maximizes its personal utility. The optimization problem to be solved by the service requester n is written as follows:

$$\max_{(p_{n,m},q_{n,m})\forall m} \sum_{m=1}^{M} \lambda_{n,m}[R + \frac{1}{c}\theta^2_{n,m}q_{n,m}(Q - q_{n,m}) - p_{n,m}] \tag{7a}$$

$$\textbf{s.t. } \frac{1}{2c}\theta^2_{n,m}q^2_{n,m} + p_{n,m} \geq \bar{U}, \forall m \tag{7b}$$

$$\frac{1}{2c}\theta^2_{n,m}q^2_{n,m} + p_{n,m} \geq \frac{1}{2c}\theta^2_{n,m}q^2_{n,m'} + p_{n,m'}, \forall m \neq m' \tag{7c}$$

$$0 \leq q_{n,1} < \cdots < q_{n,m} < \cdots < q_{n,M}, \tag{7d}$$

where Eq. (7a), (7b) and (7c) are the simplified versions of Eq. (3), (4) and (6), respectively, given the optimal effort $e^*_{n,m}$ that is implied by IC.1. The problem in Eq. (7a)-(7d) comprises M IR and $M(M-1)$ IC.2 conditions and a reduction procedure can be followed to obtain a tractable solution.

First, it can be proved that the M IR conditions in Eq. (7b) can be reduced to a single IR condition: $\frac{1}{2c}\theta^2_{n,1}q^2_{n,1} + p_{n,1} = \bar{U}$. Indeed, given that $\theta_{n,m} > \theta_{n,1}$, the IC.2 condition gives: $\frac{1}{2c}\theta^2_{n,m}q^2_{n,m} + p_{n,m} \geq \frac{1}{2c}\theta^2_{n,m}q^2_{n,1} + p_{n,1} > \frac{1}{2c}\theta^2_{n,1}q^2_{n,1} + p_{n,1} \geq \bar{U}$, which means that the satisfaction of the IR condition of the lowest provider type $\theta_{n,1}$ implies the satisfaction of the IR conditions of all provider types. The latter can be, also, considered as equality to maximize the requester's n utility.

Next, to proceed to the reduction of the $M(M-1)$ IC.2 conditions, we define the Downward (DIC) and Upward (UIC) IC.2 conditions between the providers m and m', with $m' \in \{1, \ldots, m-1\}$ and $m' \in \{m+1, \ldots, M\}$, respectively.

Proposition 4. *The DIC conditions can be reduced to the local DIC conditions between the providers $m, m-1, \forall m \in \mathcal{M}$.*

Proof. Assume three adjacent provider types, i.e., $\theta_{n,m-1} < \theta_{n,m} < \theta_{n,m+1}$. By combining $\theta_{n,m+1} > \theta_{n,m}$ and the IC.2 condition $\frac{1}{2c}\theta^2_{n,m}q^2_{n,m} + p_{n,m} \geq \frac{1}{2c}\theta^2_{n,m}q^2_{n,m-1} + p_{n,m-1}$, we get $\frac{1}{2c}\theta_{n,m+1}(q_{n,m} - q_{n,m-1}) > \frac{1}{2c}\theta_{n,m}(q_{n,m} - q_{n,m-1}) \geq p_{n,m-1} - p_{n,m}$. By utilizing this property, we get $\frac{1}{2c}\theta_{n,m+1}q_{n,m+1} + p_{n,m+1} \geq \frac{1}{2c}\theta_{n,m+1}q_{n,m} + p_{n,m} \geq \frac{1}{2c}\theta_{n,m+1}q_{n,m-1} + p_{n,m-1} \geq \cdots \geq \frac{1}{2c}\theta_{n,m+1}q_{n,1} + p_{n,1}$. This outcome is generalized for the provider types $\theta_{n,m-1}$ and $\theta_{n,m}$. Consequently, the satisfaction of the DIC conditions between the providers $m, m-1$, results in the satisfaction of all the DIC conditions. □

Proposition 5. *The UIC conditions can be reduced to the local DIC conditions between the providers $m, m-1, \forall m \in \mathcal{M}$.*

Proof. Similar to the proof of Proposition 4, it can be shown that the UIC conditions are reduced to the local UIC conditions between the providers $m, m+1, \forall m \in \mathcal{M}$, or equivalently $m-1, m$, suggesting the local DIC conditions. □

Concluding the outcome of Propositions 4 and 5, the IC.2 conditions in Eq. (7c) can be substituted by the following M conditions: $\frac{1}{2c}\theta^2_{n,m}q^2_{n,m} + p_{n,m} = \frac{1}{2c}\theta^2_{n,m}q^2_{n,m-1} + p_{n,m-1}$.

After completing the IR and IC.2 constraints reduction process, the problem in Eq. (7a)-(7d) is transformed as follows:

$$\max_{(p_{n,m},q_{n,m})\forall m} \sum_{m=1}^{M} \lambda_{n,m}[R + \frac{1}{c}\theta^2_{n,m}q_{n,m}(Q - q_{n,m}) - p_{n,m}] \tag{8a}$$

$$\textbf{s.t. } \frac{1}{2c}\theta^2_{n,1}q^2_{n,1} + p_{n,1} = \bar{U} \tag{8b}$$

$$\frac{1}{2c}\theta^2_{n,m}q^2_{n,m} + p_{n,m} = \frac{1}{2c}\theta^2_{n,m}q^2_{n,m-1} + p_{n,m-1}, \forall m \tag{8c}$$

$$0 \leq q_{n,1} < \cdots < q_{n,m} < \cdots < q_{n,M}. \tag{8d}$$

The optimal solution $(\mathbf{p}^*_n, \mathbf{q}^*_n)$ to the problem in Eq. (8a)-(8d) can be obtained via the application of the Karush-Kuhn Tucker (KKT) conditions, where $\mathbf{p}_n$ and $\mathbf{q}_n$ are the vectors of the down and installment payments of the different types of providers, respectively.

IV. Benchmark Contract Theory-based Trading Models

This section introduces two one-shot contract theory-based auctions that primarily differ from the proposed model in Section III in the fact that they unilaterally deal with the existence of asymmetric information between the service requester and the prospective service providers, either during or after the contracting phase, resulting in pure Adverse Selection and pure Moral Hazard problems, respectively.

A. Pure Adverse Selection Problem

In this benchmark case, the problem of asymmetric information after the contracting phase regarding the provider's allocated computing resource to the service requester n is removed, and each prospective provider's m effort is considered to be truthfully predetermined as $\hat{e}_{n,m}$, proportional to the provider's type $\theta_{n,m}$. The pure Adverse Selection problem to be solved by the service requester n includes the IR, IC.2 and monotonicity conditions, and is given by:

$$\max_{(p_{n,m},q_{n,m})_{\forall m}} \sum_{m=1}^{M} \lambda_{n,m}[R+\theta_{n,m}\hat{e}_{n,m}(Q-q_{n,m})-p_{n,m}] \tag{9a}$$

$$\textbf{s.t. } \theta_{n,m}\hat{e}_{n,m}q_{n,m}+p_{n,m}-\frac{1}{2}c\hat{e}_{n,m}^2 \geq \bar{U}, \forall m \tag{9b}$$

$$\theta_{n,m}\hat{e}_{n,m}q_{n,m}+p_{n,m}-\frac{1}{2}c\hat{e}_{n,m}^2 \geq \theta_{n,m}\hat{e}_{n,m'}q_{n,m'}+p_{n,m'}-\frac{1}{2}c(\hat{e}_{n,m'})^2, \forall m \neq m' \tag{9c}$$

$$0 \leq q_{n,1} < \cdots < q_{n,m} < \cdots < q_{n,M}. \tag{9d}$$

It can be easily found that the optimal solution to the problem in Eq. (9a)-(9d) for a single provider m is $p^*_{n,m} = \bar{U}+\frac{1}{2}c\hat{e}_{n,m}^2$ and $q^*_{n,m}=0$. Obviously, when the provider's effort required to successfully complete the requester's task has been truthfully agreed during the contracting phase, then there is no need to provide a bonus, i.e., an installment payment, after the completion of the task.

B. Pure Moral Hazard Problem

This benchmark case is supplementary to the one in Section IV-A, and removes the asymmetry of information during the contracting phase regarding the provider's type. The pure Moral Hazard problem to be solved by the requester n for each one of the different prospective service providers separately, includes the IR and IC.1 conditions, and is expressed as:

$$\max_{(p_{n,m},q_{n,m})} R+\frac{1}{c}\theta_{n,m}^2 q_{n,m}(Q-q_{n,m})-p_{n,m}, \forall m \tag{10a}$$

$$\textbf{s.t. } \frac{1}{2c}\theta_{n,1}^2 q_{n,1}^2+p_{n,1} \geq \bar{U}, \tag{10b}$$

where it is considered that the optimal provider's effort to the requester is equal to $e^*_{n,m}=\frac{1}{c}\theta_{n,m}q_{n,m}$, as pointed in the analysis in Section III.

The optimal solution to this problem, considering a provider m, is derived as $p^*_{n,m}=\bar{U}-\frac{1}{2c}\theta_{n,m}^2R^2$ and $q^*_{n,m}=R$. In the pure Moral Hazard case, the requester promises to offer its whole revenue R to the prospective provider upon the completion of its task to motivate the latter to provide the most of its effort.

V. Evaluation & Results

In this section, we evaluate the operational characteristics of the proposed computing resource trading mechanism in collaborative MEC networks, and especially, compare its performance against the benchmark cases that are introduced in Section IV. For demonstration purposes, we consider a service requester, whose computation task to be offloaded is calculated as $W_n = B_n\phi_n$ [CPU cycles], where $B_n \in [1,2]$ MBytes and $\phi_n \in [20,40]$ CPU cycles/Byte. The system comprises of $M = 10$ prospective service providers of different types, whose total computing capabilities and effective capacitance coefficients are $F_m \in [1,2]$ [CPU cycles/s] and $k_m = 10^{-27}$, respectively. Unless otherwise specified, the contract theory-related parameters of both the proposed model in Section III and the benchmark models in Section IV are set as follows: $R = 1$, $Q = 1$, $C = 1$, $\bar{U} = 0.5$. Last, the truthfully predetermined effort of the provider at the pure Adverse Selection problem is defined as $\hat{e}_{n,m} = \theta_{n,m}, \forall m \in \mathcal{M}$. The results presented subsequently have been averaged over 100 different service requester's computation tasks and service providers' contract theory types realizations.

Fig. 1 investigates the operation of the proposed computing resource trading mechanism under the joint Adverse Selection and Moral Hazard problem, denoted as "Proposed", against the benchmark cases of "Pure Adverse Selection" and "Pure Moral Hazard". The horizontal axes in Fig. 1 refer to the different providers' types sorted in ascending order, i.e., $\theta_{1,1} \leq \cdots \leq \theta_{1,m} \leq \cdots \leq \theta_{1,10}$, denoted by an index for notation simplicity. As a result, the higher the provider's index, the higher its type is. First, Fig. 1a depicts the different providers' effort to the service requester, which exhibits an increasing trend as the providers' types increase. Indeed, the more willing a service provider is, then the more its investment in the collaborative MEC system in terms of its effort is. For the chosen numerical values of the contract theory-related parameters, i.e., $R = 1$, $Q = 1$, $C = 1$, $\bar{U} = 0.5$, the two benchmark cases yield identical providers' efforts, whereas the proposed model concludes in slightly lower providers' efforts, especially considering high providers' types. This observation is easily justified considering the twofold asymmetry of information that is taken into account that makes the service requester conservative in offering contract items that motivate higher providers' efforts closer to the ones in the benchmark cases.

In Fig. 1b-1c, we place our focus on the installment and down payments to be paid by the service requester to the different prospective service providers'. Fig. 1b-1c illustrate the findings of Section IV with respect to the optimal contract items in the benchmark cases, which indicate that in the pure Adverse Selection case that the providers' efforts are a priori known, only a down payment is offered that increases as the providers' types and efforts increase (Fig. 1c). On the contrary, in the pure Moral Hazard case that the only asymmetry lies in the unknown providers' efforts, the requester offers an installment payment that is equal to the revenue $R = 1$ that is obtained from the successful completion of the

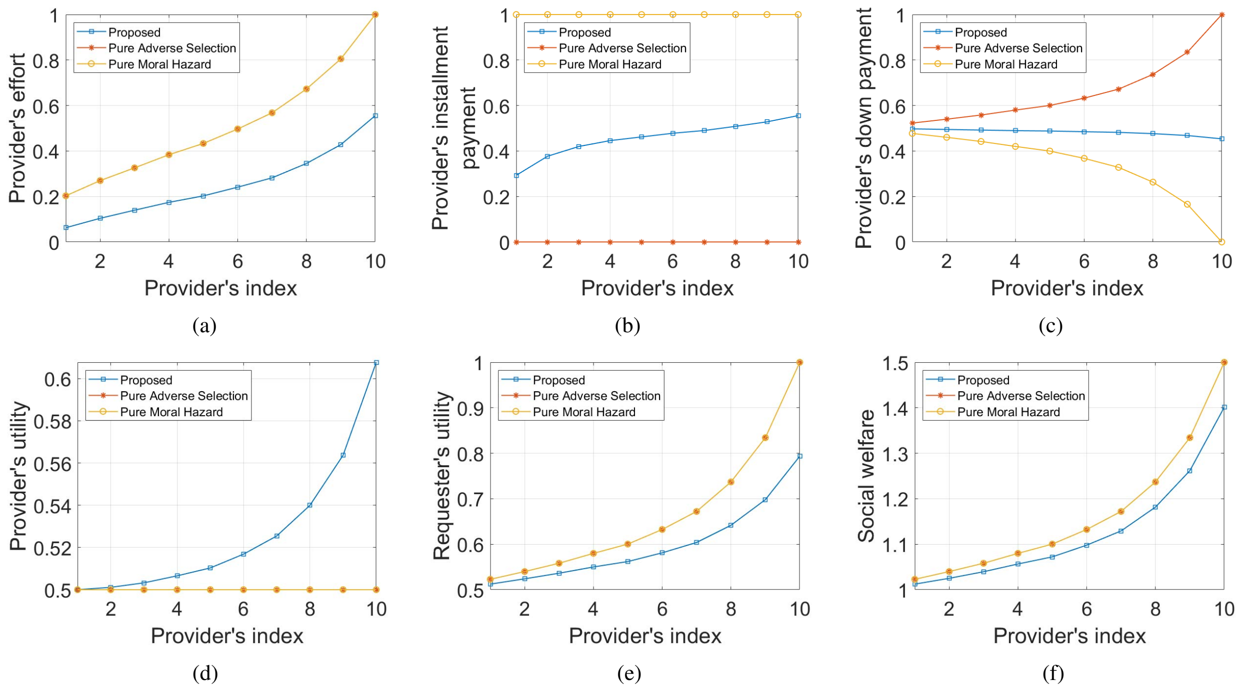
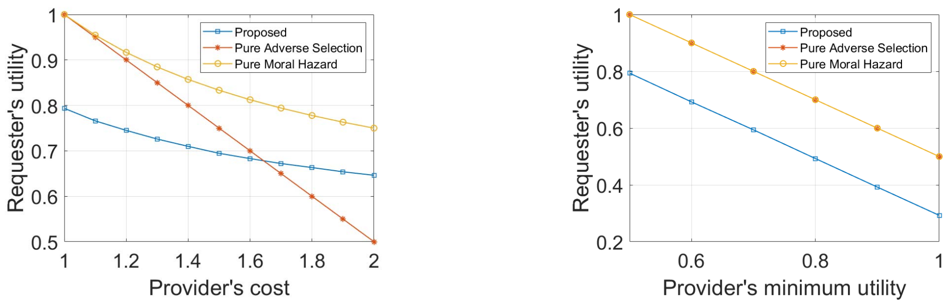


Fig. 1: Comparative evaluation of the operation characteristics between the proposed model and benchmark cases.

task (Fig. 1b), while the down payment exhibits a decreasing behavior as the providers' types increase, indicating a higher willingness to sign the contract regardless of the economic incentives to be initially provided (Fig. 1c). Apparently, the proposed model lies in between the two benchmark cases regarding both the providers' installment and down payments. It is remarkable to notice that as the providers' types and efforts increase, their installment payments increase, whereas their down payments present a slightly decreasing tendency as a means of balancing the aggregate payments (down and installment) to the providers' as their types increase.

In Fig. 1d-1f, we study the providers' and the requester's achieved utilities,as defined in Eq. (1)-(2), as well as the total system's social welfare that is defined as the summation of the both trading parties' utilities. Fig. 1d shows that in the two benchmark cases that only one type of asymmetry of information is considered, the service requester makes the most of the service providers, by marginally ensuring the latters' participation in the contract and marginally satisfying their minimum acceptable utility value $\bar{U} = 0.5$. In the proposed model, the requester seems to slightly overestimate the providers' efforts and provide higher overall payments, resulting in slightly higher utilities to the providers compared to the benchmark cases, which increase as the providers' types and efforts increase. Fig. 1e, also, justifies this behavior with reference to the requester's achieved utility at the different contract theory models. Last, the social welfare metric that is investigated in Fig. 1f, presents similar performance for the three different contract theory models, which emphasizes that the proposed one manages to effectively achieve a balance between adequate economic incentives and computing resource allocation, while taking two different types of asymmetric information into account.

After a comprehensive study of the different contract models' operation characteristics, given fixed values of the contract theory-related parameters, we subsequently investigate the impact that the different values of the providers' cost of effort $c \in [1, 2]$ and minimum acceptable utility $\bar{U} \in [0.5, 1]$ have on the requester's utility at the different contract theory models. It should be noted that when different values of either the cost parameter c or the minimum utility $\bar{U}$ are examined, the rest of the contract theory-related parameters' values remain unchanged, as defined at the beginning of this section. The obtained numerical results are presented in Fig. 2, where the different values of the two parameters c and $\bar{U}$ are depicted in the horizontal axes of Fig. 2a and Fig. 2b, respectively. The vertical axes in Fig. 2 correspond to the requester's utility, when the provider $m = M$ with the highest provider type $\theta_{n,M}$ is agreed to collaborate with the service requester. Fig. 2a reveals the decrease in the requester's utility as the provider's cost of effort gets higher. In the pure Adverse Selection case, the requester's utility decreases proportionally to the provider's cost increase. Apparently, the fact that the provider's effort is predetermined is more costly for the service provider and thus, the service requester compared to the other contract theory models, at high values of the provider's cost. On the other hand, the pure Moral Hazard and the proposed contract models exhibit a decrease in the rate at which the



(a) (b)

Fig. 2: Evaluation under different values of the providers' cost and minimum acceptable utility, between the proposed model and benchmark cases.

requester's utility decreases, while the difference/gap between them diminishes for high cost of effort values, given the generally reduced utility values that the service requester achieves in the proposed model. Last, considering the results in Fig. 2b, all considered contract theory models result in decreased requester's utility values in a proportional manner to the increase of the provider's minimum acceptable utility.

VI. Conclusion & Future Work

In this paper, an one-shot auction based on contract theory is introduced to facilitate the computing resource trading process between a service requester and multiple service providers in a collaborative MEC network. Specifically, with the assistance of contract theory, the optimal economic incentives to be provided to the prospective providers are determined, taking into account the existence of asymmetric information both during and after the contracting phase. To deal with the asymmetry of information regarding each provider's willingness to cooperate (provider's type), the service requester designs a set of contract items that comprise the economic incentives, which are tailored to each provider's type. Each service provider is, then, allowed to autonomously select the contract item and the computing resource allocation (effort) that maximizes its personal utility. Furthermore, to address the asymmetry of information with reference to the prospective provider's ultimate effort, the service requester designs and offers a two-stage payment to be paid prior and after the successful completion of the offloaded computation task, respectively. Numerical results complement the theoretical analysis of the proposed contract model, validating its effectiveness and efficiency to concurrently capture two different types of private information under a unified model.

Part of our current and future work focuses on the extension of the proposed contract theory model via the inclusion of multiple service requesters that concurrently compete for the available service providers, by properly adjusting their offered economic incentives. Therefore, the resulting multiple-requester multiple-provider system setting suggests the joint utilization of contract and game theories.

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