Multitask Age of Federated Information via Game Theoretic Distributed Control

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***Abstract*—Internet of things (IoT) applications require up-to-date information about the system conditions. This can often be provided from multiple alternative sources that sense the environment, but act without centralized coordination. In this paper, we consider a scenario where multiple sources can provide information for a number of tasks of the IoT application, assuming that the information content of multiple sources is generally redundant, yet one single source is generally insufficient for all tasks. In so doing, we seek for the minimization of the age of federated information (AoFI), a metric describing the age of information from multiple sources, considering that the epochs of successful updates are only those where all tasks are covered. At the same time, we would like to contain the number of active sources for cost reasons. To this end, we tackle the problem through a game-theoretic approach, where individual sources act as players minimizing a linear combination of AoFI and activation cost. We prove that this framework identifies efficient Nash equilibria very close to the optimum performance. However, the latter can only be achieved through centralized control, whereas the former allows for distributed implementation, which is key in IoT scenarios.**

***Index Terms*—Distributed control, Internet of things, Game theory, Age of information.**

I. Introduction

In recent years, the Internet of Things (IoT) has transformed the development of real-time applications by allowing interconnected devices to communicate and process data at unprecedented speeds. This advancement has enabled the creation of smart home ecosystems, where devices such as thermostats and security cameras can be monitored and controlled in real time [1], [2]. Similarly, healthcare applications now utilize wearable devices to track vital signs of patients, alerting healthcare providers to any anomalies [3]. Furthermore, in smart cities, AI-powered road cameras and urban sensors efficiently manage vehicular traffic and public services, resulting in a more responsive and adaptive environment [4].

All these applications require up-to-date information to operate coherently with the cyber-physical realm they belong to, which requires proper management of the sensing units. However, continuous measurement is neither energetically sustainable nor always necessary as long as the information remains sufficiently current. In the past decade, the evaluation of the timeliness of status updates using a metric known as the Age of Information (AoI) has gained significant popularity [5]–[8].

AoI, defined in the seminal paper [9], is the time elapsed since the last successful status update. The original scenario considers a single link with one source and one receiver, but in reality, the sensing paradigms for the aforementioned applications are often many-to-many, making the data collection process challenging [10]. What is worse, multiple sources are often redundant in their content [11], needing careful selection to avoid temporal redundancy of information, yet doing nothing on its spatial redundancy instead.

The problem here is that, for most applications, just selecting one source is not enough to provide the information required by the whole set of tasks, but choosing all sources is definitely redundant. To capture this point, we exploit the concept of *age of federated information* (AoFI) that was originally introduced in [12] for participatory ecosystems, where sources decide independently about their activity during a specific evaluation epoch. The evaluation of AoFI is akin to that of AoI but considers a successful update to happen only in those epochs, where a sufficient number of sources, intermediate between only one and all of them, is active.

In the present paper, we expand this idea to consider a bipartite graph of sources and tasks, where each source covers only *some* of the tasks, and the successful update happens when all tasks are successfully covered. For this scenario, we seek distributed control of the individual activation of each source, which again corresponds to the decision to send information for a specific time epoch. To identify efficient decentralized solutions, we employ an approach based on game theory [13].

Specifically, seeking distributed approaches that obtain low AoFI would lead to the obvious Nash equilibrium (NE) where all nodes are active. However, since we also strive to contain the number of active sources, we show how the problem can be framed as a game where individual players try to minimize a global-local combination made of two components: a penalty for the entire network (the AoFI) and an individual cost term. This leads to implicitly penalizing solutions where the number of active sources is excessive.

We prove that the best NEs of the game in pure strategies are close to the optimal system performance. Conversely, mixed-strategy NEs, which correspond to a fully agnostic distributed implementation, perform far worse than the one achieved in

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pure strategies, suggesting that there should be an equilibrium selection procedure in place to favor the emergence of pure-strategy NEs.

The remainder of this paper is organized as follows. In Section II, we review related works. Section III presents the system model and analysis. Numerical results are shown and discussed in Section IV, and Section V concludes the paper.

II. Related Work

The idea of applying game theory to problems of AoI or other AoI-related metrics is not itself new and has been successfully applied in many papers. However, these mostly consider multiple sources as players with opposing objectives, for example seeking to minimize their own AoI [6], [13], or even adversaries that try to sabotage each other, as typical of game-theoretic security investigations [8], [14]. To the best of our knowledge, we are the first to apply game theory with the different purpose to derive distributed policies that admit implementation in the IoT. In other words, in our scenario, the game-theoretic interaction is not motivated by competition over a shared resource, but simply due to the (voluntary) lack of run-time coordination between the nodes.

The concept is also presented in [12], which suggests AoFI for data originating from various sources. However, that work only addresses a single destination and oversimplifies information redundancy by presuming that all nodes are identical and provide uniform content. However, in this paper, the presence of task-specific information from different sources is represented using a bipartite graph structure, enabling a more comprehensive description of practical scenarios.

We observe that the idea of AoFI is somehow intermediate between the standard minimization of AoI as originally proposed by [9] and the so-called "age of correlated information" proposed by [15]. The former usually means that if multiple sources are available, each one of them is equally good to update the receiver. The latter is fundamentally the same concept as AoFI; however, it specifically addresses situations where all sources need to be active for a successful update. This scenario can be considered as a particular instance in AoFI analysis (e.g., if each source is dedicated to a unique task). However, one can argue that AoFI offers a greater level of flexibility between these two polar cases.

We note that [16] does a similar analysis for AoI reduction in a multi-source context using bipartite graphs, but there the graph structure is created as an auxiliary instrument for the evaluation, and is not a preexisting input as in our case.

In general, there are several papers considering AoI from multiple sources, but usually sharing the same medium [10], [17], [18]. Thus, the problem is seen as the development of a centralized scheduling strategy for medium usage among the sources, one at a time. Our scenario is inherently different in that we foresee simultaneous activation of multiple sources over the same epoch, and we also seek distributed implementations, due to our orientation towards IoT scenarios.

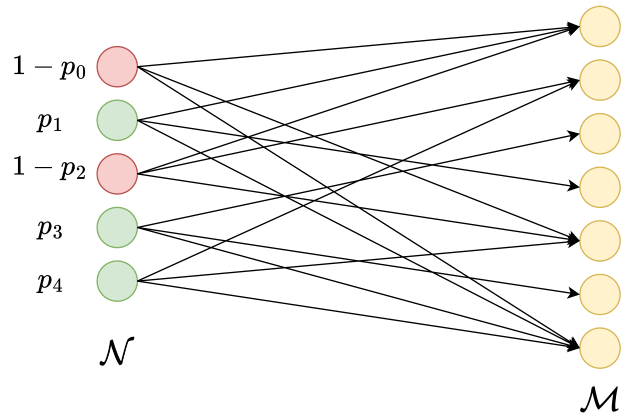


Fig. 1. Graphical representation of the scenario. Green sources are active and red ones are inactive. p_i is the probability source i is active.

III. System Model

Consider a set $\mathcal{N}$ of N sources that can be activated according to a probability vector $\boldsymbol{p} = [p_0, \dots, p_{N-1}]$, and a set $\mathcal{M}$ of M tasks. Each source i is capable of solving only a subset $\mathcal{K}_i \subset \mathcal{M}$ with probability 1. Moreover, consider $|\mathcal{K}_i| = K$ to be the same for each source i. This particular scenario can be represented as a coverage problem on a directed bipartite graph. An example is reported in Fig. 1 where we set $N = 5$, $M = 7$ and $K = 3$. Note that the green nodes are active sources with probability p_i and completely cover the set $\mathcal{M}$, while the red nodes are inactive sources with probability $1 - p_i$ and do not contribute in any way to the coverage of the set of tasks. Note that this is not the only possible solution as there are multiple sources that can cover the same tasks and, therefore, are exchangeable.

We consider the coverage of the task set $\mathcal{M}$ as the success condition. To this end, we introduce a parameter $\alpha \in [0, 1]$ that controls the coverage required to make the interaction end in a success. Let y be the fraction of tasks covered by active sources, if $y \geq \alpha$ then the probability of success is exactly y, otherwise it is 0. In the remainder of this paper, we will focus on two values for α: we denote $\alpha = 0.7$ and $\alpha = 1$ as Soft Coverage (SC) and Hard Coverage (HC), respectively, the latter implying that success is achieved if and only if all tasks are covered.

The collective goal for each source is to minimize a penalty combining the expected AoFI and an individual cost term. AoFI [12] is a metric that maximizes the freshness of information like AoI and is computed as the time difference between the current time instant t and the last successful update τ_i

$$\delta(t) = t - \tau_i \,, \tag{1}$$

but it is best suited to collaborative scenarios as it considers that some sources may refrain from collaborating. In these scenarios, the expected AoFI can be written as [13]

$$\mathbb{E}[\delta] = \frac{1}{P_{\text{succ}}} - 1 \,. \tag{2}$$

The probability of success P_{succ} is computed through the total probability theorem by conditioning the probability of success to the probability of having a binary activation pattern $\boldsymbol{x} = [x_0, \ldots, x_{N-1}] \in \{0,1\}^N$

$$P_{\text{succ}} = \sum_{\boldsymbol{x}} P[\text{succ}|\boldsymbol{x}] \cdot P[\boldsymbol{x}] \,. \tag{3}$$

In this expression, conditional probability $P[\text{succ}|\boldsymbol{x}]$ is computed by looking at the coverage achieved on $\mathcal{M}$ according to the value of α (i.e., whether we seek for HC or SC). The probability of the activation pattern $\boldsymbol{x}$ is computed as a product rule, since all sources activate independently, as

$$P[\boldsymbol{x}] = \prod_{i=0}^{N-1} p_i x_i + (1-p_i)(1-x_i) \tag{4}$$

Each source i incurs a cost each time it is activated. It is on average a function of the source's probability of activation

$$\mathcal{C}_i = c \cdot p_i \,, \tag{5}$$

where c is a cost factor that includes the energy of the computation of the tasks and transmission of the results. We also define the global penalty of probability vector $\boldsymbol{p}$ as

$$\mathcal{W} = \mathbb{E}[\delta] + \sum_{i=0}^{N-1} \mathcal{C}_i \,. \tag{6}$$

An optimal allocation for the activation probability vector is a solution to the following mixed integer optimization problem

$$\min_{\boldsymbol{p}} \quad \mathcal{W} \tag{7a}$$

$$\text{s.t.} \quad 0 \le p_i \le 1 \tag{7b}$$

$$x_i \in \{0,1\} \tag{7c}$$

It can be proven that the solution is in a vector of $0-1$ choices, i.e., $\boldsymbol{p}^* \in \{0,1\}^N$, where pattern $\boldsymbol{x}$ has the least number of sources active to guarantee success.

A. Game Theoretic Model

The interaction between sources can be represented as a static game of complete information $\mathcal{G} = \{\mathcal{N}, \mathcal{A}, \mathcal{U}\}$ where $\mathcal{N}$ is the set of sources, i.e., the players, $\mathcal{A} \in \{0,1\}^N$ is the set of the actions of the players, which are binary values that correspond to stay inactive and active as 0 and 1, respectively, and $\mathcal{U}$ is the set of individual objectives. The latter correspond to minimizing a global-local penalty, combining the AoFI and the individual cost sustained by the node when active as in (5)

$$\mathcal{P}_i = \mathbb{E}[\delta] + \mathcal{C}_i \,. \tag{8}$$

With this formulation, game $\mathcal{G}$ admits a solution in normal form [13], found by computing the payoff tensor A_i for each source. This is a N-dimensional tensor that contains the payoff for each player depending on its action and the ones taken by all the other players. We can collect all the payoff tensors in a vector $\boldsymbol{A} = [A_0, \ldots, A_{N-1}]$.

In general, game $\mathcal{G}$ admits multiple NEs in pure and mixed strategies. We can easily enumerate all the ones in pure strategies in polynomial time and exponential space [19]. We note

Algorithm 1 Indifference Equation

Input A_i: payoff tensor for player i; $\boldsymbol{p}$: array of probabilities of length N
Output *cond*: Evaluation of the indifference equation

procedure IndifferenceEq(A_i, $\boldsymbol{p}$)
  $cond \leftarrow 0$
  $\boldsymbol{p}_{\text{mod}} \leftarrow \boldsymbol{p} \setminus p_i$ ▷ Remove element i from $\boldsymbol{p}$
  for $j \in \{0,1\}$ **do**
    $v \leftarrow A_i[\ldots, j, \ldots]$ ▷ Get payoffs for action j of player i
    for $k \in \{\text{length}(\boldsymbol{p}_{\text{mod}}) - 1, \ldots, 0\}$ **do**
      $v \leftarrow v.\text{reshape}\left(\left\lfloor \frac{v.\text{size}}{2} \right\rfloor, 2\right)$
      $v \leftarrow v \times \begin{bmatrix} 1-p_k \\ p_k \end{bmatrix}$ ▷ Matrix product
    end for
    assert v is a scalar after the cycle
    $cond \leftarrow cond + v \cdot (-1)^j$
  end for
  return *cond*
end procedure

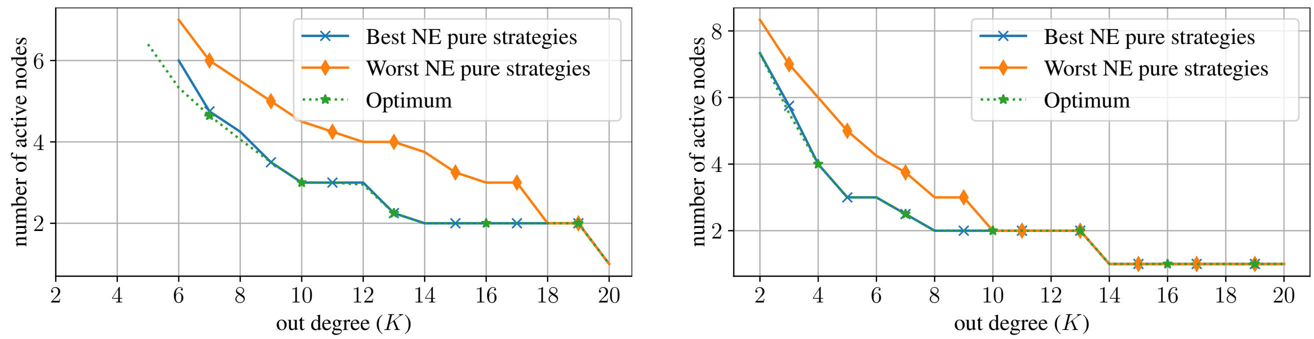
Algorithm 2 Find mixed NE

Input N: number of players in the game; $\boldsymbol{A} = [A_0, \ldots, A_{N-1}]$: Array of payoff tensors for each player; θ: threshold for numerical solution
Output $\boldsymbol{p}^*$: optimal array of probabilities

$conditions \leftarrow []$ ▷ Empty list of conditions
$bounds \leftarrow [(0,1)] * N$ ▷ Each element in $\boldsymbol{p}^*$ is a probability
$p0 \leftarrow$ InitP0(N) ▷ Starting value for $p0$
for i, $A_i \in$Enum($payoffs$) **do**
  $conditions[i] \leftarrow$ IndifferenceEq(A_i, $\boldsymbol{p}$)
end for
$\boldsymbol{p}^*$, $cost \leftarrow$LeastSquares($conditions$, $p0$, $bounds$)
if $cost > \theta$ **then**
  $\boldsymbol{p}^* \leftarrow NaN$ ▷ There is no solution in considered domain
end if
return $\boldsymbol{p}^*$

that the game has $N > 2$ players with exactly 2 actions, which implies that an exhaustive search requires 2^N evaluations. However, to the best of our knowledge, there is no algorithm in the literature to solve these types of problems for mixed-strategy NEs [20]. For this reason, we propose a heuristic algorithm that uses the extensive-form payoff tensor vector $\boldsymbol{A}$ to compute a mixed NE strategy if it exists.

This approach consists of two phases. First, we compute the indifference equations for the actions of each player. An indifference equation for a pair of actions is found by equating the expected payoff obtained by player i when choosing one of its actions when all other players mix their actions with probability p_j, $j \neq i$. The main loop of the procedure extracts



(a) (b)

Fig. 2. Number of active nodes as a function of the out degree K. (a) uses HC and (b) uses SC as success criterion, $N = 10$ sources, $M = 20$ tasks, $c = 1$.

the payoffs of player i for each of its actions and multiplies them by the probability of all the other players will play the sequence of actions that lead to that outcome starting from the *least significant bit* in the index inside the tensor when player i is removed.

We can iterate the solution of the system of equations until the expected payoff for the two actions available to each player falls within a numerical threshold. The pseudocode for this procedure is reported in Alg. 1.

Moreover, we also need to compute mixed NEs, which are found as solutions of the system of N indifference equations. There are many possible algorithms to solve nonlinear systems of equations, but we choose to use least squares algorithm with trust region reflective method [21] reformulating the system of equations as a minimization problem. With this procedure, we are sure to satisfy the constraints on the system variables, i.e. the probability for each node to be active, and we also compute how far the result is with respect to the optimal solution. Therefore, we consider a solution to be good enough if the sum of the squared residuals of optimization is smaller than a threshold θ that can be tuned to be arbitrarily small. The pseudocode for this procedure is reported in Alg. 2.

We further compute the Price of Anarchy (PoA) and Price of Stability (PoS) to evaluate the performance of the distributed solutions. PoA is computed as the global welfare cost of the worst NE over the welfare of the best centralized optimal solution [22]

$$PoA = \frac{\max_{s \in \text{NE}} \mathcal{W}^s}{\min_{s \in \mathcal{T}} \mathcal{W}^s} . \quad (9)$$

Similarly, the PoS is the global welfare cost of the best NE over the welfare of the best centralized optimal solution [23]

$$PoS = \frac{\min_{s \in \text{NE}} \mathcal{W}^s}{\min_{s \in \mathcal{T}} \mathcal{W}^s} . \quad (10)$$

By definition $PoS \leq PoA$ and if the best NE solution is the same as the optimal one, then $PoS = 1$.

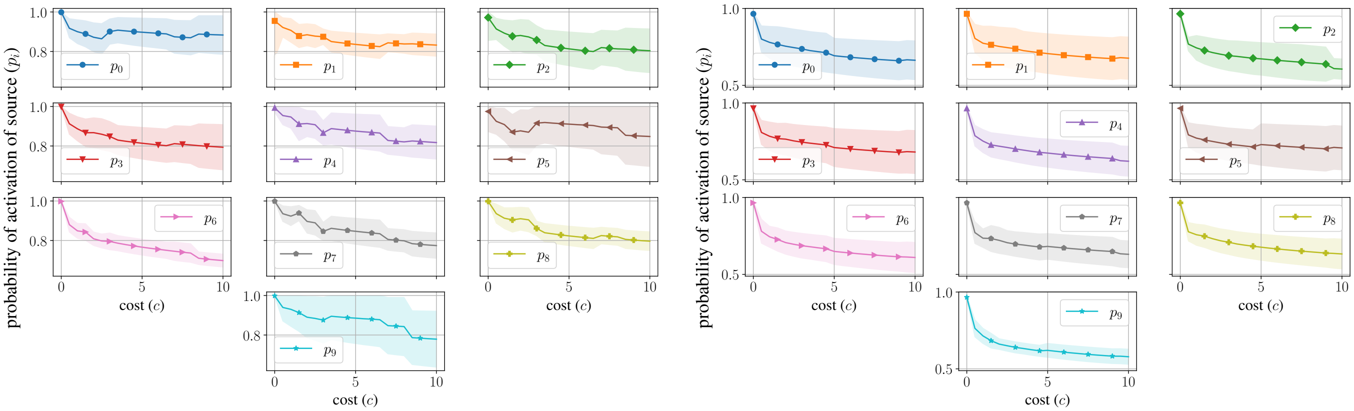
IV. Numerical Results

In this section, we report the numerical solutions to the model's equation defined in Sec. III. For all the following graphs, we have fixed the number of sources $N = 10$ and the number of tasks $M = 20$ while varying the out degree of the sources K and the cost factor c in (5). Recall that for the SC success condition $\alpha = 0.7$. Furthermore, we fix $\theta = 0.05$ in the heuristic algorithm to compute the mNE.

Fig. 2 reports the number of active nodes for different types of solutions as a function of the out degree K of the sources for a cost factor $c = 1$. In all plots, the number of active nodes for the mNE is not shown since they are always N whenever the mNE exists. In Fig. 2a, which reports the number of active nodes in the HC criterion, we can see that there is a threshold $K^* = 5$ at which we start obtaining solutions, which means that K^* is the minimum out degree to guarantee full coverage of the task set $\mathcal{M}$. We start obtaining NEs in pure strategies at $K = 6$. It is important to note that not all NEs have the same number of active nodes and therefore have the same performance in terms of global welfare $\mathcal{W}$. As the out degree of sources increases, all NEs in pure strategies converge towards the optimum. We can make similar remarks in Fig. 2b, where the SC criterion is shown. In this particular case, the threshold $K^* = 2$ is also the beginning of the emergence of pure-strategy NEs.

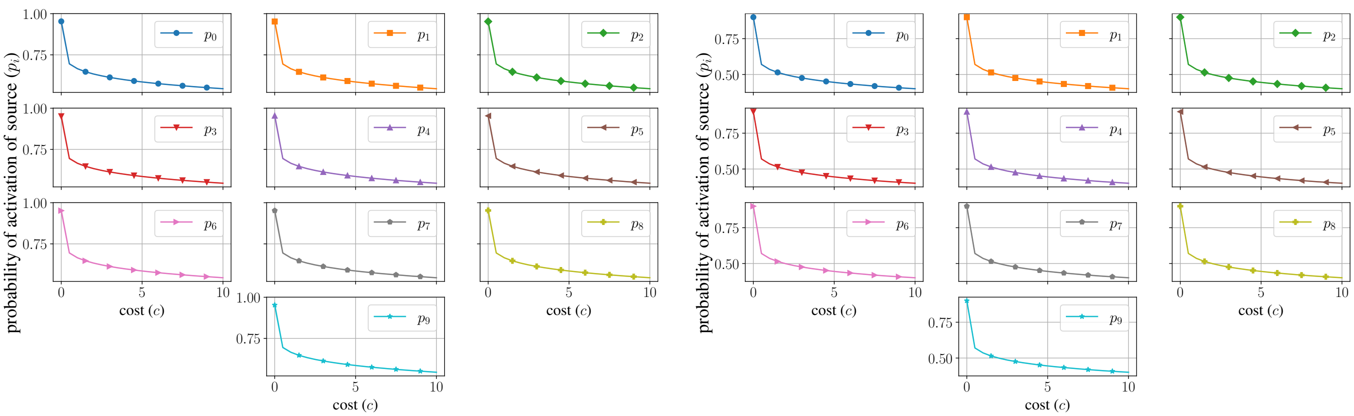
In Fig. 3 and Fig. 4 we display the activation probability p_i for each node i at the mNE with the HC and SC criterion, respectively, when the out degree K is 12 for Figs. 3a- 4a and 17 for Figs. 3b- 4b as a function of cost c. As stated in the previous paragraph, for HC the mNE starts to emerge much later than SC. Moreover, the activation pattern for the sources is significantly influenced by the topology of the connections as can be inferred by the wide confidence intervals that include one standard deviation above and below the mean of multiple runs on different topologies. This effect is less relevant when the out degree is increased as it is more likely that different subsets of sources can cover all tasks and fewer *essential* sources need to be active more than others. This phenomenon is practically non-existent for SC. In this scenario, all sources have similar behaviors as successes can occur even if not all the tasks in $\mathcal{M}$ are covered. Also, increasing the out degree of sources only reduces their activation probability, but does not determine the shutdown of one of them.

In Fig. 5 we show the PoA computed as the quotient between the global welfare of the mNE and the optimal solution. For



(a) (b)

Fig. 3. Mean activation rate for each source with 1 standard deviation confidence at mixed strategy Nash Equilibrium. HC is used as a success criterion, $N = 10$ sources,$M = 20$ tasks. (a) has $K = 12$ and (b) has $K = 17$.



(a) (b)

Fig. 4. Mean activation rate for each source with 1 standard deviation confidence for each source at mixed strategy Nash Equilibrium. SC with $\alpha = 0.7$ is used as a success criterion, $N = 10$ sources,$M = 20$ tasks. (a) has $K = 12$ and (b) has $K = 17$.

the HC case in Fig. 5a the PoA does not follow a monotonic behavior when increasing the out degree K, instead the better performance for cost $c < 8$ is obtained by $K = 10$. However, PoA values are really high, as a PoA of 3 indicates that an optimal centralized activation strategy would be 3 times more efficient. For SC in Fig. 5b the performance is even worse, as for some values of c and K the PoA is even above 4. This indicates that the reduction of activation probability is not enough to counterbalance the fact that, at the optimum, as K increases, there are fewer and fewer sources active, thus drastically improving global welfare.

Fig. 6 shows the PoS computed as the ratio between the global welfare of the best NE in pure strategies and the optimal allocation. For HC in Fig. 6a the PoS is not very far from 1 for $K = 6$ and, increasing the out degree, it reaches the optimal value. Similarly, for SC in Fig. 6b the PoS is always 1, which means that there exists a NE in pure strategies that reaches the global centralized optimum. This result suggests that equilibrium selection is required to ensure that sources prefer pure strategies instead of mixed ones [24].

V. Conclusions

We analyzed the distributed minimization of AoFI for independent sources covering multiple tasks. We computed the NEs in pure strategies and developed an algorithm to find the ones in mixed strategies under parametric success conditions. We computed the PoA and PoS by comparing the global welfare obtained by distributed solutions and centralized optimization. We showed that distributed solutions in pure strategies are close to optimum, whereas mixed strategies solutions are inefficient from a global perspective. This result suggests the need for an equilibrium selection mechanism to force the distributed choice of a pure strategy NE. This would achieve near-optimal performance through independent decisions by the sources.

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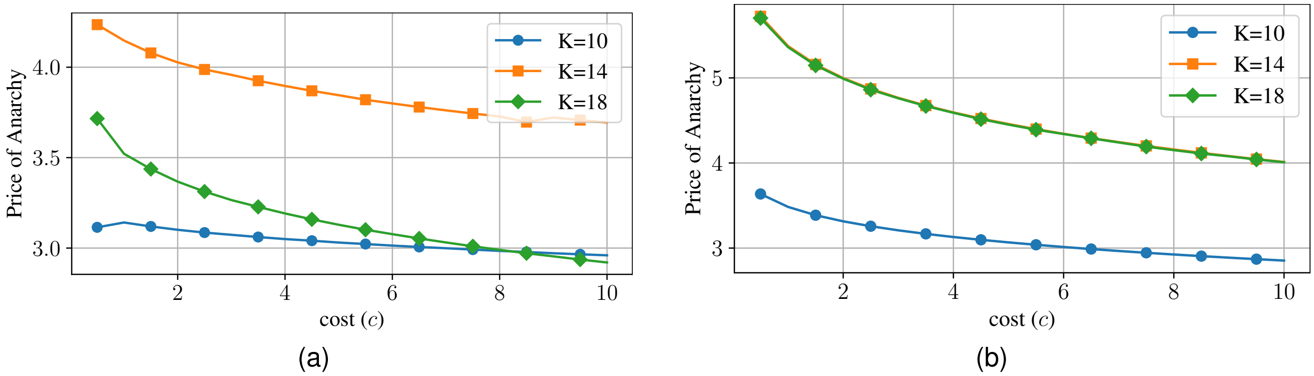

Fig. 5. Price of Anarchy as a function of cost c for various values of the out degree K. (a) uses HC and (b) uses SC with $\alpha = 0.7$ as a success criterion, $N = 10$ sources, $M = 20$ tasks.

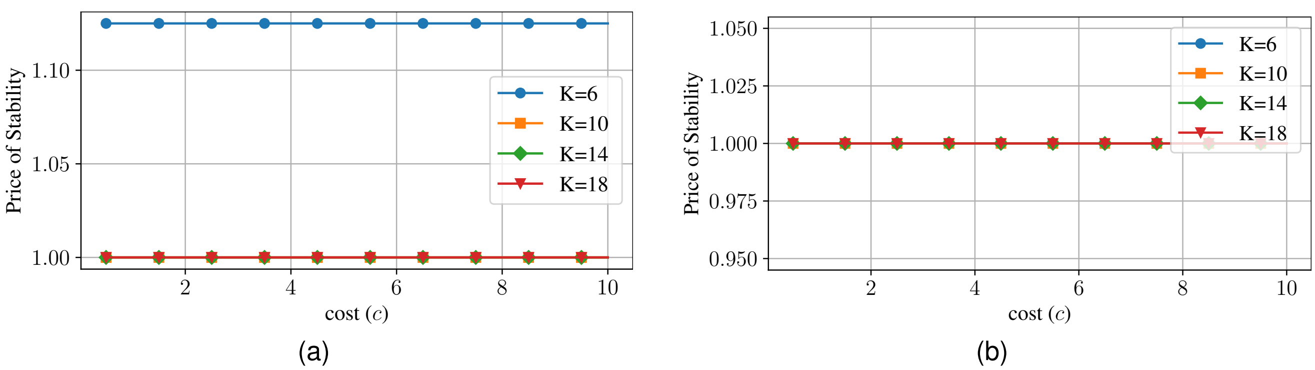

Fig. 6. Price of Stability as a function of cost c for various values of the out degree K. (a) uses HC and (b) uses SC with $\alpha = 0.7$ as a success criterion, $N = 10$ sources, $M = 20$ tasks.

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