A Truthful Online Mechanism for Resource Allocation in Fog Computing

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I. Introduction

The Internet of Things (IoT) is developing rapidly, and it is estimated that by 2025, 22 billion active devices will be in the IoT (Lueth, 2018). Since it is impossible to let the often low-powered IoT devices perform all computing tasks, a common solution is to combine IoT and cloud computing (Sajid et al., 2016). However, cloud computing alone cannot satisfy all the needs from the IoT, and fog computing has been proposed to complement it (Bonomi et al., 2012). To make the most of the fog resources and maximise the efficiency, good resource allocation mechanisms for fog computing are needed.

To address these challenges, researchers have proposed many resource allocation mechanisms for fog computing or similar computing paradigms in order to save energy, reduce cost or improve quality of service (Aazam and Huh, 2015; Cardellini et al., 2015; Gu et al., 2018). However, most of these mechanisms were not specifically designed for settings where users act strategically to maximise their utility. To address this problem, some researchers have proposed truthful mechanisms that incentivise users to truthfully reveal their private information (Chawla et al., 2017; Zhu et al., 2018). However, these approaches cannot be applied directly to our model due to subtle but important differences.

In this paper, we are the first to formulate the fog computing resource allocation (RAFC) problem as a constraint optimisation problem that considers bandwidth constraints and allows flexible allocation of virtual machines (VMs) and of the bandwidth. Furthermore, we design a *dominant-strategy incentive compatible* (DSIC) and *individually rational* (IR) mechanism for realistic fog settings to maximise social welfare[1]. DSIC mechanisms guarantee that regardless of others' behaviours, users always maximise their utility by reporting truthfully. Furthermore, under an IR mechanism, no user will get a negative utility by participation.

II. The Fog Resource Model

Then, we briefly describe our model of RAFC. The fog contains a number of geo-distributed FNs and locations, which are interconnected through data links, as shown in Figure 1.

[1]We define social welfare as the difference between the value of all fog tasks and the operational costs of all fog tasks.

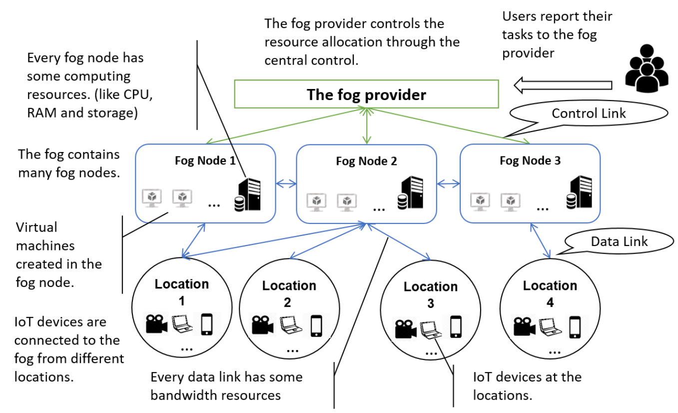

Fig. 1: General view of a fog computing system.

Here, FNs have computational resources (such as CPU, RAM and storage) and data links have bandwidth resources, and different resources have different fixed operational costs. FNs and data links together offer these resources to satisfy the needs of fog agents by means of processing tasks using VMs. IoT devices at different locations are connected to FNs of the fog through data links. Furthermore, the fog provider controls the resource allocation of the fog through a central point of control and control links. More specifically, the central point of control is a server that receives reports of tasks from fog agents and decides how to allocate resources to satisfy these agents and the payment for each agent.

Another essential part of our model is fog agents. They report their tasks to the fog provider through their IoT devices over time, which includes the resource requirements, the time constraints and the valuation functions of the tasks. For example, a picture processing application can have computing tasks like adding filters or compressing photos. To finish a task of adding filters to 100 photos, bandwidth resources are needed to send the images to and from the FN, and computational resources are needed to process the image. The time constraints of this task could be like this: the task can start right now, and the result should be sent to the agent in 30 seconds because agents usually do not want to wait for too long to add a filter to their photos. If the task is completely finished before the deadline, the agent can get all the value of this task. However, if filters have only been added to 50 photos at the deadline, the agent can still get part of the value. When receiving the reports from the agents, the fog provider decides whether to accept them, how to allocate resources to satisfy the demands of the accepted tasks and how much is the corresponding payment through an online mechanism. The social welfare of the allocation is the sum of value fog agents get by processing tasks minus the sum of the fog provider's operational costs, while the revenue is the sum of the fog provider's income minus its operational costs. To achieve this, the fog provider solves a constraint optimisation problem. The objective function maximises the total social welfare, and the constraints include computational resource constraints for the fog and time constraints for fog tasks. Please refer to Bi et al. (2019a) for details of this optimisation problem.

III. Flexible Online Greedy Mechanism (FlexOG)

Next, we briefly introduce our proposed mechanism FlexOG. After receiving a report of task i, FlexOG finds the allocation that maximises the social welfare of all flexible tasks given the constraints of their committed usage time. Then, FlexOG computes the usage time for task i from its corresponding allocation scheme and commits it to task i, which means that task i is guaranteed to get this usage time before its reported finish time. Afterwards, FlexOG requires payment for task i as the marginal total operational cost, and task i is put to the set of flexible tasks.

Theorem 1: The FlexOG mechanism is DSIC and IR.

Please refer to our paper (Bi et al., 2019b) for the details of FlexOG and the proof of Theorem 1.

IV. Simulation Results

We have evaluated our mechanism by running simulations with different parameters. Across all of these settings, trends are similar. In particular, the FlexOG's performance in social welfare is typically around 90% of the offline optimal, and between $5-10\%$ better than OG's.

First, we compare the total social welfare achieved by FlexOG with other benchmarks under different resource coefficients k indicating the abundance of the resources in Figure 2.[2] The figure shows that FlexOG consistently achieves better social welfare than other truthful benchmark mechanisms. In addition, our mechanism also performs close to offline optimal, achieving around 90%, which indicates that our mechanism is efficient even though it is online. Although online optimal performs about 10% better than FlexOG, its performance drops below that of FlexOG when just 20% of users misreport. This means that, in a strategic setting where users can misreport, FlexOG can actually achieve significantly more social welfare than online optimal.

[2]All figures are with 95% confidence intervals based on 200 trials, and the relative tolerance is set to 1% for offline optimal, and 5 % for others. (A 1% tolerance means that the CPLEX optimiser stops when a solution is within 1% of optimality)

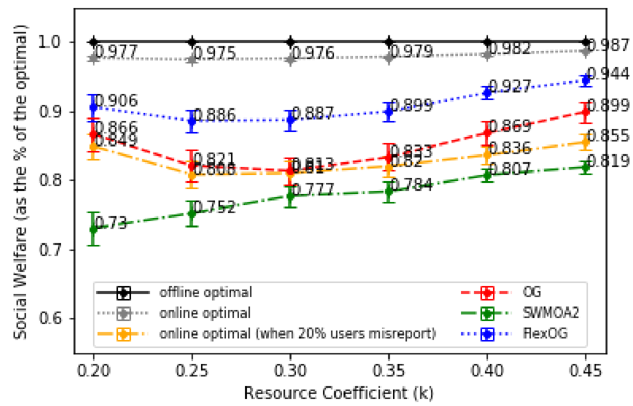

Fig. 2: Social welfare achieved by the mechanisms

V. Conclusions

This paper formulates the RAFC problem as a constrained optimisation problem and proposes a novel truthful online mechanism for solving it. In the future, we plan to improve the scalability of FlexOG and to combine online mechanism design and machine learning to enhance social welfare further.

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