Reinforcement Learning-based Computation Resource Allocation Scheme for 5G Fog-Radio Access Network

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***Abstract*—Fog computing has emerged as one of the key building blocks of fifth generation mobile networks (5G) because of its ability to effectively meet the demands of real-time or latency-sensitive applications. To introduce fog in 5G, particularly in the radio access network (RAN), intermediate network devices such as remote radio heads, small cells and macro cells are equipped with virtualised storage and processing resources to constitute the fog RAN (F-RAN). However, these resources are limited and inefficient management could cause a bottleneck for F-RAN nodes. To this end, this paper focuses on developing a dynamic and autonomous computing resource allocation scheme for F-RAN considering delay requirements of users at a node. The proposed algorithm uses reinforcement learning to optimise latency, energy consumption and cost in the F-RAN. The performance and computational complexity of the proposed algorithm will be evaluated as part of a simulation and the results compared with other algorithms from existing studies with a similar objective function.**

***Index Terms*—fog computing, 5G RAN, reinforcement learning, edge computing, machine learning**

I. Introduction

The ever-increasing need to achieve low latency and ultra-high reliability has led to the emergence of the fog computing paradigm, whose fundamental principle is to bring cloud computing capabilities to the edge of the network closer to end devices and users [1].

Fog computing relies on the convergence of software-defined networking (SDN) and network function virtualisation (NFV) to extend the architecture of the traditional heterogeneous cloud radio access network (H-CRAN) as a means to overcome the fronthaul burden and consequently meet the demands of next generation applications. This has given rise to the notion of introducing fog in 5G RAN to create the fog RAN (F-RAN). The F-RAN approach equips edge devices with storage and computing resources, which are virtualised as isolated virtual machines (VMs) so as to divide the function of conventional base stations into two parts: remote radio heads (RRH) for radio signal transceiving, and baseband unit (BBU) for high-speed baseband processing [2].

Despite all of the attractive features of fog, the constrained computing ability still causes bottlenecks for the F-RAN nodes (FNs) if not managed appropriately. Thus, there is a need to efficiently manage the limited resources allocated by the core network among FNs. It is important to ensure that applications have sufficient access to resources near the edge, however designing a scheduling and computation resource allocation scheme is challenging. To this end, machine learning (ML) has been developed as a promising contender.

Based on our literature review, there is no autonomous virtual resource allocation which allows each node to manage its compute power allocation independently, although learning-based resource allocation has been implemented in [3]–[5] through a centralised controller that makes decisions for the service provider. The work in [6] considers autonomous learning where smart sensors offload their tasks to nearby FNs. In this paper, computing resources are dynamically reserved for FNs by considering traffic characteristics of their users, so that FNs can independently regulate their own resource through learning in order to minimise the cost among their users.

The remainder of this paper is outlined as follows. After presenting the paper contributions and expected results in Section II, the system model and problem formulation are described in Section III. The proposed resource allocation approach is detailed in Section IV and finally, Section V concludes the paper with a review of the research objectives and a summary of future work.

II. Paper Contributions

This paper anticipates bringing the following specific major contributions:

1) A two-level framework for compute power virtualisation and allocation in F-RAN is proposed; the unused resource at the core is dynamically reserved to the F-RAN and autonomously allocated by the FNs to their users.
2) The resource allocation problem in 5G F-RAN is formulated as a multi-objective Markov Decision Process to optimise latency, energy consumption and cost in

massive Machine Type Communications (mMTC) applications for 5G networks.

3) A reinforcement learning-based algorithm for dynamic resource management of virtualised cloud computation resources in a distributed fog computing network is devised. The algorithm independently manages computing resources allocated to F-RANs based on the feedback of the average utility and resource utilisation of their users.

III. System Model

In the network, a set of small-cell FNs is denoted by $N = \{1, 2, ..., |N|\}$ and a set of total sensors is denoted as $K = \{1, 2, ..., |K|\}$. A set of sensors for a specific FN n is denoted by K_n and k_n denotes a single sensor of the FN.

For fog processing, a FN n needs to allocate the limited computation resources (in CPU cycles/s) to the application of sensor k. The application of processing sensor data is described by $J_{k_n} = \{D_{k_n}, app_{k_n}, T_{k_n}^{max}\}$, where D_{k_n} denotes the size of sensor data (in bits), app_{k_n} is the minimum processing density (in CPU cycles/bit), and $T_{k_n}^{max}$ is the maximum tolerable latency (in seconds). The number of CPU cycles necessary to process the data is modelled as $C_{k_n} = D_{k_n} app_{k_n}$. Since the output after processing is usually small, only the uplink communication is considered for simplicity.

The assumption is that the fog processing only begins after all the sensor data has been received by the FN. Then, the computing delay and energy consumption of fog computing are given respectively by:

$$T_{k_n}^{fog} = D_{k_n}/r_{k_n} + C_{k_n}/f_{k_n}^{fog} \tag{1}$$

$$E_{k_n}^{fog} = p_{k_n}^{com} D_{k_n}/r_{k_n} + p_{k_n}^{id} C_{k_n}/f_{k_n}^{fog} \tag{2}$$

where $f_{k_n}^{fog}$ denotes the fractional resources (in CPU cycles/s) allocated to sensor k of FN n , $p_{k_n}^{com}$ is the transmission power of sensor, $p_{k_n}^{id}$ is the power consumption in idle mode and $r_{k_n}$is the achievable transmission rate (bits/s).

For remote processing in the cloud, the application needs to be transmitted from the sensor k to the FN n through wireless links, and then forwarded by the FN to the cloud through a wired link. If an application J_{k_n} is offloaded to the cloud server, then k_n first transmits the data of side D_{k_n} through a wireless link to the FN, which then forwards J_{k_n} to the cloud server through a high-speed wired link. The data rate of the wired link is denoted as $R_{k_n}^{fc}$ (in bits/s), and the cloud processing capability as $f_{k_n}^{c}$ (in CPU cycles/s). The delay in wired transmission is given by $T_{k_n}^{fc} = D_{k_n}/R_{k_n}^{fc}$ and the delay in cloud processing is given by $T_{k_n}^{c} = C_{k_n}/f_{k_n}^{c}$.

A. Problem Formulation

Given the defined system model, the problem of resource allocation for a fog computing system is formulated. The proposed approach performs resource allocation in two stages. Firstly, the core network reserves unused resources for FNs based on the minimum resource requirement ratios of each FN in the network. Then, computing resources are autonomously allocated to FN considering their resource demand using a reinforcement learning (RL) based algorithm. As the objective is to reduce cost by minimising the maximum delay and energy consumption, the resource allocation problem can be formulated as follows:

$$\min_{f_{k_n}^{fog}, p_{k_n}^{com}} \max_{k_n \subset K_n} \Sigma_{k_n \subset K_n} cost_{k_n} \tag{3}$$

where the cost function is defined as the weighted sum of latency and energy consumption.

IV. Proposed Approach

To address the resource allocation problem, RL is proposed. Among several RL techniques, Q-learning requires low computational resources for its implementation and no knowledge of the model of the environment, thus being a fitting learning technique for the resource-constrained IoT devices. Furthermore, Q-learning has been used extensively to address resource allocation problems, thus being a suitable learning technique for the problem. Given the controlled system, the learning controller repeatedly observes the current state s, takes action a, and then a transition occurs, and it observes the new state s' and the reward r^t. From these observations, it can update its estimation of the Q-function for state s and action a.

State (s): The current system state $s(t)$ is determined by the state of the fog network. The system state at time slot t is defined as $s(v, U, R, e)$, where v is the overall allocated compute resource fraction, U is the average QoS utility, R is the average CPU utilisation and e is the overall CPU reservation for the FN. The proposed Q-learning model takes action at the node level, therefore the system level resource allocation of the F-RAN is aggregated as the overall resource allocation v_n

Reward (r): The reward r is defined as the sum of average QoS utility and average CPU utilisation of the FN.

$$r_n = \beta U_n + (1 - \beta) r_n, \forall n \tag{4}$$

Action (a): The actions are a set of discrete percentages $A = \{-90\%, -80\%, ..., 0, 10\%, ..., 90\%\}$, with a negative value indicating a decrease in the FN's resource and a positive value representing an increase.

V. Conclusion

In this paper, virtualised computing resource allocation in F-RAN using RL has been considered. The proposed method determines the estimated minimum resource requirement for each FN so FNs may independently partition their own resources to ensure that sensor data is processed while adhering to the maximum delay constraints. The proposed model will be evaluated and compared using a simulator.

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