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Computation of 5G Fog-Radio Access Network Resource Allocation Scheme Using Reinforcement Learning

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Abstract - *The fogging (Fog Computing) is to improve Efficiency and reduce the amount of data transported to the cloud for processing, analysis and storage. 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. The rapid development of wireless communication technology and smart devices has made the traditional cloud-based Internet of Things architecture unable to meet the stringent requirements of 5G mobile communication networks. In order to realize high-reliability and low-latency communication for 5G.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 virtualized storage and processing resources to constitute the fog RAN (F-RAN) F-RANs have become a potential evolution path. 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 optimize 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.*

***Key Words*: Fog computing, 5G RAN, Machine Learning, Reinforcement Learning**,

1. INTRODUCTION

Fog Computing, also known as fog networking, is a decentralized computing infrastructure in which computing resources and application services are distributed in the most logical, efficient place at any point along the continuum from the data source to the cloud. The goal of fog computing is to improve efficiency and reduce the amount of data that needs to be transported to the cloud for data processing, analysis and storage. This is often done for efficiency reasons, but it may also be carried out for security and compliance reasons.

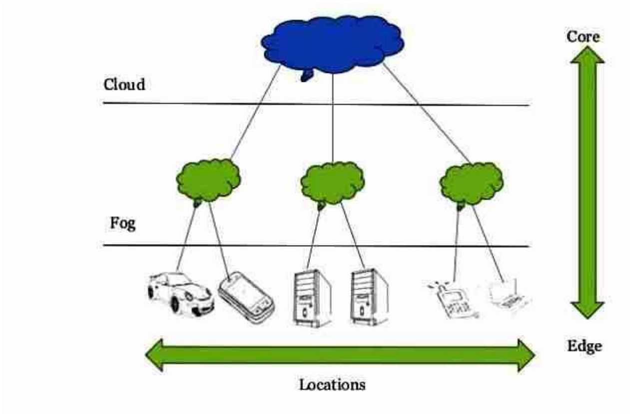

Fig -1: Fog Computing

Fog computing architecture is the arrangement of physical and logical network elements, hardware, and software to implement a useful IOT network. Key architectural decisions involve the physical and geographical positioning of fog nodes, their arrangement in a hierarchy, the numbers, types, topology, protocols, and data bandwidth capacities of the links between fog nodes, things, and the cloud, the hardware and software design of individual fog nodes, and how a complete IOT network is orchestrated and managed. In order to optimize the architecture of a fog network, one must first understand the critical requirements of the general use cases that will take advantage of fog and specific software application(s) that will run on them. Then these requirements must be mapped onto a partitioned network of appropriately designed fog nodes. Certain clusters of requirements are difficult to implement on networks built with heavy reliance on the cloud (intelligence at the top) or intelligent things (intelligence at the bottom), and are particularly influential in the decision to move to fog-based architectures. The Open Fog consortium, which is developing reference architecture, introduced three objectives of fog framework development. First, the fog environment must be horizontally scalable. This means that you will support multiple vertical industry use cases. Second, it must work across the continuum from cloud to things. Third, it must be a system-level technology that extends across the net-work protocol from the object through the network edge to the various network protocols

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]. The Open Fog Consortium, a group of research institutes and companies that support the standard development of fog technology, is committed to delivering "fog computing to the computing community". Fog computing creates a network connection with less delay between the device and the analysis endpoint. This reduces the amount of bandwidth required. The 5G mobile connection expected to be launched after 2018 is expected to spread more rapidly to fog computing. According to Andrew Anders, senior vice president of technology planning and network architecture at Century Link, 5G technology requires very dense antenna placement. The distance between the antennas should not exceed 20 km. In this case, by creating a fog computing architecture that includes a central control between the antenna points, it is possible to manage applications running on this 5G network and support connectivity to back-end data centers or the cloud. 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 virtualization (NFV) to extend the architecture of the traditional heterogeneous cloud radio access network (H-CRAN) as a means to overcome the front haul 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 virtualized 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 trans receiving, 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 coronet work among FNs. It is important to ensure that application shave 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 centralized 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 minimize 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.

1.1 REINFORCEMENT LEARNING

Reinforcement Learning (RL) is a branch of Machine Learning (and, in a broad spectrum, of Artificial Intelligence) that follows learning by interacting paradigm. As said in [7, 8, 9], in fact, an agent interacts with an environment performing some actions over it and then, sensing the response for each action, evaluates their consequences in terms of the immediate reward (or penalty) it receives from it. Since the agent does not initially know what effect its actions have on the representation state of the environment, nor what immediate payoffs its actions will produce, it's only by trying repeatedly all actions in all environment's states that t learns which are best to perform in terms of maximizing the cumulative reward over the long run. As underlined in [8], in case of deterministic effects of the actions, the agent is able to build a predictive model of the effects of its actions on the environment, to use for planning ahead by choosing alternative sequences of actions and achieve its goal in the better possible way. Despite in case of stochastic effects of the actions (performing an action may lead to one of several different possible states) to build that predictive model is difficult, by using RL algorithms an agent can learn an optimal policy without ever planning ahead, but simply basing only on the last action it took, the state when it chose that action, the payoff received, and the current state.

RL can find application in a lot of common tasks from scientific to economic interest problems, from industrial robot control to board games solver robots, and can also find expression not only in a single agent framework but also in a multi-agent framework, sharing with game theory the role of problem solver [9]. In that specific case, agents are peer entities and collaborate with each other through an intensive exchange of information and knowledge about the environment, vesting the role of teachers and learners at the same time. In the study-case of this thesis, a single-agent RL approach is used, focusing on system performance analysis as consequence of the superposition of many agents influence, but not on the cooperative aspect of their work. The scenario presented in this thesis finds his basis in the model theorized in the following paragraph from a computational point of view.

2. RELATED WORK

For the last several years, 5G and IoT related topics have been of great interest to many researchers in the wireless communications field. Recently, a good number of works in the literature focused on achieving low latency for IoT applications in 5G F-RAN. For instance, resource allocation based on cooperative edge computing has been studied in [11], [12] for achieving ultra-low latency in F-RAN. The work in proposed a mesh paradigm for edge computing, where the decision-making tasks are distributed among edge devices instead of utilizing the cloud server. The authors in [12] considered heterogeneous F-RAN structures including, small cells and macro base stations, and provided an algorithm for selecting the F-RAN nodes to serve with proper heterogeneous resource allocation. The number of F-RAN nodes and their locations has been investigated by [12]. Content fetching is used in to maximize the delivery rate when the requested content is available in the cache of fog access points. In cloud predicts users mobility patterns and determines the required resources for the requested contents by users, which are stored at cloud and small cells. The work in [11] addressed the issue of load balancing in fog computing and used fog clustering to improve users quality of experience. The congestion problem, when resource allocation is done based on the best signal quality received by the end user, is highlighted in [12], [13]. The work in [12] provided a solution to balance the resource allocation among remote radio heads by achieving an optimal downlink sum-rate, while [12] offered an optimal solution based on reinforcement learning to balance the load among evolved nodes for the arrival of machine-type communication devices. To reduce latency, soft resource reservation mechanism is proposed in for uplink scheduling. The authors of presented an algorithm that works with the smooth handover scheme and suggested scheduling policies to ease the user mobility challenge and reduce the application response time. Radio resource allocation strategies to optimize spectral efficiency and energy efficiency while maintaining a low latency in F-RAN are proposed in [11]. With regard to learning or IoT, [12] provided a comprehensive study about the advantages, limitations, applications, and key results relating to machine learning, sequential learning, and reinforcement Learning. Multi-agent reinforcement learning was exploited in [13] to maximize network resource utilization in heterogeneous networks by selecting the radio access technology and allocating resources for individual users. The model-free reinforcement learning approach is used in [12] to learn the optimal policy for user scheduling in heterogeneous networks to maximize the network energy efficiency. Resource allocation in non-orthogonal-multiple-access based F-RAN architecture with selective interference cancellation is investigated in to maximize the spectral efficiency while considering the co-channel interference. With the help of task scheduler, resource selector, and history analyzer, introduced an FN resource selection algorithm in which the selection and allocation of the best FN to execute an IoT task depends on the predicted run-time, where stored execution logs for historical performance data of FNs provide realistic estimation of it. Radio resource allocation for different network slices is exploited in to support various quality-of-service (QoS) requirements and minimize the queuing delay for low latency requests, in which network is logically partitioned into a high-transmission-rate slice which supports ultra-reliable low-latency communication (URLLC) applications, and a low-latency slice for mobile broadband (MBB) applications.

3. PROPOSED SYSTEM

With the motivation of satisfying the low-latency requirements of heterogeneous IoT applications through F-RAN, we provide a novel framework for allocating limited resources to users that guarantees efficient utilization of the FN's limited resources. In this work, we develop Markov Decision Process (MDP) formulation for the considered resource allocation problem and employ diverse Reinforcement Learning (RL) methods for learning optimum decision-making policies adaptive to the IoT environment. Specifically, in this paper we propose an MDP formulation for the considered F-RAN resource allocation problem, and This paper anticipates bringing the following specific major Contributions:

A two-level framework for compute power virtualization 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.

The resource allocation problem in 5G F-RAN is formulated as a multi-objective Markov Decision Process to optimize latency, energy consumption and cost in massive Machine Type Communications (mMTC) applications for 5G networks.

A reinforcement learning-based algorithm for dynamic resource management of virtualized 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 utilization of their users.

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 $_{kn}$ 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

$J_{kn} = \{D_{kn}, app_{kn}, T_{kn}^{max}\}$

, where Dkn denotes the size of sensor data (in bits), app_{kn} is the minimum processing density (in CPU cycles/bit), and T max_{kn} is the maximum tolerable latency (in seconds). The number of CPU cycles necessary to process the data is modeled as $C_{kn} = D_{kn}\, app_{kn}$.

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:

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

where f^{fog}_{kn} denotes the fractional resources (in CPU cycles/s) allocated to sensor k of FN $_n$, p^{com}_{kn} is the transmission power of sensor, p^{id}_{kn} is the power consumption in idle mode and r_{kn} 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_{kn} is offloaded to the cloud server, then kn first transmits the data of side D_{kn} through a wireless link to the FN, which then forwards J_{kn}
to the cloud server through a high-speed wired link. The data rate of the wired link is denoted as R^{fc}_{kn} (in bits/s), and the cloud processing capability as f^{c}_{kn} (in CPU cycles/s). The delay in wired transmission is given by $T^{fc}_{kn}= D_{kn} /R^{fc}_{kn}$ and the delay in cloud processing is given by $T^{c}_{kn} = C_{kn}/f^{c}_{kn}$..

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 minimizing the maximum delay and energy consumption, the resource allocation problem can be formulated as follows:

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

where the cost function is defined as the weighted sum of latency and energy consumption. 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. Further More, 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^l 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 utilization 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 utilization of the FN.

$r_n = \beta U_n + (1 - \beta) r_n , \forall_n$

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.

4. CONCLUSIONS

A fog computing based radio access network (F-RAN) is Presented in this paper as a promising paradigm for the fifth generation (5G) wireless communication system to provide high spectral and energy efficiency. 5G will bring faster data speeds, low latency communications, and higher data caps for mobile devices. Major sports networks are already using 5G micro-networks to film and stream sporting events live, completely wirelessly. In this paper, virtualized 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 re-sources 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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BIOGRAPHIES

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