

# Resource Allocation for Ultra-reliable and Enhanced Mobile Broadband IoT Applications in Fog Network

Sarder Fakhru Abedin, Md. Golam Rabiul Alam, *Member, IEEE*, S. M. Ahsan Kazmi, Nguyen H. Tran, *Member, IEEE*, Dusit Niyato, *Fellow, IEEE*, and Choong Seon Hong, *Senior Member, IEEE*

**Abstract**—In recent years, in order to provide a better quality of service (QoS) to IoT devices, the cloud computing paradigm has shifted towards the edge. However, the resource capacity (e.g. bandwidth) in Fog network is limited and it is essential to efficiently bind the IoT applications with stringent QoS requirements with the available network infrastructure. In this paper, we formulate a joint user association and resource allocation problem in the downlink of the Fog Network considering the evergrowing demand of QoS requirements imposed by the Ultra-Reliable Low Latency Communications (URLLC) and enhanced Mobile Broadband (eMBB) services. First, we determine the priority of different QoS requirements of heterogeneous IoT applications at the Fog Network by enforcing the analytical framework using an analytic hierarchy process (AHP). Using the AHP, we then formulate a two-sided matching game to initiate stable association between the Fog Network infrastructure (i.e., Fog devices) and IoT devices. Subsequently, we consider the externalities in the matching game which occurs due to job delay and solve the network resource allocation problem by applying the best-fit resource allocation strategy during matching. The simulation results illustrate the stability of the user association and efficiency of resource allocation with higher utility gain.

**Index Terms**—Fog computing, Internet of Things (IoT), Ultra-Reliable Low Latency Communications (URLLC), enhanced Mobile Broadband (eMBB), Resource allocation.

## I. INTRODUCTION

The emerging Fog Network technology is considered to be indispensable for IoT devices providing a wide variety of inherent features such as low latency, location awareness, mobility and wireless access capability unlike its predecessor cloud [1]. In fact, gateway devices are most commonly considered as parts of the Fog Network infrastructure (e.g., Fog) because of their vicinity to IoT devices. With some computational and storage capabilities combined with the connectivity functions, the Fog devices seamlessly associate with the IoT devices to provide a cloud like reinforcement

Sarder Fakhru Abedin, Md. Golam Rabiul Alam, S. M. Ahsan Kazmi, and Choong Seon Hong are with the Department of Computer Science and Engineering, Kyung Hee University, South Korea (E-mail: saab0015@khu.ac.kr, robi@khu.ac.kr, ahsankazmi@khu.ac.kr, cshong@khu.ac.kr).

Nguyen H. Tran is with the School of Information Technologies, The University of Sydney, Sydney, NSW 2006, Australia, and also with the Department of Computer Science and Engineering, Kyung Hee University, Global Campus, South Korea (E-mail: nguyen.tran@sydney.edu.au)

D. Niyato is with the School of Computer Engineering, Nanyang Technological University, Singapore, and visiting research scientist, Kyung Hee University, South Korea (E-mail: dniyato@ntu.edu.sg).

to the IoT applications at the edge. In both IoT and the Fog Network, one core objective is to provide the quality of service (QoS) to the end users, which can be achieved by efficiently allocating the limited network resources to heterogeneous IoT applications and services. Therefore, the end users use the licensed or unlicensed spectrum, depending on the availability of the network resources and heterogeneous network interfaces for a wide variety of IoT applications [2]. As the number of heterogeneous IoT devices is increasing exponentially, the amount of real-time and non-real-time IoT traffic with multiple QoS requirements is also rapidly increasing. The typical QoS requirements of the Internet traffic of heterogeneous applications are depicted in Table I. Yet in IoT, any newly discovered IoT devices in the environment may necessitate entirely new IoT applications that require different resource requests and rapid resource deployment [3]. As a result, the priority of the QoS parameters in Table I is diverse.

TABLE I: Typical QoS requirements of Internet traffic [4]

Applications	Delay (s)	Throughput (Mbit/s)	BER
RT Data	0.001 ~ 1	< 10	0
Image	1	$2^{-10}$	$10^{-4}$
Audio	0.25	0.064	$< 10^{-1}$
Video	0.25	100	$10^{-2}$

In that case, the resource allocation has to be mapped to a particular IoT application, depending on the application type, resource demand, and service priority [5]. For example, the Ultra-Reliable Low Latency Communications (URLLC) service type [6] applications have high requirement of a tolerable bit error rate (BER) followed by ensuring an acceptable data delay [7]. In contrast, the enhanced Mobile Broadband (eMBB) service type [8] applications in Fog network generating real time IoT traffics [9] may have more stringent requirement on the bandwidth requirement than that of timeliness and error free communication [10].

Most of the traditional distributed and centralized resource allocation schemes for IoT mainly focus on the IoT service or task provisioning [11], [12] rather than considering the user and channel state information, and the priority of the application specific QoS parameters. As a result, QoS management for heterogeneous IoT applications is still an open issue and is not well-investigated. In a typical cellular network, the optimization [13] and game theoretic [14] resource allo-

cation and QoS management approaches are often subjected to different application specific QoS parameters. However, in IoT, it is essential to consider not only application specific QoS parameters, but also the prioritization of QoS parameters along with environmental variations such as *externalities*, [15] while allocating the application specific network resources.

Under the above circumstances, in this paper we propose a joint user association and resource allocation scheme that not only evaluates the application specific QoS requirements, but also considers the priority of the QoS parameters. Furthermore, we consider the network-wide stability during self-organizing user association and resource allocation for IoT applications in a dynamic Fog Network environment. In essence, the main contributions of this paper are as follows:

- We formulate a joint user association and resource allocation problem in the downlink of the Fog Network with QoS constraints, and we show that the centralized optimization for this problem is NP-hard. Therefore, we provide an analytical framework *AHP (Analytic Hierarchy Process)* to decompose the complex QoS management problem into manageable and tractable hierarchical sub-problems to prioritize the QoS parameters and requirements of the eMBB and URLLC service type IoT applications.
- We formulate a *two-sided matching game* to initiate the user association followed by resource allocation between the Fog Network infrastructures (i.e., Fog devices) and the IoT devices. Furthermore, the AHP based analytical framework provides a qualitative QoS evaluation that significantly enhances the performance of the matching outcome by prioritizing the application specific QoS parameters while creating the preference order of the players. We also applied the “*best-fit*” network resource allocation strategy for the matching to ensure stability in user association, which deals the externalities in the *one-to-many* matching game.
- We perform extensive numerical analysis to evaluate the performance of the proposed approach. The results show that the integrated AHP and matching game approach for QoS aware joint user association and resource allocation achieves higher utility gain for the users. In addition, the efficiency of the “*best-fit*” resource allocation strategy in the matching game outperforms the traditional matching and AHP based approach. The results also demonstrate the stability of the association between the IoT and Fog devices in the case of a dynamic and scalable network.

The remainder of the paper is organized as follows. In Section II, we present an extensive literature review based on the current research. In Section III, we present the network model and problem formulation. Section IV explains in detail how we solve the proposed optimization problem with AHP and matching theory and deal with the externalities by applying the “*best-fit*” resource allocation strategy during matching. In Section V, we present the numerical analysis to validate the performance and efficiency of our proposed approach user association and resource allocation. Finally, in Section VI we

conclude the discussion.

## II. RELATED WORKS

A number of studies have proposed new mathematical models, including optimization theory [16], game theory [17], machine learning [18] and an analytic hierarchy process (AHP) [19], to capture the user perceived QoS for enabling network performance analytics [20], [21] for network resource allocation. In order to solve the network resource allocation problem, in [22], the authors proposed a solution to the problem of assigning services with heterogeneous and noninterchangeable resource demands to the multiple network interfaces of an IoT device. However, the convergence rates of the optimization-based resource allocation approaches are slow and unsuitable for dense large scale network [23]. In fact, this may cause instability in the network, as the number of IoT devices in the network may increase or decrease over time.

In [24], the authors proposed AHP to managing resources in a large-scale heterogeneous wireless network that supports reconfigurable devices. In [25], the authors considered user centric requirements (such as bandwidth) and network centric concerns (such as load balancing and designed utility functions) to precisely quantify the relationship between the QoE and these attributes, and the preference weights are calculated by AHP. In [26], the authors focus on considering the impact of installing remotely controlled switches in the reliability indices as well as the AHP decision making algorithm for the switch allocation. However, the AHP based decision making is unable to address the effects of the preference correlation on the outcomes generated by applications that require two-sided joint decision making, where the preferences of both sides are equally important.

In [27], the authors proposed a reinforcement learning based code offloading mechanism in Fog network to ensure low-latency service delivery towards mobile service consumers. In [28], the authors proposed ThinkAir, which uses dynamic adaptation and dynamic scaling of computational power in the mobile cloud computing. The advantage of applying a reinforcement learning algorithm like Q-learning is that it can converge to the optimal value in the case of discrete problems. However, the approach is more suitable for a closed environment and becomes infeasible if the state space is too large.

The user perceived quality of the network performance should be analyzed for different QoS requirements imposed by the user centric IoT application and services at the edge of the network or Fog radio access network (F-RAN) [29]. The traditional game theoretic approaches are widely adopted in both the existing cellular and F-RAN architecture for resource allocation where the IoT devices are likely to be deployed [30] [31] [32]. However, the problem of using conventional game theoretic approaches in IoT is that, in most of the cases, the external effects and the application specific QoS priorities of the IoT devices are overlooked during two-sided decision making for the network resource allocation. Therefore, the

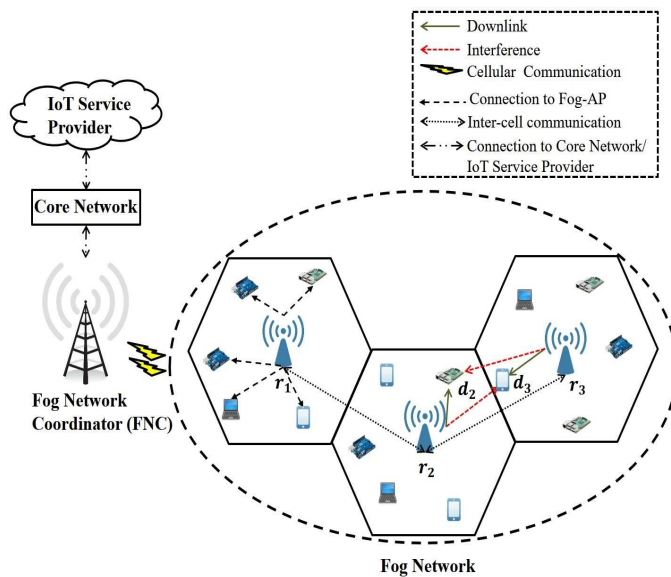


Fig. 1: Fog Network Model

stability of the matching game is not guaranteed in a dynamic IoT environment.

In the next section, the problem formulation for the joint user association and resource allocation in the Fog network model is presented in detail.

### III. NETWORK MODEL AND PROBLEM FORMULATION

#### A. Network Model

One of the fundamental challenges for Fog devices in existing cellular networks is the user association where the Fog devices and IoT devices have different sizes, capacities and capabilities [33]. In Fig. 1, let us consider a set of Fog devices  $\mathcal{R} = \{1, \dots, R\}$  where each device has a corresponding set of subchannels  $\mathcal{K} = \{1, \dots, K\}$  with a fixed bandwidth of  $b_{d,r}^k$  and these devices are statically deployed, e.g., the Fog access point (F-AP). There is also a set of IoT devices  $\mathcal{D} = \{1, \dots, D\}$  with  $\mathcal{M} = \{1, \dots, M\}$  QoS parameters deployed at the Fog Network, e.g., smart-phones, tablets, customer premises equipment (CPE). Unlike static Fog devices, IoT devices can dynamically join or leave the Fog Network environment. In addition, the service providers provide different generic types of services  $\mathcal{S} = \{1, \dots, S\}$  to the IoT devices in the Fog Network. The weights of different QoS parameters are represented as a vector  $\vec{w}_{s,m}^d$  where each entry is the respective weight of the service type specific QoS parameter. In this scenario, we assume the Fog Network Coordinator (FNC) acts as a mediator between the IoT service providers at the remote cloud and the edge level IoT devices. In this paper, we consider  $s \in \mathcal{S}$  to represent two major service types or categories such as enhanced Mobile Broadband (eMBB) and Ultra-Reliable Low Latency Communications (URLLC) where there can be many IoT application classes [34]. Additionally, the weights of different QoS requirements vary from one service type to another. For example, in eMBB services,

the core priority is to ensure high data rate or throughput whereas in URLLC the core priority is to ensure acceptable delay and bit error rate (BER) requirements. An FNC located in a particular geographic area is able to coordinate with multiple service types simultaneously. In the network model, we assume that the IoT devices are capable of executing IoT applications and the Fog devices are serving as gateways to reach the IoT service provider in the cloud. Therefore, the IoT devices associate with the Fog devices in the Fog Network to communicate with the IoT service or content providers through the FNC and core network. In such a case, the IoT devices use the limited network resources provided by the Fog devices to ensure proper channel coding and to receive the content from the remote IoT service providers. Both the Fog Network infrastructures and IoT devices distributively handle the QoS management tasks including analyzing and prioritizing the QoS requirements or parameters of the heterogeneous IoT applications provided by different service providers. Therefore, the Fog devices perform the context-aware user association for application specific network resource allocation. In addition, the Fog devices publish their resource information to the FNC so that only the subscribed and authorized IoT devices can localize and access the Fog devices.

1) *Bandwidth allocation*: Each Fog device  $r \in \mathcal{R}$  can serve multiple IoT devices  $d \in \mathcal{D}$  based on the available statistical channel state information (CSI), e.g., signal-to-interference-plus-noise ratio (SINR), line of sight component [35]. In addition, we denote by,  $\mathcal{A}_r$  the set of IoT devices that are associated with Fog device  $r \in \mathcal{R}$ . Thus, the transmission capacity between each Fog device  $r \in \mathcal{R}$  with subchannel  $k \in \mathcal{K}$  and each IoT device  $d \in \mathcal{A}_r$  is,

$$\beta_{d,r}^k(b_{d,r}^k) = b_{d,r}^k \log(1 + \psi_{d,r}^k). \quad (1)$$

In (1),  $\beta_{d,r}^k$  represents the allocated bandwidth for IoT device  $d \in \mathcal{A}_r$  that uses subchannel  $k \in \mathcal{K}$  of Fog device  $r \in \mathcal{R}$  where  $b_{max}^r = \sum_{k \in \mathcal{K}} b_{d,r}^k$  is the maximum bandwidth of the channel of  $r \in \mathcal{R}$ .  $\psi_{d,r}^k = \frac{e_{d,r}^k \kappa_{d,r}^k}{\sigma^2 + I_{d,r}}$  is the SINR when the Fog device  $r \in \mathcal{R}$  allocates its subchannel  $k \in \mathcal{K}$  to IoT device  $d \in \mathcal{D}$ . Here,  $e_{d,r}^k$  is the transmission power and  $\kappa_{d,r}^k$  is the channel gain between each Fog device  $r \in \mathcal{R}$  and the associated IoT device  $d \in \mathcal{A}_r$ . The variance of the Additive white Gaussian noise (AWGN) is denoted as  $\sigma^2$  and  $I_{d,r}$  denotes the channel interference. In our scenario, the interference  $I_{d,r} = \sum_{r' \neq r} e_{d,r'}^k \kappa_{d,r'}^k$ ,  $r' \in \mathcal{R} \setminus \{r\}$  where the transmission between Fog device  $r'$  and its respective IoT device  $d' \in \mathcal{A}_{r'}$  use the same subchannels of  $\beta_{d,r}^k$ . The transmission power and channel gain are denoted as  $e_{d,r'}^k$  and  $\kappa_{d,r'}^k$  between Fog device  $r'$  and IoT device  $d$ .

2) *Job delay*: As each Fog device  $r \in \mathcal{R}$  sends job requests to multiple associated IoT devices  $d \in \mathcal{A}_r$ , the data packet transmission process at each Fog device is modeled as an  $M/M/1$  queuing system [36] where the mean arrival traffic rate is given by  $\lambda_r$  (packets/sec) at each  $r \in \mathcal{R}$  and the packet transmission rate or service rate of the queue is  $\mu_r$  (packets/sec) with mean packet size  $N_{avg}$ . The aggregated traffic in each Fog device is,  $\lambda_r = \sum_{d \in \mathcal{A}_r} \lambda_{d,r}$ .

The packet transmission times are exponentially distributed with mean  $\frac{1}{\mu_r}$  (secs/packet) where we assume the slow fading channels. For the stability of the system, we consider the utilization of the queue is  $\frac{\lambda_r}{\mu_r} < 1$ . The mean job delay for the aggregated traffic of  $d \in \mathcal{A}_r$  including the queuing delay and transmission delay is,

$$\varphi_{d,r} = \frac{N_{avg}}{\beta_{d,r}^k(b_{d,r}^k)} + \frac{\lambda_r}{(\mu_r - \lambda_r)}. \quad (2)$$

In (2), we consider the transmission delay and queuing delay as job delay to evaluate the performance of each association between  $r \in \mathcal{R}$  and  $d \in \mathcal{A}_r$ . Furthermore, the queuing delay depends on the congestion level of  $r \in \mathcal{R}$  and the transmission delay depends on the amount of time to send  $N_{avg}$  bits into the link, where the transmission rate is  $\beta_{d,r}^k(b_{d,r}^k)$ .

3) *Bit Error Rate (BER) calculation:* The transmitted data between the associated IoT device  $d \in \mathcal{A}_r$  and Fog device  $r \in \mathcal{R}$  could be corrupted even if the interference  $I_{d,r}$  is trivial. The performance of the modulation can be expressed as  $\frac{\beta_{d,r}^k}{b_{d,r}^k}$  (bits/HZ) from (1) which represents the spectral efficiency. Thus, the BER can be calculated as [37],

$$\nu_{d,r} = \begin{cases} 0.2 \times e^{\frac{-1.6 \times \frac{e_{d,r}^k}{\sigma + I_{d,r}}}{\log(h)-1}}, & \text{if } \frac{e_{d,r}^k}{\sigma + I_{d,r}} \geq \Upsilon_r \\ 1, & \text{otherwise.} \end{cases} \quad (3)$$

In (3),  $\frac{e_{d,r}^k}{\sigma}$  is the energy per bit to noise power spectral density ratio with considering interference  $I_{d,r}$ ,  $\Upsilon_r$  is the threshold for correct modulation, and  $h$  is the given modulation index.

4) *QoS aware utility function:* Each Fog device  $r \in \mathcal{R}$  allocates the downlink bandwidth  $b_{d,r}^k$  to its associated IoT devices  $d \in \mathcal{A}_r$ . Thus, the QoS aware utility function for the association between each Fog device  $r \in \mathcal{R}$  and each of the associated device  $d \in \mathcal{A}_r$  at subchannel  $k$  is calculated by the following QoS based utility function,

$$U_{d,r}^k(b_{d,r}^k, w_{s,m}^d) = \frac{w_{s,m_1}^d \cdot \beta_{d,r}^k(b_{d,r}^k) \cdot w_{s,m_2}^d (1 - \nu_{d,r})}{w_{s,m_3}^d \varphi_{d,r}}. \quad (4)$$

The utility function in (4) effectively captures the throughput, job delay and BER that Fog devices  $r \in \mathcal{R}$  can deliver to the associated IoT devices  $d \in \mathcal{A}_r$ , given the SINR. In addition,  $w_{s,m_1}^d$ ,  $w_{s,m_2}^d$ , and  $w_{s,m_3}^d$  are the corresponding weight values of the throughput, BER and job delay for the service type  $s \in \mathcal{S}$ . Unlike the conventional cellular network, in Fog, the IoT devices  $d \in \mathcal{D}$  are part of different IoT service platform. Therefore, the utility function in (4) effectively captures the service types and weights of individual QoS parameters set by different IoT service providers. In later section we will provide an analytical framework for the IoT service providers so that the service specific weights of the QoS parameters of different service types can be calculated efficiently.

### B. Problem formulation

The goal of the resource allocation in the network is to maximize the aggregated utility of the joint association and

resource allocation subject to the QoS requirements imposed by the IoT devices. Therefore, the problem is formulated as,

$$\text{maximize}_{\Phi_{d,k}, \delta_{d,r}} \sum_{r \in \mathcal{R}} \sum_{d \in \mathcal{D}} \sum_{k \in \mathcal{K}} \Phi_{d,k} \delta_{d,r} U_{d,r}^k(b_{d,r}^k, w_{s,m}^d) \quad (5)$$

s.t.

$$\sum_{d \in \mathcal{D}} \sum_{k \in \mathcal{K}} \Phi_{d,k} \delta_{d,r} b_{d,r}^k \leq b_{max}^r, r \in \mathcal{R} \quad (6)$$

$$\Phi_{d,k} \delta_{d,r} \beta_{d,r}^k(b_{d,r}^k) \geq \beta_{sla}^d, \forall d \in \mathcal{D}, r \in \mathcal{R}, k \in \mathcal{K} \quad (7)$$

$$\Phi_{d,k} \sum_{m \in \mathcal{M}} w_{s,m}^d \leq 1, \forall d \in \mathcal{D}, k \in \mathcal{K} \quad (8)$$

$$\varphi_{d,r}(\delta_{d,r}) \leq \varphi_{sla}^d, \forall d \in \mathcal{D}, r \in \mathcal{R} \quad (9)$$

$$\nu_{d,r}(\delta_{d,r}) \leq \nu_{sla}^d, \forall d \in \mathcal{D}, r \in \mathcal{R} \quad (10)$$

$$\sum_{k \in \mathcal{K}} \Phi_{d,k} \leq 1, \forall d \in \mathcal{D} \quad (11)$$

$$\sum_{d \in \mathcal{D}} \delta_{d,r} \leq q_r, \forall r \in \mathcal{R} \quad (12)$$

$$\sum_{r \in \mathcal{R}} \delta_{d,r} \leq 1, \forall d \in \mathcal{D}. \quad (13)$$

In general, the constraints in (7)-(10) address the contextual information for the QoS aware association and allocation between each Fog device  $r \in \mathcal{R}$  and associated IoT devices in  $d \in \mathcal{D}$ . In the constraint (11),  $\Phi_{d,k}$  is the binary indicator variable such that,

$$\Phi_{d,k} = \begin{cases} 1, & \text{if } d \text{ is assigned to subchannel } k \\ 0, & \text{otherwise.} \end{cases} \quad (14)$$

In (14),  $\Phi_{d,k} = 1$  indicates that an IoT device  $d \in \mathcal{D}$  is assigned to the subchannel  $k$  of Fog device  $r \in \mathcal{R}$  and  $\Phi_{d,k} = 0$  otherwise. In (13),  $\delta_{d,r}$  is the binary indicator variable defined as follows,

$$\delta_{d,r} = \begin{cases} 1, & \text{if } d \text{ is associated with } r \\ 0, & \text{otherwise.} \end{cases} \quad (15)$$

In (15),  $\delta_{d,r} = 1$  indicates that an IoT device  $d \in \mathcal{D}$  is assigned to the Fog device  $r$ ; otherwise,  $\delta_{d,r} = 0$ . The constraint in (12) indicates that each Fog device  $r$  can be associated with a limited number of IoT devices  $d \in \mathcal{D}$  and  $q_r$  is the quota value, which is equal to the number of subchannels of Fog device  $r$ . In (13), the constraint indicates each of IoT device  $d \in \mathcal{D}$  can be associated with only one Fog device  $r \in \mathcal{R}$ . The first two constraints (7) and (6) address the network resource allocation for the application running in the IoT devices. The constraint in (6) is the bandwidth capacity  $b_{d,r}^k$  of the associated Fog device  $r \in \mathcal{R}$  when the assigned subchannel is  $k \in \mathcal{K}$  and  $b_{max}^r$  is the maximum bandwidth of the fog devices  $r \in \mathcal{R}$ . In (7), the capacity (throughput)  $\beta_{d,r}^k$  is an allocation vector with feasible allocations based on

the subchannel bandwidth  $b_{d,r}^k$  via Fog device  $r \in \mathcal{R}$  while assigning subchannel  $k \in \mathcal{K}$ , and  $\beta_{sla}^d$  is the minimum QoS requirement imposed by IoT device  $d \in \mathcal{A}_r$ .

In (9) the delay constraint is shown where the job delay is a function of  $\delta_{d,r}$ , indicating the job delay is calculated once there is an association between  $d \in \mathcal{D}$  and  $r \in \mathcal{R}$ . The delay constraint between each Fog device  $r \in \mathcal{R}$  and associated IoT device  $d \in \mathcal{D}$  is calculated as  $\varphi_{d,r}(\delta_{d,r})$ , which is less than or equal to the maximum delay  $\varphi_{sla}^d$  that a particular application running at the IoT device  $d \in \mathcal{D}$  can tolerate. The constraint in (10) accounts for the BER constraint once there is an association between  $d \in \mathcal{D}$  and  $r \in \mathcal{R}$ . The BER  $\nu_{d,r}(\delta_{d,r})$  of the association  $\delta_{d,r}$  should be less than the maximum BER  $\nu_{sla}^d$  as per the application requirement imposed by each  $d \in \mathcal{D}$ . In (8), when  $\Phi_{d,k} = 1$ , the summation of the  $\mathcal{M}$  weight factors for each QoS parameters under the service type  $s \in \mathcal{S}$  is not more than 1. Therefore, individual weights of the QoS parameters (6), (7), (9) and (10) are set for the eMBB and URLLC service types  $s \in \mathcal{S}$  which should be greater than or equal to zero. In addition, for any valid allocation under the QoS constraints in (6)-(13), the objective function in (5) is effectively maximized for the association between different IoT devices belonging to either eMBB or URLLC service types and the corresponding Fog devices where the weights of individual QoS parameters are set by different service providers.

The decision problem in (5) can be reduced to a base problem of 0/1 multiple-knapsack problem [38] with the corresponding constraints in (6)-(13), which is NP-Complete [39]. Similar to the 0/1 multiple-knapsack problem, the combinatorial nature of the problem in (5) leads to find all the feasible associations and allocations where the complexity of the problem is  $\mathcal{O}(2^{D \times R \times K})$  which grows exponentially depending on the number of IoT devices, Fog devices, and subchannels in the corresponding sets in order to maximize the network utility. In fact, there is no known polynomial algorithm which can tell, given a solution of (5), whether it is optimal. As a result, we can infer that the decision problem in (5) belongs to the same category of the problem of multiple-knapsack problem which is proven to be NP-hard [40]. Therefore, in the next section we solve the problem in (5) by adopting the AHP based matching game approach for resource allocation between the Fog devices in  $\mathcal{R}$  and IoT devices in  $\mathcal{D}$ .

#### IV. QoS AWARE RESOURCE ALLOCATION VIA AHP AND MATCHING THEORY

In this section, first we devise an analytical framework using AHP in order to qualitatively stratify the decision factors (e.g., throughput, BER, and delay) followed by learning the local and global weights for the decision factors and the IoT devices, respectively. Second, we formulate a matching game to solve the problem in (5), where the preferences of the players are created using AHP based qualitative evaluation. Finally, we apply the “best-fit” resource allocation (RA) strategy with the proposed matching game to deal with the *externalities* such

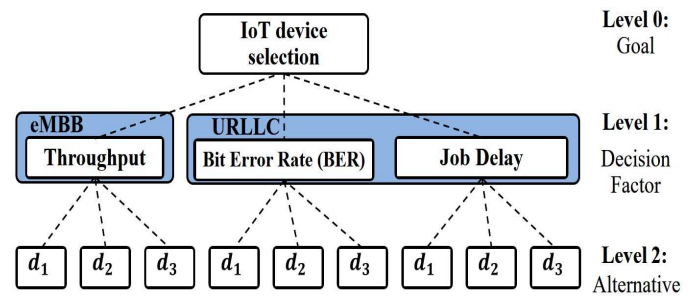


Fig. 2: AHP hierarchy for the candidate IoT devices

TABLE II: Pair-wise comparison scale

Relative importance	Description
1	Equally preferred
3	Moderately preferred
5	Strongly preferred
7	Very strongly preferred
9	Absolutely preferred
2, 4, 6, 8	Intermediate preference values between adjacent scale values
Reciprocals of above factors $i$	if $P_{i,j} = i$ then $P_{j,i} = \frac{1}{P_{i,j}}$

as “peer-effects”. The detailed discussion on the AHP and matching game with externalities is explained later in this section.

##### A. Hierarchical Stratification via AHP

In Fig. 2, the multiple criteria decision-making method, AHP, decomposes the complex QoS management problem into tractable hierarchical sub-problems.

In level 0, the goal of the AHP is the selection of candidate IoT devices. Level 1 of the hierarchy is comprised of the QoS criteria, which are considered as decision factors. The priorities of the decision factors vary from one service type to another. Last, the bottom level 2 of the hierarchy evaluates the alternative candidate IoT devices based on the evaluation of the decision factors performed in level 1.

The QoS requirements of the IoT devices are considered to be a QoS matrix  $\mathbf{Q} \in R^{d \times m}$  where each entry  $q_{d,m}$  represents the minimum QoS requirements imposed by  $d \in \mathcal{D}$ . The pairwise comparison of the candidate IoT devices is based on  $M$  QoS criteria or decision factors. Therefore, each of the factors has a weight as per the relative importance to the candidate selection problem. We assume that subjective judgments as per Table II are based on the decision factors and enforced by the service provider considering the service specific QoS requirements. There are several judgment scales that have been proposed for different decision problems [41]. However, in our proposed decision making problem, we use the linear scale since this is considered as the best scale to represent the weight ratios between the decision factors [42]. Based on our proposed multi-criteria decision problem, the AHP model can be explained through the following three steps.

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**Algorithm 1:** Pair-wise comparison matrix creation at FNC

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**Input:**  $\mathcal{D}, \mathcal{S}, \mathbf{P} \in R^{m \times m}, \mathbf{Q} \in R^{d \times m}, \vec{t}_r, \rho \leftarrow 0.1$   
**Result:**  $\mathbf{W}^r \in R^{d \times m}$

- 1 **Initialize:**  $\bar{\mathbf{P}} \in R^{m \times m}, \bar{m},$
- 2 **repeat**
- 3   **foreach**  $d \in \mathcal{D}$  **do**
- 4     **while**  $j \neq m$  **do**
- 5        $\bar{m}[j] \leftarrow \sum_{i=1}^m \mathbf{P}[i][j]$
- 6       **foreach**  $i$  in the  $j^{\text{th}}$  column of  $\mathbf{P}$  **do**
- 7           $\bar{\mathbf{P}}[i][j] \leftarrow \frac{\mathbf{P}[i][j]}{\bar{m}[j]}$
- 8           $j \leftarrow j + 1$
- 9        $\vec{w}_{s,m}^d \leftarrow \frac{1}{m} \sum_j \sum_i \bar{\mathbf{P}}[i][j]$
- 10      Update  $CR$  using (16) and (17)
- 11       $\mathbf{W}^r \leftarrow \mathbf{W}^r \cup \vec{w}_{s,m}^d$
- 12 **until**  $CR \leq \rho;$

---

1) *Step 1: Pairwise comparison for Level 1:* Each  $d \in \mathcal{D}$  corresponds to a pairwise comparison matrix  $\mathbf{P} \in R^{m \times m}$  which is also a reciprocal matrix based on the subjective judgment of the QoS parameters or decision factors provided by different service providers considering different service types. The IoT service provider uses the pair-wise comparison scale to create the pair-wise comparison matrix  $\mathbf{P}$  as shown in Table II, and then sends this matrix to the FNC for further qualitative analysis. Each entry  $m_{ij}$  in the pair-wise attribute comparison matrix  $\mathbf{P}$  represents the relative importance between the QoS attributes  $i$  and  $j$ , corresponding to the row and column respectively (lines 3-5 in Alg. 1). Then,  $\mathbf{P}$  is column-wise normalized as  $\bar{\mathbf{P}} \in R^{m \times m}$  and each entry of  $\bar{\mathbf{P}}$  represents the normalized relative weight (lines 6-8 in Alg. 1). Afterwards, the weight vector  $\vec{w}_{s,m}^d$  is calculated by averaging the rows of  $\bar{\mathbf{P}}$ , where  $\vec{w}_{s,m}^d = \{\bar{m}_1, \bar{m}_2, \bar{m}_3\}^T = \{m_{delay}, m_{BER}, m_{datarate}\}^T, \forall d \in \mathcal{D}, \forall s \in \mathcal{S}$  (line 11 in Alg.1). The weight vector  $\vec{w}_{s,m}^d$  is the normalized principle eigen vector, which represents the local weights of each QoS attribute in level 1 and is then added to the local weight matrix  $\mathbf{W}^r \in R^{d \times m}$  of  $r \in \mathcal{R}$  (line 9 in Alg. 1). Since the comparison matrix  $\mathbf{P}$  is based on the relative importance among the QoS criteria or decision factors, the logic of preference should satisfy the transitive property. Therefore, the consistency of matrix  $\mathbf{P}$  is checked through the consistency index  $CI$  [43], which represents the deviation of consistency as (line 12 in Alg. 1),

$$CI = \frac{\lambda_{max} - n}{n - 1}. \quad (16)$$

In (16),  $n$  is the dimension of the square matrix  $\mathbf{P}$ , and  $\lambda_{max}$  is the principle eigenvalue of  $\mathbf{P}$ , which is calculated through the summation of products between each entry of the weight vector  $\vec{w}_d^r$  and the sum of the columns of the pair-wise attribute comparison matrix  $\mathbf{P}$ . If the value of  $CI$  is relatively large, the inconsistency of the preferences in  $\mathbf{P}$  becomes more significant [44]. By using the consistency index

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**Algorithm 2:** Global weight vector at each Fog devices

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**Input:**  $\mathcal{D}, \mathcal{M}, \mathbf{Q} \in R^{d \times m}, \mathbf{W}^r \in R^{d \times m}$   
**Result:**  $\vec{w}_g^r$

- 1 **Initialize:**  $\bar{\mathbf{Q}} \in R^{d \times m}, \mathbf{A} \in R^{d \times m}$
- 2 Normalize  $\mathbf{Q}$  as  $\bar{\mathbf{Q}}$
- 3 **for**  $i \in \mathcal{D}$  **do**
- 4   **foreach**  $j^{\text{th}}$  factor in the  $i^{\text{th}}$  candidate in  $\bar{\mathbf{Q}}$  **do**
- 5      $\mathbf{A}[i][j] = \mathbf{W}^r[i][j] \cdot \bar{\mathbf{Q}}[i][j]$
- 6    $\vec{w}_g^r \leftarrow \sum_{i=1}^D \sum_{j=1}^M \mathbf{A}[i][j]$

---

$CI$ , the consistency ratio  $CR$  is calculated as,

$$CR = \frac{CI}{RI}. \quad (17)$$

In (17),  $RI$  is the Random Consistency Index (RCI) and the inconsistency of the matrix is acceptable if  $CR$  is less than or equal to  $\rho = 0.1$ , otherwise the subjective judgment is revised for the consistency by modifying  $\mathbf{P}$  (line 10 in Alg. 1). Finally the FNC disseminates the context information in step 1, including  $\mathbf{W}^r$  and  $\mathbf{Q} \in R^{d \times m}$  for the corresponding Fog devices in  $\mathcal{R}$ .

2) *Step 2: Pair-wise comparison in level 2:* In level 2,  $r \in \mathcal{R}$  evaluates the candidate IoT devices  $d \in \mathcal{D}$  under different decision factors  $m \in \mathcal{M}$  of the service type  $s \in \mathcal{S}$  to compute the alternative candidate matrix  $\mathbf{A} \in R^{d \times m}$  in Alg. 2. In the alternative matrix  $\mathbf{A}$ , each row represents the IoT devices  $d \in \mathcal{D}$  and the columns are the QoS parameters  $m \in \mathcal{M}$  for a given service type  $s \in \mathcal{S}$ . Each entry in the QoS matrix  $\mathbf{Q}$  is row and column normalized as  $\bar{\mathbf{Q}}$  (line 2 in Alg. 2). After that, each candidate IoT device in  $\bar{\mathbf{Q}}$  is multiplied by its corresponding weight value in the parent local vector  $\vec{w}_{s,m}^d$  from the local weight matrix  $\mathbf{W}^r$  (lines 3-5 in Alg. 2).

3) *Step 3: Weight based profiling in level 0:* At this step, the global weight vector  $\vec{w}_g^r = \{w_1, w_2, w_d\}^T$  is calculated through Alg. 2, where it takes the alternative matrix  $\mathbf{A}$  from step 2 and the local weight vector  $\vec{w}_{s,m}^d \in \mathbf{W}^r$  from step 1 as the input to generate the global weight vector  $\vec{w}_g^r$  for  $r \in \mathcal{R}$ . Each entry in  $\mathbf{A}_r$  is multiplied by its corresponding parent in  $\mathbf{W}^r$  in order to generate the global weight vector  $\vec{w}_g^r$  for  $r \in \mathcal{R}$  (line 6 in Alg. 2). The global weight vector  $\vec{w}_g^r$  represents the weights used for ranking the IoT devices based on the QoS evaluation in level 1 and level 2 of the AHP.

### B. Resource Allocation via Matching

In this stage, we find a stable matching or association between two sets  $\mathcal{D}$  and  $\mathcal{R}$  considering the individual preferences of the players (IoT and Fog devices) in order to perform the resource allocation (RA). For such an association, we model our problem as the “one-to-many” matching game, which solves the classical “College Admissions” problem [45]. In addition, the pairwise comparison matrix and the global weight vector from AHP are used as input parameters to create the preference profile of players in the “one-to-many” matching game.



1) *Matching game formulation*: In our formulation, we define ‘‘College’’ as the Fog devices with quota  $q_r \geq 1$  and ‘‘Student’’ as the IoT devices with quota  $q_d = 1$ , where each Fog device can be associated or matched with IoT devices up to their quota limits. However, in the proposed matching game, we introduce a *dynamic quota* in which Fog device  $r$  can allocate the network resource (i.e., bandwidth) of different portion sizes to the associated IoT devices in  $d \in \mathcal{A}_r$ . The portion sizes of the allocations are based on the QoS requirements of  $d \in \mathcal{D}$  and sustained until the QoS requirements are not violated. Therefore, The outcome of the matching game is a matching function  $\delta$  that mutually assigns each player  $r \in \mathcal{R}$  and  $d \in \mathcal{D}$  under the following conditions of the matching  $\delta : \mathcal{D} \cup \mathcal{R} \implies 2^{\mathcal{D} \cup \mathcal{R}}$  such that,

- (1)  $\delta(r) \subseteq \mathcal{R}$  such that  $|\delta(r)| \leq q_r, \forall r \in \mathcal{R}$
- (2)  $\delta(d) \subseteq \mathcal{D}$  such that  $|\delta(d)| \leq 1, \forall d \in \mathcal{D}$
- (3) If  $r \in \delta(d)$  then  $\delta(r) = \mathcal{A}_r, \forall r \in \mathcal{R}$
- (4)  $d \in \delta(r)$  if and only if  $\delta(d) = \{r\}, \forall d \in \mathcal{D}$  and  $\forall r \in \mathcal{R}$ .

Here,  $q_r$  is the maximum resource capacity of  $r \in \mathcal{R}$  and each  $d \in \mathcal{D}$  can associate with exactly one  $r \in \mathcal{R}$  as per (12) and (13) in problem (5) where  $|\delta(\cdot)|$  is the cardinality of the matching instance  $\delta(\cdot)$ . In addition, if there is a matching  $\delta$  between IoT device  $d$  and Fog device  $r$ , the Fog device  $r$  adds the matching  $\delta$  to the accepted list  $\mathcal{A}_r$ .

2) *Preference Profile of Players*: The global weight vector  $\vec{w}_g^r$  and the corresponding local weight vectors  $\vec{w}_d^r \in \mathbf{W}^r, \forall d \in \mathcal{D}$  from the AHP are the parameters used to create the preference lists for the players in the matching game. The preference relation between the players in the preferences lists  $p_d, \forall d \in \mathcal{D}$  and  $p_r, \forall r \in \mathcal{R}$  hold the transitive property within the matching framework as defined in Definition 1.

**Definition 1.** A matching game is defined using two sets of players  $\mathcal{R}$  and  $\mathcal{D}$  where the corresponding transitive preference relations  $\succ_r$ , and  $\succ_d$  of each player in  $r \in \mathcal{R}$ , and  $d \in \mathcal{D}$ , respectively, are used to build preferences over one another.

In a *matching game*, the preference list of each  $r \in \mathcal{R}$  is denoted as  $p_r$  and the rank or preference  $\succ_r$  of the IoT devices in  $p_r$  is based on the respective weight values in  $\vec{w}_g^r$ , given as,

$$d \succ_r d' \Leftrightarrow w > w' \text{ where } (w, w') \in \vec{w}_g^r \text{ and } d \neq d',$$

where Fog device  $r$  prefers IoT device  $d$  more than IoT device  $d'$  in  $p_r$ , as the weight value  $w$  of IoT device  $d$  is higher than the weight value  $w'$  of IoT device  $d'$ .

Likewise, each IoT device  $d \in \mathcal{D}$  receives the respective local weight vectors  $\vec{w}_d^r, \forall d \in \mathcal{D}$  from the Fog devices  $r \in \mathcal{R}$  and measures the channel condition using (1) and (3) so that  $d \in \mathcal{D}$  can calculate the expected utility as,

$$\bar{U}_{d,r} = w_{s,m_1}^d \cdot \beta_{d,r}(b_{d,r}) \cdot w_{s,m_2}^d (1 - \nu_{d,r}). \quad (18)$$

In (18), the expected utility function captures the service type based QoS requirements  $\beta_{d,r}$  and  $\nu_{d,r}$  with the respective QoS parameters weight values  $w_{s,m_1}^d$  and  $w_{s,m_2}^d$ . The weight values are calculated by the Fog devices in  $r \in \mathcal{R}$  according to (6)-(8) and (10) in problem (5). The expected utility also

reflects the achievable degree of satisfaction under an error-free communication based on the statistical channel state information (CSI) between the corresponding  $d \in \mathcal{D}$  and  $r \in \mathcal{R}$ . Therefore, in  $p_d$ , the preference relation  $\succ_d$  of  $d$  with the Fog devices  $r \in \mathcal{R}$  can be represented as,

$$r \succ_d r' \Leftrightarrow \bar{U}_{d,r} > \bar{U}_{d,r'}, r \neq r',$$

where IoT device  $d$  prefers Fog device  $r$  more than the Fog device  $r'$  in  $p_d$ , as the expected utility  $\bar{U}_{d,r}$  of the Fog device  $r$  is higher than the expected utility  $\bar{U}_{d,r'}$  of the Fog device  $r'$ .

3) *Externalities in Matching*: In the case of a ‘‘one-to-many’’ matching game, the existing matchings or associations  $\delta_{d,r}$  become unstable due to the externalities or environmental variations. Thus, it is not possible to apply the ‘‘Deferred Acceptance’’ algorithm directly to guarantee stable matching for resource allocation without considering externalities. In the proposed matching game, we consider the performance of the matching instances which are affected by additional externalities such as the average job delay in (9) and BER in (10) which depend on the corresponding congestion level on each  $r \in \mathcal{R}$  and channel interference. Therefore, in the proposed one-to-many stable matching for the resource allocation algorithm, we consider the additional externalities as ‘‘peer-effects’’ where the stability and performance of a matching between a Fog device  $r$  and an IoT device  $d$  depend on not only the specific matching instance  $\delta_{d,r}$  but also the influence of other neighboring matching instances  $\delta_{d',r}$  of the same Fog device  $r$ . Based on the current scenario, we formulate the definition of a *blocking pair* in Definition 2,

**Definition 2.** A blocking pair of a matching  $\{d', r\} \in \delta_{d',r}$  is a pair of players  $\{d, r\} \notin \delta_{d',r}$  such that:

- a)  $\hat{\beta}_r(\hat{b}_r) \geq \beta_{sla}^d, d \succ_r \emptyset$  and  $r \succ_d \delta'(r')$
- b)  $\hat{\beta}_r(\hat{b}_r) < \beta_{sla}^d, \hat{\beta}_r + \sum_{d' \in \mathcal{A}_r} \beta_{d',r}(b_{d',r}) \geq \beta_{sla}^d, \{d\} \succ_r \{d'\}$  and  $r \succ_d \delta'(r')$
- c)  $U_{d,r} < \bar{U}_{d,r}, \{d\} \succ_r \{d'\}$  and  $r \succ_d \delta'(r')$ .

where  $\succ_d$  and  $\succ_r$  indicate the preference relation between the matching instances  $\delta(\cdot)$  and  $\delta'(\cdot)$ , respectively. In addition,  $\delta_{d',r}$  is the matching between IoT device  $d'$  and Fog device  $r$  and  $\delta'_{d',r}$  is the matching between IoT device  $d$  and Fog device  $r'$ , where the matching instance  $\delta_{d,r}$  is the blocking pair. In condition (a), if Fog device  $r$  has enough residual quota  $\hat{\beta}_r(\hat{b}_r) = \beta_{max}^r(b_{max}^r) - \sum_{d' \in \mathcal{A}_r} \beta_{d',r}(b_{d',r})$  and IoT device  $d$  prefers Fog device  $r$  than its current association with Fog device  $r'$ ,  $r$  accepts the proposal from  $d$ . In condition (b), the residual quota  $\hat{\beta}_r(\hat{b}_r)$  of each Fog device  $r \in \mathcal{R}$  is fulfilled when  $\hat{\beta}_r(\hat{b}_r) < \beta_{sla}^d$  for any requesting IoT device  $d \in p_r$ . Thus, Fog device  $r$  rejects the least preferred IoT device  $d' \in \mathcal{A}_r$  in order to admit the proposal from IoT device  $d$ . Both the conditions (a) and (b) in our formulation introduce the challenge of dynamic quota in the game which is similar to [46]. However, in condition (c), we consider an additional challenge of externalities in the matching game where the matching utility  $U_{d,r'}$  between IoT device  $d$  and Fog device  $r'$  is less than the expected utility  $\bar{U}_{d,r'}$  which indicates the degradation of the matching performance due to externalities

in (2) and (3). In such case, both IoT device  $d$  and Fog device  $r$  deviate from their current associations and create the blocking pair.

4) *Proposed Matching Algorithm:* At each iteration  $l$ , each IoT device  $d \in \mathcal{D}$  starts making proposals to the most preferred Fog device  $r \in \mathcal{R}$  that appears in its preference list  $p_d$  (lines 3-4 in Alg. 3). After receiving the proposal from IoT device  $d$ , Fog device  $r$  holds the proposal if it has not received any other proposals (line 6 in Alg. 3). If IoT device  $d$  previously matched with any other Fog device  $r' \in p_d \setminus \{r\}$ ,  $d$  compares the utility from prior the matching  $\delta_{d,r'}$ ,  $U_{d,r'}$  with the expected matching utility from  $\delta_{d,r}$ ,  $\bar{U}_{d,r}$  (line 7 in Alg. 3). Since the utility function in (18) effectively captures the performance parameters (1) and (3) of the matching, the utility function represents the overall performance gain of any matching instances. Therefore, if the expected utility of matching  $\delta_{d,r}$  is higher than the prior utility of matching  $\delta_{d,r'}$ , IoT device  $d$  puts the matching  $\delta_{d,r'}$  in its rejection list  $\mathcal{L}_d$  and a new matching instance  $\delta_{d,r}$  is created (lines 8-9 in Alg. 3). Consequently, Fog device  $r'$  also removes the matching  $\delta_{d,r'}$  from its accepted list  $\mathcal{A}_{r'}$  and Fog device  $r$  adds the matching  $\delta_{d,r}$  to its accepted list  $\mathcal{A}_r$  (lines 10-11 in Alg. 3). Otherwise, IoT device  $d$  puts Fog device  $r$  in its rejected list  $\mathcal{L}_d$  and continues making proposals as per the preference order of its preference list  $p_d$  (line 14 in Alg. 3). If Fog device  $r$  has no residual quota to support the new proposal from IoT device  $d$ , Fog device  $r$  first checks the accepted list  $\mathcal{A}_r$  for any least preferred existing matching instance (line 17 in Alg. 3). Second, if there exists any least preferred matching  $\delta_{d',r}$ , Fog device  $r$  rejects and removes the matching  $\delta_{d',r}$  from  $\mathcal{A}_r$  to accommodate the more preferred matching  $\delta_{d,r}$  (lines 19-23 in Alg. 3). In the case of any mutual rejection between two players, the corresponding preference lists and the residual capacity of Fog device  $r \in \mathcal{R}$  are updated accordingly (lines 12, 15, and 23 in Alg. 3).

In the proposed matching game, we have applied the “best-fit” resource allocation strategy to deal with the *externalities*, ensuring the stability of the matching game. First, Fog device  $r$  calculates the residual quota  $\tilde{\beta}_r$  after temporarily allocating the network resources to the IoT devices in the accepted list  $\mathcal{A}_r$  (line 2 in Alg. 4). If there exists any  $\delta(r) \in \mathcal{A}_r$  that violates the QoS conditions given in (6), (7), (9) and (10), the utility of that matching  $U_{d,r}$  also degrades. Therefore, Fog device  $r$  sequentially finds the least preferred IoT device  $d' \in p_r$  other than IoT device  $d \in p_r \setminus \{d'\}$  and creates a temporary allocation  $\beta_{temp}^r(b_{temp}^r)$  (lines 3-5 in Alg. 4). Second, if the temporary allocation can accommodate IoT device  $d$ , Fog device  $r$  rejects the proposal from the least preferred IoT device  $d'$  and allocates the network resource to the more preferred IoT device  $d$  (lines 6-7 in Alg. 4). However, if IoT device  $d$  is the least preferred in  $\mathcal{A}_r$ , Fog device  $r$  breaks the association with  $d$ , and the corresponding preference lists and rejected lists are updated (line 9 in Alg. 4). The algorithm converges and becomes stable when the matching of two consecutive iterations  $l$  remains unchanged (line 22 in Alg. 3).

**Theorem 1.** *Alg. 3 produces stable association.*

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**Algorithm 3:** Matching algorithm with externalities

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**Input:**  $\mathcal{D}, \mathcal{R}, p_d, p_r, \mathbf{W}^r$

1 **Initialize:**  $\mathcal{A}_r = \{\emptyset\}; \mathcal{L}_d = \{\emptyset\}; l \leftarrow 0$

**Matching:**

2 **repeat**

3    $l \leftarrow l + 1$

4   Each  $d \in \mathcal{D}$  proposes the most preferred  $r \in p_d^{(l)}$  and  $r \notin \mathcal{L}_d^{(l)}$

5   **while**  $p_d^{(l)} \neq \emptyset$  and  $\exists d \in p_r^{(l)}$  **do**

6     **if**  $d \succ_r \emptyset$  and  $\tilde{\beta}_r^{(l)}(\tilde{b}_r) \geq \beta_{sla}^d$  **then**

7       **if**  $\bar{U}_{d,r} > U_{d,r'}$  **then**

8           $\mathcal{L}_d^{(l)} \leftarrow \mathcal{L}_d^{(l)} \cup \{\delta(d)^{(l-1)}\}$

9           $\delta(r)^{(l)} \leftarrow d$

10          $\mathcal{A}_{r'}^{(l)} \leftarrow \mathcal{A}_{r'}^{(l)} \setminus \{\delta(r')^{(l)}\}$

11          $\mathcal{A}_r^{(l)} \leftarrow \mathcal{A}_r^{(l)} \cup \{\delta(r)^{(l)}\}$

12         Update  $p_{r'}^{(l)}, p_d^{(l)}, \tilde{\beta}_r^{(l)}(\tilde{b}_r)$

13       **else**

14           $\mathcal{L}_d^{(l)} \leftarrow \mathcal{L}_d^{(l)} \cup \{\delta(d)^{(l)}\}$

15          Update  $p_r^{(l)}, p_d^{(l)}, \tilde{\beta}_r^{(l)}(\tilde{b}_r)$

16       **else**

17          **for**  $d' \in \mathcal{A}_r^{(l)}$  **do**

18           **if**  $(d, \delta^{(l)}) \succ_r (d', \delta^{(l-1)})$  **then**

19              $\mathcal{L}_{d'}^{(l)} \leftarrow \mathcal{L}_{d'}^{(l)} \cup \{\delta(d')^{(l)}\}$

20              $\delta(r)^{(l)} \leftarrow d$

21              $\mathcal{A}_{r'}^{(l)} \leftarrow \mathcal{A}_{r'}^{(l)} \setminus \{\delta(r)^{(l-1)}\}$

22              $\mathcal{A}_r^{(l)} \leftarrow \mathcal{A}_r^{(l)} \cup \{\delta(r)^{(l)}\};$

23             Update  $p_{r'}^{(l)}, p_{d'}^{(l)}, \tilde{\beta}_r^{(l)}(\tilde{b}_r)$

24           **else**

25              $\mathcal{L}_d^{(l)} \leftarrow \mathcal{L}_d^{(l)} \cup \{\delta(d)^{(l)}\}$

26             Update  $p_r^{(l)}, p_d^{(l)}, \tilde{\beta}_r^{(l)}(\tilde{b}_r)$

27 **until**  $\delta_{d,r}^{(l)} \neq \delta_{d,r}^{(l+1)}$ ;

28 Calculate matching utilities based on  $\mathcal{A}_r^{(l)}$  using (1), (2), (3), (4) and  $\mathbf{W}^r$

29 **Resource Allocation:**

30 Apply Alg. 4: alloc( $\mathcal{R}, \mathcal{A}_r^{(l)}, \mathcal{L}_d^{(l)}, p_r^{(l)}, p_d^{(l)}$ )

31 **Output:**  $\delta_{d,r}^{(l)}$

---

*Proof.* Please see the technical report in [47] for more detailed discussion about the proof of convergence and an example scenario of the user association and resource allocation using AHP and matching game.  $\square$

The complexity of Alg. 3 is quantified by the complexity of building the preference profiles by both Fog devices and IoT devices which are inputs for Alg. 3. For each Fog device, the complexity of building the preference profile using standard sorting algorithm is  $\mathcal{O}(R \log(R))$  and similarly the complexity of building the preference profile of all the IoT devices is  $\mathcal{O}(D \log(D))$ . Therefore, the input of Alg. 3 is  $\sum_{d \in \mathcal{D}} |p_d| + \sum_{r \in \mathcal{R}} |p_r| = 2DR$  where  $|p_d|$  and  $|p_r|$  are the length of the respective preference profiles of IoT device and Fog device. As Alg. 3 terminates after a finite number of



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**Algorithm 4:** Best Fit RA:  $\text{alloc}(\mathcal{R}, \mathcal{A}_r, \mathcal{L}_d, p_r, p_d)$

---

**Input:**  $\mathcal{R}, \mathcal{A}_r, \mathcal{L}_d, p_r, p_d$   
**Result:**  $\mathcal{A}_r, \mathcal{L}_d, p_r, p_d$   
**1 Initialize:**  $\beta_{temp}^r(b_{temp}^r) = \{\emptyset\}$   
**2**  $\tilde{\beta}_r(\tilde{b}_r) \leftarrow \beta_{max}^r(b_{max}^r) - \sum_{d \in \mathcal{A}_r} \beta_{d,r}(b_{d,r})$   
**3 while**  $\exists d \in \mathcal{A}_r$  and  $U_{d,r} < \tilde{U}_{d,r}$  **do**  
**4**   **if**  $(d, \delta(r)) \succ_r (d', \delta(r)) \in \mathcal{A}_r$  **then**  
**5**      $\beta_{temp}^r(b_{temp}^r) \leftarrow \tilde{\beta}_r(\tilde{b}_r) + \beta_{d',r}(b_{d',r})$   
**6**     **if**  $\beta_{temp}^r(b_{temp}^r) \geq \beta_{sla}^d$  **then**  
**7**       Update  $\mathcal{L}_{d'}, p_{d'}, \mathcal{A}_r, p_r, \tilde{\beta}_r(\tilde{b}_r)$   
**8**     **else**  
**9**       Update  $\mathcal{L}_d, p_d, \mathcal{A}_r, p_r, \tilde{\beta}_r(\tilde{b}_r)$

---

iterations, it can be seen that the worst case time complexity of Alg. 3 is linear in the size of the preference profiles with  $\mathcal{O}(\eta) = \mathcal{O}(DR)$  where  $D$  and  $R$  are the numbers of IoT devices and Fog devices respectively. In case of Alg. 4, the standard best-fit algorithm is used where the time complexity is  $\mathcal{O}(DR \log(DR))$ . Therefore, the proposed approach is suitable for practical implementation.

## V. SIMULATION AND ANALYSIS

### A. Simulation Setting

**TABLE III:** Simulation Settings

Simulation Parameters	Values
No. of Fog devices	10
No. of IoT devices	50
Radius of Fog device	250 (m)
Radius of FNC	800 (m)
Maximum Bandwidth	20 MHz
Thermal noise	175 dBm/Hz

For the simulation, we consider a network composed on 10 Fog devices and 50 IoT devices. The transmit power of each Fog device is 33 dBm and the path loss  $L(\Delta_{d,r}) = 37 + \Delta_{d,r}$  is calculated over the distance  $\Delta_{d,r}$  between the IoT devices and Fog devices. We assume lognormal shadowing with standard deviation of 4 dB for the Fog devices. The minimum required SINR for each IoT device is 9.56 dB and the power density of thermal noise power is 175 dBm/Hz. In the simulation, the typical QoS requirements of the IoT devices are set based on Table I where the constant packet size is 1500 bytes. Using the simulation, we compare our proposed algorithm with the two well-known baseline solutions which are deferred acceptance (DA) algorithm [48] and analytic hierarchy process (AHP) [49]. The DA approach considers the distance  $\Delta_{d,r}$  between the IoT devices and Fog devices in order to create the preference list. The AHP based approach considers the global weights for not only sorting the preference list for IoT devices and Fog devices, but also accepts the requests until the quota requirements are fulfilled. The main parameters for the simulation are provided in Table III.

### B. Simulation Results

Fig. 3 depicts the performance gap and average utility of the associations, where the number of Fog device is 3 and the number of IoT device is 10. The complexity of the exhaustive search algorithm is growing exponentially (i.e.,  $\mathcal{O}(2^{D \times R \times K})$ ) where the optimal solution is one of the possible combinations of the subsets of the sets  $\mathcal{D}, \mathcal{R}$  and  $\mathcal{K}$ . Therefore, we consider a small network for comparing our proposed approach with the optimal solution. The proposed AHP based matching approach produces sub-optimal results but in case of real-time- IoT services, the proposed approach converges much faster than the exhaustive search based resource allocation. Apart from that, in the proposed AHP based matching approach, the decision of the association between IoT and Fog devices is QoS aware and thus the average utility of the association between IoT and Fog devices increases as the network size increases. Moreover, the performance gaps in terms of average utility between the proposed AHP based matching with externalities, DA, and AHP are correspondingly up to 23.32%, 39.1319%, and 69.2315% when the network size is  $|\mathcal{D}| = 10$ . In Fig. 3, we observe that the average utilities of all the methods are monotonically increasing up to a network size of  $|\mathcal{D}| = 8$ . However, the performance gap increases slightly after the network size  $|\mathcal{D}| = 8$  because of the impact of interference during the association. Since the final outcomes of the exhaustive search based solution are generated after iterating over all the possible association and allocation combinations, the optimal average utilities after  $|\mathcal{D}| = 8$  experience comparatively less interference than the sub-optimal average utilities of the proposed approach. Nonetheless, the proposed algorithm converges to a stable solution even though there is noticeable interference which degrades performance gain compared to the optimal solution. In fact, none of the QoS requirements is violated due to the interference effect in the proposed approach while achieving the desired matching stability. On the other hand, we observe a significant performance loss in the DA and AHP based approaches due to the increased interference level compared to the optimal solution which further solidifies the effectiveness of the proposed approach. Besides, the AHP approach only defines the preference lists of the Fog devices, and thus is unable to improve the performance of the IoT devices. On the other hand, the deferred acceptance (DA) approach defines the preference order for both the IoT and Fog devices based on the distance. Therefore, the number of requests from the IoT devices to the nearby Fog devices increases when the area is densely overloaded with the IoT devices. Overall, the utility gain of the proposed solution is significantly higher than those of the deferred acceptance (DA) and AHP based approach due to the efficiency of the proposed solution in handling the ‘‘peer-effects’’, which provides a higher number of associations. Fig. 3 also shows that the proposed AHP based QoS aware matching approach provides joint decision making for the associations with enhanced SINRs. Therefore, the average throughput of the associations increases and a smaller BER is achieved with lower delay than that of the DA and AHP which are the context unaware approaches.

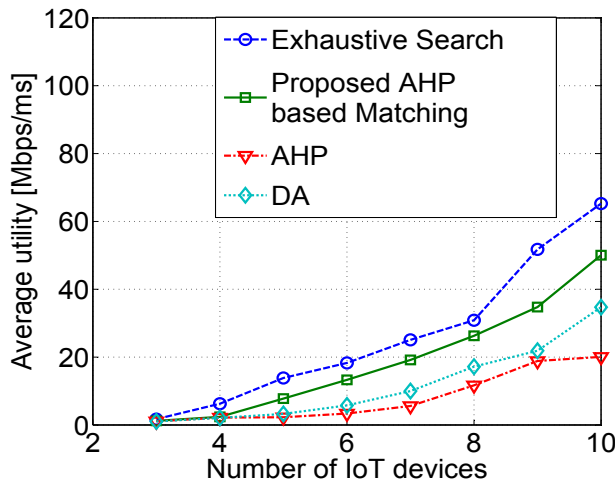


Fig. 3: Average utility comparison between the optimal and the proposed method,  $\mathcal{R} = 3$ ,  $\mathcal{D} = 10$

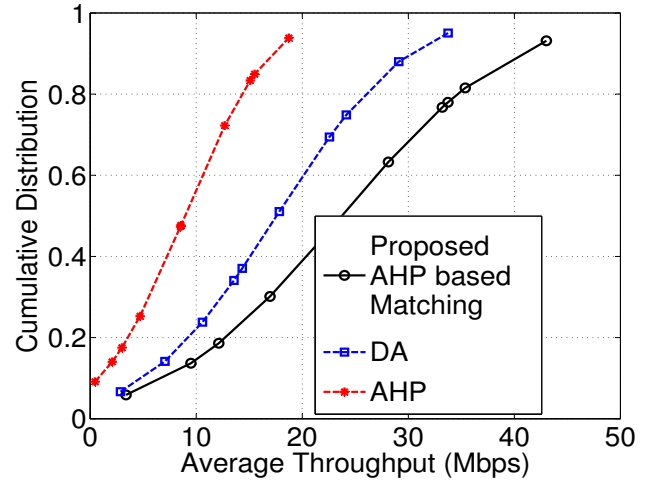


Fig. 4: Average throughput comparison between different methods,  $\mathcal{R} = 10$ ,  $\mathcal{D} = 50$

Fig. 4 shows the evaluation of the average throughput of the associations in the proposed AHP based matching approach, DA, and AHP. The throughput of the associations are improved significantly in the proposed AHP based matching approach compared to the other context-unaware methods. The average throughput between the proposed approach and the DA approach is relatively close at the beginning when the network size is small (i.e.,  $|\mathcal{D}| = 10$ ). Since the association between the IoT devices and Fog devices in the DA approach depends on the RSSI, each IoT device tends to become associated with the closest Fog device. As a result, as the network size increases, the proposed approach outperforms the DA approach due to effective load balancing whereas the DA approach needs to deal with the large unequal loads. Apart from that, the QoS unaware methods (i.e., DA and AHP) can not guarantee stability in the association and thus are unable to improve the user’s QoS satisfaction through the achievable throughput. The results also demonstrate that the “best-fit” algorithm for handling the “peer-effects” in the proposed matching approach provides better throughput than that of the DA algorithm, which is unable to address the “peer-effects” during resource allocation. As a result, we also observe the throughput gain between the proposed approach and the DA as well as AHP approaches correspondingly up to 28.89% and 55.56%. This result clearly confirms the usefulness of the proposed approach in terms of the significant performance gain.

Fig. 5 demonstrates the utilization of the Fog devices or network resources under the proposed approach and DA algorithm. As the number of IoT device increases, in the proposed approach, the utilization of the Fog devices or the network resources increases significantly due to the increased number of associations per Fog devices compared to the DA approach. However, in Fig. 5, we observe that the effect of externalities is not significant up to  $|\mathcal{D}| = 20$ . Moreover, the performance gap increases between the proposed approach and DA when  $|\mathcal{D}| = 25$  as the DA approach is unable to handle the “peer-effects” and is thus unstable. Due to this reason, the number of rejections by the Fog devices increases, which negatively

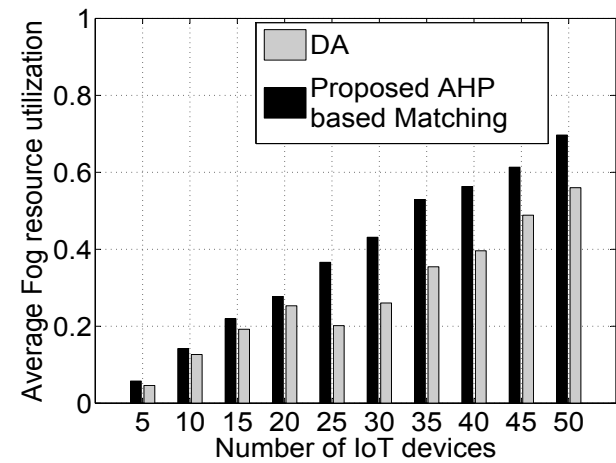


Fig. 5: Average network utilization between different methods,  $\mathcal{R} = 10$ ,  $\mathcal{D} = 50$

impacts the network resource efficiency by 15.7143% when the network size reaches  $|\mathcal{D}| = 50$ .

The bandwidth is limited in each of the Fog devices and therefore, the bandwidth should be utilized efficiently. Fig. 6 illustrates the bandwidth efficiency of each of the Fog devices for a varying number of IoT devices in the network. The proposed AHP based matching approach efficiently utilizes the channel capacity of the Fog devices as the number of simultaneous associated IoT devices increases. The average bandwidth efficiency between the proposed AHP based matching game and the DA approach is fairly similar till the network size is  $|\mathcal{D}| = 20$ . However, the bandwidth efficiency increases the most when the network size is medium and the density is from  $|\mathcal{D}| = 25$  to  $|\mathcal{D}| = 35$ . As the network size grows (i.e.,  $|\mathcal{D}| > 35$ ), the bandwidth efficiency gap between the proposed AHP based matching and DA approach slightly decreases due to increasing interference level. As a result, the number of allocation per Fog device slightly decreases. However, the bandwidth efficiency gap is still significant between the proposed approach and the DA approach. One of the reasons

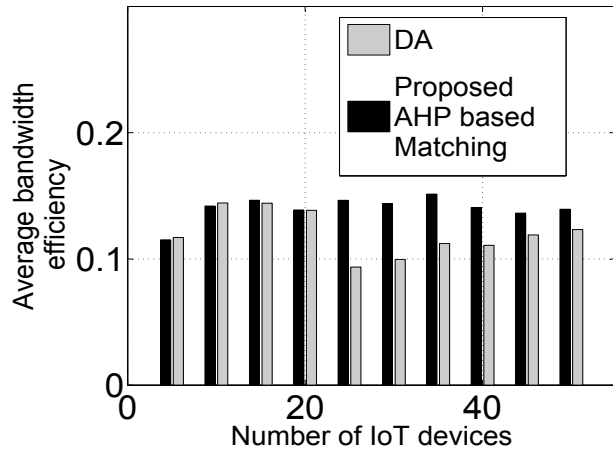


Fig. 6: Average bandwidth utilization between different methods,  $\mathcal{R} = 10$ ,  $\mathcal{D} = 50$

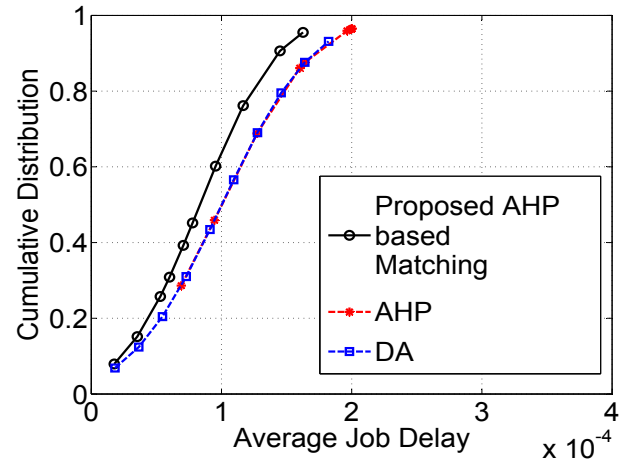


Fig. 8: Average job delay comparison between different methods,  $\mathcal{R} = 10$ ,  $\mathcal{D} = 50$

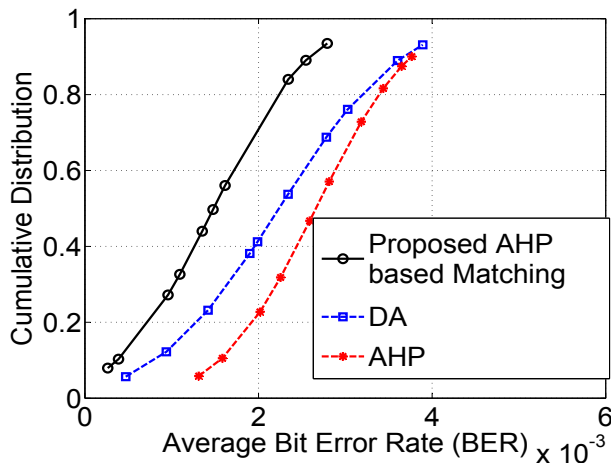


Fig. 7: Comparison of average bit error rate (BER) between different methods,  $\mathcal{R} = 10$ ,  $\mathcal{D} = 50$

behind this is that the proposed “best-fit” resource allocation scheme demonstrates the multi-user diversity [50] where the Fog devices are able to choose relatively high quality of channels so that the IoT devices can receive data more reliably.

In Fig. 7, the average bit error rate of the proposed approach is smaller than the DA and AHP based approach. This phenomenon is expected, as in the proposed AHP based matching approach, the associations have a higher SINR gain when the network size is small, ( $|\mathcal{D}| = 20$ ) and the externalities is still not significant during the allocation. With increasing number of IoT devices joining the network, the bit error rate difference between the DA and AHP approaches becomes indistinguishable. On the other hand, the received bit error rate after applying the proposed AHP based matching algorithm is increasing but compared to other two algorithms the increasing rate still complies with the QoS constraints and which shows the efficiency of handling the externalities.

From Fig. 8, we observe that the average job delay increases in the DA algorithm and AHP approach than the proposed

AHP based matching. The reason behind this increased delay is due to the congestion level at each Fog devices in the DA algorithm and AHP approach as the network size is  $|\mathcal{D}| > 20$ . Since the proposed AHP based matching game approach applies the “best-fit” allocation policy, the issue of dealing with the ‘externalities’ during the network resource allocation is properly handled which ensures necessary load balancing. As a result, the congestion level is much lower in the proposed approach that those of the other two methods. In Fig. 8, it is also observed that the received BER after applying the DA approach is slightly higher than that of the AHP. The reason behind this is that, in the AHP based approach, the overloaded Fog devices tend to reject the IoT devices after there is no available network resource in order to converge to a stable solution where the decision of resource allocation is one sided. On the contrary, in the DA approach, the decision is two-sided; thus, once an IoT device gets rejected by the corresponding Fog device, the IoT device still has the option to propose to its next preferred Fog device in the respective preference list. As a result, the number of allocations is comparatively higher in DA approach than that of the AHP approach. However, the DA approach cannot conclusively converge to an allocation solution and also unable to solve the issue of “peer-effects” which is necessary to provide load-balancing to avoid congestion at the Fog devices. In fact, the Fog devices remain over-loaded in the DA approach than that of the proposed approach. The reason behind is that, for any new allocation at the Fog devices, the proposed approach always checks the performance of the current allocations that have been made to the IoT devices through “best-fit” algorithm before accepting new allocation. As a result, the congestion level is significantly lower in the proposed approach than that of the DA approach that leads to incurring lower job delay for the proposed AHP based matching game. In addition, in the proposed approach, the delay constraint of the IoT devices is tolerable and does not violate the job delay QoS requirement of the IoT devices. On the other hand, the performance gain of the associations through the DA and AHP approach reduces

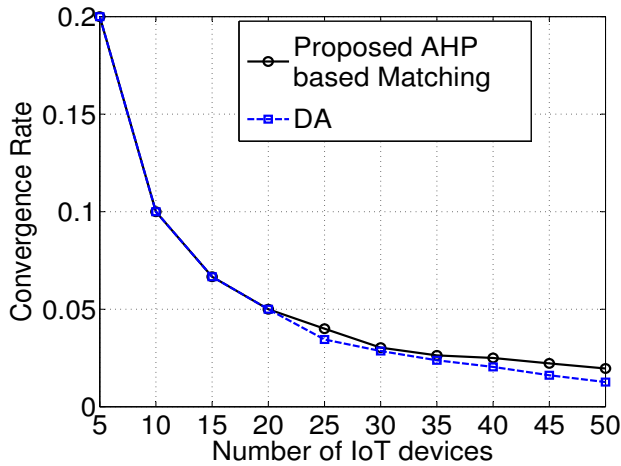


Fig. 9: Rate of convergence between different methods,  $\mathcal{R} = 10$ ,  $\mathcal{D} = 50$

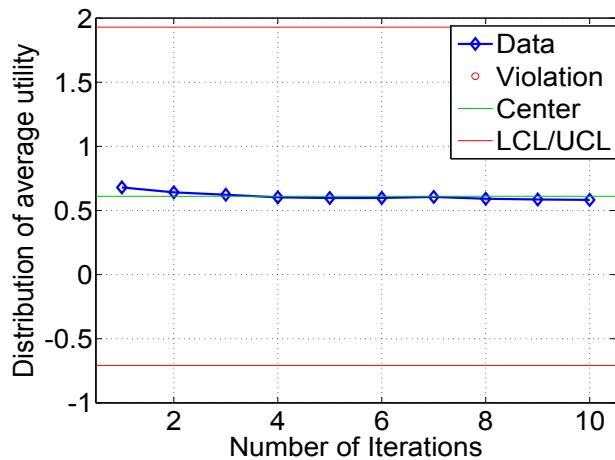


Fig. 10: Normalized average utility of the associations for  $\mathcal{D} = 50$

due to the violation of the job delay requirement.

Fig. 9 depicts the convergence (Order 1 convergence) of the proposed AHP based matching approach and DA algorithm. Since the proposed approach is an iterative algorithm, under the “peer-effects”, the solutions generated by the proposed algorithm converge to a desired solution with slightly larger number of iterations than that of the DA algorithm. Therefore, the convergence rate of the proposed AHP based matching is slightly slower than that of the DA algorithm (as the number of IoT devices is larger) and the “best-fit” algorithm is implemented to find the stable allocation. However, the proposed algorithm guarantees both the convergence and stability in spite of the “peer-effects” whereas the DA algorithm cannot guarantee the desired stability.

Fig. 10 shows the control chart of the utility distribution of the associations in the proposed AHP based matching approach, where the utility is well-balanced, and there is no violation, and the normalized average utility of the associations at each iterations is close to the central line. At each iteration, the IoT device density at each Fog device increases and when

the IoT device density is much lower, the performance gain in terms of utility is quite higher than the average line and tends to upper control limit (UCL). As the IoT device density in the network increases (i.e.,  $|\mathcal{D}| > 35$ ), the normalized average utility per Fog device slimly tends toward lower control limit (LCL) which is expected due to externalities. However, none of the distributions violates the upper (UCL) and lower control limit (LCL) even though the negative effect of externalities at higher IoT device density.

## VI. SUMMARY

In this paper, we have focused on ensuring the quality of service for end users by efficiently allocating the limited network resources to the heterogeneous IoT applications. Therefore, we have proposed an analytic hierarchy process based matching approach for self-organizing, and distributed user association and resource allocation that are scalable and well applicable to the dense Fog environment. Unlike conventional resource allocation schemes for IoT, we have efficiently mapped the network resources to the IoT applications by considering analytic hierarchy process based analytics, resource demand, and application type of the QoS parameters for the IoT applications. We have also provided a real-world example to demonstrate the proposed approach for user association and resource allocation in the Fog environment. In addition, we have investigated the effects of externalities or environmental variations on the outcomes of the matching game through extensive analysis. The simulation results show that, the proposed approach is able to address externalities in the matching game using the “best-fit” resource allocation strategy, and we have observed significant performance gains compared to the other conventional resource allocation schemes. We have also validated the stability, complexity and, convergence of the proposed user association and resource allocation algorithm.

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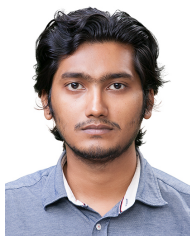
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**Sarder Fakhru Abedin** received his B.S. degree in Computer Science from Kristianstad University, Kristianstad, Sweden, in 2013. Since March 2014, he has been working toward the Ph.D. degree in Computer Science and Engineering at Kyung Hee University, South Korea. His research interests include Internet of Things (IoT) network management, Cloud computing, Fog computing, and Wireless sensor network. Mr. Abedin is a Member of the KIISE.



**Md. Golam Rabiul Alam** received Ph.D. in Computer Engineering from Kyung Hee University, South Korea in 2017. He also received the B.S. and M.S. degrees in Computer Science and Engineering, and Information Technology respectively. His research interest includes affective computing, health informatics, body area networks, ambient intelligence and persuasive technology. He is a member of IEEE IES, CES, CS, SPS, CIS, and ComSoc. He is also a member of KIISE and received several best paper awards from prestigious conferences.



**S. M. Ahsan Kazmi** received his Masters degree in Communication System Engineering from the National University of Sciences and Technology (NUST), Pakistan, in 2012, and his Ph.D. degree in Computer Science and Engineering from Kyung Hee University, South Korea, in 2017. His research interests include applying analytical techniques of optimization and game theory to radio resource management for future cellular networks.



**Nguyen H. Tran** (S'10-M'11) received the BS degree from Hochiminh City University of Technology and Ph.D. degree from Kyung Hee University, in electrical and computer engineering, in 2005 and 2011, respectively. Since 2018, he has been with the School of Information Technologies, The University of Sydney, where he is currently a Senior Lecturer. He was an Assistant Professor with Department of Computer Science and Engineering, Kyung Hee University, Korea from 2012 to 2017. His research interest is to applying analytic techniques of optimization, game theory, and stochastic modeling to cutting-edge applications

such as cloud and mobileedge computing, data centers, heterogeneous wireless networks, and big data for networks. He received the best KHU thesis award in engineering in 2011 and best paper award at IEEE ICC 2016. He has been the Editor of IEEE Transactions on Green Communications and Networking since 2016, and served as the Editor of the 2017 Newsletter of Technical Committee on Cognitive Networks on Internet of Things.



**Dusit Niyato** (M'09-SM'15-F'17) Dusit Niyato is currently a Full Professor in the School of Computer Engineering, at Nanyang Technological University, Singapore. He received the B.Eng. from King Mongkuts Institute of Technology Ladkrabang (KMUTL) in 1999 and the Ph.D. in Electrical and Computer Engineering from the University of Manitoba, Canada in 2008. His research interests are in the area of green communication, Internet of Things (IoT), and sensor networks.



**Choong Seon Hong** (S'95-M'97-SM'11) received the B.S. and M.S. degrees in electronic engineering from Kyung Hee University, Seoul, South Korea, in 1983 and 1985, respectively, and the Ph.D. degree from Keio University in 1997. In 1988, he joined KT, where he was involved in broadband networks, as a Member of Technical Staff. From 1993, he joined Keio University, Japan. He was with the Telecommunications Network Laboratory, KT, as a Senior Member of Technical Staff and as the Director of the Networking Research Team until 1999. Since 1999, he has been a Professor of the Department of Computer Engineering, Kyung Hee University. His research interests include future internet, ad hoc networks, network management, and network security. He has served as a General Chair, TPC Chair/Member, or an Organizing Committee Member for international conferences, such as NOMS, IM, APNOMS, E2EMON, CCNC, ADSN, ICPP, DIM, WISA, BcN, TINA, SAINT, and ICOIN. He is currently an Associate Editor of the IEEE Transactions on Network and Service Management, International Journal of Network Management, and the IEEE Journal of Communications and Networks, and an Associate Technical Editor of the IEEE Communications Magazine. He is a member of the ACM, the IEICE, the IPSJ, the KIISE, the KICS, the KIPS, and the OSIA.