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Additive Logarithmic Weighting for Balancing Video Delivery over Heterogeneous Networks

Cristina Desogus, *Member IEEE*, Matteo Anedda, *Member IEEE*, Mauro Fadda, *Member IEEE* and Maurizio Murroni, *Senior Member IEEE* [1]

***Abstract*—The demand of media delivery services has increased with the popularity of social media and with the evolution of the user's devices (i.e., smartphones, laptops, and tablets) pushing towards new contents distribution models. The coexistence of go-live and on-demand media content requires a combined broadcast/unicast delivery model with the efficient management of the wireless access as a key issue. A twofold target needs to be reached: optimizing the load balance among coexisting networks and offering adequate quality of service (QoS) to users. To achieve this target for mobile video service delivery over heterogeneous networks (HetNet) scenarios, this paper proposes a solution based on an additive logarithmic weighting (ALOW) algorithm combining received signal power, network load, packet delay, user's equipment, and user's credit budget. ALOW is optimized by means of a cooperative game theory (GATH) approach. The proposed solution, named ALOWGATH (i.e., ALOW + GATH), has been tested on realistic HetNet scenarios and compared to the state of the art of the network selection and balancing algorithms. Results show an improved performance in terms of throughput, satisfaction index and overall video quality delivered, with reduced computational complexity.**

Keywords - video delivery, multicast, broadcast, heterogeneous networks, load balancing, QoS, traffic and performance monitoring, game theory.

I. INTRODUCTION

Video and high- Quality of Services (QoS) based applications ask for data transmission with high-reliability and extended coverage to guarantee an adequate quality also to devices in disadvantaged positions [1]. Social media applications together with devices as smartphones, laptops, or tablets are leading to replace traditional unicast connection (i.e., point-to-point - P2P) with new delivery schemes for allowing users to share self-produced live video content or to receive live video streaming or video-on-demand contents.

The 3rd generation partnership project (3GPP) introduced the evolved multimedia broadcast/multicast services (eMBMS) to provide long term evolution (LTE) [2] transmissions from a single source to multiple devices, using a common channel to share the same content in order to improve the management of available radio resource [3]. Nevertheless, nowadays mobile users are able to access the Internet also via other wireless technologies, such as wireless fidelity (WiFi) standard 802.11n/ac [4], constraining to implement other mixed schemes.

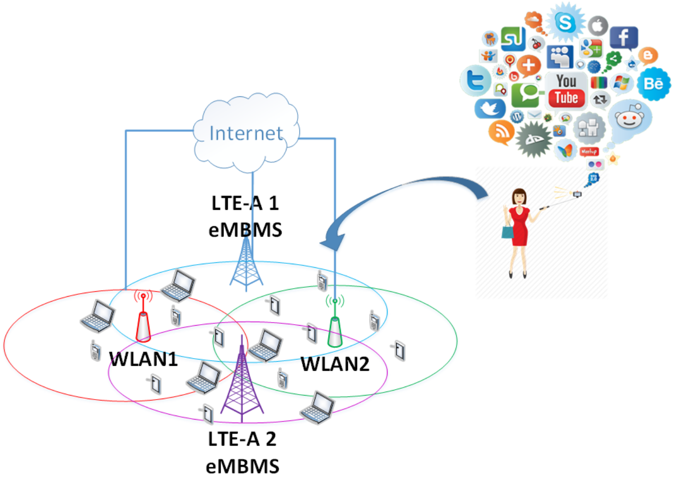

Fig. 1: Heterogeneous Multicast Network Scenarios

In this context, the "always best connected" (ABC) vision emphasizes the heterogeneous scenario where different access networks cooperate to provide a global wireless infrastructure in which users can enjoy an optimal service delivery via the most suitable wireless network that satisfies their interests among all the available wireless networks [5]. ABC gains even more importance both in social media applications (e.g., Facebook live, IGTV, Periscope) and mobile on demand programs offered by over the top (OTT) content providers. A way to achieve ABC is to perform traffic balancing on heterogeneous networks both to preserve the available networks from saturation and to avoid performance degradation.

Driven by this data centric new generation of devices, a new paradigm, well known as heterogeneous network (HetNet), has been developed. A HetNet is a network containing nodes with different characteristics such as transmission power and radio frequency coverage area [6]. An example of a HetNet scenario is shown in Fig. 1, where a user goes live on a social platform with self made video content, delivered to other interested users via multicast, using different network access options.

This variety of HetNet available to a user brings the need to select the network that offers the best performance in terms of QoS. To solve this problem, several innovative access network selection methods, after presented in section II, were recently proposed to ensure users the highest QoS without any additional request in terms of bandwidth or other resources. These algorithms offer a dynamic handover and device performance maximization in terms of power received, energy saving, and costs reduction.

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This type of algorithms, while solving the problem of the best candidate network, do not take into consideration scenarios in which all users select the same network and send it to saturation. The saturation of the network causes the performance to seriously deteriorate.

To mitigate this critical issue, several algorithms have been developed performing network balancing. Load balancing access network selection algorithms, described in section II, combine input parameters such as power of received signal, throughput, packet delay, energy consumption, and business parameters. However, they do not take into account:

- the type of traffic that the users are currently requesting;
- the kind of device they are using;
- a priority level that a user may have compared to other users.

All these algorithms allow users to take opportunistic decisions, regardless of the behavior and needs of other users. To overcome this limitation, we present a new HetNet selection algorithm based on additive logarithmic weighting (ALOW) method that combines both information related to class of devices, requested services, priorities, and data related to received signal power, network load, and packet delay. The allocation of resources is obtained with a balancing algorithm based on game theory (GATH) and Nash equilibrium (NE) [7]. Through which it is possible to direct the behavior of users avoiding saturation of network and planning to intervene, if it occurs.

The result of applying the proposed additive logarithmic weighting game theory-based (ALOWGATH) solution on realistic heterogeneous network scenarios, compared to the state of the art of the network selection algorithms shows an improved QoS metrics performance in terms of throughput (i.e., up to 9%), and video quality delivered compared to two current state of the art methods (i.e., ARMANS and HUMANS), shortly presented in section II. Moreover, this result is achieved with reduced computational complexity.

The rest of the paper is organized as follows: section II introduces the background related to access network selection algorithms; in section III, the proposed solution is described while section IV illustrates the scenario used for testing the system. Results are described in detail in section V. Finally, section VI draws the conclusions and introduces the future work to be done.

II. RELATED WORKS

The main challenge for users equipped with a multi-mode device is to exploit the "best" radio access network (RAN), intended as the RAN offering the highest QoS. Network selection is complex, depending on the capacity to rely on a large number of parameters, such as service class type, user preferences, mobile devices, battery level, network load, time of the day, service price, etc. Moreover, the procedure is further complicated by the combination of static and dynamic information involved in decision-making, the data accuracy, and the effort to collect it with available resources (e.g., battery, memory, and device processor), that may lead to limitation in performance due to devices characteristics.

The selection decision needs to be performed a first time to start the connection, and then repeated as part of the handover procedures, so whenever the situation of the network or device undergoes a change. In the last few years, different approaches have been proposed to select the candidate networks and to achieve a network load balancing, thus preventing the networks from saturating with consequent performance decline and QoS degradation.

In [8], the selection of candidate networks is based on the received signal strength. Using the repeated prisoner's dilemma game, the solution models the interaction user-network as a cooperative game showing that defining the incentives and disincentives for cooperation against defection allows achieving high QoS. This solution, based on the multiplicative exponential weighted (MEW) algorithm, was developed to perform a selection procedure over 3rd-generation (3G) networks not allowing to migrate the method for its use in a 4/5G perspective.

Also in [9], the MEW algorithm was performed to determine the score of each network that the user can access, through multiplicative mathematical operations. This method was applied to the selection of the candidate network. This document combined various inputs such as received signal strength, throughput, packet delay, cost per user, type of traffic required, and type of device.

In [10], the authors focused on the realization of a heterogeneous network environment with a combination of macro and small cells to spread the traffic load, increase the bitrates, and maintain high QoS.

In [11], a self-organizing network (SON) was proposed to simplify network management, performing evaluation and decision actions based on a set of rules and metrics. SON coordination becomes very complicated with a varied control structures. To overcome this limitation, cognition is addressed for enabling devices to independently learn the required optimal configurations.

Several approaches have been presented in [12], where three different directions based on current key challenges were followed:

- adaptive multimedia solutions aim to maintain high levels of quality perceived by the user by efficiently using the resources of the wireless network, either automatically through the services offered by the device, or through techniques for the adaptation of video delivery on the Internet;
- energy efficient solutions take into account the energy consumption of the mobile device to prevent mobile users from running out of battery during a video session. Mechanisms were classified into five macro categories: surveys and studies on energy consumption, selection of the energy efficient network, energy efficiency based on operating modes, cross-layer solutions for energy saving, and energy efficient multimedia processing and delivery. Their purpose is to identify the energy source and to manage its consumption allowing energy savings and increasing battery life;
- multipath content delivery solutions aim to address a problem caused by the increase in the use of video-

type multimedia applications, requiring a continuously expanding network able to offer a large amount of bandwidth. Currently, no single-access network technology would be able to meet these new traffic requests. One solution for integrating these bandwidth-rich multimedia applications would be to split traffic across multiple routes.

Another challenging topic is the management of network saturation, also considering the upcoming 5G networks growing and the massive use of Internet of Things (IoT) devices.

In [13], a virtual network embedding (VNE) algorithm is proposed to flexibly select the appropriate functional split for each small cell to jointly minimize the inter-cell interference and the fronthaul bandwidth utilization by dynamically selecting the appropriate functional split.

In [14], the authors proposed an algorithm that balances the small-cells networks avoiding the collapse of one or more of them which would create a significant worsening of the throughput. The algorithm is based on the progress of the overloaded and adjacent cells, adapting the state of the network load and considering the load estimate. The use of resources depends on the quality of the signal and the traffic requests of the user equipment (UE) connected in. The proposed solution does not fit heterogeneous networks and can only be used on networks that rely on the resource blocks (RBs), which are the basic resources of LTE.

In [15], the ORCHESTRA framework was proposed to manage the different devices based on a fully transparent virtual medium access control layer and an software-defined networking-like controller with global intelligence, introducing capabilities such as packet-level dynamic and intelligent handovers, scheduling, load balancing, and replication.

In [16] the authors developed PARMANS which supports load balancing and high quality multimedia delivery over heterogeneous wireless network environment (HWNE). P-ARMANS distributes content with different types of traffic and load among typical and business users at higher QoE levels compared to a classic no-priority approach. Markov Decision Process (MDP) procedures are characterized by multi-stage decision problems and are widely used for solving complex issues such as network selection in HWNEs. However, PARMANS does not consider cooperative behaviour among users.

Another algorithm for balancing networks in Dense Network scenarios was presented in [17]. The algorithm performs the balancing taking into account the throughput, energy consumption and user mobility. In order to plan energy consumption, improve performance in terms of data usage by offering better coverage in terms of the number of users served.

A good strategy for balancing networks is to use the GATH [18]. GATH is widely used in the management of HetNet to make choices that require the presence of different types of network selection criteria that have a competitive behavior between them (i.e., for networks and users). In literature, there are many examples of how GATH can be used to solve problems related to HetNet.

In [19], an algorithm based on GATH together with a self-optimizing power control scheme was proposed to solve a priority access problem applying the separation between primary and secondary users. For channel assigning strategy, they consider the allocation to be done dynamically on the basis of cell selection game. Their proposed scheme outcomes better system throughput, capacity as well as increased revenue of operators considering optimal price for consumers. The NE was used to study spectrum sharing within a heterogeneous network, in order to offer the maximum QoS to the users while reducing the co-channel interference.

In [20], the authors proposed a solution based on an analytical hierarchy process (AHP) to establish a hierarchy between the network evaluation criteria for different service requests. The hierarchy of the network obtained from the AHP analysis is then combined with the non-cooperative GATH to find the optimal network for specific assistance requests. The strategic game is formed on the network scores of different service requests for different RANs. Users willing to pay network providers for service requests are used to model a network game against a user. The NE of this game represent the RANs selected by each user with the highest result. All these methods showed good performance but none of them solved the problem of the presence of zeros in the score function and the absence of a balance between the networks. Moreover, all these works do not take into account the required type of traffic, the device being used, and the user priority defined as the capability to satisfy user requests compared to others. To overcome these issues, in [21] an adaptive real-time multi-user access network selection algorithm is presented for load-balancing over heterogeneous wireless networks (ARMANS) through the definition and use of four different QoS classes, as defined by the WiFi standard. However, this work has a limited number of connection points to the network, a limited number of users with different priorities. Moreover, the balancing takes place in a global manner without the presence of specific users priorities. Furthermore, ARMANS uses a MEW score function which presents the limit of the presence of zeros, forcing the algorithm not to take into account networks with an utility function (UF) (i.e., a measure of the parameters of the candidate network) equal to zero even in the presence of UFs that show very high values. Another novel method was proposed in [22], where the authors developed a network selection algorithm based on hybrid unicast-multicast utility, called HUMANS, which offers the option to select multicast transmissions in the network selection process during video delivery. The solution aims to serve users with good channel conditions through the use of unicast transmissions, while delivering content to users with poor channel quality via multicast. This allows offering high performance solutions in terms of percentage of interruption and average quality of transmission, both in low and high density scenarios, also ensuring operators more efficient use of the resources made available. Although HUMANS shows high performance in ultra dense networks scenarios, it uniquely performs a network selection procedure without any balance of the traffic load. In this work, the authors are presenting a new algorithm able to exceed the limitations showed by ARMANS and HUMANS solutions, and capable to perform a real time load balancing over heterogeneous wireless networks using a dynamic logarithmic function based on user's characteristics. The

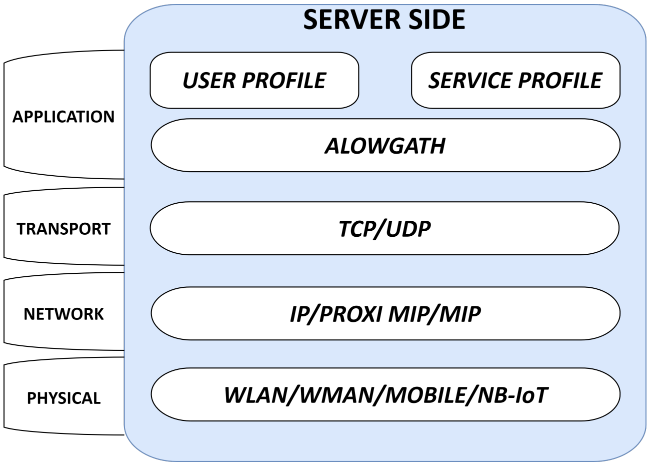

Fig. 2: Server Side Protocol Stack

previous solutions are enhanced proposing a novel additive logarithmic algorithm, based on the GATH, that improve the load balancing and the redistribution of resources between users. ALOWGATH allows to guarantee additional resources for users joining the system and, at the same time, avoids bringing the system to saturation. ALOWGATH is compared with ARMANS and HUMANS to show how the balance of the network via GATH and ALOW method, offers the algorithm greater stability and balancing taking into account the same criteria. Furthermore, the use of a MEW method has a higher computational burden than the ALOWGATH method. The use of this method therefore allows to reduce the latency times due to the calculation of the candidate network.

III. Proposed Solution - ALOWGATH

In this paper, authors propose to use an additional logarithmic weighted method that carries out the selection of a network taking into account several user's heterogeneous parameters:

- available load;
- perceived signal to interference plus noise ratio (SINR) level;
- economical availability (i.e., in terms of type of contract with the service provider);
- mobility.

At the same time, network overhead is avoided by using a GATH-based network balancing method, which allows effective distribution of resources through cooperative behavior. In this section, ALOWGATH is described by focusing on its architectural scheme and on the main features and functional parameters.

The ALOWGATH algorithm can be located at server side at application layer of the TCP/IP model, as shown in Fig. 2. The protocols used in the lower layers can be considered as "transparent" for the user: e.g., a video service can use UDP protocol in the transport layer, while a messaging application exploits a TCP protocol. At the same time, it will be able to receive useful information from other layers (e.g., network status). To perform network balancing, ALOWGATH needs information about user profile and network status. This information is collected through network monitoring mechanisms, such as the services offered by the IEEE 802.21 media independent handoff (MIH) standard [23], and special applications that allow user to set its own preferences. In fact, the IEEE 802.21 MIH standard has been developed to offer all the useful tools for carrying out the handover.

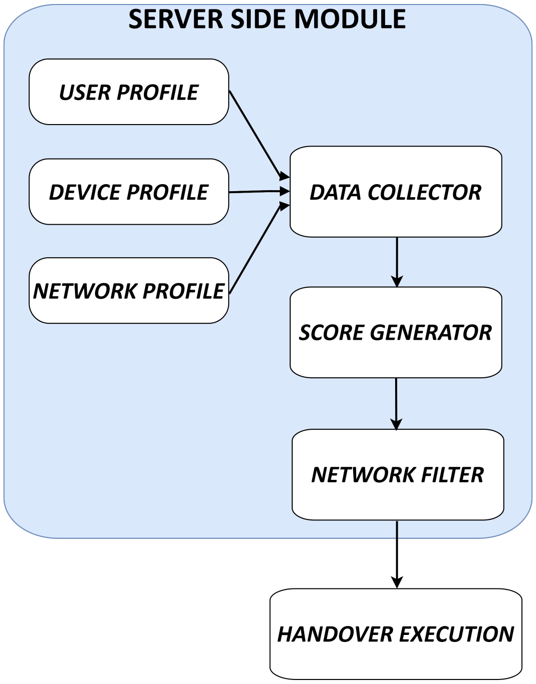

Fig. 3: Server Side Module

The data collector stores information about network, user, and device profile and sends them as input to the score generator. The score generator creates a list of available networks that is used by the network filter to evaluate the candidate network. Finally, the handover procedure can start. The server side module is summarized in Fig. 3. The client side module has a passive role, receiving the list of the available networks, with their corresponding scores, from the server side module. Once the client receives this list, it selects the first available network on the list.

The ALOWGATH framework is represented in Fig. 4. Two macro areas can be identified, the first one concerning the decision criteria and the second one dealing with the algorithm. The decision criteria area contains all the information necessary to implement the UFs to define the candidate network.

A. Decision Criteria

ALOWGATH needs several information to select the candidate network. These data concern user profile, network characteristics, and required service. Decision criteria is the module that collects all these functional information as shown in Fig. 4:

- **User Profile** is the profile of a user and provides preferences and information as the tariff plan or priority. A graphical user interface (GUI) installed on a device

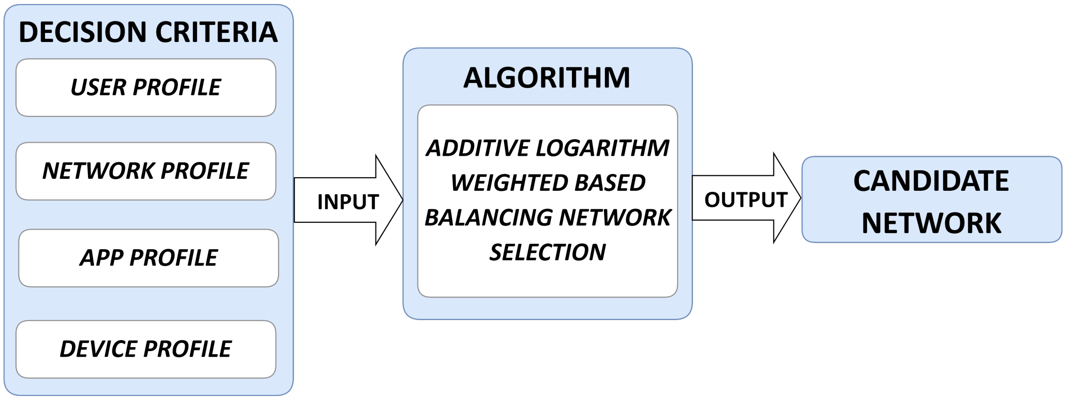

Fig. 4: ALOWGATH framework

- allows to extract it. During the creation of the profile, a user can decide how to weight the different parameters on which the ALOW algorithm is based, as described in next subsection. This procedure allows the algorithm to efficiently adapt to the needs of the user.
- **Network Profile** collects information about the QoS of available wireless networks (i.e., throughput, delay, and transmitted power). This is provided through the IEEE 802.21 MIH standard.
- **Application Profile** characterizes a service performing on a device in a precise moment, as different services have different requirements. For example, a video streaming application requires a minimum bandwidth to guarantee a minimum quality level.
- **Device Profile** gives information about its location, to know real-time movement speed and resolution of display, useful to calibrate a service based on video content.

Four main UFs are considered by the ALOWGATH algorithm as shortly described in next subsection.

1) Utility Functions:

1) **Load UF**: quantifies, for each network, the load available for each user connected to it.
2) **SINR UF**: quantifies the SINR perceived by each user connected to a specific network.
3) **User's budget UF:** give information about each user's economical availability, rules, and specific constraints.
4) **Speed UF:** states the mobility of each user in terms of speed.

In this subsection, the four UFs are shortly described:

- **Load UF** – u_l is computed to evaluate the available load using the equation (1):

$$u_l = \begin{cases} 0, & \text{if } c_{available} < l_j \\ c_{available} - \sum_j l_j, & \text{if } l_j < c_{available} < c_{max} \\ 1, & \text{otherwise} \end{cases} \tag{1}$$

  where $c_{available}$ is the total available load for the $i-th$ network (kbps) and l_j is the load for the j-th user connected to the $i-th$ network (kbps). The load UF has values within the [0,1) interval.
- **SINR UF** – u_s, useful to estimate the perceived SINR, follows this equation (2):

$$u_s = 1 - \frac{P}{I+N} \tag{2}$$

  where P is the power of the received signal, I is the interference between cells, and N is the channel noise.
- **User's budget UF** – u_c (3) quantifies the economical availability, following the paradigm "lower is better":

$$u_c = \begin{cases} 0 & \text{if } 0 \leq t \leq t_{min} \\ 0.5 & \text{if } t_{min} \leq t \leq t_{max} \\ 1 & \text{otherwise} \end{cases} \tag{3}$$

  where t is the paid traffic threshold that the user has available, t_{min} is the minimum threshold that the user wants to preserve for his own traffic, and t_{max} is the maximum traffic limit available to the user.
- **Speed UF** – u_v states the mobility. In terms of speed, users can be divided into three categories:
  - high speed: more than 15 Kmph, typically for vehicular users;
  - low Speed: less than 15 Kmph, for pedestrian or slow vehicles (e.g., a bicycle or wheelchairs);
  - stationary users: the user does not need mobility support.

  It is defined as (4):

$$u_v = \begin{cases} 0 & \text{if high speed} \\ 0.5 & \text{if low speed} \\ 1 & \text{otherwise} \end{cases} \tag{4}$$

UFs have different units of magnitude that make a fair comparison impossible. For this reason, each UF is normalized with the respective weight, attributed considering the importance of a particular UF with respect to the others, within the score function.

2) Weights: The value of the single weight has to satisfy the constraint in equation (5):

$$w_l + w_s + w_c + w_v = 1 \tag{5}$$

where w_l, w_s, w_c, and w_c represent the weights of load, SINR, user's budget, and speed UFs, respectively.

TABLE I: Utility Functions Comparison

	Load	SINR	User's Budget	Speed
Load	1	7	7	5
SINR	$\frac{1}{7}$	1	1	$\frac{1}{5}$
User's Budget	$\frac{1}{7}$	1	1	$\frac{1}{5}$
Speed	$\frac{1}{5}$	5	5	1

TABLE II: Example of weight for Utility Function

Utility	Weight
Load	0.6
SINR	0.1
User's Budget	0.1
Speed	0.2

Weight values are determined by means the Saaty scale [24], based on AHP method [18].

AHP is a multi criteria decision analysis (MCDA). The MCDA is oriented to support the decision making in the case of a big amount of requests and conflicting decisions.

AHP is based on five steps: starting from the definition of the criteria that contribute to the decision, a hierarchical value is attributed to them and a symmetric comparison matrix is calculated; the criteria are then grouped in pairs. Local weights are assigned to each pair. An analysis of the consistency of the opinions formulated is carried out. Finally, the global weights are defined according to the principle of hierarchical composition.

During the weight assignment phase, the following scale is considered [24]:

$$\begin{cases} 1 & \text{if } i \text{ and } j \text{ are equally important} \\ 3 & \text{if } i \text{ is a little more important than } j \\ 5 & \text{if } i \text{ is more important than } j \\ 7 & \text{if } i \text{ is definitely more important than } j \\ 9 & \text{if } i \text{ is absolutely more important than } j \\ \frac{1}{3} & \text{if } i \text{ is a little less important than } j \\ \frac{1}{5} & \text{if } i \text{ is fairly less important than } j \\ \frac{1}{7} & \text{if } i \text{ is definitely less important than } j \\ \frac{1}{9} & \text{if } i \text{ it is absolutely less important than } j \end{cases}$$

where i and j are the pairs of variables to which the weights must be attributed.

Through these steps the comparative values indicated in table I were obtained, where the most important value was given to the load, whereas a lower value was attributed to the SINR, User's budget, and speed, respectively.

Once weights are assigned, a weight matrix is created [25]. The matrix used in the presented study is:

$$U = \begin{pmatrix} 1 & \frac{1}{7} & \frac{1}{7} & \frac{1}{5} \\ 7 & 1 & 1 & 5 \\ 7 & 1 & 1 & 5 \\ 5 & \frac{1}{5} & \frac{1}{5} & 1 \end{pmatrix} \tag{6}$$

Starting from matrix U, by applying the priority assignment method, a priority normalized eigenvector W is calculated, as shown in (7).

$$W = (0.6, 0.1, 0.1, 0.2) \tag{7}$$

The weight values calculated for the UFs are summarized in table II.

B. ALOW Algorithm

The ALOW algorithm is used to evaluate the scoring of each network the user can access. It receives as input data from network, user, device, and application profiles, returning as output the candidate network. Each score is determined by ALOW method performing a decision making mechanisms, as indicated in literature by [26]. Alternative criteria are normalized with their weights, depending on the different relevance attributed to them.

The UF applied to this algorithm, that is the reputation value that we attribute to the selected network, is given by:

$$\begin{aligned} ln(U^i) = w^l * ln(u_l) + w^s * ln(u_s) + \\ + w^c * ln(u_c) + w^v * ln(u_v) \end{aligned} \tag{8}$$

where $ln(u_l), ln(u_s), ln(u_c)$, and $ln(u_v)$, are UF for load, SINR, user's budget, and speed, respectively, while w^l, w^s, w^c, w^v are weights of the single UFs.

The weights attributed are initially calculated as previously shown in section III-A2. Then the user can change their values according to different needs. For example, if a user needs to save money because he has finished the gigabits available in his contract, he will give more importance to the UF that deals with the cost to the user. If instead he needs more bandwidth for the service he will give more importance to Load UF. The weight assigned to each UF based on the choices made by the user influences the selection of the candidate network.

C. Game Theory

The GATH is a mathematical tool finalized to the comprehension and modeling of competitive situations involving the interaction of rational decision makers with common and conflicting interests. It has been widely used in telecommunications to solve problems related to resource management or allocation, and, more in general, in the engineering field when there is the need of strategical interaction and modelling between several actors.

The main components of the GATH are outlined as follows:

- the set of players, that is entities able to make the decision;
- the set of actions (i.e., strategy set) that players can accomplish;
- the set of payouts that players can get to have a utility;
- the balance, i.e. the combination of strategies that lead to the best payoff possible;
- the NE balance is achieved by combining strategies aimed at obtaining the users' payoff finding a solution to the game.

Within a heterogeneous network scenario it is possible to identify different types of games by differentiating the type of players. They can be grouped into games between users, games between networks, and games between users and networks. In this study we will focus on the game between users.

The game between users takes into consideration the problem caused by the fact that users, when egoistically choose the network considering to be the best, lead to network congestion and consequently to degradation of performance. This type of game is a non-cooperative type.

At this point, there are limits due to the user's need to obtain the best network and the costs due to congestion of the selected network.

For this reason, cooperative games have been proposed, in which users collaborate to obtain the mutual benefit of satisfying bandwidth requirements while maintaining a good level of QoS. In the case of limited resources, each user has a reduction in bandwidth in order to avoid the cost of performance degradation.

The cost of each user depends on the congestion of the selected network, as shown in 9:

$$u_k(i, \sum u_l \in K) \tag{9}$$

where u_k is the k^{th} user, $\sum u_l \in K$ indicates the total number of users in the network, i is the boolean value that indicates whether the user has selected the i^{th} network.

To obtain an NE, the situation must be reached where no player can have greater advantages by unilaterally changing his strategy.

In this considered case, the solution to the problem with NE is obtained when all users are able to choose the network that involves the minimum cost in terms of QoS. This can be indicated as:

$$\zeta_{ki} u_k(i, \sum u_l \in K) \leq u_k(i, \sum u_l \in K) \tag{10}$$

where $\zeta_{ki} u_k(i, \sum u_l \in K)$ is a binary variable representing whether user k is within the coverage of network i^{th}.

In our case study, the users and the networks each of them can access are considered the players. The set of actions or strategies that can be taken by the users during the game are: bandwidth request, subscription with network operator, network resources release, and user mobility inside network cell increasing or decreasing the QoS. The action to be considered for the network are dynamic resources offered in order to satisfy the largest number of users.

The winning users are given by the profit they can get in terms of bandwidth and QoS, estimated using the UF. On the other hand, the network profit is to offer the service as many users as possible avoiding network saturation.

In this study, we focused on the users behavior, identifying two possible attitudes they can take:

- **Cooperative**: users cooperate to get the mutual benefit of meeting the bandwidth requirement by maintaining a good level of QoS. In case of limited resources, each user has a decrease in bandwidth in order to accommodate new users.
- **Non-cooperative**: users do not cooperate with each other and try to maximize their QoS level. In case of limited resources, they do not undergo bandwidth and no further users are accepted within the network.

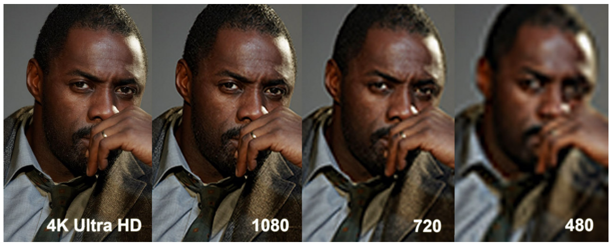

Fig. 5: Variable Resolution Encoding

TABLE III: Lowered Encoding Video

Name	Resolution	Bitrate HQ (Mbps)	Bitrate lowered (Mbps)
1080p	1920x1080	9.0	6.0
720p	960x720	4.0	4.0
576p	768x576	2.5	2.3
480p	640x480	2.0	1.5

In this paper, cooperative behavior of users has been investigated. Fig. 5 shows what happens when bandwidth reduction occurs: while maintaining the same resolution the bit rate is gradually lowered, affecting the perceived quality.

It can be noted that the variation of the bitrate leads to a deterioration of the image quality until the total loss of the QoS, considerably lowering the quality of experience (QoE) even in the presence of small screens.

Starting from the data summarized in table III, the bitrate will be lowered from the high quality (HQ) to the next level and the video frames will be decreased (e.g., from 30 fps to 25 fps).

For lower values, the risk is to provide bad quality videos involving a drastic lowering of user's satisfaction, even if the audio component does not change during the quality down phase.

D. ALOWGATH Algorithm

Fig. 6 shows the ALOWGATH flowchart. At first, ALOWGATH seeks a candidate network (CN) able to meet the traffic user's request, in terms of available bandwidth resources. In case of positive feedback, network selection is carried out using ALOW algorithm; in case of bandwidth saturation a GATH approach is employed to release resources needed to accommodate new user's requests.

A pseudo-code of ALOWGATH is presented described in algorithm 1.

The purpose of the ALOWGATH algorithm is to obtain the CN between the available networks by each users. Available networks are all those networks that the user can connect to. ALOWGATH performs several steps to select the CN, shortly summarized as follows:

1) Available networks are collected within a list of networks (LoN) available for user.
2) To ensure that the CN is calculated, some variables are initialized, such as:
    - CN, that has a null starting value;
    - Score represents the UF value for each considered network;

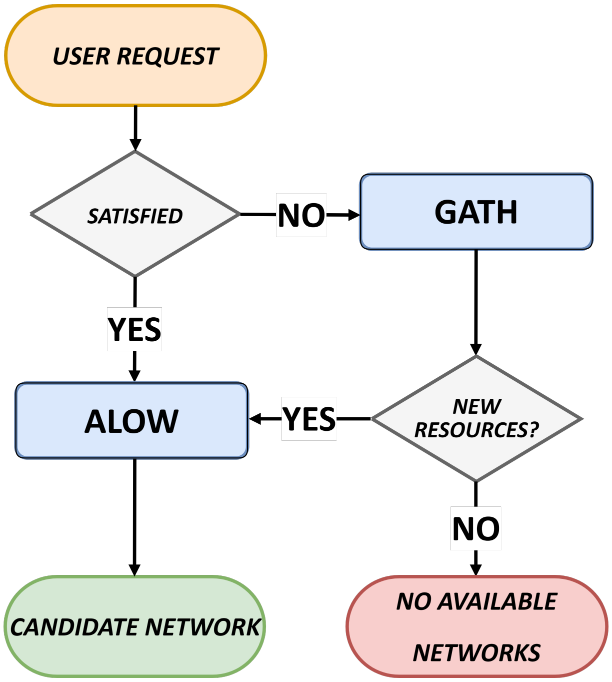

Fig. 6: ALOWGATH Algorithm Flowchart

Algorithm 1: ALOWGATH Algorithm

```
Result: This algorithm return the Candidate Network
        = CN
Input: User = us;
User Requests = UR;
List of Network available for user = LoN;
List of Users in Network = UoL;
Minimum Threshold = mTS;
Local Threshold = LT.
begin
    CN = null;
    Score = 0;
    BestScore = 0;
    LT = MaxThreshold
    foreach n in LoN do
        Score =$w^l * ln(u_l) + w^s * ln(u_s) + w^c *$
         $ln(u_c) + w^u * ln(u_u)$;
        if Score $\geq$ BestScore then
            BestScore = Score;
            CN = n;
        end
    end
    while CN.bandwidth() $\leq$ UR OR LT $\geq$ mTS do
        Use GameTheory Algorithm;
        foreach u in UoL do
            u.AdaptStreaming();
        end
        LT.lowerThreshold();
    end
    UoL.AddUser(us);
    return (CN);
end
```

- BestScore identifies the best network at a specific time for a user.

3) For each network n into the LoN available for each user, Score is calculated using ALOW as shown in equation 8.
4) If the obtained Score is higher than BestScore, BestScore is replaced with Score value and n becomes the new CN.
5) The CN's searching procedure ends when all n within LoN have been evaluated. However, CN must handle the user's traffic request (UR).
6) If the available bandwidth of CN is lower than UR, the GATH algorithm is performed.
7) Until the available bandwidth of CN is lower than the threshold or higher than the minimum possible threshold, for all users (us) connected to the CN the streaming threshold is lowered using the values in table III.
8) Finally, considering the selected CN, if the requested services can be guaranteed by lowering the users threshold, the algorithm can end. Otherwise, the UR will be rejected and the user's access will be denied.

E. Computational Complexity

The computational complexity of ALOWGATH is $O(nlogn)$, indeed, lower than the computational complexity of ARMANS and HUMANS that, using a MEW method, have a computational burden of $O(2^n)$. Only mathematical calculation performed by the device has been taken into account in calculating the computational burden. The other steps of the algorithm do not involve computation charges. Specifically, the individual UFs are input for the device, in the form of a numerical value, while the functionality of the GATH has computation burden equal to 1 as it is a simple selection.

IV. SCENARIOS AND SIMULATION SET-UPS

The performance of the proposed algorithm has been evaluated in two scenarios: a general case and a real scenario representing the seaside area of Cagliari, Italy.

A. Scenario 1 - General Case

This general scenario is characterized by a HetNet composed by a LTE eNodeB (eNB) and two access points (APs) for the 802.11ac standard, as shown in Fig. 7.

The distance between APs is equal to 120 m, whereas the eNB is placed to enclose the APs in LTE radio coverage. The HetNet is progressively loaded periodically adding a user, up to 200 users. The idea is to progressively overload the network. Each user:

- has a pseudo random position within an area of 1 km^2: the position was calculated through a uniformly distributed random function using a method provided by the simulator to indicate the area within which the user is placed;
- has uniformly distributed random speed between 0 and 20 kmph;

TABLE IV: Encoding Video and Audio Data Rate

Name	Resolution	Video [Mbps]	Audio [kbps]
1080p HQ	1920x1080	9.0	128
720p HQ	960x720	4.0	128
576p HQ	768x576	2.5	64
480p HQ	640x480	2.0	64

TABLE V: Type of Traffic - CISCO 2020

Traffic Type	Total Traffic 2020	Downlink%	Uplink %
Video	82%	98%	2%
Other traffic	18%	76%	24%

- performs video content traffic at different resolution, to be delivered to devices with different screen resolution according to table IV.

The simulations were conducted in accordance with data provided by Cisco for the years 2017-2022 [27], showing that most of the traffic was video traffic type. Specifically, as shown in table V, the video traffic mainly involved is from downlink transmissions.

As far as APs are concerned, in accordance with the specifications in the 802.11n standard we considered different Modulation and Coding Schemes (MCSs) as in table VI. MCSs were chosen to cover the distance between APs as to avoid service interruption. A user is associated to a MCS related to the AP location. As can be seen in Fig. 8, close to the AP the user will have MCS equal to 31 that corresponds to a maximum data rate of 600 Mbps, while as it moves away from the AP, this value gradually decreases up to a minimum value (i.e., 0 Mbps at 120 m). For higher distances, there is further signal decay up to total loss for distances greater than 250 m. For this reason, it was chosen to impose the user's position within a 250 m radius from the AP.

Considering the cellular network, the maximum MCS supported by a LTE user is obtained evaluating the perceived SINR and its corresponding channel quality indicator (CQI), as shown in Fig. 9. The simulation set-up for this first scenario is characterized by the parameters listed in table VII.

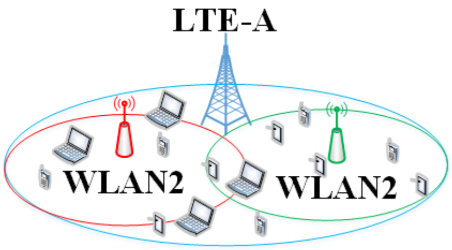

Fig. 7: Scenario 1

TABLE VI: Scenario 1 - MCS and Data Rate

MCS	Data Rate [Mbps]	Distance [m] %
31	600	10
30	540	20
20	270	40
18	135	80
8	30	90
0	15	120

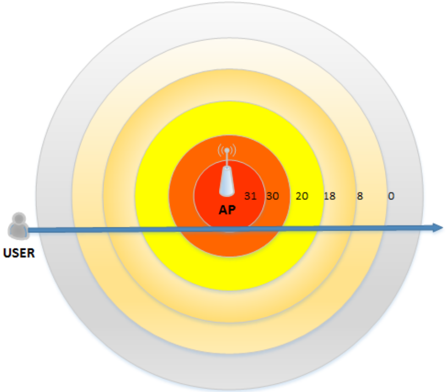

Fig. 8: Scenario 1 - 802.11 MCSs

TABLE VII: Set-up for Scenario 1

Parameters	WiFi Network	LTE Network
Technologies	802.11n	LTE cat 6
Number of AP/eNB	2	1
Radius Cell	250 m	500 m
Transmission Power	20 dBm	46 dBm
Bandwidth	40 MHz	20 MHz
Data rate Max	600	300
Propagation Model	Hybrid model	Hybrid model

B. Scenario 2 - Real Case

The second scenario represents a urban pedestrian seaside area located in Cagliari, Italy. 24 APs have been installed to serve the area along the seafront, approximately 2 Km long, distant from each other 80 m on public lighting poles at a height of 10 m from the ground. The area is also covered by the LTE service through a eNB. In Fig. 10, the real urban scenario is shown. The red points represent the APs whereas the eNB location is depicted in blue. The peculiarity of this real scenario is that shows an overestimated number of APs considering the size of the area to cover; this coverage solution

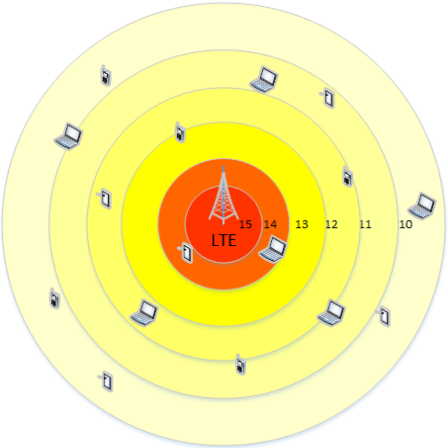

Fig. 9: Scenario 1 - LTE MCSs

Fig. 10: Real Urban Scenario - Seaside Area in Cagliari

TABLE VIII: Cellular Network Characteristics

Provider	Network type	Distance	SS
Operator 1	LTE-A	450 m	-104 dBm
Operator 2	LTE-A	500 m	-115 dBm
Operator 3	LTE-A	600 m	-123 dBm

depends on the fact that this area is often designated to host big live music events (i.e., to serve overcrowded areas). This is a typical case where the delivery of user generated multimedia content is requested by the users, therefore it was considered as significant to evaluate the performance of the proposed system.

We performed on site measurements to evaluate the quality of the signal perceived by users conducted using a third party application named "Network Cell Info Lite", a tool for monitoring and self testing the cellular network [28] which also provides the cell map and signal strength (SS) indicators. The information obtained through the measurement system is summarized in table VIII, including SS, eNB distance, LTE cell ID (LCID), and available technology.

A second series of measurements has been carried out to analyze the behavior of the WiFi signal at various locations along the seafront through "Analyzer WiFi", an application that allows to scan all the WiFi networks detectable from a smartphone and provides useful information to evaluate performance. The app shows the active networks in a considered area indicating their names, the band (i.e., 2.4 or 5 GHz), the Mac address, the type of protection, and the ones with the most powerful signal. Moreover, a time chart gives the trend of the signal strength in a certain time period.

Their received power level is comparable and equal to -70 dBm. Similarly, a mobile device receives signals as it is under the coverage range of the eNodeB within a radius of 250 m. The SS of the N-th APs, with N indicating the number of APs in the scenario, gradually decrease as we move away from them.

As for the general case, the scenario was populated until saturation. In this case, users requesting video content services were progressively added up to 1000, randomly placed, moving with variable speed uniformly distributed (i.e., between 0 and 20 kmph). During the simulation, the AP characteristics were adjusted based on the APs actually installed along the way. The technical data of the installed APs can be obtained from the CISCO website, as shown in table IX. Similarly, for LTE the characteristics of the installed devices were obtained by the service providers. The simulation set-up for this second scenario is characterized by the parameters listed in table X.

TABLE IX: Technical Data for APs

Freq [GHz]	Standard	MCS Type	MCS Number	dBm
2.4	802.11n HT20	0/8 HT20	22	−96
		1/9 HT20	22	−94
		2/10 HT20	21	−92
		3/11 HT20	21	−89
		4/12 HT20	21	−85
		5/13 HT20	21	−82
		4/14 HT20	20	−81
		5/15 HT20	19	−79
2.4	802.11n HT40	0/8 HT40	21	−93
		1/9 HT40	21	−91
		2/10 HT40	21	−89
		3/11 HT40	21	−86
		4/12 HT40	21	−82
		5/13 HT40	21	−79
		6/14 HT40	19	−78
		7/15 HT40	18	−77
5	802.11a	6 Mbps	24	−97
		9 Mbps	24	−96
		12 Mbps	23	−94
		18 Mbps	23	−92
		24 Mbps	22	−90
		36 Mbps	21	−87
		48 Mbps	20	−85
		54 Mbps	20	−83
5	802.11n HT20	0/8 HT20	23	−98
		1/9 HT20	23	−96
		2/10 HT20	22	−93
		3/11 HT20	21	−90
		4/12 HT20	21	−84
		5/13 HT20	20	−82
		6/14 HT20	19	−80
		7/15 HT20	15	−79
5	802.11n HT40	0/8 HT40	23	−94
		1/9 HT40	22	−93
		2/10 HT40	21	−91
		3/11 HT40	20	−88
		4/12 HT40	19	−85
		5/13 HT40	18	−81
		6/14 HT40	18	−78
		7/15 HT40	14	−76

TABLE X: Set-up for Scenario 2

Parameters	WiFi Network	LTE Network
Technologies	802.11n	LTE cat 6
Number of AP/eNB	24	2
Radius Cell	250 m	500 m
Transmission Power	Table IX	46 dBm
Bandwidth	40 MHz	20 MHz
Data rate Max	300	300
Propagation Model	Hybrid model (in/out)	Hybrid model (in/out)

V. RESULTS

For each scenario, simulations were performed using ns-3, a discrete-event network simulator for Internet systems [29]. We performed a comparative analysis between ALOWGATH and ARMANS considering the scenario 1, characterized by the presence of a single eNB and 2 APs. Due to this particular configuration, it was not possible the comparison with HUMANS which was developed for ultra dense HetNets. A full comparative analysis of the three solutions (i.e., ALOWGATH, ARMANS, and HUMANS) was carried out considering the scenario 2 presented in subsection IV-B.

The results are evaluated in terms of average throughput, aggregated throughput, peak signal-to-noise ratio (PSNR), and average PSNR. The use of the PSNR as evaluation parameter is due to the choice of simulating video content based services.

TABLE XI: Simulation Results for Scenario 1

	ALOWGATH	ARMANS
Av Thr [Mbps]	8.55	8.11
Av PSNR	28.99	27.99

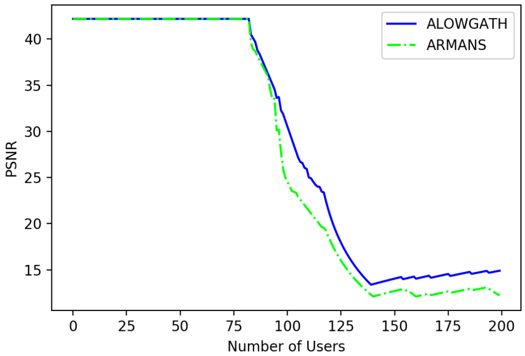

Fig. 11: PSNR Trend for Scenario 1

A. Results for Scenario 1

The first scenario presents a general case, in which there are two APs and one ENb.

The results obtained show an improvement in performance both in terms of average throughput and in terms of average PSNR compared to ARMANS, as shown in table XI. Specifically, the average throughput shows an improvement of 9%, while the average PSNR is about 4%.

Furthermore, the trends of the QoS parameters taken into consideration show how the presence of balancing via GATH makes the algorithm more stable and performing than ARMANS.

Fig. 11, represents the PSNR variation with the number of users for ALOWGATH and ARMANS. The trends are similar up to the saturation point, which occurs with 85 users. For saturated networks, ALOWGATH outperforms ARMANS in balancing the networks.

The trend of the aggregate throughput, that is the sum of all the throughput received by all the served users, is presented in Fig. 12 while Fig. 13 shows the average throughput trend. Both confirm the superior performance for ALOWGATH, especially when the system approaches saturation.

In particular, Fig. 13 shows how ALOWGATH shows a better trend with a decidedly less steep degrowing curve, therefore with a lower performance decline.

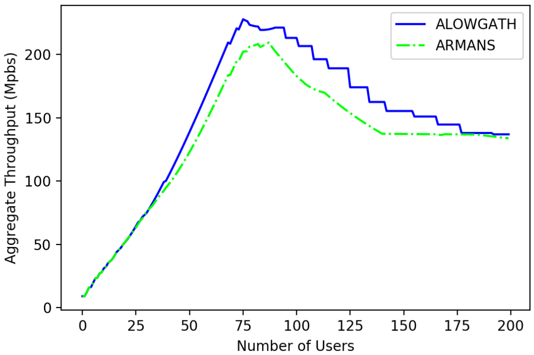

Fig. 12: Aggregate Throughput Trend for Scenario 1

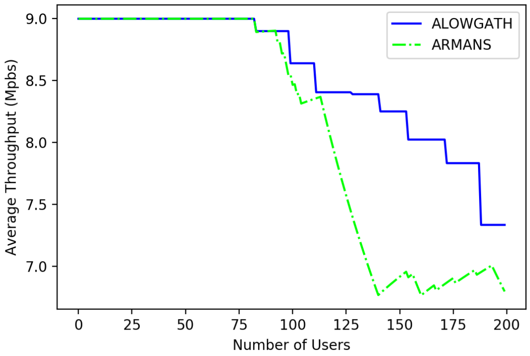

Fig. 13: Average Throughput Trend for Scenario 1

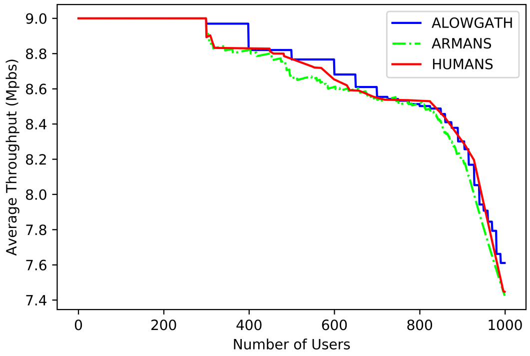

Fig. 14: Average Throughput Trend for Scenario 2

B. Results for Scenario 2

This real scenario is characterized by the presence of eight APs against only one eNBs to serve users. Comparative results

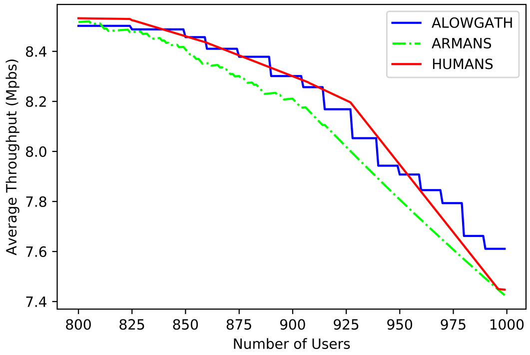

Fig. 15: Average Throughput Trend for Scenario 2 considering 800 to 1000 users

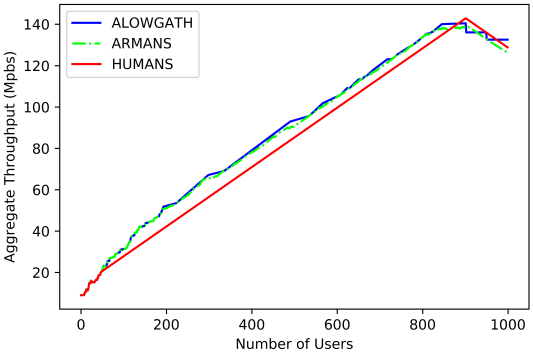

Fig. 16: Aggregate Throughput Trend for Scenario 2

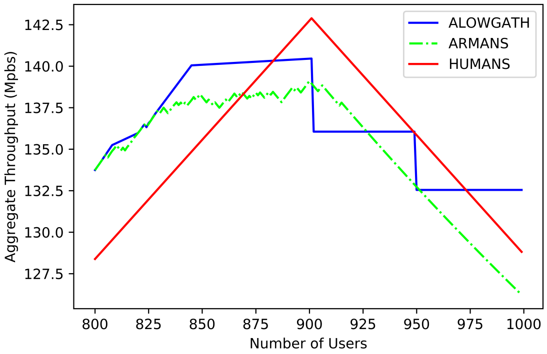

Fig. 17: Aggregate Throughput Trend for Scenario 2 for 800 to 1000 users

in Table XII indicate how the use of the GATH for balancing heterogeneous networks provides benefits in terms of average throughput.

TABLE XII: Simulation Results for Scenario 2

	ALOWGATH	ARMANS	HUMANS
Av Thr [Mbps]	8.71	8.45	8.27
Av PSNR	28.99	27.99	28.45

On the other hands, despite the average PSNR is comparable for the three methods, ALOWGATH still slightly outperforms both ARMANS and HUMANS. Fig. 14 compares the average throughput variation for the three algorithms. As can be observed, ALOWGATH presents a stepped trend due to the GATH approach. In fact, the throughput is maintained equal for all the users in the network until all of them can be served, than its value is decreased to accept new users.

This particular characteristic leads to guarantee higher values of average throughput, compared to ARMANS and HUMANS. As the number of users increases, ALOWGATH increases the performance with respect to ARMANS and HUMANS as shown in Fig. 15, where a focus over the trend considering a network with more than 800 users is presented.

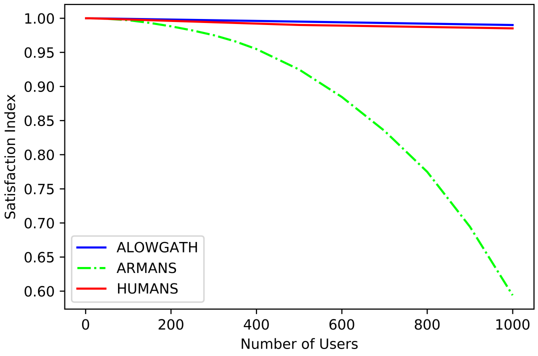

Fig. 18: Satisfaction Index Trend for Scenario 2

Fig. 16 shows how the aggregate throughput variation for the three algorithms are approximately overlapped till about 800 users. In Fig. 17, where the throughput trend from 800 to 1000 users is presented, it is possible to notice that:

- between 800 and 890 users interval, ALOWGATH outperforms ARMANS and HUMANS;
- HUMANS presents a pick at 900 users, than starts to decrease;
- for more than 970 users, ALOWGATH restarts to ensure higher performance.

In fact, ALOWGATH allows the networks to saturate smoothly and outperforms both ARMANS and HUMANS, guaranteeing increased performance for this particular scenario.

Finally, the satisfaction index (SI), that indicates the value of appreciation perceived by users in terms of the ratio between the data rate received and the data requested by each user, has been evaluated and the results are summarized in Fig. 18. The satisfaction of users is comparable considering ALOWGATH and HUMANS solutions, while ARMANS shows a SI which start decreasing as the number of users overcomes 170.

VI. CONCLUSIONS

As for the balanced video delivery in heterogeneous networks scenario, this paper has presented ALOWGATH, a new HetNet selection algorithm based on additive logarithmic weighting that combines information related to the class of device, the requested service, priorities, data related to received signal power, network load, and packet delay. Resource allocation is performed using a balancing algorithm based on Game Theory (GATH) and Nash equilibrium (NE).

To evaluate the effectiveness of the solution, ALOWGATH was compared with ARMANS and HUMANS algorithms in two different scenarios. The results showed improved performance in terms of average throughput, aggregate throughput, and satisfaction of users, other that video quality delivered to users. Moreover, the computational complexity of ALOWGATH is lower than the computational complexity of ARMANS and HUMANS that carry out a multiplicative exponential weighted (MEW) method.

In the future, the algorithm can be improved by allowing the user to choose the type of traffic he intends to use in order to be able to customize the performance on the type of traffic required, allowing the use of multiple types of services simultaneously.

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