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A dynamic access point allocation algorithm for dense wireless LANs using potential game

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A B S T R A C T

This work introduces an innovative Access Point (AP) allocation algorithm for dense Wi-Fi networks, which relies on a centralised potential game developed in a Software-Defined Wireless Networking (SDWN)-based framework. The proposed strategy optimises the allocation of the Wi-Fi stations (STAs) to APs and allows their dynamic reallocation according to possible changes in the capacity of the Wi-Fi network. This paper illustrates the design of the proposed framework based on SDWN and the implementation of the potential game-based algorithm, which includes two possible strategies. The main novel contribution of this work is that the algorithm allows us to efficiently reallocate the STAs by considering external interference, which can negatively affect the capacities of the APs handled by the SDWN controller. Moreover, the paper provides a detailed performance analysis of the algorithm, which describes the significant improvements achieved with respect to the state of the art. Specifically, the results have been compared against the AP selection considered by the IEEE 802.11 standards and another centralised algorithm dealing with the same problem, in terms of the data bit rate provided to the STAs, their dissatisfaction and Quality of Experience (QoE). Finally, the paper analyses the trade-off between efficient performance and the computational complexity achieved by the strategies implemented in the proposed algorithm.

1. Introduction

WI-FI networks are now ubiquitously deployed, e.g., in apartment buildings, work places and public spaces such as airports, shopping malls and university campuses. Dense IEEE 802.11 Wireless Local Area Networks (WLANs) employ IEEE 802.11 Access Points (APs) configured to work on overlapping Radio Frequency (RF) channels to provide Wi-Fi stations (STAs) with sufficient signal coverage and efficient connectivity. However, Wi-Fi operators need to deal with the ever-increasing requirement of higher bandwidth, different Quality of Service (QoS) based on users' applications, and better connectivity. Addressing this challenge is becoming increasingly daunting due to a massive diffusion of bandwidth-hungry Wi-Fi applications. Considering that the Wi-Fi spectrum capacity is limited, the serious increment of wireless traffic demand is now causing over-congestion within the WLANs.

Hence, the selection of an appropriate AP during the association process plays a major role in guaranteeing a fair and balanced allocation of Wi-Fi resources among STAs. A number of contributions can be found in the state of the art dealing with AP allocation aiming to maximize the QoS of a certain Wi-Fi user [1–19]. Our solutions presented in [16–19] are among the few contributions that try to address the AP allocation challenge while also recognising the heterogeneous QoS demands of STAs. These contributions propose association strategies that match the suitability of users' traffic with a particular AP in terms of their QoS demand. In these previous contributions, we proposed an AP selection framework built on top of a Software-Defined Wireless Networking (SDWN) architecture [20]. In this architecture, the SDWN controller is the central entity that manages the Wi-Fi networks and executes the AP selection algorithm.

Although these contributions all offer QoS aware AP selection algorithms, they assume that the availability of Wi-Fi network resources and AP bandwidth capacities is always the same. In real-

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ity, Wi-Fi networks are prone to changes, perhaps due to the presence of external interference, which affects the availability of their resources. In fact, many Wi-Fi networks operate in environments where certain APs are exposed to external interference from inaccessible sources. For instance, many Wi-Fi networks deployed in public spaces such as airports and train stations have to coexist with other Wi-Fi networks owned by small shops and operate on the same transmission channels. In such situations, AP selection should be able to cope with these changes in conditions by reallocating STAs to another AP should their current AP resources drop below a given level.

However, since most of the mentioned contributions adopt a static centralised approach to the AP selection problem, the introduction of dynamic reallocation of STAs according to changes in the capacity of the Wi-Fi network might result in extra computational complexity and scalability issues at the central control entity.

In this paper, we aim to address these limitations by introducing a novel AP allocation algorithm for dense Wi-Fi networks, which relies on a centralised potential game supported by the SDWN-based framework proposed in [17–19]. Due to the dynamic nature of the analysed scenario, the search for an optimal solution to the allocation problem in real time may not be feasible, making the use of suboptimal heuristics mandatory. Under these premises, the use of potential games to approximate the optimal allocation may be suitable. Potential games [21] are typically employed in order to execute a distributed optimization of resource allocation by means of their convergence to a Nash Equilibrium (NE) that can be always reached [22]. On the other hand, the development of potential games in dense distributed networks, such as the one considered in this paper, is commonly characterized by high complexity because each player typically needs to acquire relevant data from the other players of the network, which makes this approach not scalable. However, the use of SDWN as a management framework in our work allows us to reduce the implementation complexity by playing the potential game at the central controller. Moreover, our potential game-based approach adopts two commonly-used game theory strategies explained throughout the rest of the paper. The difference between these strategies and their pros and cons are described in detail in Sections 5 and 6, respectively. In [18,19], we proposed a preliminary version of the AP allocation approach based on the potential game, which we have extended in this paper in the facets illustrated in Section 2.

The proposed AP allocation algorithm helps to optimise the allocation of AP resources to STAs, which is very important in conditions where these resources become scarce. Our simulation results show that the algorithm achieves a reduction of users' dissatisfaction of up to roughly 56% in comparison with the most relevant existing algorithm presented in [17]. Moreover, our performance analysis illustrates that the computational complexity of our algorithm is reduced even for a high number of STAs.

The rest of the paper is organized as follows: Section 2 illustrates the state of the art and our new contributions. In Section 3 we present the system model together with the formulation of the problem and the framework based on SDWN. Section 4 includes a detailed description of the potential game. In Section 5 we describe the AP allocation algorithm relying on the potential game. In Section 6 we define the simulation model we implemented to assess the proposed algorithm and the analysis of the performance. Finally, we provide our conclusions and future work in Section 7.

2. Related works and new contributions

AP allocation is a problem broadly addressed in the state of the art. In this section, we first analyse the main papers for dealing with AP allocation found in the literature and then present the motivations behind our work and new contributions. Typically, existing works on AP allocation are divided into distributed (e.g. [1–11]) and centralised (e.g. [12–19,22]) solutions. Specifically, in the case of distributed strategies, the user devices first gather measurements related to certain performance metrics from the network and then choose the best AP based on such measurements. In the case of centralised solutions, the decision on the selection of the best AP is performed by a controller based on its overall view of the managed network.

Examples of distributed solutions can be found in the literature that are based on game theory [1–5], neural networks [6], cross-layer approaches [7–9], and Clear Channel Assessment Threshold (CCAT) adjustment that takes into account co-channel interference [10]. Moreover, the authors in [11] presented a classification of works dealing with AP selection for IEEE 802.11 Wi-Fi networks and then introduced a distributed strategy, which addresses Quality of Experience (QoE) enhancement.

For centralised solutions, the authors in [12] first presented a classification of fairness criteria, which are largely used in centralised resource assignments. Then, they proposed an AP association algorithm to obtain proportional fairness based on a function, which represents a performance revenue and is achieved every time a new STA tries to connect to the network. Moreover, in [13] the authors proposed a detailed survey of load balancing strategies based on different metrics and approaches. The works proposed in [14–19] considered SDN-based platforms to implement centralised approaches to address AP selection for Wi-Fi users. Finally, the work in [22] proposed a cloud-based access node selection approach using a potential game.

An important drawback of the solutions proposed in [1–15,22] is that all the Wi-Fi users are treated in the same manner. In reality, each Wi-Fi user may be running a certain service or experiencing an application that needs particular QoS requirements. The works proposed in [16–19] overwhelm such a drawback through the introduction of an association approach, which matches each user traffic with the most suitable AP depending on the corresponding bit rate requirements. Among these works, we introduced an innovative and efficient reallocation of APs to the STAs when needed using the centralised potential game in [18,19] to improve the results presented in [16,17]. However, these works do not consider possible changes in the capacity of a Wi-Fi network due to dynamic interference that can negatively affect the performance of the network. The novel contributions of the AP allocation algorithm proposed in this paper with respect to our works published in [16–19] can be summarized as follows:

- Wi-Fi dense radio environments are characterized by sources of interference, which are not under the control of our SDWN architecture [20,23]. In this context, we implemented an innovative AP allocation algorithm, which takes into consideration such interference. The proposed implementation allows us to efficiently reallocate relevant APs to STAs' flows connected to the network when the external interference negatively affects the capacities of these APs managed by the SDWN controller. We will demonstrate the benefits of this approach in Section 6.
- For the first time, we exploit the centralised nature of SDWN and the network programmability it offers in order to consider two different strategies in our potential game-based algorithm, named *Best response strategy* and *Better response strategy* [22]. Note that although the work in [22] proposed a detailed access node selection solution based on a potential game, it does not consider the QoS requirements of users and is not tailored for dense 802.11 Wi-Fi networks. In Section 6 we will analyse the benefits and disadvantages of each of these strategies. Moreover, the use of SDWN allows us to exploit the benefits of a po-

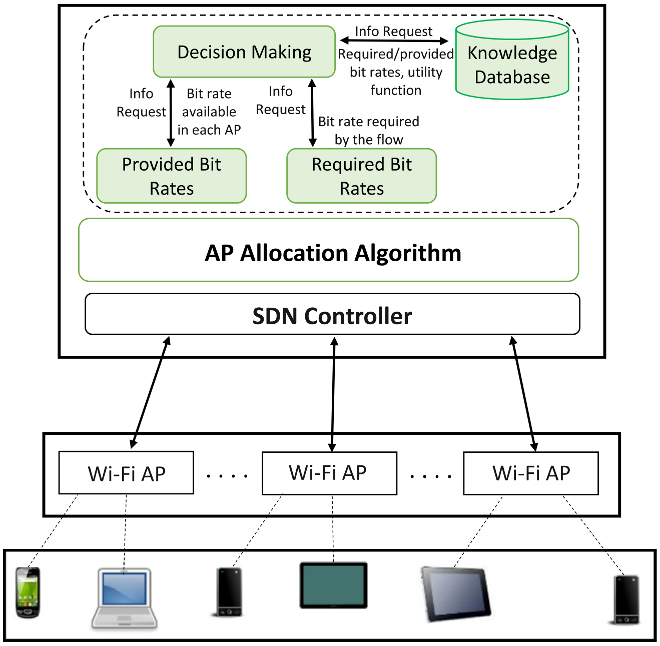

Fig. 1. SDWN-based Wi-Fi Management Framework.

tential game while overcoming its drawbacks in terms of scalability.

- In terms of evaluation, we have enhanced the analysis of the performance results in [18,19] through QoE assessment, and provided a detailed discussion on the trade-off between performance results and computational complexity for the two strategies implemented in our potential game.

3. System model and problem formulation

In this paper, we deal with a dense Wi-Fi environment, where a set of APs are managed centrally using the SDWN-based framework illustrated in Fig. 1. We exploit the centralised nature of this framework for the implementation of an algorithm that associates a set of downlink application flows required by Wi-Fi STAs to the managed APs that could satisfy their QoS requirements in terms of the data bit rates. In detail, every time a flow attempts a connection to the network, the controller performs a centralised potential game to obtain an optimized AP allocation for all the flows currently active in the network. Note that the working principle of the proposed algorithm will be detailed in Section 5.

3.1. Wi-5 SDWN framework

The framework considered for this work is based on the architecture developed for the EU H2020 Wi-5 (*What to do With the Wi-Fi Wild West*) project [24], which addresses spectrum congestion in Wi-Fi networks by relying on SDWN as an approach to manage the APs. In such an architecture, management strategies are designed as applications on top of the SDWN controller using its northbound API. The architecture already offers a number of applications that deal with the spectrum congestion problem in Wi-Fi networks [25–27]. In the Wi-5 architecture, a spectrum plane has been considered in order to strengthen the operational capabilities of IEEE 802.11 APs through the introduction of novel primitives for monitoring and configuration [28]. This approach enables us to make APs programmable and allows fine-grained spectrum assignment and management [20,28,29].

The aim of this paper is the evaluation of the proposed algorithm in the framework illustrated in Fig. 1 that, as we will detail in Section 6, has been simulated in order to achieve preliminary performance results. The next step will be the implementation and real-time evaluation in the above-mentioned Wi-5 architecture.

As shown in Fig. 1, the framework relies on some modules to gather periodic measurements from the radio environment, monitor the STAs' flows that try to connect to the network, and associate such flows to the best AP. In detail, the framework consists of the following entities:

- *Provided bit rates*: This module gives the bit rate available in each AP of the network that can be provided to a new flow. It is computed at the physical layer and leans on the channel bandwidth, the monitored inter-AP interference, and the location of the STA trying to connect to the network. Moreover, this bit rate is mapped to the best Modulation Coding Scheme (MCS) to obtain the highest bit rate that can be provided based on the Orthogonal Frequency Division Multiple Access (OFDMA) modulation scheme included in the latest 802.11 protocols, such as 802.11g and n.
- *Required bit rates*: This module gives the QoS demand in terms of the minimum data bit rate of the flow requesting connection, which is a common requirement for online applications such as Voice over IP (VoIP) and YouTube, as we will explain in Section 6. It can be obtained through, for instance, a Machine Learning (ML) based solution (e.g. [30]), which can be easily implemented in our framework. Details on ML-based classification strategies that could be employed here can be found in [17].
- *Knowledge database*: This module stores the following information: (1) the QoS requirements in terms of the data bit rate corresponding to each active flow computed by the *Required Bit Rates* module; (2) the link capacity in terms of the bit rate available for each active flow in the network and computed by the *Provided Bit Rates* module; and (3) the latest evaluated network utility function *U*, which is a metric used in the AP allocation algorithm and detailed in the next subsection. The data stored in *Knowledge Database* is updated either in the case of a new flow connecting to the network, or when an active flow disconnects.
- *Decision making*: This module allows an AP allocation every time a new flow attempts a network connection. It first gathers a set of information from the *Required Bit Rates, Provided Bit Rates* and *Knowledge Database* modules. Then, it uses this information to play the potential game and assign the most suitable AP to each active flow in the network based on our algorithm. The details of the algorithm are provided in Section 5.

3.2. Problem formulation

To better formulate the problem of AP allocation and flow association, let us consider N as a set of IEEE 802.11 APs, where $n = |N|$ is the size of this set of APs. We also assume that these APs are providing connectivity to a set of flows with different QoS demands, represented as M, where $m = |M|$ is the size of this set of flows. The notations and definitions utilized in this paper are summarized in Table 1.

Let $\psi_{i,j}$ indicate the Signal to Interference plus Noise Ratio (SINR) for flow i when connected to AP j. Note that $\psi_{i,j}$ is measured at the position of the STA requiring that AP j serves its flow i. The value of $\psi_{i,j}$ is defined as follows [17]:

$$\psi_{i,j} = \frac{g_{i,j} \cdot p_j}{\sum_{k \in N'} g_{i,k} \cdot p_k + N_0} \tag{1}$$

Here, $g_{i,j}$ is the channel gain from AP j to flow i, including the transmitter gain, receiver gain and path loss between the AP and the STA requiring the flow connection. p_j is the transmit power of

Table 1
Notations and definitions

Notation	Description
N	Set of APs
n	$n = \|N\|$, the number of APs
M	Set of flows
m	$m = \|M\|$, the number of flows
$\psi_{i,j}$	SINR of flow i connected to AP j
$g_{i,j}$	Gain from AP j to flow i
p_j	Transmit power of AP j
N_0	Additive Gaussian white noise
$b_{i,j}$	Link capacity for flow i connected to AP j
BW_j	Bandwidth assigned to AP j
$R_{i,j}$	Bit rate provided to flow i by AP j
A_j	Number of flows connected to AP j
C_j	Maximum capacity of AP j
$\Omega_{i,j}$	Sigmoid function for flow i from AP j
$R_{req,i}$	Bit rate required by flow i
$f_{i,j}$	Fittingness factor metric for flow i from AP j
U	Network utility function
AP_i	AP allocated to flow i
Γ	Formal game
S_i	Strategies used by player i
s_i	Strategy selected by player i
s_{-i}	Strategies selected by all players apart from player i
u_i	Utility function of player i
V	Potential function

AP j. N_0 is the additive Gaussian white noise. $N' \subseteq N$ is the set of APs that interfere with AP j and affect the SINR experienced by flow i. Note that we consider the interference only from APs transmitting in the downlink direction for the computation of the SINR, since the number of downlink flows is much greater than the amount of uplink flows in typical Wi-Fi networks [31]. However, as we will explain in Section 6.3, we also present an experiment with sources of external interference, which can include also APs not managed by our controller and STAs transmitting in the uplink direction.

The bit rate levels available in each AP vary between 1 Mbps and 54 Mbps according to 802.11g, which is the standard considered in the Wi-5 project. Each of these bit rate levels represents the link capacity $b_{i,j}$ between flow i and AP j that is measured through $\psi_{i,j}$ by the Shannon–Hartley theorem [17] and given by the *Provided Bit Rates* module. In detail, a parameter $b'_{i,j}$ is first calculated as follows:

$$b'_{i,j} = BW_j \cdot log_2\left(1 + \psi_{i,j}\right) \tag{2}$$

Here, BW_j is the bandwidth given to AP j in Hz. Once $b'_{i,j}$ is determined, $b_{i,j}$ is calculated by mapping $b'_{i,j}$ to the level closest to but below the bit rate level provided by the OFDMA scheme supported by 802.11g.

Once $b_{i,j}$ has been calculated, $R_{i,j}$ that represents the bit rate provided to flow i by AP j, can be calculated through the resource allocation algorithm defined in [17]. This algorithm has been implemented for a dense Wi-Fi environment where all the users have the same opportunity to transmit. Further details on this resource allocation algorithm can be found in [17]. The value of $R_{i,j}$ is also related to the total number of flows allocated to AP j and denoted here as A_j, and to the highest capacity C_j in bps available in AP j. $R_{i,j}$ can be expressed as a function ω of these parameters:

$$R_{i,j} = \omega\left(b_{i,j},\ A_j, C_j\right) \tag{3}$$

We now illustrate the Fittingness Factor (FF) metric used in our algorithm, which is a performance parameter based on the concept proposed in [32]. Specifically, FF is based on the function introduced in [17,33] with its value ranging between 0 and 1. In our AP allocation algorithm, FF allows us to compute the suitability of an AP j to meet a wireless user's QoS demand for a particular flow i. FF is formulated through the extension of a sigmoid function $\Omega_{i,j}$ [34] that indicates the bit rate reachable by flow i from AP j for the demanded bit rate.

Since our objective is to devise an AP allocation algorithm in a dense Wi-Fi environment where radio spectrum is a scarce resource, it is important to define FF so that it penalises APs that waste this resource, i.e. offering a higher transmission bit rate than required. Therefore, for each flow i and each AP j, we define the FF parameter for our algorithm as follows:

$$f_{i,j} = \frac{1 - e^{-\frac{\Omega_{i,j}}{\rho \cdot \left(R_{i,j}/R_{req,i}\right)}}}{\lambda} \tag{4}$$

In (4), λ is a normalization factor considered to guarantee that FF is included between 0 and 1, $\Omega_{i,j}$ represents the mentioned sigmoid function, and both can be calculated as follows:

$$\Omega_{i,j} = \frac{\left[\rho \cdot \left(R_{i,j}/R_{req,i}\right)\right]^{\xi}}{1 + \left[\rho \cdot \left(R_{i,j}/R_{req,i}\right)\right]^{\xi}} \tag{5}$$

$$\lambda = 1 - e^{-\frac{1}{(\xi-1)^{1/\xi} + (\xi-1)^{(1-\xi)/\xi}}} \tag{6}$$

In (4)–(6), ξ and ρ are shaping parameters that represent the various degrees of elasticity between required bit rate $R_{req,i}$ and the bit rate $R_{i,j}$ provided in the AP. Note that the selection of these metrics affects the behaviour of the FF defined in (4), which influences the suitability of the AP for a particular flow with respect to the bit rate availability and bit rate requirement. Moreover, ξ and ρ are values fixed in the controller, not related to the radio access technology providing connection to the users and, therefore, only influence the behaviour of the FF. For instance, as we will indicate in Section 6.1, in this paper we consider $\xi = 5$ that allows a smooth decrease of the FF when the available bit rates gradually become larger than the requirements, and $\rho = 1.3$ meaning that the maximum value of the FF is obtained when the assignment equals the requirement (i.e., when $R_i/R_{req,i} = 1$) [17]. This selection always allows us to prioritize the most suitable APs rather than those guaranteeing the highest QoS in the optimization problem, which is the principal aim of the algorithm based on the potential game. Note that the performance analysis implications of using different values for parameters ξ and ρ are out of the scope of this paper. However, different behaviours of the FF and consequent changes of the performance results obtained selecting different values of ξ and ρ can be found in referenced paper [17].

In addition, to optimise the suitability of APs to serve flows, the algorithm also needs to optimise the allocation of these flows among APs such that it avoids spectrum congestion as much as possible. For this purpose, we define the network utility function U introduced in the previous subsection as the log-sum of the FFs of all the m flows served by the network. More specifically, we aim to guarantee a proportional fairness in the AP allocation. Therefore, we need to use U to optimise the sum of the logarithms of the FFs computed for each flow i with its serving AP AP_i. However, since it is possible that a FF value is zero, we need to modify the objective function U such that we bypass a possible inclusion of a zero value in the logarithm argument. This leads to U optimising the sum of the logarithms calculated from the FF plus one for each flow i served by AP AP_i [22]:

$$U = \sum_{i=1}^{m} \log\left(f_{i,AP_i} + 1\right) \tag{7}$$

4. Potential game

In game theory, a potential game is a particular case of a formal one. Therefore, let us start by introducing a formal game, which is characterized by the following parameters: i) a set of players, ii) the space of strategies, and iii) a utility function that has to be optimised. Such parameters are denoted as $\Gamma = \{M,\ \{S_i\}_{i\epsilon M},\ \{u_i\}_{i\epsilon M}\ \}$.

Here, M is the set of players, which in our work is the set of flows active in the network. S_i is the set of strategies that player i, i.e. flow i in this paper, employs. $u_i : S \rightarrow \mathbb{R}$ is the utility function of player i, with $S = \times_{i\epsilon M} S_i$ being the strategy space of the game and defined as the Cartesian product of the strategy sets of all the flows.

Each strategy $s \in S$ includes one particular strategy from every player (i.e. flow), where $s = (s_1, \ldots, s_{i-1}, s_i, s_{i+1}, \ldots s_M)$ and can also be denoted as $s = (s_i, s_{-i})$. Here, s_i is the strategy selected by player i and $s_{-i} = (s_1, \ldots, s_{i-1}, s_{i+1}, \ldots s_M)$ are the strategies selected by the other players. Accordingly, we first formulate the AP allocation problem as a formal game using the utility function $u_i(s) = u_i(s_i, s_{-i})$. Note that in this context, strategy s_i represents the selection of an AP j to serve flow i, i.e. $s_i = j$ and s_{-i} represents the selections of other APs to serve all the other flows. However, a key issue that arises when formulating the AP allocation problem as a formal game is the selection of u_i to obtain an efficient general performance including the individual actions of all the players, which in this context are represented by the flows. Furthermore, it is also desirable to have a point of equilibrium in order to guarantee the convergence of the game when trying to achieve the optimisation. Therefore, we consider the Nash Equilibrium (NE) for the game Γ, which is a specific profile $s^* \in S$ of actions for every flow $i \in M$. It guarantees the condition denoted as follows [21]:

$$u_i\left(s_i^*, s_{-i}^*\right) \geq u_i\left(s_i, s_{-i}^*\right) \tag{8}$$

Here, s_i ($\neq s_i^*$) represents any strategy of player i from strategy space S_i, and s_{-i}^* are the strategies of all the other players in the profile s^*. Note that the condition formulated in (8) needs to be addressed for all $s_i \in S_i$. The convergence of the game to a NE guarantees the achievement of a stable solution. Furthermore, if any change in the considered scenario is detected, the network will be able to respond to such a change. In fact, any deviation from the converged NE triggers the game in order to achieve a new one.

Let us discuss the development of our AP allocation approach designed as a potential game. In detail, the potential game is a specific game characterized by a potential function defined as V: $S \rightarrow \mathbb{R}$ to address the following condition [21]:

$$\begin{aligned} \Delta u_i &= u_i(s_i, s_{-i}) - u_i\left(s_i', s_{-i}\right) = \Delta V \\ &= V(s_i, s_{-i}) - V\left(s_i', s_{-i}\right),\ \ \forall i \in M,\ \ \forall\ s_i, s_i' \in S_i \end{aligned} \tag{9}$$

Eq. (9) guarantees that each interest of a certain player is coordinated with the interest of all the players because any change Δu_i in the utility function of player i is straightly related to the same change ΔV for the potential function. Hence, any player choosing a strategy, which enhances its utility given all the strategies of all the other players, will automatically allow us to improve the potential function. Moreover, if only one player enhances its utility function given the latest action of all the other players, the process will always converge to a NE in a limited number of steps [22].

As we have introduced in Section 1, in our centralised strategy, the flows are the players. However, it is worth noting that STAs only gather and send information to the central controller but do not exchange information among them nor actually take the decision on the AP that serves its flows. The decision on the proposed AP allocation is performed by the SDWN controller that plays the game internally for all the active flows in the network. In this specific case, potential function V is represented as the objective to be optimised, which is network utility U defined by (7). We consider utility function u_i equivalent to potential function V for our problem (identical interest games), which ensures that (9) is satisfied, and then, the game is potential:

$$u_i(s_i, s_{-i}) = \sum_{k=1}^{m} \log\left(f_{k,s_k} + 1\right) \tag{10}$$

Here, s_k is the strategy of player (or flow) k, i.e., its allocated AP AP_k. For the proposed algorithm, a repeated sequential game with round robin scheduling is played by the SDWN-based controller until it finds a configuration s^* that achieves the pure NE [35]. The strategy space S_i for a generic flow i is the set $W_i \subseteq N$ of APs providing coverage to flow i and the round robin scheduling is based on two possible implemented strategies defined as follows:

- *Best response strategy*: in this case, at each game step and for each flow or player i, the SDWN-based controller looks for the best u_i in the set S_i=W_i. Thus, a strategy t_i is a best response if:

$$u_i(t_i, s_{-i}) \geq u_i(s_i, s_{-i}),\ \ \forall\ s_i \in W_i \tag{11}$$

Therefore, at each step and for each flow i, condition (10) is computed $|W_i|$ times, considering $|W_i|$ is the number of APs included in W_i.

- *Better response strategy*: in this case, at each game step and for each flow or player i, the SDWN-based controller looks for a strategy in the set S_i=W_i that improves its previous u_i. Thus, a strategy t_i is a better response if:

$$u_i(t_i, s_{-i}) \geq u_i\left(s_i', s_{-i}\right) \tag{12}$$

where s_i' represents the strategy of player i in the previous game step. Therefore, at each step and for each flow i, condition (10) is computed up until finding the first AP included in W_i that improves u_i.

Further details on the implementation of both possible strategies in the proposed algorithm will be provided in the next section.

5. AP allocation algorithm

5.1. Best response strategy

As mentioned previously, the objective of the algorithm proposed in this paper is to find the most suitable AP for each downlink flow requested by a user of the Wi-Fi network. In this subsection, we illustrate the *Best Response Strategy* described below as *Algorithm 1* and executed by the controller each time a new downlink flow tries to join the network, which can be either a new flow for an STA already connected but requiring a change to the bit rate of its application, or a flow for a new STA.

First, the *Decision Making* module in Fig. 1 gathers from the *Provided Bit Rates* module all the link capacities. These link capacities are the bit rates that the APs can guarantee to the new flow trying to connect, and are calculated through (3), which is shown as the line 1 of *Algorithm 1*. Second, the *Decision Making* module obtains the QoS requirements of the new flow in terms of the bit rate from the *Required Bit Rates* module (line 2 of *Algorithm 1*). This information is used later to calculate the FF metric.

Third, the algorithm acquires from the *Knowledge Database* the information corresponding to all the other flows already active in the network (line 3 of *Algorithm 1*). This information includes the bit rate requirements and the provided bit rates, which can be computed using (1)–(3), as well as the latest calculated network utility U.

Fourth, the *Decision Making* module executes the round robin scheduling until it reaches the NE (line 6 of *Algorithm 1*). In detail, for each flow i connected to the network and for each AP providing coverage to flow i (i.e., the APs included in the set $W_i \subseteq N$), the *Decision Making* module calculates u_i in order to optimise it through

Algorithm 1 - AP Allocation.

1: **get** info on new flow from *Provided Bit Rates*
2: **get** info on new flow from *Required Bit Rates*
3: **get** info on all active flows and last U from *Knowledge Database*
4: **include** info on new flow in set M
5: NE_reached=0
6: **while** NE_reached==0 **do**
7: detected_change=0
8: **for** i=1 to m **do**
9: **for** j=1 to $|W_i|$ $(W_i \subseteq N)$ **do**
10: update FFs for APs influenced when selection s_i is the w_j-*th* AP with $1 \leq w_j \leq n$
11: **compute** $u_i = \sum_{k=1}^{m} \log(f_{k,AP_k} + 1)$
12: **if** $u_i > U$ **do**
13: detected_change=1
14: allocate AP w_j to flow i
15: $U = u_i$
16: **end if**
17: **end inner for**
18: **end outer for**
19: **if** detected_change==0 **do**
20: NE_reached=1
21: **end if**
22: **end while**
23: **update** the *Knowledge Database*

condition (11). This optimisation will need to take into account the requirements of all the m flows active in the network (lines 8-18 of *Algorithm 1*).

To achieve the optimisation, the *Decision Making* module first uses (4)-(6) to update all the FFs of the flows influenced by flow i connecting to AP w_j in set W_i (line 10 of *Algorithm 1*), and then applies the new FF values for each flow k connected to its own AP, i.e., AP_k, to calculate u_i through (10) (line 11 of *Algorithm 1*). Afterwards, if u_i is higher than the latest value of U, the *Decision Making* module assigns AP w_j to flow i, and updates U (lines 12-16 of *Algorithm 1*).

The round robin scheduling stops when the NE is reached, i.e. condition *NE_reached=1* occurs (lines 19-21 of *Algorithm 1*). Finally, the *Decision Making* module updates the *Knowledge Database* by storing the required bit rate of the new flow, the updated bit rates of other flows that have been affected when the NE has been reached, and the new value of U (line 23 of *Algorithm 1*). Note that this optimisation process might result in a horizontal handover of some users to other APs. However, as demonstrated in [28,36], our Wi-5 SDWN architecture allows seamless handover solutions to move STAs among APs when needed, such as when the potential game is triggered, without noticeable data loss.

5.2. Better response strategy

In the case of *Better Response Strategy*, the sequence of steps for the algorithm implemented in the SDWN-based controller includes a *break* command after the line 15 of *Algorithm 1*, which interrupts the 'inner for' when the utility function for a certain flow is improved in the first possible AP.

5.3. Computational complexity

Let G be the number of game cycles performed to get the NE, m the number of flows active at a particular time, and w the average number of APs that can be allocated to a new flow. This means that the 'while loop' is executed G times, the outer 'for loop' is repeated m times, and the inner 'for loop' is executed w times. Hence, the computational complexity of the proposed AP allocation algorithm can be denoted as *O(Gwm).* Note that in the case of the *Better Response Strategy* the complexity can be reduced because this solution looks for the first available AP that can improve U during the round robin scheduling. The reduction of complexity achieved by the *Better Response Strategy* with respect to the *Best Response Strategy* will be discussed in detail in Section 6.

6. Performance evaluation

The objective of this section is to demonstrate the performance gains of our algorithm presented in Section 5 through a simulation campaign. Hence, we have carried out a detailed set of experiments by using a MATLAB-based simulator that implements our SDWN controller managing the APs of a dense IEEE 802.11 environment as illustrated in Section 3.1. The use of simulators is effective and convenient for us to validate solutions and achieve preliminary performance results. Thus, they were used to assess the capability of our algorithm before its real-time implementation in the Wi-5 architecture detailed in [29].

Note that the Wi-5 architecture includes all the entities of the framework illustrated in Fig. 1 and can provide all the input needed for the real-time execution of the algorithm, such as the available bit rate and the type of application flow, in the order of milliseconds through its monitoring capability [23]. For instance, in [37] we demonstrated how the controller is able to compute in real-time the available bit rate for a certain flow while the STA that required it was moving, i.e., the available bit rate was dynamically updated in relation to available APs. This information, together with the bit rate requirement, was then used to compute the updated FF in real-time, which is a key metric needed as an input to the potential game.

6.1. Scenario and metrics

For the assessment of our AP allocation algorithm, we simulated the SDWN-based controller in a scenario based on the system model illustrated in Fig. 1. Specifically, the scenario includes a set N of *5* IEEE 802.11g APs (i.e. n=5) randomly distributed in an area of 100m $\times$ 100m with a minimum distance of 7 meters between them, and a set M of 100 flows progressively created and distributed uniformly (i.e. $m \in \{1, \ldots, 100\}$). IEEE 802.11g APs are configured to work on the Industrial, Scientific and Medical (ISM) 2.4 GHz radio bands, which include 3 non-overlapping channels (i.e., channel 1, 6 and 11). Hence, the n ($\geq$ 4) APs in the considered scenario are the starting point of the densification problem, which becomes more serious when the number of STAs connected to the network increases to 100 [38,39]. Note that the selection of this area represent general dense Wi-Fi environments, which have been considered to address the use cases analysed in the context of the Wi-5 project [24, 38].

The data bit rate requirements for the flows of the STAs that try to join the network have been randomly selected from a set of bit rates ranging from 40 kbps to 2 Mbps. The transmit power of all the APs is 25 dBm. The values of BW_j in (2) and C_j in (3) are, respectively, 20 MHz and 54 Mbps for all the APs included in the network. Finally, ξ and ρ in (4)–(6) are 5 and 1.3, respectively.

Moreover, the averaged outcome of 10 independent simulations has been considered to generate all the results in all the experiments illustrated in the next subsections, which have provided a sufficient number of samples to achieve an accurate computation of the performance metrics. Specifically, in order to ensure that the results provide realistic values and are statistically meaningful in the considered scenario, the confidence intervals have been included in the performance analysis.

To benchmark the performance of our AP allocation algorithm, we analyse a comparison against the following referenced solutions:

Table 2
Mean opinion score (MOS)

MOS	Quality	Damage
5	Excellent	Imperceptible
4	Good	Detectable/Not Disturbing
3	Fair	Lightly Disturbing
2	Poor	Disturbing
1	Bad	Very Disturbing

Table 3
Bit rate requirements and MOS

Application	Bit Rate	MOS	Quality	Damage
VoiP G.729	40 kbps	3.92	Good	Detectable/Not Disturbing
VoiP G.726	60 kbps	3.85		
YouTube	500 kbps	4.5		
Premium YouTube	1 Mbps	4.5		
Netflix	2 Mbps	4.5		

- AP selection based on the highest Received Signal Strength Indicator (RSSI), which is the solution proposed in the 802.11 standards;
- Our previous AP selection approach proposed in [16,17] that allocates an AP to a flow based on a metric named *Network Fittingness Factor* (*Network FF*). This metric jointly addresses the data bit rate demand of a flow trying to connect to the network, and the data bit rate demand of the other flows active in the network. Our choice of this algorithm is justified by the fact that it uses the same SDWN-based framework described in Section 3.1. This algorithm also shows that the use of the Network FF provided improvements over the state of the art such as the work presented in [15]. Note that the computational complexity of this AP selection approach is also linearly related to the number of STA flows, i.e. $O(m)$. Further details about this algorithm are provided in Appendix 1;
- A centralized optimal solution that looks for the allocation of the flows to the APs that maximizes the value of the utility U. This optimal solution is obtained using brute force search by evaluating the network utility function U for all the possible combinations of APs and flows. In the worst case, i.e., when $W_i = N$ for each flow i included in set M, the number of combinations to evaluate is N^m.

For the evaluation of our algorithm against the above two approaches, we consider the following performance parameters:

- *Data bit rate*: This is the average data bit rate achieved at the end of the simulation by all the STAs' data flows connected to the network.
- *Dissatisfaction*: This is the percentage of flows that joined the network with their provided bit rates lower than their requirements, and it is updated by each new AP allocation.
- *Percentage of flows that reach a good mean opinion score (MOS)*: This parameter is used to measure the QoE perceived by a user when running an application that generates a downlink flow [40]. This metric is an arithmetic mean of all the scores achieved by performing subjective tests. Such scores vary from 1, which is the lowest one, to 5, which represents the highest possible score, as illustrated in Table 2. The scores correspond to specific qualities of connection and any damage to it from the user perspective. In this paper we consider as a performance metric the percentage of flows that can achieve at least a Good MOS (GMOS) at the end of the simulation.
- *Price of anarchy (PoA)*: This parameter is the ratio between the worst possible NE and the optimal solution. It is used to measure the efficiency of the proposed game with regard to the optimum.

Note that the QoS requirements of the active flows generated randomly from devices joining the network represent most common online applications such as VoIP, Video Streaming, etc. which are illustrated in Table 3. For each application, the table includes the following parameters: (i) the minimum bit rate requirements, (ii) the MOS reachable in case such requirements are met, (iii) the quality of the connection that can be experienced by the STAs, and (iv) the damage related to such a quality.

Table 4
Average data bit rates for 100 flows

Solution	Data Rate (kbps)
Best Game	696
Better Game	677
Network FF	610
Optimal	706
RSSI	476

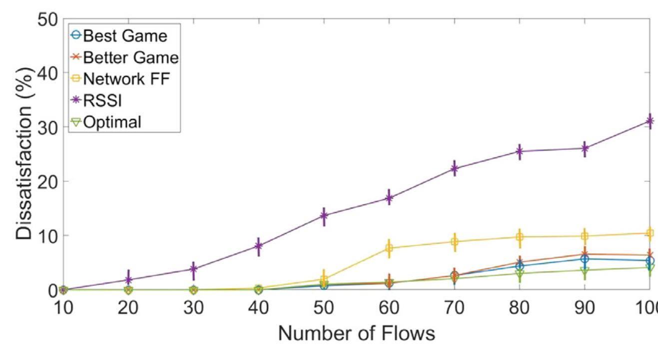

Fig. 2. Dissatisfaction as a function of number of flows.

In the case of VoIP, the minimum bit rate requirements that can assure a GMOS are approximately 40 kbps and 60 kbps, when codec *G.729* and *G.726* are used respectively[1]. In the case of video streaming, the minimum bit rate requirement to guarantee a GMOS on YouTube is 500 kbps, and it is 1 Mbps in the case of premium shows such as movies and live events[2]; whereas 2 Mbps is the bit rate suggested for videos on Netflix[3]. In [17] the relations between the GMOS and the corresponding minimum bit rate requirements presented in Table 3 are analysed in detail.

Note that, for the sake of simplicity, we illustrate in the analysis of the performance the achieved results only for downlink transmissions, including the case of VoIP. This is a reasonable assumption since maintaining the minimum bit rates needed for VoIP shown in Table 3 assures the GMOS for both downlink and uplink transmissions.

6.2. Performance of the AP allocation

The results shown in Table 4, Figs. 2, 3 and Table 5 illustrate the performance achieved by our Potential Game-based AP allocation algorithm in terms of *Data rate, Dissatisfaction, GMOS* and *PoA*, respectively, against the state of the art. As observed in Table 4, the *Best Response Strategy* of our AP allocation algorithm outperforms the RSSI-based solution in terms of the data rate by 32% and the Network FF-based algorithm by 12%, when all 100 flows are connected to the network. The results in Table 4 also show that the

[1] http://www.cisco.com/c/en/us/support/docs/voice/voice-quality/7934-bwidth-consume.html (last access June 2019).
[2] https://support.google.com/youtube/answer/78358?hl=en-GB (last access June 2019).
[3] https://help.netflix.com/en/node/306 (last access June 2019).

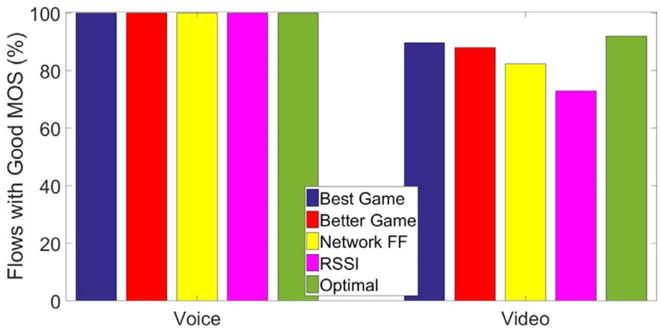

Fig. 3. Good Mean Opinion Scores for 100 flows.

Table 5
Estimated price of anarchy (PoA) for different numbers of flows

Number of Flows	PoA
10	1.03
20	1.08
30	1.07
40	1.14
50	1.11
60	1.10
70	1.05
80	1.06
90	1.10
100	1.20

Better Response Strategy outperforms the RSSI-based approach and the Network FF-based algorithm by 30% and 10%, respectively. Finally, from the table we can observe that both games reach a value of average data rate close to the one achieved through the optimal algorithm.

The results presented in Fig. 2 show that using both strategies of our algorithm results in less flow dissatisfaction than the Network FF-based and RSSI-based approaches. In detail, from this figure we can say that when all 100 flows are connected to the network, the *Best Response Strategy* outperforms the Network FF-based algorithm by around 48%, and the RSSI-based solution by 83%. The results also show that the *Better Response Strategy* outperforms the Network FF-based algorithm and the RSSI-based approach, by 38% and 79%, respectively. Furthermore, from the figure we can observe that in terms of *Dissatisfaction*, both games also obtain a result close to the one achieved through the optimal approach. Finally, the figure shows the 95% confidence interval bounds [41] for different values of flows, which confirms the low variability of the proposed solution.

The results presented in Fig. 3 show the performance in terms of the percentages of flows that have achieved at least a GMOS for 100 flows connected to the network. Specifically, in the figure, the left hand side presents the performance obtained in the case of Voice, whereas the right hand side presents the performance achieved in the case of Video. These results show that in the case of Voice, all the solutions can assure a GMOS to all the flows connected to the network. On the other hand, the results also show that our Potential Game-based AP allocation algorithm with both strategies outperforms both of the other solutions in terms of the percentage of flows experiencing a video streaming and achieving at least a GMOS. The *Best Response Strategy* and the *Better Response Strategy* outperform the Network FF-based approach by 8% and 6%, respectively, and the RSSI-based solution by 19% and 17%, respectively. Note that again in this case, both games obtain a result close to the one achieved through the optimal approach.

Finally, the results in Table 5 show the estimated values of PoA for different numbers of flows. In order to obtain these values, 10 different instances of the game have been computed for each of the 10 independent simulations. Specifically, for each independent simulation an estimated PoA has been calculated as the ratio between the optimal solution and the worst NE obtained from the 10 instances of the game. Then, the results illustrated in Table 5 are the values averaged for the 10 independent simulations. From the table we can see that the PoA is within 1.05 and 1.2 for all the evaluated number of flows, which illustrates an efficient gap between the game and the optimal solution.

Table 6
Average Data Bit rates for 100 Flows with External Interference

Solution	Data Rate (kbps)
Best Game	678
Better Game	666
Network FF	539
Optimal	687
RSSI	368

6.3. Impact of external interference

Although the previous results show the performance of our algorithm in a context where all the APs are under the management of the same SDWN controller, there are many situations where these APs are operating alongside other devices not managed by the controller but on the same radio channel or transmitting in the uplink direction. Such situations result in external interference to the APs' operations. The presence of this interference could reduce the connection capacity offered by the APs. Therefore, the allocation of an AP that could satisfy a user under these constrained conditions becomes more challenging.

To assess the performance of our algorithm in the presence of external interference, we added two sources of interference to our initial simulation scenario illustrated in Section 6.1, which can be represented by any device transmitting on the same unlicensed band, such as wireless users' devices that could generate uplink transmissions, or APs that are not under the management of the SDWN controller. Then, we repeated the experiment. Specifically, in this new experiment, the sources of external interference have been operative for certain periods of time during the simulation in different Radio Frequency (RF) channels that are selected randomly. We assumed that these sources interfered with two of the APs managed via the SDWN network, causing a reduction of the average SINR experienced in the affected APs by 2 dB and, therefore, a reduction of the available capacity in terms of their provided bit rates to the connected users. This assumption about the external interference in the simulated scenario and its impact on the affected APs considered in this subsection are representative of a detailed empirical analysis in [23].

The results shown in Table 6, Figs 4, and 5 illustrate the achieved performance in terms of *Data rate, Dissatisfaction* together with the 95% confidence interval bounds for different values of flows, and *GMOS*, respectively. These results show that, under these new conditions, our AP allocation algorithm with its two strategies incur a marginal reduction of the performance results previously illustrated in Table 4, Figs. 2 and 3.

For instance, the performance of the *Best Response Strategy* in terms of *Data rate, Dissatisfaction* and *GMOS* in the case of video streaming when 100 flows are connected, varied from 696 kbps, 5.4%, and 89.7% to 678 kbps, 6.3% and 88.7%, respectively. Note also that the optimal approach experiences a marginal reduction of its performance results. However, our proposed algorithm based on the potential game still achieved results close to the ones obtained through the optimal strategy. On the other hand, under the same

Table 7
Summary of the gains achieved through the potential game-based AP selection

	Without External Interference						With External Interference					
	Network FF			RSSI			Network FF			RSSI		
	DR	Dis.	MOS	DR	Dis.	MOS	DR	Dis.	MOS	DR	Dis.	MOS
Best	12%	48%	8%	32%	83%	19%	21%	56%	13%	48%	84%	27%
Better	10%	38%	6%	30%	79%	17%	19%	49%	12%	45%	80%	26%

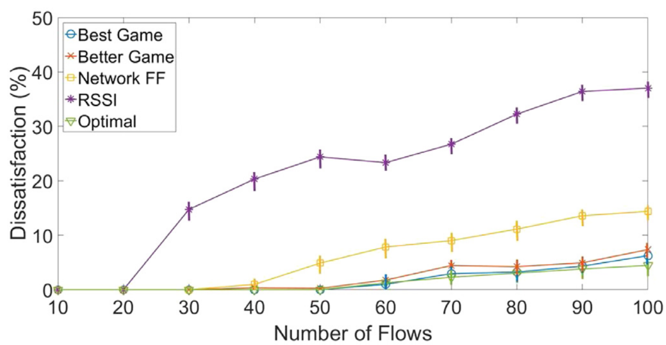

Fig. 4. Dissatisfaction as a function of number of flows with external interference.

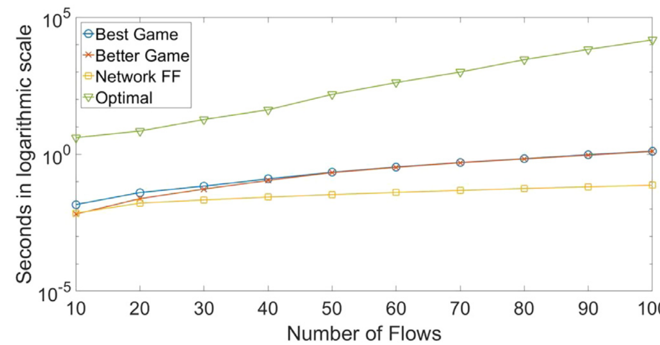

Fig. 6. Computation time for different numbers of flows

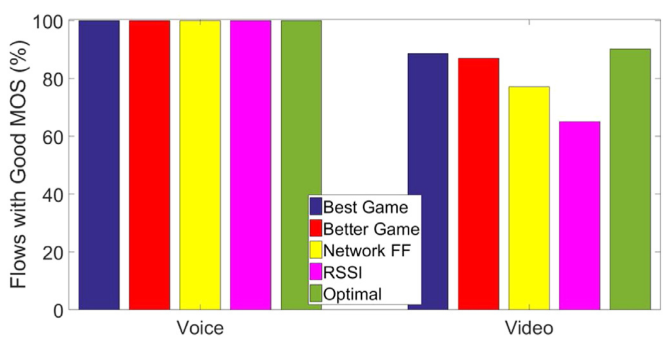

Fig. 5. Good Mean Opinion Scores for 100 flows with external interference.

conditions, the Network FF-based and the RSSI-based approaches experience a considerable reduction of the achieved performance illustrated in the previous subsection, especially in the case of 100 flows connected to the network. For instance, in the case of the Network FF-based approach, results in terms of *Data rate, Dissatisfaction* and *GMOS* in the case of video streaming for 100 connected flows, go down from 610 kbps, 10.4%, and 82.4% to 539 kbps, 14.4% and 77%, respectively.

Table 7 summarizes the gains achieved through our Potential Game-based solutions with respect to the Network FF-based and the RSSI-based strategies in terms of *Data rate, Dissatisfaction* and *GMOS* in the case of video streaming (named *DR, Dis.*, and *MOS* in the table, respectively) in both considered scenarios, i.e., when the external interference is not considered and when it is included in the performance evaluation.

For instance, from the table we can observe that the *Best Response Strategy* improves on the Network FF-based approach by 12%, 48% and 8%, in terms of *Data rate, Dissatisfaction* and *GMOS* in the case of video streaming when the external interference is not considered in the scenario. These gains increase up to 21%, 56% and 13% when the external interference negatively affects the capacities of the APs managed by our SDWN controller.

These results show that our algorithm still outperforms the two referenced solutions even in the presence of external interference. This is due to our algorithm's adaptability to reallocate certain flows to different APs when the external interference causes a deviation from the NE, which forces the controller to play the potential game and reach a new NE.

6.4. Analysis of computational complexity

In the previous sections, we have demonstrated the benefits of our algorithm against the state of the art in terms of the performance results obtained for the STAs in the two different scenarios. In this subsection we analyse and compare the *Computational Complexity* in the cases of the *Best Response Strategy, Better Response Strategy*, optimal approach and Network FF-based solution, which all improve on the 802.11 standard approach based on the highest RSSI.

Specifically, Fig. 6 illustrates the computation time in seconds on a logarithmic axis needed to run all the considered algorithms in our MATLAB-based simulator for different numbers of flows. The simulations have been performed on an Intel Core i7-8700 CPU running at 3.20 GHz and with 64 GB of RAM. This figure shows that although the optimal approach allows us to obtain the best performance results, it undoubtedly needs considerable computational time in the dense scenario considered in this paper, i.e., more than 4 hours in the case of 100 flows, compared to the other solutions based on the FF. In addition, it can be seen that for the optimal approach, the computational time increases exponentially as the number of flows grows, unlike for the solutions based on the potential game and the Network FF. Moreover, we can observe that even if the required times for the potential games are slightly higher than in the Network FF-based approach, they still require a low computational time. Specifically, in case of 100 flows, the computational time is 0.1, 1.6 and 1.7 seconds in case of Network FF, *Better Response Strategy* and *Best Response Strategy*, respectively.

6.5. Discussion

The results illustrated in Section 6.2 show that our algorithm with its two strategies provides better performance than the Network FF and RSSI-based solutions in terms of Data rate, Dissatisfaction and GMOS in the case of video streaming, and results are close to the ones achieved through the optimal approach. Our algorithm also outperforms Network FF and RSSI-based solutions in the presence of external interference. In addition, we have illustrated the significant computational time of the optimal approach that makes it inefficient in the considered scenario. Moreover, although our Potential Game-based algorithm incurs higher computational complexity than the Network FF-based solution, this complexity is reduced even for a high number of flows, making the proposed strategies scalable as the traffic grows.

In summary, these results prove that our game-based AP allocation solutions yield better results in terms of the performance experienced by the STAs at the expense of a bounded increase in the computational complexity. In addition, it must be noted that the Better Response Strategy slightly reduces the computational complexity with the Best Response Strategy (for example, 6% for 100 flows) at the expense of a minor reduction in the performance results as we can observe in Tables 4, 6 and 7, and Figs. 2–5. Therefore, from our performance analysis we can claim that in the scenario considered in this paper, both the Better and Best Response Strategy provides a good trade-off between the performance results and computational complexity compared to the state of the art.

7. Conclusion and future work

This paper has proposed a novel AP allocation algorithm based on a centralised potential game developed in a SDWN-based framework. The proposed algorithm includes two possible approaches named Best Response Strategy and Better Response Strategy. Both approaches support an optimised allocation of Wi-Fi STAs to manage APs and also a novel dynamic reallocation of the STAs due to, for example, external interference from sources inaccessible through our framework, which causes a decrease of the Wi-Fi network capacity.

In order to demonstrate the achievements of our algorithm, we have provided a comparison against the AP selection approach used by the IEEE 802.11 standards and another solution considered in the state of the art. We have highlighted how our algorithm built on the potential game achieves important improvements on the two considered approaches in terms of the data rate, dissatisfaction of Wi-Fi users and their QoE. Furthermore, we have illustrated how our solution obtains performance results close to the ones achieved through an optimal approach with a much lower computational complexity.

As part of our future work, the algorithm presented in this paper will be implemented and evaluated in the SDWN-based testbed being developed by the Wi-5 project [24]. Note that the OpenFlow protocol implemented in the controller southbound API has been extended in the Wi-5 SDWN platform in order to manage connection requests from STAs and their AP allocations. This capability will enable the assessment of: (i) the merits of the algorithm presented in this paper in real-time scenarios and (ii) the analysis of new metrics crucial in such scenarios, e.g. the convergence rate of the algorithm. Moreover, the FF formulation will be extended in order to include further metrics to define flow QoS requirements, such as delay and jitter.

CRediT authorship contribution statement

Alessandro Raschellà: Conceptualization, Visualization, Formal analysis, Data curation, Writing - original draft, Writing - review & editing. **Faycal Bouhafs:** Conceptualization, Visualization, Formal analysis, Data curation, Writing - original draft, Writing - review & editing. **Michael Mackay:** Conceptualization, Visualization, Formal analysis, Data curation, Writing - original draft, Writing - review & editing. **Qi Shi:** Conceptualization, Visualization, Formal analysis, Data curation, Writing - original draft, Writing - review & editing. **Jorge Ortín:** Conceptualization, Visualization, Formal analysis, Data curation, Writing - original draft, Writing - review & editing. **José Ramón Gállego:** Conceptualization, Visualization, Formal analysis, Data curation, Writing - original draft, Writing - review & editing. **Maria Canales:** Conceptualization, Visualization, Formal analysis, Data curation, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

None.

CRediT authorship contribution statement

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Appendix 1

To solve the AP selection problem, papers [16,17] introduce a parameter called *Network Fittingness Factor* (net_f), considered also in paper [19], and based on the FF concept illustrated in Section 3. net_f includes a *Standard Deviation Function* (σ) indicating the change of the average FF that can occur when an AP j begins providing services to a new STA's flow i. Specifically, for each AP j, the bit rate provided to each active flow is recalculated using Eqs. (2) and (3) by taking into account the effect provoked by the connection of flow i. Considering the new values of the bit rates, the FFs of the active flows are updated using (4). Then, the standard deviation is computed through the following formula:

$$\sigma_{i,j} = \sqrt{\frac{\sum_{k=1}^{K}\left(f_{k,j} - \overline{f_j}\right)^2}{K}} \tag{13}$$

where $\overline{f_j}$ is defined as follows:

$$\overline{f_j} = \frac{1}{K}\sum_{k=1}^{K} f_{k,j} \tag{14}$$

In (13) and (14), K is the number of all active flows in AP j that involves the other flows active in the AP with their FFs updated, and the new flow i. Considering that there are n APs, which can be allocated to flow i, net_f is used to optimise the following parameters: i) the FF of the AP allocated to the new data flow, and

ii) the standard deviation factor to retain the global network performance as much as possible, in order to find the most suitable AP for the new flow. This optimisation is formulated as follows:

$$net_{f_i} = \arg max_{j\in\{1,\ldots,n\}}\left\{F_{i,j}\right\} \tag{15}$$

where $F_{i,j} = f_{i,j}(1 - \sigma_{i,j})$

Therefore, net_{fi} calculated using (15) has the objective to optimise the performance of the new flow to the allocated AP by maximizing its FF, while also guaranteeing the overall network performance by reducing the negative effect on the other active flows by using the standard deviation.

Let us focus on the algorithm implemented in the SDWN controller when a new flow i tries to connect. In this case, the *Decision Making* module collects all the link bit rate availabilities, which each AP can guarantee to flow i, from the *Provided Bit Rates* module and computed using (3). The *Decision Making* module also obtains from the *Knowledge Database* the information on all the other flows already active in the network, i.e., their bit rate demands and provided bit rates. Afterwards, for each AP j in the network, the *Decision Making* module considers all the gathered information to: 1) calculate the updated bit rates available for the flows in AP j through (3) by taking into account the impact of a possible connection to new flow i; 2) consider the bit rate demand of all the flows allocated to AP j to calculate the *Standard Deviation Function* ($\sigma_{i,j}$) for AP j using (13); and 3) choose the most suitable AP for flow i based on the net_{fi} in (15).

As introduced in Section 6, the computational complexity of this approach is linearly related to the number of flows (i.e. m), denoted as $O(m)$. All the details of the algorithm together with a further explanation of its computational complexity can be found in [17].

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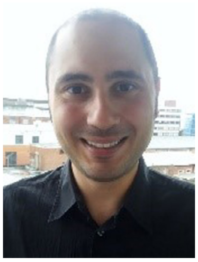

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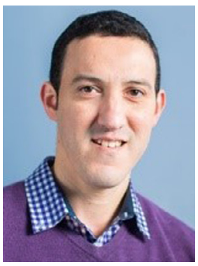

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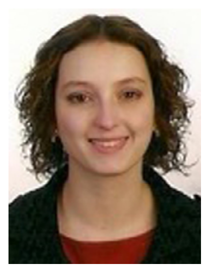

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