User-centric Network Selection in Multi-RAT Systems

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***Abstract*—Rising numbers of mobile devices and wireless access technologies motivate network operators to leverage spectrum across multiple radio access networks, in order to significantly enhance quality of service as well as network capacity. However, there is a substantial need to develop innovative network selection mechanisms that consider energy efficiency while meeting application quality requirements. In this context, this paper proposes an efficient network selection mechanism over heterogeneous wireless networks. We consider different performance aspects, as well as network characteristics and application requirements, so as to obtain an efficient solution that grasps the conflicting nature of the various objectives and addresses this ultimate tradeoff. The proposed methodology advocates a user-centric approach toward the utilization of heterogeneous wireless networks to enhance system performance and support reliable connectivity.**

***Index Terms*—Heterogeneous wireless environment, network selection, multi-RAT architectures, vertical handover.**

I. INTRODUCTION

Utilization of multi-Radio Access Technology (RAT) in conjunction with device/infrastructure intelligence is expected to be a fundamental characteristic of future 5G technologies [1]. In these deployments, each user device may employ multi-RAT to communicate with the network infrastructure. Thus, it is crucial to develop techniques that can efficiently utilize the available radio resources across different spectral bands using various RATs [2]. In this context, vertical handover becomes a key feature of future mobile networks, and due to mobility and mobile node's requirements, the connections with other hosts may be switched from one access point to another within the same Radio Access Network (RAN) using multi-RAT, or between different RANs. This switching and selection between different RANs needs to be done taking into consideration different network characteristics and application requirements [3].

In future wireless networks, both short- and long-range technologies can cooperate and exploit the interactions between various devices and networks, as well as between the devices themselves, to enhance system performance and user experience [4]. For instance, several studies have recently emerged to develop specifications enabling integration of WLAN with cellular networks. The WLAN community has also coped with this trend with new initiatives, such as Hot Spot 2.0 and novel high-efficiency WLAN standardization, to investigate RAN-based integration solutions [1]. These studies target increasing cooperation between 3GPP Long Term Evolution (LTE) and WiFi radio technologies. In this context, the authors in [1] consider convergence of WLAN-based small cells with operator-managed cellular deployment, where they explain different feasible architectural options for integration and their associated performance benefits. The work in [5], instead, solves the network selection problem for real-time businesses using auction mechanism and leveraging the concept of upset price in order to maximize the online profits.

Several studies have also investigated a cost-function-based network selection approach, where the decision is based on monetary cost, power consumption, network conditions, and user preferences [6][7][8]. Other studies have considered the resource allocation problem for parallel transmission utilizing multiple RATs [9][10]. However, the formulated problem in [9] is NP-hard, and a suboptimal allocation strategy is developed by exploiting the intrinsic quasiconcavity of the problem. In [10], the authors present a framework of Multi-RAT system, where a small cell serves a number of mobile users via IEEE 802.11 WLAN and 3GPP LTE access technologies. A scheduler at the small cell is proposed to minimize the total transmission power subject to quality of service constraints on the users transmission rates. In [11], an urban deployment scenario is investigated, where WiFi small cells are overlaid on top of the 3GPP LTE network. The authors propose user-centric network selection algorithms to minimize feedback overhead taking into account user preferences.

In this paper, we address the important issue of selecting the best network connection among multiple RANs. In the proposed approach, a user takes the responsibility of network selection decision (user-centric approach) [12]. However, we integrate networks particularities and application characteristics to find the optimal RAN(s) that allows all users to meet the system constraints. Specifically, our model supports multi-RAN selection with the aid of a Multi-objective Optimization Problem (MOP) that accounts for (i) QoS (in particular, data latency), (ii) monetary cost, and (ii) energy consumption. Our main contributions of this work can be summarized as follows:

1) We formulate a network selection multi-objective

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optimization problem that aims at selecting the RAN(s) that optimize the overall user objective. This optimization is formulated as a linear programming problem, considering that the available RANs for each user are changing dynamically over time.
2) We propose an iterative, user-centric scheme for access network selection that is distributed and quickly converges to the optimal solution.
3) The convergence behavior of the proposed algorithm is analyzed and proved analytically.
4) The proposed scheme is evaluated through simulation and compared to an existing network selection algorithm. Our results show the gain provided by our solution, and its ability to adapt to varying network conditions.

The rest of the paper is organized as follows. Section II introduces the system model under study. Section III presents the proposed network selection optimization problem. While Section IV describes our network selection algorithm. Section V shows simulation results. Finally, Section VI concludes the paper.

II. System Model

We consider a wireless network, where there are multiple RANs available to which users can connect and transmit their data. Without loss of generality, we focus on a heterogeneous m-health system, as shown in Figure 1; however, the proposed scheme can be applied to a wide range of applications with different characteristics.

In the scenario under study, a PDA (Personal/Patient Data Aggregator) transfers its EEG data to a M-Health Cloud (MHC) via wireless transmission [13]. The multiple RANs that are available share the same system control plane. Such heterogeneous wireless environment allows the PDA to be always best connected anywhere and anytime [12]. It is assumed that the EEG data is collected from the patient using EEG Headset [14], then it is sent to the PDA (i.e., smartphone) that compresses the gathered data using adaptive compression techniques [13], and forwards it to the MHC. Each RAN has different characteristics, such as energy consumption, monetary cost (i.e., requested payment for using network services), and transmission delay. Also, the RANs characteristics may continuously change over time, due to mobility, varying propagation conditions or data traffic dynamics.

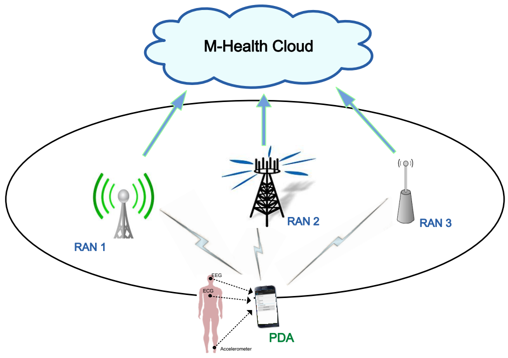

Fig. 1. System scenario under study.

III. Network Selection Optimization

We first introduce the application and network requirements, which will be addressed in our problem. We then formulate a multi-objective optimization problem that each PDA should solve, subject to the system constraints.

A. Performance metrics

The objective of the proposed optimization problem is threefold: (i) minimizing transmission energy consumption, (ii) minimizing monetary cost, and (iii) meeting the medical data QoS requirements. Following [15], the estimated energy consumption for PDA i to send data of size l_i bits over RAN j, with bandwidth w_j and data rate r_{ij}, is

$$\widetilde{E}_{ij} = \delta_j \left(\frac{l_i \cdot N_0 \cdot w_j}{r_{ij} \cdot g_{ij}} (2^{\frac{r_{ij}}{w_j}} - 1) \right) + c_j \,. \tag{1}$$

In the above expression, N_0 is the noise spectral density, while the channel gain g_{ij} is defined as

$$g_{ij} = k \cdot \alpha \cdot |h_{ij}|^2 \tag{2}$$

where $k = -1.5/(\log(5\text{BER}))$, α is the path loss, and $|h_{ij}|$ is the fading channel magnitude for PDA i over RAN j. In (1), δ_j and c_j are specific parameters that differ for each network interface [16]. They can be found in the radio interface specifications, or they can be obtained by running simulations for various amounts of data to define a power consumption pattern for each interface [12].

The efficient network selection mechanism should also meet the application demands and users' requirements in terms of QoS. There is a natural human tendency to reduce the monetary cost, hence it is worthy to consider it as one of the objectives that need to be optimized. The monetary cost resulting from using a RAN j by PDA i to send l_i bits is expressed in Euro and defined as:

$$\widetilde{C}_{ij} = l_i \cdot \varepsilon_j \tag{3}$$

where ε_j is the monetary cost per bit for RAN j. This monetary cost can be acquired through the use of the IEEE 802.21 standard [17], which allows a user device to gather information about the available wireless networks [12]. Such value can also be stored on each PDA in advance and updated if there are any changes in pricing.

Looking at the application's QoS requirements, it is of paramount importance to ensure a swift transfer of medical data toward the MHC. We therefore consider as additional performance metric the latency experienced by data when PDA i uses RAN j, i.e.,

$$\widetilde{\tau}_{ij} = \frac{l_i}{r_{ij}} \,. \tag{4}$$

Note that, another critical QoS parameter in healthcare applications is signal distortion, which needs to be kept at an acceptable level: $D_i \leq D_{th}, \quad \forall i \in N$, where D_i is the distortion for the data transferred by PDA i and D_{th} is the maximum distortion threshold [13]. Thus, given the number l_s of raw bits as input to the encoder of PDA i, the number of output bits to be transmitted over a radio channel is given by $l_i = l_s(1 - \kappa_i)$, with κ_i being the data compression ratio adopted by PDA i. Since the distortion constraint is only a function of the compression ratio κ_i, which does not depend on the chosen RAN, in the following we will consider the value of κ_i as equal to the maximum value that allows a PDA not to exceed the target distortion threshold.

Looking at the above expressions, it can be seen that there is a tradeoff between different objectives. As the data rate over RAN j increases, the latency τ_{ij} decreases, while the energy consumption increases. Also, it is often the case that RANs providing higher data rates have a higher monetary cost. Thus, in order to achieve the aforementioned system goals, it is necessary to find the optimal tradeoff between different conflicting objectives with the aid of Multi-objective Optimization Problem (MOP). We take this challenge in the next section, where our optimization problem is formulated.

B. Optimization Problem

We consider a weighted-sum approach to formulate our MOP. Generally, we define a single Aggregate Objective Function (AOF) which turns the multiple objectives into a single objective function including transmission energy consumption, monetary cost, and data transfer delay from the PDA to the MHC. However, each objective presents different ranges and units of measurement, hence we need first to normalize these quantities in order to make them adimensional and comparable. We will denote the normalized energy, monetary cost (hereinafter referred to as cost for brevity), and latency by E_{ij}, C_{ij} and τ_{ij}, respectively.

Given the generic PDA i and denoted by M the number of RANs to available i, the objective of our optimization problem is to assign the PDA to the optimal RAN(s) that minimize the transmission energy consumption E_{ij}, monetary cost C_{ij}, and transmission delay τ_{ij} in the system, while meeting application's QoS requirements:

$$z = \min_{P_{ij}} \sum_{j=1}^{M} P_{ij} \cdot U_{ij} \tag{5}$$

$$s.t. \qquad \frac{P_{ij} \cdot l_i}{r_{ij}} \leq T_{ij}, \quad \forall j \in M \tag{6}$$

$$\sum_{j=1}^{M} P_{ij} \geq 1, \tag{7}$$

$$0 \leq P_{ij} \leq 1, \quad \forall j \in M \tag{8}$$

where $U_{ij} = \alpha_i \cdot E_{ij} + \beta_i \cdot C_{ij} + \gamma_i \cdot \tau_{ij}$ is the utility function of PDA i over RAN j. The weighting coefficients represent the relative importance of the three objective functions in the problem; it is assumed that $\alpha_i + \beta_i + \gamma_i = 1$. Moreover, in (5) we consider a network indicator P_{ij} that represents the fraction of data that should be transmitted through RAN j by PDA i.

The network capacity constraint is represented by (6), where T_{ij} is the maximum throughput that RAN j can provide to PDA i (resource share); we remark that T_{ij} depends on the number of PDAs accessing the RAN. We assume that the network can notify the PDA about the data rate r_{ij} as well as T_j, which is the aggregate throughput that network j can support. Clearly, r_{ij} is highly dependent on channel radio propagation conditions and on the network access technology. The highest data rate can be provided by each network (e.g., 11Mbps for IEEE 802.11b and 54Mbps for IEEE 802.11g) [12]. The unknowns in this problem are the P_{ij}'s, i.e., each PDA needs to determine on which RAN(s) it will transmit and the amount of data that the PDA should transfer through each RAN. The problem is a Linear Programming (LP) problem.

IV. AUTONOMOUS ACCESS NETWORK SELECTION

In this section, we propose a distributed, iterative algorithm for optimal network selection, which we name Autonomous Access Network Selection (AANS) scheme. According to AANS, once obtained a list of the available RANs, each PDA i solves the problem in (5) locally and sets the values of P_{ij} for each RAN so that its obejctive function is minimized while the system constraints are met. In order to solve the problem, the weights α_i, β_i and γ_i are assumed to be pre-defined and specified according to application requirements and/or PDAs' preference. Also, the value T_{ij} is initially set to $T_{ij} = T_j/N_j, \forall j$, where N_j is the number of PDAs using RAN j, assuming that all users receive the same resource share on RAN j. As foreseen by several standards, the RAN can notify users about the value of N_j. However, the value of T_{ij} can also be set initially to any arbitrary value.

After having solved the optimization problem under the above conditions, the PDA broadcasts the actual value of T_{ij}'s it has computed and intends to "consume" over RAN j (i.e., $\widetilde{T}_{ij} = \frac{P_{ij} \cdot l_i}{r_{ij}}$). At the RAN level, the actual demand from all users is calculated, and each RAN j can use whatever mechanism to allocate free resources among competing users (e.g., using proportional fairness, equal allocation, etc.) [18][19]. Thus, each RAN can update and return to the PDA the value of its new resource share. Accordingly, the PDA solves the optimization problem again, obtaining the new optimal values of P_{ij}'s. The procedure can be repeated until convergence is reached, or a maximum number of iterations has been reached. The main steps of the AANS algorithm are illustrated in Algorithm 1.

Below, we prove that the convergence of AASN scheme is guaranteed.

Theorem: *Regardless of the scheduling mechanisms implemented at the available RANs, the proposed AANS scheme converges to the optimal solution of the LP formulation in (5).*

Proof: The AANS algorithm initially starts assuming an equal resource share among PDAs. However, as long as no new users are added to the RANs (i.e., N_j is fixed), and according to the constraint in (6), the actual resource share for any PDA can be less than or equal to this initial arbitrary value. Therefore, after the first iteration, there may be an additional free resource shares on certain RANs that were not available at the previous iteration. Thus, these RANs can update the PDA with the new value of its resource share $T_{ij}(t+1)$. It is worth mentioning here that whatever the re-assignation mechanism used at the RANs

Algorithm 1 Autonomous Access Network Selection (AANS) algorithm at PDA i

1: **Initialization:**
   α_i: energy weight, β_i: cost weight, γ_i: latency weight
   T_{ij}: initial resource share on RAN j
   r_{ij}: data rate on RAN j
   ε_j: monetary cost of RAN j
   $t = 0$.
2: Determine the list of available RANs
3: Solve optimization problem in (5)-(8)
4: Obtain optimal P_{ij}'s
5: Broadcast requested $\widetilde{T}_{ij}$'s
6: Get updated $T_{ij}(t+1)$ from RAN j
7: t++
8: **if** $z(t+1) \neq z(t) \wedge t < n_{iter}$ **then**
9:    Go to step 3
10: **else**
11:    Break % The saturation has been reached.
12: **end if**
13: **Output:**
   Selected RAN(s) and corresponding optimal P_{ij}'s

to reallocate the freed resources and update the PDA with $T_{ij}(t+1)$, it always follows that

$$T_{ij}(t+1) \geq T_{ij}(t), \quad \forall t, j. \tag{9}$$

As a result, the constraint in (6) will always become looser, which will be reflected directly to the values of P_{ij}. Looking at (5), it is evident that the objective function can be decreased at each iteration if the value of P_{ij}'s corresponding to the lowest values of U_{ij}'s can be increased, which means transmitting more data on RANs with lower utility. While, according to the constraint in (7), the value of P_{ij}'s corresponding to the highest values of U_{ij}'s will be decreased. Thus, from (9) we can conclude that the objective function will always decay with increasing number of iterations until it saturates at $z(t+1) = z(t)$, and this will happen regardless of the scheduling mechanisms implemented at the available RANs. ■

It is also worth mentioning that the objective function will always saturate at $\widetilde{T}_{ij}(t+1) = \widetilde{T}_{ij}(t)$, which means that the PDAs are not willing to give away any of the resources assigned to them by the RANs. However, due to network dynamics, the available RANs can change the assigned resource shares of PDAs (i.e., T_{ij}'s) to any other arbitrary values. This should trigger the PDAs to run the AANS algorithm again and update their allocation.

V. Simulation Results

We now show the convergence time and evaluate the system performance via simulation. To this end, we consider the network topology shown in Figure 1, where each PDA can connect to four RANs with different characteristics. We have: RAN_1 with a monetary cost per bit $\varepsilon_1 = 610^{-6}$ Euro/bit and data rate $r_1 = 4$ Mbps; RAN_2 with $\varepsilon_2 = 310^{-6}$ Euro/bit and $r_2 = 2.5$ Mbps, RAN_3 with $\varepsilon_3 = 0$ Euro/bit, $r_3 = 1.5$ Mbps; RAN_4 with $\varepsilon_4 = 110^{-6}$ Euro/bit and $r_4 = 2$ Mbps. A PDA can capture 4096 samples of epileptic EEG data [20]. Each raw sample is represented using 12 bits. Thus, after the compression, the length of data to be transmitted will be $l_i = 46$ KB. Moreover, to model small scale channel variations, flat Rayleigh fading is assumed, with Doppler frequency of 0.1 Hz. The other physical layer parameters over the available RANs are set to: noise spectrum density $N_0 = -174$ dBm, bandwidth $w = 0.5$ MHz, and path loss $\alpha = 3.6 * 10^{-6}$.

We first compare the performance of the proposed AANS algorithm against a baseline algorithm in which we consider the same idea of Enhanced Power-Friendly Access Network Selection solution (E-PoFANS) presented in [12]. In the algorithm in [12], a score for each of the candidate RANs is computed using the same utility function as U_{ij}. Then, the outcome is ranked and the network with the lowest score is selected as a target network.

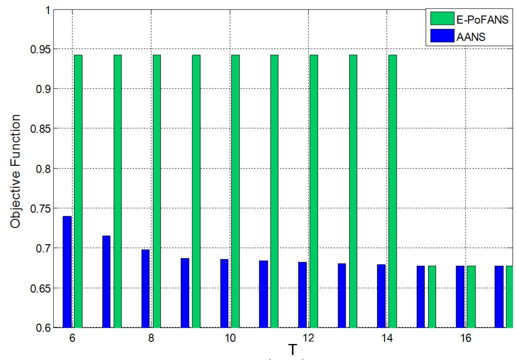

Fig. 2. A comparison between proposed AANS algorithm and the E-PoFANS algorithm.

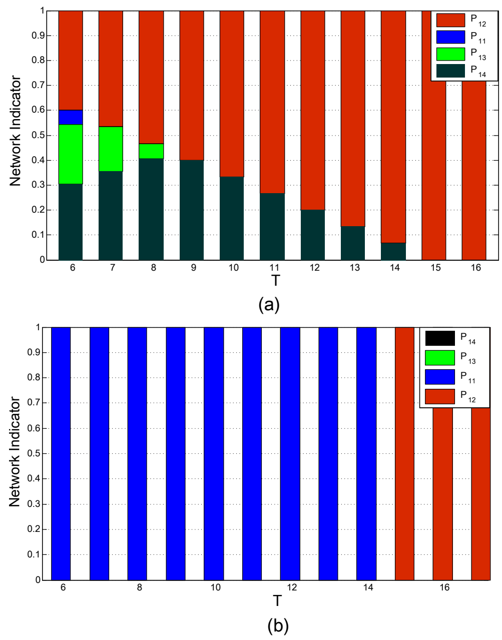

Fig. 3. Obtained network indicators (P_{ij}) using (a) AANS and (b) E-PoFANS.

Figure 2 and Figure 3 depict the value of objective function in (5) for a generic user PDA, and the values of its obtained network indicators P_{ij}'s over different RANs, respectively, when AANS and E-PoFANS are adopted. Here we consider the resource share to be $T_{ij} = T_j/N_j$ $\forall i, j$. We remark that E-PoFANS selects only the candidate network with lowest score, thus in this case P_{ij} takes a value equal to either 0 or 1. Our scheme instead takes different candidate networks into account and selects the optimal RAN(s) that minimize the PDA's aggregate objective, i.e., P_{ij} can take any value between 0 and 1. PDAs are therefore allowed to transmit using different RANs simultaneously instead of being limited to one fixed-assigned RAN (see Figure 3). This leads to a reduced cost function compared to when E-PoFANS is used, as shown in Figure 2.

Figure 4 illustrates the convergence behavior of our AANS algorithm. Recall that initially all PDAs are assumed to get the same resource share on a RAN. Each PDA solves its optimization problem in (5) and obtains a "worst-case" value for its objective function (at the first time step). After that, the PDAs exchange the computed P_{ij}'s and solve the problem again using the values of resource share T_{ij} that have been updated according to the actual PDAs' allocation (at the second time step). As a result, PDAs obtain a reduced value of objective function. The mechanism is iterated, however we observe that very few iterations are needed in order to reach convergence.

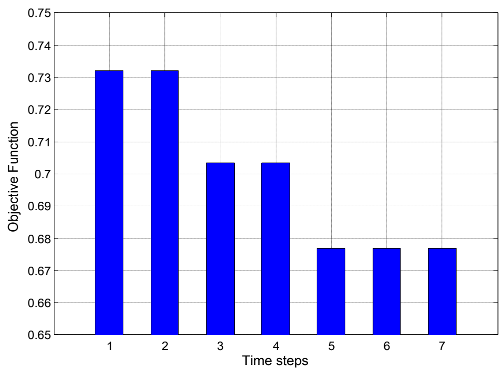

Fig. 4. Convergence behavior of the proposed AANS algorithm.

Finally, Figure 5 assesses the ability of our scheme to adapt to network dynamics. In particular, we assume that the number of PDAs that can access the available RANs varies over time, as shown in Figure 5-(b). As expected, when the number of PDAs decreases, the resource share for each PDA grows and the value of the aggregate objective functions drops; the opposite occurs when new PDAs join the network. Interestingly, however, the network quickly adapts to any change in the scenario by assigning more or less resources to the PDAs and swiftly reaching convergence to the optimum (see Figure 5-(a)).

VI. Conclusion

Given the increasing tendency to deploy dense heterogeneous networks, in this paper we addressed a network scenario where multiple radio access technologies can be simultaneously exploited by users so as to improve their wireless connectivity. We proposed a dynamic network selection mechanism that enables energy efficient and high quality patient health monitoring by targeting jointly RAN selection and traffic load adaptation. In the proposed scheme, transmission energy, application quality of service requirements, and monetary cost are considered as main performance metrics and integrated into a multi-objectove optimization problem. Simulation results show the efficiency of our scheme compared to an existing network selection algorithm, as well as its ability to adapt to varying network conditions.

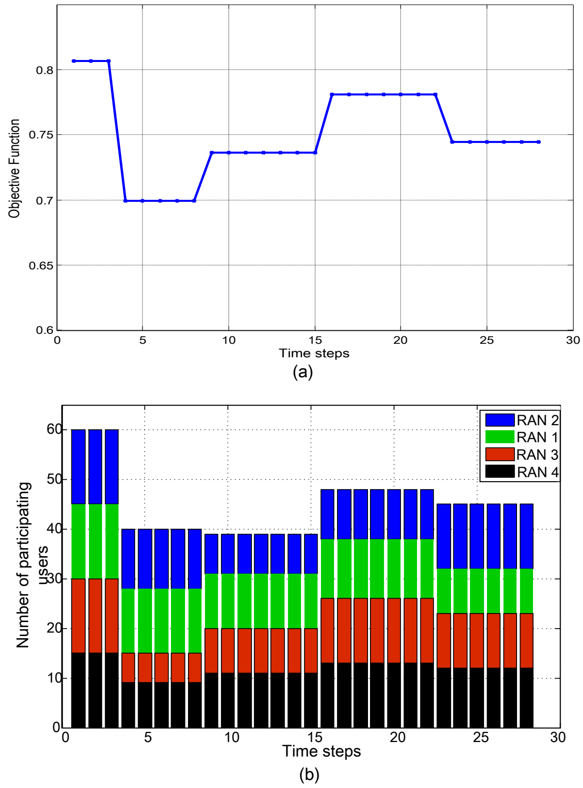

Fig. 5. Temporal evolution of the system performance: (a) aggregate objective function, with varying (b) number of admitted PDAs.

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