Dynamic Network Selection in Heterogeneous Wireless Networks: A User-centric Scheme for Improved Delivery

Dynamic Network Selection in Heterogeneous Wireless Networks

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***Abstract*—The increasing tendency toward the extreme network densification has motivated network operators to leverage spectrum across multiple radio access networks, in order to significantly enhance spectral efficiency, quality of service, as well as network capacity. There is therefore a substantial need to develop innovative network selection mechanisms that consider energy efficiency while meeting application quality requirements. In this context, in accordance with the new trends foreseen for 5G systems, we propose a user-centric scheme for efficient network selection. Our solution accounts for network characteristics and application requirements, as well as for different user objectives by assigning them different weights and dynamically updating them. Numerical results show the efficiency of the proposed solution and its ability to grasp the conflicting nature of users' objectives while achieving an excellent balance between them. Results also show that our solution leads to a significantly increased operating time of user devices.**

***Index Terms*—Heterogeneous wireless environment, network selection, multi-RAT, multi-objective optimization.**

I. Introduction

It is well known that today's radio technologies, such as 3G, 4G and WiFi a/g/n, could be jointly exploited to provide Internet connection to users with high levels of quality of experience [?]. Simultaneously leveraging multiple points of access becomes even more important as the user demand and quality of service (QoS) requirements increase, while the available wireless resources remain limited. Accordingly, the upcoming 5G systems are expected to be dense and irregular heterogeneous networks (HetNets), where the user should be able to access the system through different points of access. In this context, it is crucial to develop techniques that can efficiently leverage the available radio resources across different spectral bands using multi-Radio Access Technology (RAT).

Due to mobility and users' requirements, the association with network infrastructure may be concurrent, exploiting the multihoming feature of mobile devices to establish simultaneous associations with different access networks, or switch from one point of access point to another, within the same Radio Access Network (RAN) or across different RANs. In both cases, several schemes have been proposed in the literature for network selection and association in HetNets. The proposed approaches can be broadly classified into four categories: cost-function based, decision making processes using game theory, Markov decision processes (MDPs), and optimization based. Cost function-based schemes proactively select the network with the highest/lowest utility or cost function [?][?]. Although the approach can achieve a near optimal solution, it is often hard to prove it. According to the game theory approach, instead, users in different service areas compete for the bandwidth offered by different wireless networks [?][?]. The resulting algorithms are, in general, complexity-prohibitive, and their convergence is not guaranteed. Even in case of convergence, they do not necessarily converge to an optimal solution. MDPs have been used also to study network switching between different RATs [?][?]. However, finding the optimal solutions is again cumbersome, especially in the case of large networks [?]. Formulating network selection problem as an optimization problem with low or moderate complexity is also not a trivial task. Finding optimal resource allocation and user association, subject to resources and/or power constraints, may result in an NP-hard problem [?]. One way to make the problem tractable is by using constraints relaxation or variables transformation, or by envisioning online adaptive methods such as Q-learning [?]. Finally, the existing work on concurrent association mainly focus on designing a traffic scheduler over different device interfaces considering users incentives for collaboration and bandwidth sharing [?], a transport-layer control protocol to enable concurrent multipath transport [?], or content-aware transport-layer protocols [?]. An excellent review of mathematical methods that can be applied to the network selection problem, including cost-function, multiple attribute decision making, fuzzy logic, game theory, combinatorial optimization, and Markov chain, can be found in [?].

In this paper, we use an approach based on low-complexity linear program, combined with game theoretic approach in order to address the problem of networks selection over HetNets. In particular, we adopt a user-centric approach, which allows each user equipment (UE) independently to select one or more RANs to use simultaneously, and to determine the amount of data to send over each of the selected RANs. The user decision accounts for both the user specific objectives and the characteristics of the available RANs. Indeed, relying on our conference paper [?], we address multi-RAN selection by formulating a Multi-objective Optimization Problem (MOP) that accounts for (i) QoS (in particular, data latency) requirements, (ii) monetary cost, and (ii) energy consumption. Our work significantly advances the state-of-

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the-art by incorporating in our solution a dynamic weights update mechanism, which makes the scheme adaptive to changes in the system and in the operational conditions. Also, by optimally selecting a RAN according to both the user battery level and the monetary budget, our mechanism also provides fairness among different user objectives (i.e., energy saving, monetary cost and service latency) while significantly enhancing the UE operating time.

Our main contributions can be therefore summarized as follows: (i) we formulate a multi-objective optimization problem that aims at optimally selecting the RAN(s) according to the user's objectives and time-varying network characteristics, (ii) we develop a dynamic weights update mechanism that aims to maximize the user equipment operating time, (iii) we propose a distributed, user-centric scheme for access networks selection that provides the optimal solution from a user point of view, even under dynamic conditions, (iv) we evaluate the proposed scheme through simulation and compare it to an existing cost-function-based network selection algorithm. Our results show the ability of our solution to adapt to varying network conditions, while providing a UE operating time that is three times that given by the cost-function-based algorithm, and improves by 15% the performance of our previous study in [**?**].

The rest of the paper is organized as follows. Section **??** introduces the system model under study and the proposed network selection optimization problem. Section **??** describes our network selection algorithm with dynamic weights update, while Section **??** illustrates simulation results. Finally, Section **??** concludes the paper.

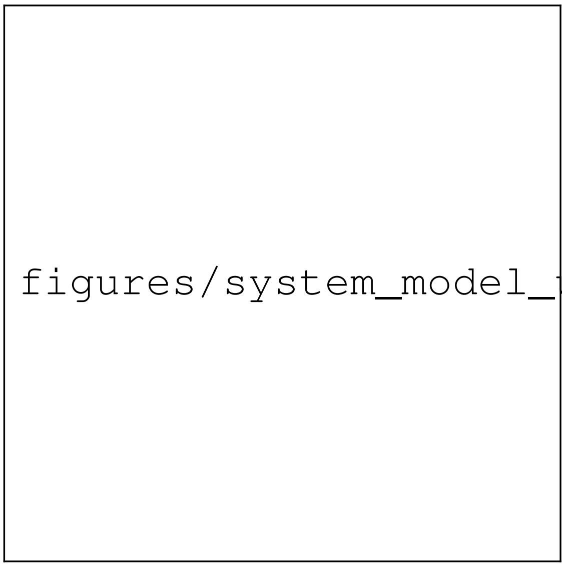

Fig. 1. System scenario under study.

II. Optimal User-centric Selection

We consider a wireless heterogeneous network system (see Figure **??**) where multiple RANs are available to users[1] for Internet connectivity; the proposed methodology, however, can be applied to a wide range of applications and systems with different characteristics. In our system, each RAN may have different characteristics, such as energy cost, monetary cost (i.e., requested payment for using network services), and transmission delay. Furthermore, the RANs characteristics may change continuously over time, due to varying propagation conditions, user mobility, or data traffic dynamics. The goal is clearly to ensure that UEs are best connected, anytime and anywhere [**?**]. In order to achieve this goal, we adopt a user-centric approach, i.e., the UE is in charge of (i) optimally selecting the RAN(s) to be used for data transfer and (ii) determining the amount of data to be transferred through each link. The UE makes optimal network selection and data transfer decisions by formulating and solving a multi-objective optimization problem, subject to the system constraints, as described below.

[1] It is assumed that the UEs are backlogged, i.e., they always have data to send.

A. Performance metrics

The objective of the proposed optimization problem is threefold: (i) minimizing transmission energy consumption at the UE, (ii) minimizing user's monetary cost, and (iii) meeting QoS requirements of the user traffic. The estimated energy consumption, monetary cost, and the expected latency provided by each RAN are defined as in [**?**]. The notations adopted here are given in Table **??**. The energy consumption for UE i to send l_i data bits over a generic RAN j is defined as a function of the transmission rate, path loss, antenna gain, and fading channel magnitude as in [**?**]. Furthermore, for efficient network selection mechanism, it is worthy to consider the monetary cost as one of the critical factors, since there is a natural human tendency to reduce the monetary cost. The monetary cost resulting from using a RAN j by UE i is expressed in Euro as a function of the transmitted data length and the monetary cost per byte. This monetary cost information can be obtained with the aid of the IEEE 802.21 standard, which allows a user to gather information about the available wireless networks [**?**].

TABLE I
Notation Summary

Notation	Description
r_{ij}	Transmission data rate for UE i over RAN j
M	Number of RANs available to the generic UE i
T_{ij}	Maximum throughput that RAN j can assign to UE i
P_{ij}	Network indicator
C_b	Percentage of money budget in the UE's account

Regarding application's QoS requirements, it is crucial to ensure a swift transfer of the user traffic. We thus consider as additional performance metric the expected latency provided by each RAN, which is given by the transmission time and the access channel delay that UE i expects to experience when transmitting l_i bits through RAN j. In other words, it represents the estimated end-to-end delay when using a given technology [**?**], [**?**].

We remark here that there is exists a clear tradeoff between the above objectives. The higher the data rate over RAN j, the higher the energy consumption and the lower the latency. Furthermore, it is often the case that RANs providing higher data rates have a higher monetary cost. Thus, it is critical to find the optimal tradeoff among such conflicting objectives in order to achieve the aforementioned system goals. In addition, the established tradeoff needs to be fair so as to ultimately maximize the UE operating time. We take these challenges in the next section, by formulating a multi-objective optimization problem (MOP) with dynamic weights.

B. Optimization Problem

We define a single aggregate objective function in order to turn the user's multiple objectives into a single objective function including transmission energy consumption, monetary cost, and data transfer delay. Each objective however has different ranges and units of measurement, consequently we first normalize these quantities in order to make them comparable. We denote the normalized energy, monetary cost (hereinafter referred to as cost for brevity), and latency by E_{ij}, C_{ij} and τ_{ij}, respectively.

Next, let us first assume that the system operational conditions do not vary over time. In this case, the MOP that allows UE i to jointly and efficiently use the RANs, subject to system and application constraints, is defined as:

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

$$s.t. \qquad \frac{P_{ij} \cdot l_i}{r_{ij}} \leq T_{ij}, \quad \forall j \in M \tag{2}$$

$$\sum_{j=1}^{M} P_{ij} \geq 1, \tag{3}$$

$$0 \leq P_{ij} \leq 1, \quad \forall j \in M\,. \tag{4}$$

In the above objective function, $U_{ij} = \alpha_i \cdot E_{ij} + \beta_i \cdot C_{ij} + \gamma_i \cdot \tau_{ij}$ is the utility function of UE i over RAN j, and P_{ij} represents the fraction of data that should be transmitted through RAN j by UE i. The weighting coefficients represent the relative importance of the three objective functions in the problem; it is assumed that $\alpha_i + \beta_i + \gamma_i = 1$.

The expression in (**??**) represents the network capacity constraint, where T_{ij} is the resource share of UE i over RAN j; we remark that T_{ij} depends on the number of users accessing the RAN. The network can notify the UE with the highest data rate r_{ij} (e.g., 54 Mbps for IEEE 802.11g), as well as T_{ij} that it can support [**?**]. Consequently, the unknowns in this problem are the P_{ij}'s, which identify which RANs the UE will have to use (i.e., those with $P_{ij} > 0$) and the amount of data that it should transfer through each RAN. The problem is a Linear Programming (LP) problem, which is solvable in polynomial time [**?**].

Clearly, the RANs data rate and the values of resource share T_{ij} may significantly vary over time; the former due to dynamic channel radio propagation conditions, the latter due to changes in the number of users connected to a RAN and in their associated traffic load. Thus, in the next section we address the problem of optimally selecting the available networks under dynamic operational conditions.

III. Network Selection With Dynamic Weights Update

Here we envision a scheme that lets a user continuously adapt his/her network selection decision to the changes in the RANs data rate and resource share, as well as in the UE's battery level, remaining money budget and service latency. Our scheme is based on optimally updating the α, β and γ weights by leveraging a game theoretic approach [**?**].

A. Dynamic Weights Update

Let us first focus on energy as a performance metric and consider the generic UE i. The energy weight α_i should reflect the energy budget available at the UE, i.e., the UE's battery level E_b. Hence, for small values of E_b the corresponding energy weight must be high, whereas for high values of E_b, the energy weight must be low. Consequently, we update the energy weight at time step $t+1$, $\alpha_i^{(t+1)}$ as

$$\alpha_i^{(t+1)} = \alpha_i^{(t)} + (1 - E_b)\alpha_i^{(t)}. \tag{5}$$

Similarly, the cost weight β_i is updated based on the monetary budget C_b. The updated cost weight at step $t+1$ is defined as

$$\beta_i^{(t+1)} = \beta_i^{(t)} + (1 - C_b)\beta_i^{(t)}. \tag{6}$$

As far as the delay weight γ_i is concerned, it should reflect the system ability to meet the expected delay deadline τ_m. To this end, we define a delay degradation coefficient, $\eta \geq 0$, defined as

$$\eta = \min\left(0, \frac{\tau - \tau_m}{\tau_m}\right). \tag{7}$$

This implies that, for small values of η, the corresponding delay weight should be low, while for high values of η, the delay weight must be high. Consequently, we write:

$$\gamma_i^{(t+1)} = \gamma_i^{(t)} + \eta \cdot \gamma_i^{(t)}. \tag{8}$$

According to the above equations, each objective has its own incentive to increase its weight. However, the following constraint holds:

$$\alpha_i^{(t)} + \beta_i^{(t)} + \gamma_i^{(t)} = 1, \quad \forall i \in N, \forall t. \tag{9}$$

We can therefore see the three objectives as competing entities and formulate the weights update mechanism as a dynamic sequential game. Specifically, we can define the game as follows:

- *Players:* The set of objectives for each UE (i.e., the energy consumption, cost, and latency).
- *Player's Strategy:* the player's weight update.
- *Player's Payoff:* the value added to the player's weight, which is defined as $\alpha_i^+ = (1 - E_b)\alpha_i$, $\beta_i^+ = (1 - C_b)\beta_i$, and $\gamma_i^+ = \eta \cdot \gamma_i$.

This is a zero-sum game, since one player's gain exactly equals the aggregate losses of all other players [**?**]. Moreover, the game is sequential, i.e., players make decisions one after the other. An extensive form representation of the game is provided in Figure **??**, where the labels on the branches are the payoffs of the players if they follow such branches. The numbers between parentheses at the bottom of the tree represent the possible game outcomes, in the format $O_k = (E_{bk}, C_{bk}, 1 - \eta_k)$. The outcomes are calculated as follows. Given the k-th path in the tree (i.e., the k-th sequence of branches), first we compute the value of the weights using equations (**??**), (**??**), (**??**) and, as update, the payoffs corresponding to each branch of the path. Then, we plug such weights in the optimization problem in (**??**) and solve it thus obtaining the energy, cost and latency. These values are finally used to compute E_{bk}, C_{bk}, and η_k, i.e., the game outcome O_k. It is important also to note that, due to the constraint in (**??**), some paths of the tree do not correspond to feasible outcomes, hence they can be pruned. The weights updates (payoffs) and the corresponding outcomes are then exploited for networks selection as described below.

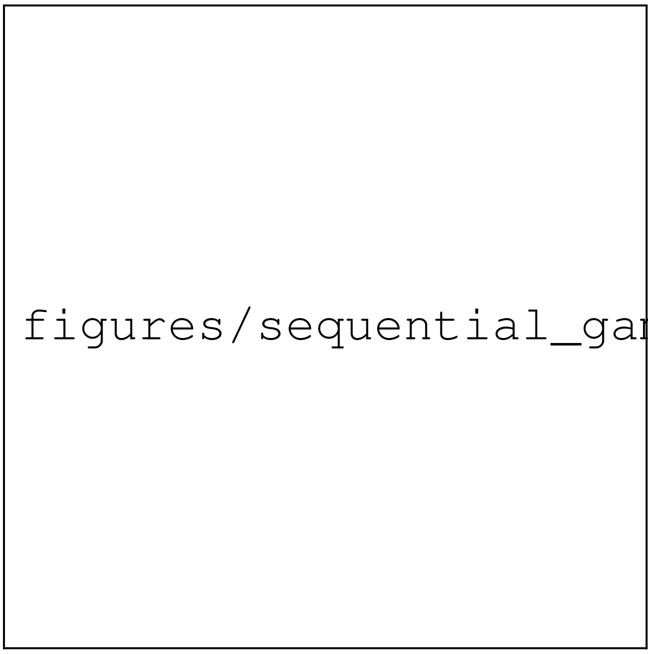

Fig. 2. Representation in extensive form of the weight update game among energy consumption, cost, and latency.

B. Autonomous Access Network Selection

In this section, we propose a distributed, iterative algorithm for optimal network selection with dynamic weights update, which we name Autonomous Selection with Weights Update (ASWU). According to ASWU, the generic UE i first acquires the list of available RANs and sets the weights α_i, β_i and γ_i to be equal. Also, without loss of generality, the value T_{ij} is initialized to[2] $T_{ij} = T_j/N_j, \forall j$, where N_j is the number of users currently using RAN j. This implies that, as foreseen by several standards, the generic RAN j notifies its users about the value of N_j and that a UE will initially assume that resources are evenly shared on RAN j.

UE i then updates the weights α_i, β_i and γ_i using the mechanism based on the sequential game described in Figure **??**. As mentioned, the possible game outcomes are calculated based on the assigned payoffs on each branch and after solving the optimization problem in (**??**) once for each path on the tree. Then, in order to maximize the UE operating time and achieve max-min fairness among energy saving, monetary cost, and delay performance, the UE selects the path, i.e., the game outcome, that maximizes the minimum value of $(E_b, C_b, 1 - \eta)$ [**?**][**?**].

By doing so, the UE can set the amount of data to be sent over every RAN according to the values of P_{ij} corresponding to the selected game outcome, or, equivalently, to the solution of the corresponding optimization problem. It can then send to every RAN the corresponding fraction of resources that it intends to "consume" over the RAN itself (i.e., $\widetilde{T}_{ij} = \frac{P_{ij} \cdot l_i}{r_{ij}}$). Once RAN j receives the values T_{ij}'s from the UEs, it computes the actual resource share. Note that each RAN can use whatever mechanism to allocate its resources among the competing users, e.g., proportional fairness, equal allocation, etc. [**?**]. The new resource share is returned to each UE. The procedure can be repeated until either convergence or a maximum number of iterations is reached.

The main steps of the ASWU scheme are illustrated in Algorithm **??**, where we recall that $F(t)$ is the minimum value of the objective function at time step t.

Algorithm 1 Autonomous Selection with Weights Update (ASWU) at UE i

1: **Initialization:**
   $t = 0$, $\alpha_i = \beta_i = \gamma_i = 1/3$, $T_{ij}(0) = T_j(0)/N_j(0)$
   $E_b = 1$, $C_b = 1$, $\eta = 0$.
2: Determine the list of available RANs
3: Update weights for all possible game outcomes using equations (**??**), (**??**), (**??**).
4: Solve optimization problem in (**??**) for each path in Figure **??**.
5: Select the outcome that maximizes the minimum value of $(E_b, C_b, 1 - \eta)$.
6: Obtain optimal P^*_{ij}'s and update weights corresponding to the selected outcome.
7: Update and send requested $\widetilde{T}_{ij}$'s
8: Get updated $T_{ij}(t+1)$'s from available RANs
9: t++
10: **if** $F(t+1) \neq F(t)$ AND $t < n_{iter}$ **then**
11:   Go to step 3
12: **end if**
   % The convergence has been reached %
13: **Output:**
   - Selected RAN(s), corresponding optimal P^*_{ij}'s, and updated weights.

We make here the following remarks. First, using our proof in [**?**], we can show that regardless of the scheduling mechanisms implemented at the available RANs, the proposed ASWU scheme converges to the optimal solution of the LP formulation in (**??**). Second, due to the network dynamics, the available RANs can change the resource shares assigned to the UEs (i.e., T_{ij}) over time. This would clearly trigger the UEs to run the ASWU algorithm again and update their data traffic allocation.

IV. Performance Evaluation

[2]Note, however, that T_{ij} can be set initially to any arbitrary value.

Here we first present the simulation setup that we used for our evaluation, then we present the performance of the proposed dynamic networks selection scheme.

A. Simulation Environment

For concreteness, we consider a practical example of an m-health application: UEs are PDAs (Personal/Patient Data Aggregators) that have to connect to the available RANs in order to transfer their gathered medical data to an M-Health Cloud (MHC). In particular, we consider a wireless brain monitoring where the PDA (i.e., smartphone) collects electroencephalogram (EEG) data from the patient using EEG Headset [?], then it forwards the gathered data to the MHC. This choice is motivated by the fact that EEG signal is the main source of information describing brain activity. Moreover, the use of EEG signal has become the most popular approach for brain-computer interface (BCI) applications because of its usability and reliability [?]. Each PDA captures 4096 samples of epileptic EEG data [?] over a time interval of 23.56 seconds, and each raw sample is represented using 12 bits.

We then consider a network topology as the one depicted in Figure ??, where each PDA can connect to four RANs, each with different characteristics. RAN_1 has a monetary cost per byte $\varepsilon_1 = 3 * 10^{-6}$ Euro/byte and data rate $r_1 = 4$ Mbps; RAN_2 has $\varepsilon_2 = 2 * 10^{-6}$ Euro/byte and $r_2 = 3.5$ Mbps, RAN_3 has $\varepsilon_3 = 0$ Euro/byte, $r_3 = 2.5$ Mbps; RAN_4 has $\varepsilon_4 = 1 * 10^{-6}$ Euro/byte and $r_4 = 3$ Mbps. Moreover, to model small scale channel variations, flat Rayleigh fading is assumed, with Doppler frequency of 0.1 Hz. Other physical layer parameters over the available RANs are set as follows: noise spectrum density $N_0 = -174$ dBm, bandwidth $w = 0.5$ MHz, path loss $\zeta = 3.6{*}10^{-6}$, and the target BER is set to $\vartheta = 10^{-6}$.

B. Simulation Results

We compare the performance of the proposed ASWU algorithm against a baseline algorithm, named Ranked Network Selection (RNS), which implements the same idea as that proposed for network selection in [?]. We also compare ASWU to the AANS algorithm we presented in [?]. In RNS [?], users compute a score for each of the candidate RANs using a cost function. The outcome is ranked and the network with the lowest score is selected as a target network. In our case, we take as cost function the same as U_{ij}, introduced in Section ??. In [?], instead, we considered the optimization problem in (??), however the weights α_i, β_i and γ_i were assumed to be pre-defined and fixed.

In what follows, we assume that the number of PDAs/users N_j that can access the available RANs varies over time, as shown in Figure ??-(b). Also, we consider the resource share to be $T_{ij} = T_j/N_j$, $\forall i, j$.

Figure ??-(a) depicts the value of aggregate cost for a generic user PDA over different RANs, where the cost for RAN j is defined as $E_{ij} + C_{ij} + \tau_{ij}$. The three algorithms, ASWU, RNS, and AANS, are considered. In RNS, the candidate network with lowest score only is selected, thus in this case P_{ij} takes a value equal to either 0 or 1.

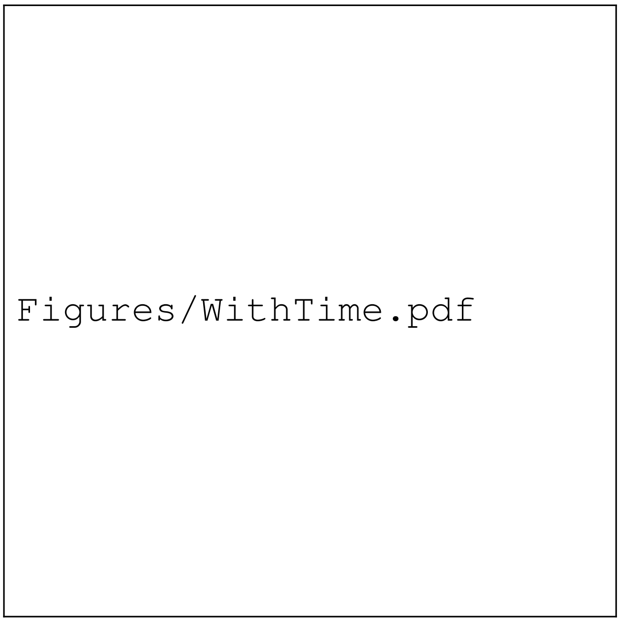

Fig. 3. Temporal evolution of the system performance: (a) aggregate cost, with varying (b) number of participating users.

Conversely, in our scheme and in AANS, PDAs consider different candidate networks and select the optimal RAN(s) that minimize the PDA's aggregate objective, i.e., the variable P_{ij}'s can take any value between 0 and 1 (see Figure ??). Consequently, in ASWU and AANS, PDAs are allowed to transmit using different RANs simultaneously instead of being limited to one RAN only. This leads to a reduced aggregate cost function compared to RNS, as shown in Figure ??. Moreover, Figure ?? and Figure ?? assess the ability of our scheme to adapt to network dynamics. As it can be clearly seen, when the number of PDAs/users decreases, the resource share for each PDA/user increases. Accordingly, the PDAs update their selected P_{ij}, which results in decreasing the value of the aggregate cost. The opposite occurs when new PDAs/users join the network. Interestingly, not only does the network quickly adapt to any change in the scenario by assigning more or less resources to the PDAs, but it also swiftly achieves the desirable operational point (see Figure ??-(a)).

Figure ?? assesses the performance of the proposed ASWU algorithm in terms of PDA operating time and delay degradation (i.e., η defined in (??)), relatively to the AANS and RNS schemes. Herein, the PDA operating time is defined as the maximum operating time till the PDA runs out of energy or monetary budget (i.e., time steps in x-axis, when $E_b = 0$ or $C_b = 0$). By leveraging the proposed dynamic mechanism for weights update, our ASWU algorithm can efficiently update the different objectives' weights such that the PDA operating time is maximized while maintaining the delay below a given delay deadline (i.e., $\eta = 0$). Thus, as the PDAs energy budget significantly decreases, the corresponding energy weight increases; a similar behavior is obtained with decreasing monetary budget and when the experienced delay exceeds the delay deadline. It follows that ASWU enables the PDA to dynamically vary its RANs' selection in order to avoid

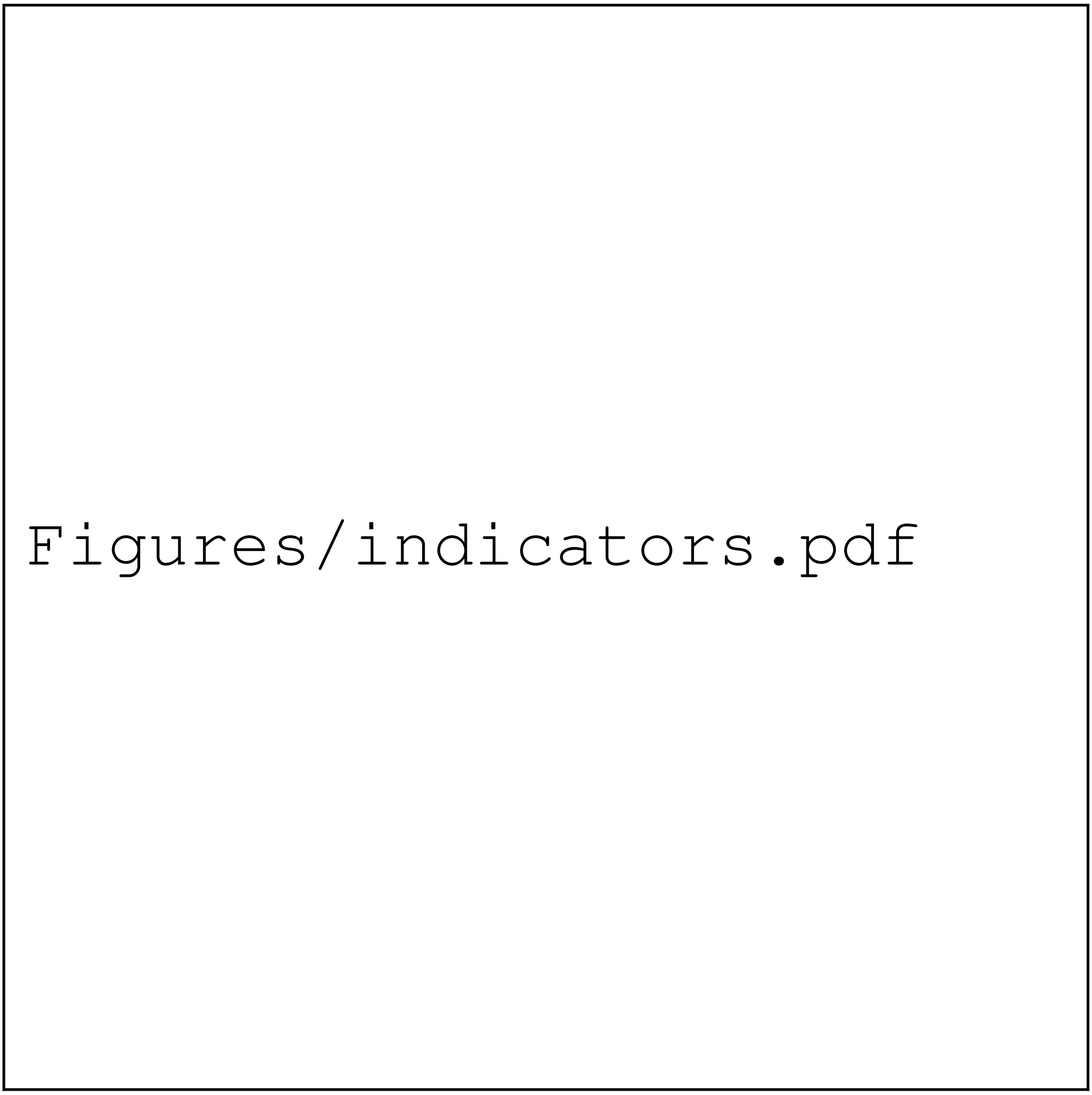

Fig. 4. Obtained network indicators (P_{ij}) using (a) ASWU, (b) AANS, and (c) RNS.

reaching zero energy/money budget (see Figure **??**-(a)). Accordingly, Figure **??**-(a) shows that ASWU can improve the PDA operating time by 15% with respect to AANS, and by 373% with respect to RNS, while achieving the best delay performance (see Figure **??**-(b)).

V. Conclusion

Given the increasing tendency toward networks densification, in this paper we addressed a network scenario where multiple radio access technologies can be simultaneously leveraged by users in order to improve their wireless connectivity. We proposed a dynamic network selection mechanism that considers fairness among different user objectives to maximize its operating time while meeting the system constraints. In the proposed scheme, transmission energy, data latency, and monetary cost are considered as main performance metrics and integrated into a multi-objective optimization problem. Simulation results show the ability of our scheme to adapt to varying network conditions, as well as its efficiency compared to an existing network selection algorithm.