Joint Performance-Resource Optimization for Improved Video Quality in Fairness Enhanced HetNets

Bharat Agarwal[1], Mohammed Amine Togou[1], Marco Ruffini[2], and Gabriel-Miro Muntean[1]

[1]School of Electronic Engineering, Dublin City University, Ireland
[2]Computer Science and Statistic Department, Trinity College Dublin, Ireland
[1]bharat.agarwal2@mail.dcu.ie, mohammedamine.togou@dcu.ie, gabriel.muntean@dcu.ie
[2]marco.ruffini@scss.tcd.ie

***Abstract*—Achieving high Quality of Service (QoS) is one of the important goals in the latest 5G Heterogeneous Networks (HetNets) environments. However, ensuring fairness among users with Reduced Power Consumption (RPC) is a major challenge. Although several studies have examined the joint issue of User Association (UA), Resource Allocation (RA), and Power Allocation (PA), there is still no optimal solution that achieves QoS fairness and RPC with low complexity and processing time. This paper proposes the Power-Performance Efficient Adaptive Genetic Algorithm (P^2EAGA) for solving the UA-RA-PA problem in HetNets. Simulation results show that P^2EAGA outperforms existing schemes in terms of variability, fairness, RPC, and QoS, including throughput, packet loss ratio, delay, and jitter. Simulation results also show that P^2EAGA generates solutions that are very close to the optimal global solution compared to the Default Genetic Algorithm.**

I. Introduction

In cellular networks, data traffic, is now growing at an exponential pace. The link capacity has been approaching the fundamental limits thanks to recent advances in communication theory. One promising solution for supporting the rapid growth of mobile data traffic is to increase the cost-efficient density deployment of Base Stations (BSs), hence creating Heterogeneous Networks (HetNets) [1], [2]. Yet, extending the network infrastructure would compound the power consumption usage. As a result, designing reduced power systems has become a critical requirement for next-generation mobile networks. HetNets, which are made up of small cells with short coverage range, enable the User Equipment (UE) to communicate with BSs at low power levels, resulting in Reduced Power Consumption (RPC), and eventually lower CAPEX and OPEX [3]. At the same time, HetNets can support high service quality as users can select from multiple options and associate with those BSs that provide good communication channel conditions (i.e high Channel Quality Index (CQI)) [3]. In this context HetNets most significant challenge is addressing the triple User Association - Resource Allocation - Power Allocation (UA-RA-PA) problem, which refers to UA to BS, RA during service, and PA for using that service. A solution to the UA-RA-PA problem should enable not only high values, but also fairness in terms of Quality of Service (QoS) distribution and RPC while considering aspects such as BS capacity, user requirements, channel quality, and BS power budget. Several approaches [4]–[8] have been proposed to address the UA-RA-PA problem in HetNets. They mainly differ in terms of architecture (*i.e.,* centralized or distributed), number and type of parameters considered, and execution time.

Wang *et al.* [4] suggested a collaborative RA approach involving UA and PA to solve the optimization problem, split into two sub-problems. Yuan *et al.* [5] proposed a joint RA and PA method in a carrier aggregation enabled HetNet. They consider a solution based on a hierarchical game to align the network operator's pricing policies with the transmit control and resource distribution of unlicensed users. Zhang *et al.* [6] proposed a joint beam and PA in a mmWave small cell to formulate the two sub-problems using mixed-integer nonlinear programming. A study by Naqvi *et al.* [7] proposed dynamic resource management to maximize the energy efficiency of cellular users while maintaining good QoS levels for device-to-device communications. Finally, Zhu *et al.* [8] proposed a joint optimization of resource (channel assignment) and PA in a NOMA system by using a matching algorithm together with optimal PA.

Despite their good performances, most of the aforementioned approaches suffer various limitations. For instance, the approach in [4] did not provide services for UEs with bad channel conditions, while [8] only focused on a single-cell network. In addition, fairness among users was not considered in [7] and both [5] and [6] have high computational complexity and long processing time. These shortcomings have motivated us to propose the **Power-Performance Efficient Adaptive Genetic Algorithm** (P^2EAGA), a decentralized solution to the UA-RA-PA problem, formulated as a '0/1' Multiple Knapsack Problem (MKP), which is an NP-complete optimization problem [2], while considering the maximum BS capacity, the Transport Block Size (TBS)[1] index, and total

[1]The TBS specifies the number of bits sent from the MAC layer to the Physical layer every TTI (Transmission Time Interval, defined as 1ms).

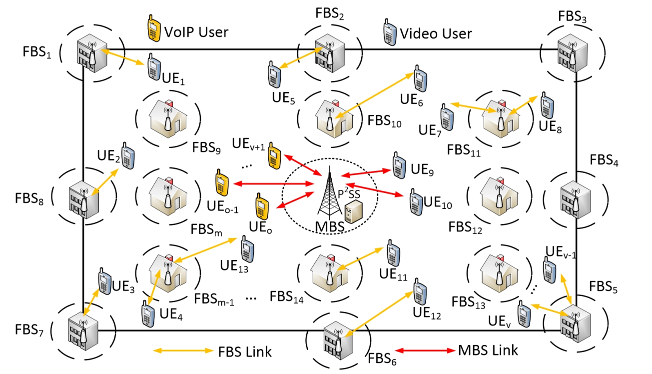

Figure 1. An example of a two-tier HetNet including 1 MBS and 18 FBSs. The FBSs are usually located at commercial and residential buildings that constitute hotspots for wireless traffic. The UEs in a region *G* are either served by either MBS or FBSs selected by Power-Performance Service Server.

BS power budget restrictions. The knapsacks are represented by BSs (Macrocell Base Station (MBS) and Femtocell Base Station (FBS)) in this solution while the items to fit into the knapsacks are represented by instances of UEs. The item weights are UE demands in the UA-RA problem and power consumption in the PA problem. The item values are the available throughput for each knapsack in both problems. Knapsack capacity for the UA-RA problem is the maximum capacity and the total power budget for the PA problem. We use a Default Genetic Algorithm (DGA) to solve the MKP problem. Based on the resource block utilization rate and TBS index, the available throughput is determined. This corresponds to the communication link between UEs and BSs. On the other hand, the power consumption is obtained based on the received signal-to-interference-noise-ratio (SINR). To the best of the authors' knowledge, no work has proposed a low complexity solution to the joint UA-RA-PA problem in fairness enhanced HetNets while considering BS capacity, user requirements, channel quality, and BS power budget.

The rest of this paper is organized as follows. Section II describes the system model. Section III introduces the proposed algorithm. Section IV describes the simulation setup and results. Finally, Section V concludes the paper.

II. System Model

As shown in Fig. 1, consider the downlink of a HetNet consisting of fixed BSs and randomly placed UEs. The area is covered by two-tiers of BSs: MBS (M_m) and FBS tier (M_f). In the coverage area of such BSs, overlaps will occur, and each UE will be within the range of at least one BS. The set of all BSs is denoted as *BS* = $\{MBS_1, ..., MBS_{M_m}, FBS_1, ..., FBS_{M_f}\}$, with the set of the BSs indices *M* = $\{$0,1, . . ., m-1$\}$, where m = $M_m + M_f$. Let S be the set of sub-channels available that can be used by each BS $i \in M$. These sub-channels are further divided and assigned to the UEs linked to each BS i. Let U = $\{0, 1, \cdots, n-1\}$ *(n = v+o , v = no. of video users, o = no. of VoIP users)*, be the set of UEs located inside the region *G*, and $\psi_j \in \Psi$ be the requested downlink rate (*i.e.,* bits per second) of UE j ($j \in U$), where Ψ is the discrete set of service classes.

We assume that each BS $i \in M$ transmits with a constant per sub-channel transmit power P_{ij}^l on sub-channel l, and the total transmit power of BS i is $\tilde{P}_i = \sum_{l \in S} P_{ij}^l (j \in U)$. In this paper, we are interested in two different types of services, *i.e.,* video service as it requires high bandwidth and VoIP (In this paper, the VoIP service is considered as a background traffic.) service. Each UE *j* can only be associated with at most one BS at any time. We define $\tilde{\mu}$ as the total path loss (i.e., follows a log-distance path loss model) between BS i and UE j in decibels (dB). Let $\tilde{U}$ ($\tilde{U} = \{1, \cdots, v\}$) be the set of UEs who are interested in video services and $\hat{U}$ ($\hat{U} = \{1, \cdots, o\}$) be the set of UEs who are interested in VoIP services ($\tilde{U} \cup \hat{U} = U$).

A. Data Rate Mapping to Power Consumption

The instantaneous SINR received at UE j from BS i on sub-channel l can be expressed as:

$$\Gamma_{ij}^l = \frac{h_{ij} P_{ij}^l}{\sum_{\tilde{i} \in M \setminus \{i\}} h_{\tilde{i}j} P_{\tilde{i}j}^l + W N_0}, \tag{1}$$

For ease of presentation, we use the Shannon capacity to calculate the downlink transmission rate. Given the SINR Γ, the achievable per sub-channel downlink rate achieved by UE *j* connected to BS *i* is given by:

$$R_{ij}^l = W log_2 (1 + \Gamma_{ij}^l). \tag{2}$$

Then, the downlink rate achieved by UE *j* is computed as:

$$\hat{R}_j = \sum_{i \in M} x_j^i \sum_{l \in S} y_{ij}^l R_{ij}^l, \forall j \in U, \tag{3}$$

where $x_j^i \in \{0, 1\}$, and $y_{ij}^l \in \{0, 1\}$ are the binary decision variable used for UA and RA (sub-channel allocation), respectively. x_j^i = 1 if UE j is associated with BS i. y_{ij}^l = 1 if sub-channel l is allocated to the downlink from BS i to UE *j*. The total number of resource blocks or sub-channels allocated by BS *i* to UE *j* for a service, *i.e.,* either for video or VoIP is given by: N_j^i = $\left\lceil \frac{\hat{R}_j}{R_{ij}^l} \right\rceil$, with $\lceil . \rceil$ denoting the ceiling function. Once we calculate the total number of resource blocks allocated, the total power consumed by UE j form BS i for that service is given by : P_j^i = N_j^i $*$ P_{ij}^l. Other notations are given in Table I.

B. Problem Formulation

In our system, there are two actors with different viewpoints and goals: UEs and BSs. On the one hand, given its QoS specifications, each UE needs to achieve the maximum data rate possible. BSs, on the other hand, want to meet UEs' QoS requirements while staying within their capability and transmit power constraints. As a result, we define the objective function as the amount of available throughput (*i.e.,* measured based on resource block usage rate) when considering the entities' perspective and objectives under the total capacity of BSs, TBS index, and BSs total transmits power constraint.

Under QoS and power provisioning, we describe the Joint Optimization Problem (JOP) for the UA-RA-PA with MBSs and FBSs as follows:

$$JOP : maximize\, f(x) = \sum_{j=1}^{n} p_j x_j \tag{4}$$

Table I
TABLE OF NOTATIONS

Notation	Description
W	sub-channel bandwidth
N_0	thermal noise spectral power
h_{ij}	channel gain between BS i and UE j
Γ_{ij}^{l}	SINR of downlink on sub-channel l
R_{ij}^{l}	data rate of downlink on sub-channel l
$\hat{R}_j$	achieved downlink rates of UE j
N_j^i	total no. of RBs allocated by BS i to UE j
P_j^i	total power consumed by UE j from BS i for a service used

subject to

$$x_j \in \{0,1\}, j \in U = \{1, ..., n\} \tag{5}$$

$$\sum_{j=1}^{m} r_{ij} x_j \leq b_i, i \in M = \{1, ..., m\} \tag{6}$$

$$q_{ij} \geq \Delta, i \in M = \{1, ..., m\}, j \in U = \{1, ..., n\} \tag{7}$$

$$r_{ij} \leq b_i, \; i \in M = \{1, ..., m\}, j \in U = \{1, ..., n\} \tag{8}$$

$$\sum_{l \in S} \sum_{j=1}^{n} P_{i,j}^{l} \leq P_i^{max}, i \in M = \{1, \cdots, m\} \tag{9}$$

$$P_{i,j}^{l} \geq 0, \forall j, l \tag{10}$$

Eq. (4) represents a *hyper-plane*, hence it is a convex function with convex constraints. Eq. (5) shows the *unique association* property, as any UE j can be associated with only one BS at any moment. We have solved the JOP by breaking it into two sub-problems. In our first sub-problem, we solve the UA-RA sub-problem while considering Eqs. (5)-(8). Then, the UA-RA sub-optimal solution is used as input to the PA sub-problem. The final output is a sub-optimal solution for the PA sub-problem which is solved while considering Eqs. (5), (9), (10).

1) ***UA-RA Sub-Problem****:* The UA-RA sub-problem is formulated as MKP for finding the sub-optimal solution, which is solved using the proposed P^2EAGA algorithm. The item weights (r_{ij}) are user demands, while item values (p_j) are the available throughput for each knapsack. Knapsack capacity (b_i) is the maximum capacity available. Eq. (6) implies that the allocation of resources to UEs should not exceed the *maximum BS capacity*[2]. Eq. (7) implies that each UE j should have a TBS index above a certain threshold Δ to participate in the UA-RA problem (*i.e., TBS index vector*). Finally, Eq. (8) indicates that each BS can serve at least one UE.

2) ***PA Sub-Problem****:* The PA sub-problem is formulated as MKP for finding the sub-optimal solution which is solved using P^2EAGA algorithm. The item weights (P_j^i) is the total power consumed by UE j from BS i for the service used (VoIP or Video), while item values (p_j) are the available throughput for each knapsack. Knapsack capacity (P_i^{max}) is defined as the total transmit power. Eq. (9) indicates a constraint on the total transmit power of each BS i while Eq. (10) ensures non-negative powers.

$$P_{acc} = \begin{cases} exp(\frac{(|f(C_1^{'}) - f(C_1)|)}{t}), \; if \; f(C_1^{'}) - f(C_1) < 0, \\ 1 \qquad\qquad\qquad\qquad\qquad , otherwise \end{cases} \tag{11}$$

[2]Eq. (6) directly covers the constraint $\sum_{i \in M} \sum_{l \in S} x_j^i y_{ij}^l \leq |S|$, which ensures that the number of sub-channels allocated to UEs by BS i does not exceed the total number of available sub-channels.

Table II
PARAMETER VALUES.

GA Parameters	Value
Population Size (n_s)	110
Number of Generations (n_g)	203
Probability of Crossover (p_c)	0.54
Probability of Mutation (p_m)	0.79
Tournament Selection "Number of Contestants" (Z)	5
SA Parameters	**Value**
Initial temp. control parameter (ρ)	0.8
Control Parameter (α)	0.71
final temperature (δ)	0.000595

$$p_{cad} = \begin{cases} p_c \qquad\qquad\qquad\qquad , if \; f(C_1) > f_{max}(C), \\ p_c \frac{f_{max}(C) - f(C_1)}{f_{max}(C)) - f_{avg}(C)}, otherwise \end{cases} \tag{12}$$

$$p_{mad} = \begin{cases} p_m \qquad\qquad\qquad\qquad , if \; f(O_1) > f_{max}(C), \\ p_m \frac{f_{max}(C) - f(O_1)}{f_{max}(C) - f_{avg}(O)}, otherwise \end{cases} \tag{13}$$

III. P^2EAGA - AN ADAPTIVE ALGORITHM

Compared to conventional algorithms, DGA has intelligence, parallelism, self-organization, and high robustness and can be used to solve combinatorial optimization problems like MKP [9]. DGA, however, has some flaws, including weak local searchability, a high convergence rate, and difficulty avoiding local optimums [10]. In order to mitigate these shortcomings, in this paper, we combine DGA with the simulated annealing (SA) algorithm and suggest an improved adaptive Genetic Algorithm. The crossover probability (p_c) and mutation probability (p_m) of the DGA are fixed values. With the evolution process, it is easy to fall into a local optimum. Adaptive adjustment of the crossover probability and mutation probability, *i.e.,* p_{cad} (Eq. (12)), p_{mad} (Eq. (13)) according to the fitness value of the population can help the algorithm jump out of the local optimum. The values of different hyper-parameters for both DGA and SA are taken from [2], [9] and are specified in Table II. In addition, while DGA is prone to premature convergence because of its weak climbing performance [11], SA has a high asymptotic convergence and speed [2]. When combined, the new algorithm leaps out of its local optimum, and the convergence speed of DGA increases. The major steps in our proposed algorithm P^2EAGA are described next:

1) **Parameter Initialization** with values as in Table II.
2) **Population Initialization:** Random generation of n_i chromosomes to form *Initial Population* of length $P_{i\tilde{j}}$.
3) **Population evaluation:** The fitness of chromosomes in the current population is calculated, and the tournament selection method is used to select the best 2 parents.
4) **Crossover operation:** Two chromosomes C_1 and C_2 are selected using tournament selection method explained in Step 3 and crossed with probability p_{cad} to generate two new chromosomes $C_1^{'}$ and $C_2^{'}$. According to the Metropolis Acceptance Criterion (MAC) [2], the proba-

bility of acceptance of new chromosomes p_{acc}[3] is given in Eq. (11) while the adaptive crossover probability p_{cad} is computed following Eq. (12) where $f_{max}(C)$ is the maximum fitness value of the population and $f_{avg}(C)$ is the average fitness value of the current population.

5) **Mutation Operation:** Based on the crossover operation, two off-springs O_1 and O_2 are created and they mutate to $O_1^{'}$ and $O_2^{'}$. Again according to MAC, mutated offsprings are accepted or not. The adaptive mutation probability p_{mad} is given in Eq. (13), where $f_{avg}(O)$ is the average fitness value of the current population.
6) **Decrease Temperature:** After each generation, decrease temperature with a factor $\alpha < 1$. SA tries to evade the local optimum by allowing temporal deterioration of actual solutions (*i.e.,* moves to a solution that corresponds to a worse objective function value), where the deterioration is controlled by a parameter temperature *t*, which determines the mobility of the system and is reduced by a positive factor $\alpha < 1$ [2].
7) **Termination Condition:** The convergence condition is met when *t* is less than the final temperature δ.

A. Phase I : UA-RA sub-problem

The objective is to design a decentralized scheme that associates each UE j with BS i that offers the highest throughput (*i.e.,* high CQI). We deploy P^2EAGA in a Power-Performance Service Server (P^2SS) near MBS to solve the UA-RA problem in episodes, according to Algorithms 1 and 2. In each episode[4] $e \in E$, $BS_i \in M$ informs P^2SS about its maximum capacity b_i, representing the Knapsack capacity. Note that BSs participating in episode e will not participate in the following episodes. Each UE $j \in \bar{U}$ will inform P^2SS about the TBS index (obtained by mapping), estimated available throughput p_j and demands r_{ij}. Let $U_p = Q \cup \tilde{Q}$ denotes the set of participating UEs where Q is the set of UEs meeting the constraint in Eq. (7) and $\tilde{Q}$ represents the remaining UEs. Note that only UEs in Q will be selected in the current episode. Vector *P*, denoting the estimated available throughput (as specified in [12]), vector *R* specifying the users demands (*e.g.,* throughput) and set Q will then be created. In this phase, an array χ is formed, which contains the best optimal solution from each generation, and it is the initial population for Phase II, as explained in Algorithm 2. All optimal solutions in χ obey UA-RA constraints in Eqs. (5), (6), (7), (8), and maximize Eq. (4).

B. Phase II : PA sub-problem

In this phase, $BS_i \in M$ informs P^2SS about its maximum power capacity P_i^{max}, representing the Knapsack capacity. Each UE $j \in \bar{U}$ will inform P^2SS about the estimated available throughput p_j and power consumption P_i^j. The

[3]This is based on the Random Walk Metropolis Algorithm (RWMA). RWMA performs random sampling from a distribution which does not support direct sampling. RWMA is the simplest version of a I^{st} order Markov Chain Monte Carlo algorithm.

[4]We solve the UA-RA-PA problem in each episode, and it will terminate when the termination condition is reached.

Algorithm 1 P^2EAGA for UA-RA - Phase I

```
foreach episode e ∈ E do
    Each BS i, i ∈ M informs P²SS b_i
    foreach j̃ ∈ Ũ do
        Inform P²SS about TBS Index q_{ij̃}
        if q_{ij̃} satisfies Eq. (7) then
            q_{ij̃} ∈ Q
        else
            UE j̃ will not participate in the problem
        Inform P²SS about p_j̃ and r_{ij̃}
    initialization: P := [p_1, p_2, ..., p_ṽ] where ṽ ≠ v, ṽ =
    length(Q); R:= [r_{i1}, r_{i2}, ..., r_{iṽ}] , U_p:= {U_1, U_2, ..., U_ṽ},
    ∀ĵ ∈ U_p; X: = 0.
    Set GA parameters: n_i, n_g, n_s, p_c, p_m, Z
    Set SA parameters: initial temp.(t) = (max{p_ĵ|∀ĵ} −
    min{p_ĵ|∀ĵ}) * ρ), α, δ
    Arrange Vector P in decreasing order.
    Create n_i population randomly of vector size P.
    while t > δ do
        for g = 1:n_g do
            for h = 1:n_i/2 do
                Select 2 chromosomes.
                Crossover the selected chromosomes genes to
                get offspring at p_cad.
                Mutate off-springs at p_mad.
            Store best solution for each generation in χ.
        t = t ∗ α;
    χ stores best sub-optimal solution from each generation of
    size a′ x b′, where a′ = |P| and b′ depends on termination
    condition.
```

Algorithm 2 P^2EAGA for PA - Phase II

```
Each BS i, i ∈ M informs P²SS P_i^max
foreach j̃ ∈ Ũ do
    Inform P²SS about p_j̃ and P_i^j̃
initialization: Same as Phase I, n_i = χ .
while t > δ do
    for g = 1:n_g do
        for h = 1:n_i/2 do
            Select 2 chromosomes.
            Crossover the selected chromosomes genes to get
            offspring at p_cad.
            Mutate off-springs at p_mad.
        Store optimal solution from each generation in χ′
    t = t ∗ α;
Best optimal solution with highest fitness value
```

optimal solutions from phase I will be the initial population in this phase and when the convergence criterion is met, we get the global optimal solution which satisfies Eqs. (5), (9), (10) and maximize Eq. (4). Each episode e in both phases I and II includes a *diversification (exploration)* and an *intensification (exploitation)* phase. In the former, only UEs in Q are selected; the ones in $\hat{Q}$ are considered in the next episode $e+1$. In the latter, after solving Eq. (4) subject to Eqs. (5), (6), (7), (8), (9) and (10), UEs in Q will get associated with BS i, and resources will be allocated to them. After each episode, the set $\bar{U}$ is updated so that it contains only UEs in $\tilde{Q}$ and those who were not part of the obtained near-optimal solution.

IV. Performance Evaluation

A. Verification of Adaptive Genetic Algorithm

The convergence of the two algorithms running on a single MKP instance is shown in Fig. 2. DGA does not converge to any sub-optimal value because of the significant unpredictability and the poor selection of chromosomes due to constants p_c and p_m. On the other hand, $P^2EAGA-WT$[5] converges to a particular sub-optimal value. However, we observe that it oscillates between identical values, implying that a termination condition should be incorporated rather than running the algorithm for a number of generations. By introducing the SA termination condition along with MAC, P^2EAGA reached a higher sub-optimal solution, i.e., narrowing the performance gap. The term "$global\,optimal$" (Fig. 2) refers to the best solution for the MKP instance in question. The global optimal values were taken from GitHub[6]. Note that obtaining these values is inefficient in terms of time and resources.

Fig. 3(a) illustrates the Arithmetic Mean (AM) of the ten runs of meta-heuristics (DGA, P^2EAGA) on ten different instances of the MKP while Fig. 3(b) depicts the distribution of near-optimal value ($f(e)$)[7] per instance. DGA corresponds to the Default Genetic Algorithm without any adaptive parameters, MAC and SA convergence conditions. We observe that P^2EAGA is the closest to the optimal solution compared to DGA. Indeed, DGA is a population-based algorithm with high exploration and high exploitation, but has difficulty avoiding local optima and has a high convergence rate. Adaptive genetic operators, including MAC and SA convergence conditions, help find the best starting solution and save significant time when searching for global optimum. By combining these three aspects, *i.e.,* adaptive genetic operators, MAC and SA termination condition, P^2EAGA achieves the global optimum with a low convergence time.

Fig. 3(c) shows the AM of execution time (s) for P^2EAGA and DGA for ten runs on ten different knapsack instances. P^2EAGA incurs an average execution time that is 72% shorter than that of DGA. This confirms that our proposed scheme has reduced complexity while incurring low processing time.

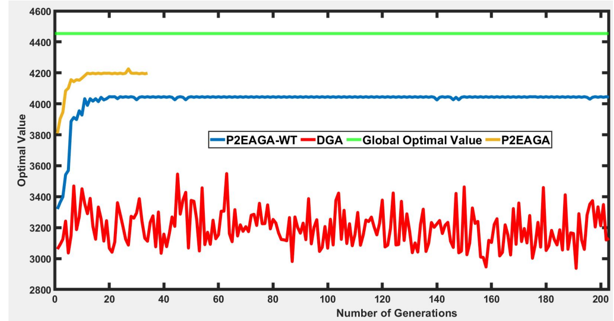

Figure 2. Comparison between two versions of GA on a single MKP instance

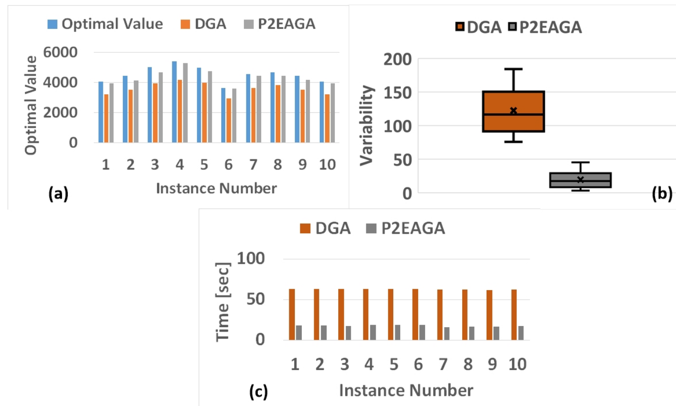

Figure 3. (a) Comparisons of optimal values between two different versions of GA. (b) Variability between two different versions of GA. (c) Execution time for different versions of GA

Table III
Default Simulation Parameters

Parameter	Value
Area of Region (G)	500m x 500m
UE traffic demand (Video) (ψ_j)	3.5 Mbps
Total transmit power of BSs	$\{46, 26\}$ dBm
Capacity of MBS and FBS	100.8 Mbps
# of RBs $\|S\|$	100
Power/RB for MBS and FBS	0.39 W/RB and 0.0039 W/RB

B. QoS Assessment

We performed comprehensive simulations in NS-3 to evaluate our proposed algorithm. For all our experiments, we considered one MBS and eighteen FBSs deployed at fixed locations. All FBSs are initially switched off and are turned on sequentially when needed using control signals. We randomly deployed UEs ($|U|$ = 70, $|\bar{U}|$ = 50, $|\hat{U}|$ = 20) following a homogeneous Poisson Point Process for the different experiments and considered a discrete user demand (*i.e.,* requested data rate). To simulate channel fading, we used a log distance path loss model. The other simulation parameters are presented in Table III. Fig. 4 depicts the QoS metrics perceived by users in a HetNets environment. P^2EAGA performance was compared with that of two other schemes: Default Single-Cell (DSC)

[5] $P^2EAGA-WT$ is an enhanced version of DGA in which we introduced adaptive p_c and p_m as defined in Eqs. (12) and (13). We called this version "$without\,termination$" because it runs for the defined number of generations as SA is not used.

[6] Knapsack GitHub - https://github.com/madcat1991/knapsack

[7] *f(e)* is the final output obtained from Algorithm 1 and 2. AM is calculated as $\frac{1}{T}\sum_{p=1}^{T} f_p(e)$, where T = 10.

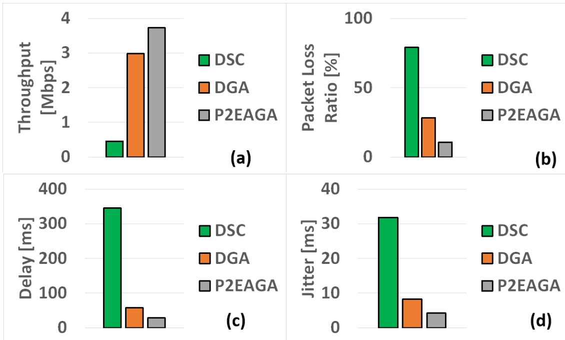

Figure 4. QoS Metrics for 50 video users under three different schemes.

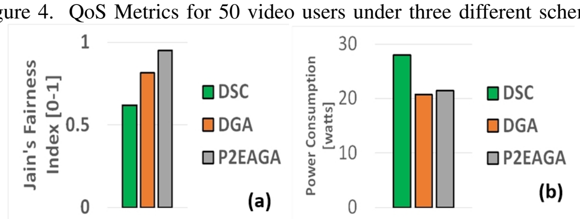

Figure 5. (a) Jain's Fairness Index for 50 video users under three different schemes. (b) Power Consumption by users under three different schemes.

and DGA. In DSC, all UEs try to establish a connection with MBS only.

Fig. 4(a) shows that P^2EAGA incurs an average throughput of 3.73 Mbps which is 20% and 88% higher than DGA's (2.98 Mbps) and DSC's (0.45 Mbps), respectively. Fig. 4(b) shows that P^2EAGA incurs the least packet loss ratio (10%) compared to DGA (28.3%) and DSC (79%). Fig. 4(c) illustrates that P^2EAGA experiences the shortest delay (28.11 ms) which is 50.89% and 91% lower than DGA's (57.25 ms) and DSC's (345.29 ms). Finally, Fig. 4(d) shows that P^2EAGA produces the lowest jitter (4.18 ms) compared to DGA (8.27 ms) and DSC (31.85 ms). Fig.5(a) depicts the fairness of throughput among UEs in HetNets. We observe that under P^2EAGA, around 95% UEs have similar throughput as Jain's Fairness Index is approximately 0.95, whereas it is around 0.81 and .62 under DGA and DSC, respectively. Hence, it can be concluded that our proposed ensure high fairness among users in comparison to the other two schemes by associating UEs with the BS that offers high CQI. Fig.5(b) represents the RPC for 70 UEs. Under DSC, the total power consumption (TPC) is around 28W, where 20W (71.43% of TPC) were consumed by the 50 video users while the remaining 8W were consumed by the 20 VoIP users. Under DGA, the TPC is around 20.73W, where 12.73W were consumed by the 50 video users (61.40% of TPC) while the remaining 8W were consumed by the 20 VoIP users. Under P^2EAGA, the TPC is 21.48W, where 13.48W were consumed by the 50 video users (62.75% of TPC) while the remaining 8W were consumed by the 20 VoIP users. The TPC is slightly higher under P^2EAGA than DGA because more UEs are attached to MBS than FBSs.

V. Conclusions and Future Work

This work offers P^2EAGA, an algorithm for addressing the UA-RA-PA problem in HetNets that provides high fairness in terms QoS while also minimizing CAPEX and OPEX using RPC. The UA-RA-PA problem was formulated as a MKP where BSs represent the knapsacks and UEs are the items to be fitted into the knapsacks. Simulation results show that the proposed solution outperforms alternative solutions in terms of complexity, processing time, fairness, and QoS metrics. Future work will integrate the dynamics of interference mitigation with UA-RA-PA in a joint solution.

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