TLBO-based Resource Allocation scheme in 5G H-CRAN

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Abstract-In the direction of resource allocation in 5G and beyond networks, Device-to-Device (D2D) communication is proven to be a promising technology and improves the system throughput. At the same time, the reuse of cellular user's resource block by multiple D2D users introduces interference, which ultimately degrades the system's throughput. Hence, in this paper, we have proposed an efficient resource allocation scheme using Teacher Learner Based Optimization (TLBO) in the context of Heterogeneous Cloud Radio Access Networks (HCRAN) so that the system performance is improved. At first, the cellular user's resource block is assigned to the D2D users based on the calculated data rate at the corresponding cellular user. Consequently, TLBO is applied to this assignment matrix to obtain the optimum assignment/allocation of the cellular user's resource blocks to D2D users. The simulation results demonstrate the efficiency of the proposed scheme compared to the existing related schemes.

Keywords—D2D communication, 5G, HCRAN, Resource allocation, TLBO.

I. INTRODUCTION

The remarkable increase in the connected devices, sophisticated applications, and data rate stipulate radical change in the traditional Radio Access Networks (RAN). Further, Cloud Radio Access Networks (CRAN) is considered as a significant idea towards the 5th generation (5G) and beyond networks. One of the prospective enablers of 5G is resource allocation, which can improve the system performance through proper user assignment, power allocation, and spectrum utilization in CRAN. Beneath resource allocation, device-to-device (D2D) communication catches the attention of recent research and plays a significant role in the 5G and beyond networks. In this context, Heterogeneous-CRAN (HCRAN), which includes a macro base station (BS) along with femto/pico/small BSs, incorporates cloud computing and supports D2D communication [1]. In this work, we have considered the seven cell architecture, where the RRHs are connected to the Base Band Processing Unit (BBU) pool through frounthaul as depicted in Figure 1. As shown in Figure 1, all the RRHs with cellular users forms a flexible HCRAN which supports D2D communication. In order to enhance the macro system's throughput, efficient D2D communication is employed, results in increase in the network efficiency. Apart, network efficiency (throughput, energy efficiency, spectrum efficiency and delay) can be significantly improved through D2D communication, where nearby users can directly communicate with each other without referring to BS. The nearby devices reuse the

cellular user's resource block, thus resulting in performance degradation through interference. Therefore, to improve the throughput, a proper and efficient resource allocation scheme is required. Hence, in this paper population-based resource allocation scheme is designed, where Teacher Learner Based Optimization (TLBO) is employed to allocate the resource blocks of the cellular users to one or more D2D users.

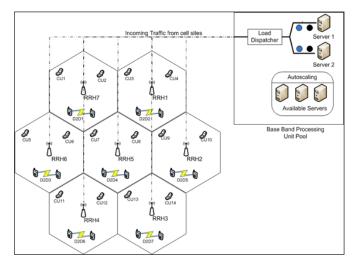


Figure 1: General architecture of HCRAN [2]

A. Contribution

The primary contribution of this paper is summarized as follows:

- To assign cellular user's resource block to D2D user in one to many fashion for efficient communication.
- To optimize the resource allocation scheme using swarm intelligent based TLBO algorithm.
- To show the competence of the proposed scheme through simulation.

II. RELATED WORK

Resource allocation in 5G-HCRAN with D2D communication and interference mitigation problem has gained significant attention [3]. To utilize the advantage of D2D technology, cellular networks are introduced with D2D communication. D2D communication plays a vital role in Ultra-Reliable Low latency Communication (URLLC). In [4], the D2D communication

feature is presented for wireless industrial applications. Their work has proposed a priced-Deferred Acceptance algorithm to match the D2D users with cellular users. Next, similar works, i.e., matching theory-based resource allocation in D2D communication, is presented in [1], [5], where constrained-DA-based matching is proposed for efficient matching between D2D users and cellular users. They have considered oneto-many matching, i.e., one or more D2D users reuse a single cellular user's resource block. One more work based on matching theory is presented in [6], where one-to-one matching is employed, and consequently, the authors applied a resource exchange strategy. Authors in [7], [8] have presented a joint channel and power allocation scheme for D2D communication in HCRAN. They have given a geometric vertex search approach along with 3D matching technique to improve the throughput. Recently, swarm-based intelligence and other optimization techniques have been introduced in the efficient resource allocation for D2D users. In [9], authors have applied a Genetic Algorithm to optimize the resource allocation process. They have considered a 2-point crossover mechanism with a 0.5 crossover rate followed by a mutation with a 0.05 rate. Another optimization technique, i.e., a modified sinecosine mechanism, is presented in [10], where an interference matrix is generated first, and consequently, the modified sinecosine algorithm is employed on this generated interference matrix. Next, learning-based resource allocation is employed in the work [11], where the support vector machine technique is used to reuse the resource block. In [12], the Ant Colony Optimization technique is used to allocate the resources in HCRAN. In this direction, in this paper, we have presented a novel resource allocation scheme for D2D communication in HCRAN. The proposed scheme employs TLBO to assign cellular user's resource blocks to one or more D2D users.

III. SYSTEM MODEL

A. Scenario Depiction

In this work, we have considered the scenario of HCRAN with downlink transmission as depicted in Figure 2. In this case, we have considered one **BS**, K number of **RRHs**, M no. of **MUEs** (CUs) and N no. of **D2D** pairs, all are assumed to be distributed randomly within the coverage of **BS** (macro cell). D_n^T and D_n^R represents the transmitter and receiver of D_n pair respectively. Again let $RUE_{k,l}$ be the l^{th} RUE in RRH_k . We have also assumed that the total number of resource blocks of the system is M and each one is allocated to a **MUE**. In order to reuse the allocated sub-channel of **MUE**, we have again assumed that each **DUE** and **RUE** are authorized to access only one sub-channel, but each sub-channel can have multiple **DUE**s and **RUE**s unless the **MUE**'s interference does not go beyond the interference threshold.

B. Interference Analysis

Let P_{BS} , P_k and P_n be the transmission powers of the BS, RRH_k and D_n^T respectively. Now the channel gains of communication link in i^{th} sub-channel are represented as $g_B^i, g_{k,l}^i$ and g_n^i for BS to MUE, RRH_k to RUE_l and from

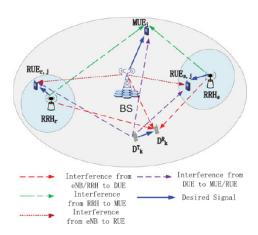


Figure 2: System model of HCRAN [1]

 D_n^T to D_n^R respectively. Also, the channel gains of interference link in i^{th} sub-channel are represented as $g_{B,k,l}^i, g_{B,n}^i, g_k^i, g_{k,n}^i, g_n^i, g_{n,k,l}^i$ and $g_{n,n'}^i$ for BS to $RUE_{k,l}$, BS to D_n^R, RRH_k to MUE^i, RRH_k to D_n^R, D_n^T to MUE^i, D_n^T to $RUE_{k,l}$ and from D_n^T to D_n^R , respectively. To exemplify the reuse of the sub-channel, we further considers: $\lambda_{k,l}$ as

$$\lambda_{k,l} = \begin{cases} 1, & if \ RUE_{k,l} \ is \ assigned \ to \ i \\ 0, & Otherwise \end{cases}$$

Similarly,

$$\gamma_n^i = \begin{cases} 1, & if \ D_n \ is \ assigned \ to \ i \\ 0, & Otherwise \end{cases}$$

Now, let us consider that RUE and D2D pair reuse the subchannel i of MUE_i , then the signal-to-interference plus noise ratio (SINR) at MUE_i is given by

$$SINR_{MUE}^{i} = \frac{P_{BS}.g_{B}^{i}}{I_{MUE}^{i} + \sigma^{2}}$$

where σ represents the thermal noise at the receivers side and I_{MUE}^i represents the total interference at MUE^i experienced from the RRHs and D2D transmitters, given by $I_{MUE}^i = \sum_{k=1}^K \lambda_k^i P_k g_k^i + \sum_{n=1}^N \gamma_n^i P_n g_n^i$.

Hence, the data rate achievable at MUE_i , when RUEs and D2D pairs reuses the sub-channel i is given by

$$DR_{MUE}^{i} = B_{i}log_{2}(1 + SINR_{MUE}^{i}) \tag{1}$$

Here, B_i is the bandwidth of sub-channel i. Similarly, the date rate at $RUE_{k,l}$ for sub-channel i is given by

$$DR_{RUE_{k,l}}^{i} = B_{i}log_{2}(1 + SINR_{RUE_{k,l}}^{i})$$
 (2)

where
$$SINR_{RUE_{k,l}}^{i} = \frac{P_k.g_{k,l}^{i}}{I_{RUE_{k,l}} + \sigma^2}$$
 and $I_{RUEk,l} = \frac{1}{2}$

 $P_B g_{B,k,l}^i + \sum_{n=1}^N \gamma_n^i P_n g_{n,k,l}^i$ is the total interference experienced by $RUE_{k,l}$ from the BS and D2D transmitters. Again, the date rate achievable at D_n in sub-channel i is given by

$$DR_{D_n}^i = B_i log_2(1 + SINR_{D_n}^i) \tag{3}$$

where $SINR_{D_n}^i = \frac{P_n.g_n^i}{I_{D_n} + \sigma^2}$ and $I_{D_n} = P_Bg_{B,n}^i + \sum_{k=1}^K \lambda_k^i P_k g_{k,n}^i + \sum_{n'=1, n \neq n'}^N \gamma_n^i P_n g_{n,n'}^i$ is the total interference experienced by D_n from the BS, RRHs and D2D transmitters in the sub-channel i.

IV. PROBLEM FORMULATION

While maintaining the interference threshold at the MUEs, the sub-channel assignment mechanism for the RUEs and D2Ds is the key challenge in the resource allocation problem. Now, let us consider $DR_{RUE_{k,l}}^{min}$ and DR_{Dn}^{min} represents the minimum data rate constraint for $RUE_{k,l}$ and D_n respectively. I_{MUE}^{th} represents the interference threshold at MUE. Hence, the objective function or the sub-channel assignment problem can be presented as

$$max\left(\sum_{i=1}^{M}DR_{MUE}^{i} + \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{i=1}^{M}\lambda_{k,l}^{i}DR_{RUE_{k,l}}^{i} + \sum_{n=1}^{N}\sum_{i=1}^{M}\gamma_{n}^{i}DR_{D_{n}}^{i}\right)$$
(4)

such that

$$I_{MUE}^{i} \le I_{MUE}^{th}, \quad \forall \ i \ in \ M$$
 (C1)

$$\sum_{i=1}^{M} \lambda_{k,l}^{i} DR_{RUE_{k,l}}^{min}, \quad \forall \ k \ in \ K$$
 (C2)

$$\sum_{i=1}^{M} \gamma_{D_n}^i DR_{D_n}^{min}, \quad \forall n \ in \ N$$
 (C3)

$$\sum_{i=1}^{M} \lambda_{k,l}^{i} \le 1, \quad \forall k \text{ in } K$$
 (C4)

$$\sum_{i=1}^{M} \gamma_n^i \le 1, \quad \forall n \text{ in } N$$
 (C5)

Here, Equation 4 represents the objective function that maximizes the sum data rate of all the communication links. Next, all the constraints are given by Equation C1 to C5. Here, Equation C1 represents the constraint on each MUE i that its interference must be lower than the Interference threshold value. Equations C2 and C3 represent the constraint on the minimum data rate of each RUEs and D2Ds. Further, Equations C4 and C5 define the constraint on each RUE and D2D that each must be assigned with at most single subchannel.

Here, it can be observed that the considered problem is non-convex in nature, and it is a mixed integer non-linear problem. Further, if there are a large number of D2D pairs, RUEs, and MUEs in the scenario, then the formulated problem is very complex and challenging to obtain an efficient solution. Thus, in this work, we have proposed a population-based TLBO mechanism to get the optimal solution for reusing the subchannel by multiple D2Ds and RUEs.

V. TLBO BASED RESOURCE ALLOCATION SCHEME

This section presents the solution for the problem, which we have formulated in the previous section using the TLBO mechanism. TLBO was at first introduced by Rao et al. in [13]. TLBO stimulated from the viewpoint of teaching and learning. In this method, the teacher influences the learner's output, which is illustrated as their score or grades. Generally, the teacher is considered highly knowledgeable who shares their knowledge with the learners; this improves the outcome of the learners. It is observable that a good teacher will have a good impact on the outcome of the learners. Apart from the teacher, the learners can also interact to obtain a better outcome. Like some existing optimization techniques, TLBO is also a population-based algorithm aiming to reach the global optimum solution from the set of solutions. The two elementary phases of TLBO are the Teacher phase and the Learner phase, which are discussed below:

A. Teacher's phase

A teacher contributes to improve the mean knowledge of the learners(class) to his own level of knowledge. But, in practice, this process solely depends on the learner's capability.

In this phase, a new solution is generated using the mean of the population and the teacher. Here, the teacher is considered a solution with the best fitness value. Next, each existing solution i is modified by using the following Equation 5 at iteration k.

$$X_{new,i}^k = X_i^k + r(X_{best}^k + T_f X_{mean}^k)$$
 (5)

Here, $X_{new,i}^k$ is the new solution, X_i^k is the current solution, X_{best}^k is the teacher at k_{th} iteration, X_{mean}^k represents the mean of the population, $T_fin\{1,2\}$ refers to the teaching factor which takes value either 1 or 2, r is a random number between 0 and 1. If the value of $X_{new,i}^k$ is not within bounds, then instead of corner bounding, we have modified the TLBO mechanism through random bounding, i.e., $X_{new,i}^k = random(min, max)$.

Finally, the new solution is replaced with the current solution if it evaluates to an improved one.

B. Learner's phase

The learners learn and enhance their knowledge through the teacher and with the interaction with the other learners.

In this phase, a new solution is generated with the help of other learners (partners). Another learner is selected randomly from the population. Here, each solution i at iteration k is modified using the two possible ways according to Equation 6.

$$X_{new,i}^{k} = \begin{cases} X_{i}^{k} + r(X_{i}^{k} - X_{p}^{k}) & \text{if } f_{i} < f_{p} \\ X_{i}^{k} - r(X_{i}^{k} - X_{p}^{k}) & \text{if } f_{i} \ge f_{p} \end{cases}$$
(6)

such that $X_i^k \neq X_p^k$. Here, $X_{new,i}^k$ is the new solution, X_i^k is the current solution, X_p^k is the partner solution, r is a random number between 0 and 1. f_i and f_p represents the fitness value

of the current and partner solutions respectively. Again, if the value of $X_{new,i}^k$ is not within bounds, then instead of corner bounding, we have modified the TLBO mechanism through random bounding, i.e., $X_{new,i}^k = random(min, max)$.

Finally, the new solution is replaced with the current solution if it evaluates to an improved one.

The proposed resource allocation scheme for RUE and D2D pairs uses a TLBO mechanism with the objective function of Equation 4 and with constraints Equations C1 to C5. Algorithm 1 describes the proposed allocation scheme using the TLBO mechanism.

Algorithm 1 TLBO algorithm for resource allocation

- 1: Input: Population size, No. of iterations
- 2: Initialize P_{BS} , P_k , P_n , M, K, N.
- 3: Initialize coordinates of BS, RRHs, MUEs, RUEs and D2D pairs.
- 4: Assign one cellular user to each sub-channel randomly.
- 5: Calculate data rate of each user as per Equations 1 to 3.
- 6: Assign RUE and D2D pairs to at most one sub-channel based on the calculated data rate.
- 7: Consider this assignment matrix is the initial population, evaluate the population and identify the teacher.
- 8: Generate new solution using Equation 5.
- 9: If $X_{new_k}^i$ is better than X_k^i then
- 10: Select partner solution X_p^k s.t. $X_i^k \neq X_p^k$.
- 11: Generate new solution using Equation 6.
- 12: If $X_{new_k}^i$ is better than X_k^i then
- 13: Accept.
- 14: Else Reject.
- 15: Else Reject.
- 16: Do the steps from 7 to 15 for No. of iterations.
- 17: Output: Final Solution

At first, mention the values of transmission powers, the number of users, population size, and the number of iterations for the proposed algorithm. Initialize the coordinates for BS, RRH, MUEs, RUEs, and D2D pairs. Now, assign one cellular user to each sub-channel randomly and assign D2D pairs and RUE to at most one sub-channel to obtain maximum data rate and consider this assignment matrix as initial population. Identify the teacher based on the evaluation of the initial population. Perform the Teacher phase and Learner phase of the TLBO algorithm for the given number of iteration. Since the TLBO mechanism is based on the greedy selection, the final solution obtained is optimum.

VI. SIMULATION RESULTS

In this section, the evaluation of the proposed resource allocation scheme is presented using simulation under the 7 cell architecture, where seven macro BSs are employed.

A. Simulation parameters

The simulation is done in Python, where the maximum distance between D2D pairs is considered as 50 m. The interference threshold is set to -174dBm/Hz. In this system,

each MUE is pre-allocated to the available resource blocks randomly. All simulation parameters are depicted in Table I. All the simulation results are obtained by taking an average of over 100 runs.

Table I: Simulation parameters

Parameters	Values
System bandwidth	10 MHz
Cellular transmission power	45 dBm
D2D transmission power	24 dBm
Noise	-147 dBm/Hz
Max. no. of cellular users	30
Max. no. of D2D pairs	80
Max. no. of resource blocks	30
Number of iterations	100
Initial population	100

B. Performance analysis

For evaluation, the proposed scheme is compared with random, graph-based and particle swarm optimization algorithm [10].

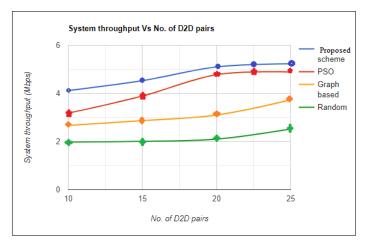


Figure 3: System throughput Vs No. of D2D pairs

At first, the system throughput is compared when the number of cellular users is 5, and the results are illustrated in Figure 3. As illustrated from Figure 3, the system throughput is improved when the number of D2D users is increased. As the number of D2D users increases, in the proposed scheme, the multiple D2D users effectively reuse the resource block, resulting in improved system throughput. Further, the proposed scheme outperforms as compared to the considered methods. The random allocation scheme performs the worst, as it randomly allocates the resource block without evaluating the interference mitigation.

In the second simulation, the performance is evaluated in terms of interference when the number of cellular users is 10, depicted in Figure 4. As observed from Figure 4, in the random allocation scheme, the interference increases linearly with the number of devices, resulting in system's throughput

degradation. The reason is obvious that the random scheme does not consider the interference mitigation strategy. The interference generated by the proposed scheme is significantly less as compared to other schemes and increases little when the number of D2D users increases.

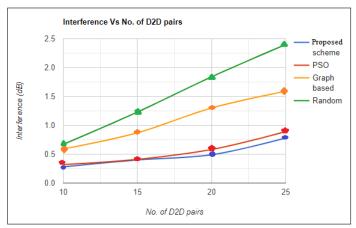


Figure 4: Interference Vs No. of D2D pairs

Figure 5, represents the evaluation of the system throughput with the interference threshold at cellular users when the number of the cellular user: M=5 and number of D2D users: N=20. As depicted, the random allocation scheme performs worst, and the proposed scheme outperforms among other schemes. It is also observed that, as the interference threshold increases, the system's throughput increases for all the schemes. The interference threshold plays a significant role in the system performance, and it defines trade-off between the system's throughput and the quality of service.

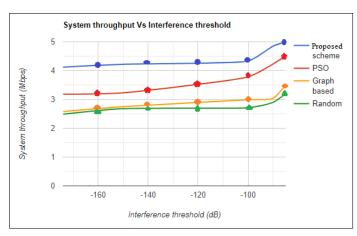


Figure 5: System throughput Vs Interference threshold

The rate of convergence with the number of iterations is shown in Figure 6. As illustrated, as the number of iterations increases, the system throughput is more converged. It is observed that the proposed scheme and the PSO are converged at approx. sixty iterations, and the graph-based scheme is converged at approx. eighty iterations, and finally, the number of iterations does not affect the random allocation scheme.

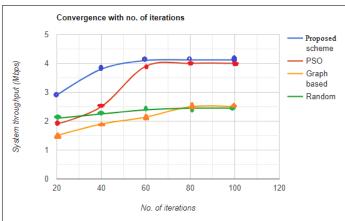


Figure 6: Convergence with no. of iterations

In the fifth simulation, the performance of the proposed scheme is evaluated in terms of fairness [1] as illustrated in Figure 7. Here, Jain's fairness index is used as considered in [14]. The value of the fairness index lies between 0 and 1. The value more nearer to 1 indicates more fairness. As depicted in Figure 7, the value of the fairness index of the proposed scheme is good as compared to others. Also, with the increase in the number of users, the value of the fairness index almost remains the same for the proposed scheme and performs analogously to PSO as the number of users crosses 60.

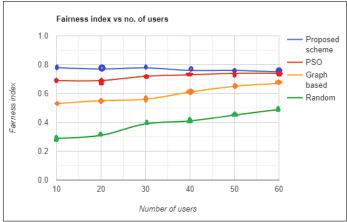


Figure 7: Fairness index Vs no. of users

VII. CONCLUSION

In this work, we have considered the downlink scenario for the resource allocation in HCRAN with D2D communication. Here, multiple D2D users and RUEs are allowed to reuse the single cellular user's (MUE's) resource block. This resource allocation problem is devised as a mixed-integer nonlinear problem for which a TLBO mechanism is proposed to solve this formulated problem. An efficient resource allocation scheme is achieved through TLBO, which enhances the system's throughput. The effectiveness of the proposed scheme is demonstrated using the simulation in Python. The results

show the competency of the proposed scheme with the related existing schemes.

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