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INTERFERENCE MITIGATION FOR DYNAMIC USER CONNECTIVITY USING SDN AND RADIO RESOURCE MANAGEMENT IN CELL-LESS NETWORKS

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Abstract

Next Generation communications aim to improve Quality of Service (QoS) via ultra-reliable low latency communication (URLLC), enhanced Mobile Broadband (eMBB), and massive machine type communication (mMTC). However, interference poses challenges in wireless domains. Interference mitigation is a fundamental goal, enabling centralized routing-based interference avoidance through Software Defined Networking (SDN) and Radio Resources Management (RRM). The goal of this paper employs SDN technology, RRM approach and the particle swarm optimization (PSO) technique to generate dynamic bias for calculate cell spectral efficiency (CSE) when users encounter interference from the same tier and other tiers BSs in both cellular and cell-less networks. The static biasing scheme's performance for values between 0 dB to 30 dB that compares with dynamic bias. The simulation results show that when the static bias value increases from 0 dB to 20 dB, the CSE increases. After the static value reaching 30 dB the interference occurs and the CSE value decreases in the cellular network. The CSE value rises with the increases of the static bias value from 0 dB to 30 dB in the cell-less network. The CSE value in cell-less network is higher than the CSE value in cellular network. The CSE value in the dynamic bias is higher than the static bias.

Keywords: 5G, Cell-less network, Particle swarm optimization, Radio resource management, SDN.

1. Introduction

One of the main design challenges in wireless systems is interference avoidance [1]. Interference is an issue that presents challenges for Heterogeneous Network (HetNets) [2]. It is also important to note that interference reduces the signal-to-noise plus interference ratio (SINR). Due to the fact that low SINR might reduce the value of spectral efficiency (SE), exceptionally excellent interference management is required for the co-channel deployment in HetNet [2]. A number of technologies have been used to mitigate interference in mobile communication, including the Global System for Mobile Communication (GSM), Code Division Multiple Access (CDMA), and Wideband Code Division Multiple Access (WCDMA) [3].

Coordinated Multipoint (CoMP), network Multiple Input Multiple Output (MIMO), duplex, and other techniques have been proposed as ways to overcome Ultra-Dense Network (UDN) like inter-cell interference (ICI), ping-pong handover, network congestion, and convergence issues, they were unable to address problems like computing complexity, signal overhead, or practical benefits that fall short of theoretical gains [4]. With the rapid advancement of information technology, 5G and 6G network management systems are moving toward integration, dissemination, diversity, and intelligence, a general insight is provided by some of the pertinent studies on 5G and 6G [5].

One of the technologies that offers solutions is the Software Defined Networking (SDN) [6]. SDN is a new paradigm in network design that offers promising innovations in network programmability and permits highly abstracted network management. As per the use cases, flexibility is deemed essential for the architecture of 5G and 6G networks, as SDN technology permits adaptable adjustments to various scenarios [5].

SDN has made it possible to break through barriers in traditional networking. Strong, efficient, and unique routing opportunities are made possible by SDN's centralized design, a comprehensive approach to SDN installation opens up multiple avenues for integrating interference mitigation techniques and makes it possible for a network's control plane and data plane to be separated, and it also makes it simple for network managers to update the services the network offers from a single location [7, 8].

Combining the ideas of softwarization, virtualization, centralization, network MIMO, and cooperative radio resource management (RRM), cell-less networks represent a unique and rapidly developing technology [4]. The novel cell-less architecture permits a mobile terminal to select one or more base stations and access points (BSs/Aps) to access via various uplinks and downlinks based on the wireless channel status ant its requirements. Also, the mobile terminal can decide not to access any BSs/Aps when it is idle, in order words, before beginning to send data, a mobile terminal does not associate with any BSs/APs [4].

The boundaries of the cells are hidden from the UE perspective in the cell-less design [9]. It is expected that wireless architectures of the future to be cell-less and the performance of the system as a whole will be greatly affected by the utilization of an innovative cell-less architecture [10]. The concept of cell-less RAN architecture, which was introduced recently, matches the expectation to achieve more spectral efficiency (SE). However, the use of any novel solution like cell-less throughout the entire network, require challenging and time consuming [4].

Therefore, the coexistence of recently deployed designs with current networks needs to become possible [4].

RRM, also known as cooperative scheduling, is a technique that improves system performance and may even surpass cellular competing ones. RRM employs a range of strategies and processes to maximize the utilization of the limited number of radio units, these strategies enable resources to dynamically adjust user access in response to radio environment [4]. RRM manage interference between BSs. System capacity is increased by the more efficient use of spectrum through dynamic segmentation and distribution of radio resources in the frequency and temporal domains. There is increasing interest in integrating backhaul issues into HetNets resource allocation and interference control systems, according to recent research [11].

Exploring efficient RRM techniques for cell-less networks appears to be crucial. Despite several techniques have suggested, but they have not able to achieve the maximum effect of potential of efficient resource scheduling algorithms in a cooperative within a cell-less network [4]. Further research was still needed to fully understand the practical challenges of scaling up the network with the higher order users and their accompanying serving Aps [4]. To generate dynamic bias, it is recommended to use a particle swarm optimization (PSO) algorithm. PSO is a stochastic optimization technique used to solve various optimization problems [12]. It involves subpopulations, smaller groups divided into population intelligence algorithms, and particles, potential solutions [12].

PSO algorithms continuously adjust placements and velocities, interacting with other particles and the global optimal solution. This close collaboration can successfully solve several static optimization issues [12]. The aim of this paper to propose a cell-less network with the RRM technology and SDN controller for future 6G networks in order to reduce interference and enhance the CSE. We use the PSO algorithm to generate the biasing factors, find the best particles, and compute the CSE in cellular and cell-less networks when users encounter interference from the same tier and other tiers BSs, as well as to compare the cases of dynamic bias and static bias through user connections in both cellular and cell-less networks.

The rest of this paper is prearranged as follows: Section 2 presents the related works on SDN and RRM. Section 3 explains the proposed cell-less system model and configuration. In section 4, presents the employment of the process for creating the dynamic biasing factors using PSO. Section 5 presents an explanation of SDN-based interference mitigation. Section 6 presents the simulation evaluation for the cell-less model. Section 7 concludes the paper.

2. Related Works

This section briefly discusses a software defined network (SDN) and radio resource management (RRM) that increase network capacity:

Shami et al. [13] developed an algorithm for identifying UEs that benefit from coordinated multipoint joint transmission mode and efficiently allocating radio resources (RR) from multiple base stations (BSs). It used joint user-centric clustering and multi-cell resource management (RM) and proposed a multi-cell resource allocation mode to address resource mis-matching due to load imbalance.

Cicioğlu and Çalhan [14] aimed to build a more robust handover-based on long short-term memory with SDN in considering the number of handover, linear regression, support vector machine (SVM), and tree algorithm performance have been investigated for handover. Iqbal et al. [15] introduced a machine learning-based self-adaptive resource allocation scheme for ultra-dense 5G HetNets, optimizing power transmission through cooperative learning, minimizing interference, ensuring minimum QoS requirements, and improving user capacities. Boutiba et al. [16] suggested modelling radio resource management (RRM) in 5G NR with network slicing through the use of a Mixed Integer Linear Program (MILP). They demonstrated that addressing the issue requires exponential time, they suggested a polynomial time method based on a Deep Reinforcement Learning (DRL) solver and assessed its performance across various network configurations.

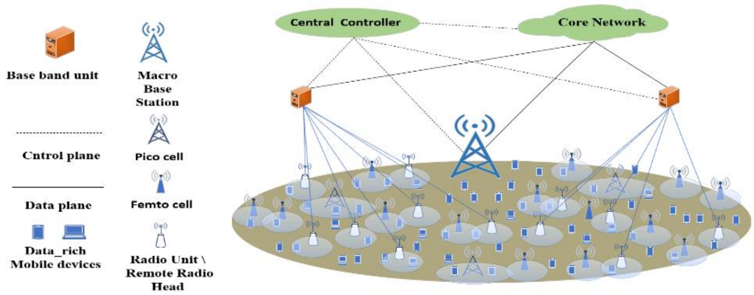
Iqbal et al. [17] proposed and evaluates a Q-learning based on RRM system employing independent and cooperative learning for both distributive and cooperative schemes. For optimal convergence, the suggested Q-learning solution follows to the $\epsilon-$greedy policy. Mangipudi and McNair [18], presented research on handovers using SDN architectures for radio access technologies, focusing on advanced architectures, offloading techniques, and implementation approaches, aiming to improve network performance and interconnection between HetNets.

Anis et al. [19], proposed a dynamic scheduler for ultra-dense 5G cellular networks to optimize system capacity. It suggested assigning radio resources strictly to device to device (D2D) users, a strategy that could significantly improve spectrum efficiency and system capacity. Saxena et al. [20], explored the impact of wireless technology on vehicle-to-x communication in autonomous vehicles, highlighting the integration of 5G, HetNets, and SDN in Intelligent Transportation Systems (ITS), highlighting the global market growth. Oulahyane et al. [21] examined the limitations of conventional methods and suggested a new dynamic resource allocation strategy for intelligent and adaptable 5G network management that based on SDN. Their methodology aims to ensure an optimal user experience and enhancing network efficiency through the intelligent utilization of resources.

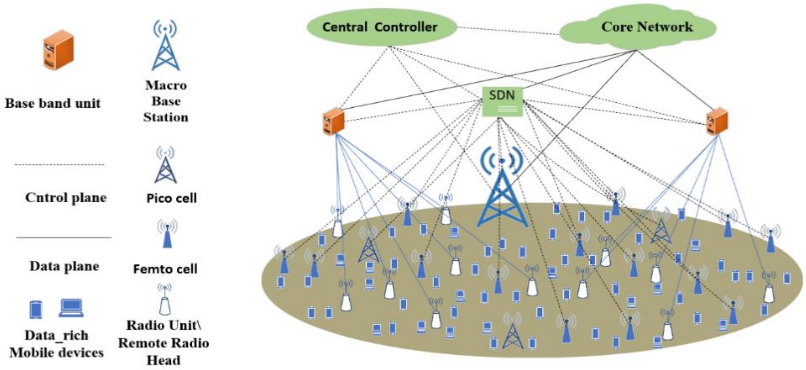
3. System Model and Configuration

In this work, a PSO technique will be used to compute the CSE in multi-tiers heterogeneous. In both cell-less and cellular networks, the PSO is utilized to create dynamic bias values and compare them against static biasing for associated users. Figure 1 shows the suggested system made up of both cellular and cell-less networks. We employ a downlink HetNets with four layers and m BSs. Conventional macrocell are represented by Tier1, femtocells by Tier2, picocells by Tier3, and Radio Units (RUs) by Tier 4. We will compute the CSE for the BSs specified as $M = \{1,2, . . . , m\}$, where M is the total number of BSs in this network.

As seen in the figure, a mobile terminal in a cell-less network does not associate with any BS, whereas a terminal in a cellular network associated with one BS. In this case, the mobile terminal can communicate in flexible way in a cell-less network with one or more BSs. In this paper, the CSE is calculated with a different number of users in case when a user experiences interference from the same tier and other tiers BSs. The PSO technique utilized to generate the dynamic bias values and calculate the CSE in both cellular and cell-less networks.



(a) Cellular network



(b) Cell-less network

Fig. 1. Architectures: (a) cellular network and (b) cell-less network.

The following formula is used to determine the SINR that user i receives interference from the same tier and other tiers BSs j, [22]:

$$SINR_{i,j} = \frac{p_j\, g_{ij}}{\sum_{l\in A,\ i\neq j} p_l\, g_{il} + \sigma^2} \tag{1}$$

where p_j is the transmitted power of BS j, g_{ij} is the channel gain combining path loss and shadowing between user i and BS j, A represents the set of all BSs excluding the serving BS j, σ^2 is the noise power. The transmissions bit-rate are model using the truncated Shannon bound (TSB) model in the following way [22]:

$$Th = \begin{cases} 0, & SINR < SINR_{min} \\ \gamma log_2(1 + SINR), & SINR_{min} < SINR < SINR_{max} \\ Th_{max,} & SINR > SINR_{max} \end{cases} \tag{2}$$

where γ is the attenuation factor, $SINR_{max}$ is the maximum value of $SINR$ to achieved the maximum throughput, Th is the achieved throughput in bps/Hz, $SINR_{min}$ is the minimum SINR value that is necessary to guarantee satisfactory QoS, and Th_{max} .

As stated in [23], the TSB parameters are α = 0.65, $SINR_{min}$= 1.8 dB, $SINR_{max}$ = 21 dB, and Th_{max} = 4.5bps/Hz. A user is drawn to the BS that offers the largest biased $SINR'$ and is determined based on the SINR biased idea depending on the subsequent [24]:

$$SINR' = SjSINR \tag{3}$$

where the biasing value for BS j is represented by Sj. Notably, no bias is imposed for the macro BS (i.e. $S_{1=1}$) Bias values of Sj > 1 are possible for each cells BS j. Carefully choosing the biasing values is necessary to maximize the CSE.

4. Employing PSO for Dynamic Biasing

PSO is an extremely effective computer technique utilized for solving optimization issues. Its relationship to artificial life (A-life) in general, fish schooling, bird flocking and swarming theory specifically [25]. One of the subfields of artificial intelligence (AI) is PSO. PSO algorithm is utilized to repeatedly the optimal solution following the initialization of a set random particles by monitoring two extreme values, the particles self-adjust producing the personal best position (pbest) and the global best particle (gbest) [26, 27].

The population used in the PSO optimization process is referred to as a swarm. Here's a brief description of how the PSO works. Every particle is a potential solution to the current optimization problem, every particle in the swarm accelerates toward both the global best location that it has found thus far and the direction of its individual best solution thus far throughout each iteration, this implies that all of the other particles will approach a particle that finds a promising new solution, further probing the area as they do so [28].

As comparing PSO algorithm to other methods of optimization, it depends only on the beginning points group, calculation is significantly easier in the engineering problems and scientific research, it can be easy to employ as it is very simple and can be easy to execute but the dynamic nature of the biasing adjustments can cause delay in achieving convergence [29]. Frequent recalibrations or updates to the strategy might slow down the optimization process, the process of continually updating and recalibrating biasing parameters can lead to increased computational demands [29]. In this study, use a PSO to dynamically produce biasing values for every BS is used to acquire dynamically the per BS biasing values that can maximize the possible CSE. Each particle updating its position and velocity-based on the following equations [24]:

$$v_{id} = wv_{id} + c_1 r_1 (pbest_{id} - x_{id}) + c_2 r_2 (gbest_d - x_{id}) \tag{4}$$

$$x_{id} = x_{id} + v_{id} \tag{5}$$

where w is inertia weight; v_{id} is the particle velocity vector; x_{id} is the existing position of particle; $pbest_{id}$ is the position of the best option; $gbest_d$ is the swarm's finest particle overall; c_1, c_2 reasoning acceleration coefficients and common acceleration coefficients, respectively; r_1 *and* r_2 are two uniform random variables (URV) in the range of [0,1]. The following equations are used to compute the CSE [22]:

$$system\ throughput = \sum_{k=1}^{N} \sum_{j=1}^{M} D_{ki}\ Th_{ki} \tag{6}$$

$$CSE = \frac{system\ throughput/BW}{N} \tag{7}$$

$$D_{ki} = \begin{cases} 1, & if\ a\ user\ i\ is\ connected\ to\ BSK \\ 0, & if\ a\ user\ i\ is\ not\ connected\ to\ BSK \end{cases}$$

where N is the total number of BSs, M is the number of UEs, BW is the bandwidth PSO's job in this work is to find the optimal particle to maximize CSE, and procedures for producing dynamic biasing values. In this work, Identifying the best particle to optimize cell spectral efficiency and creating dynamic biasing values is the responsibility of PSO. The specific algorithm is shown in Fig. 2.

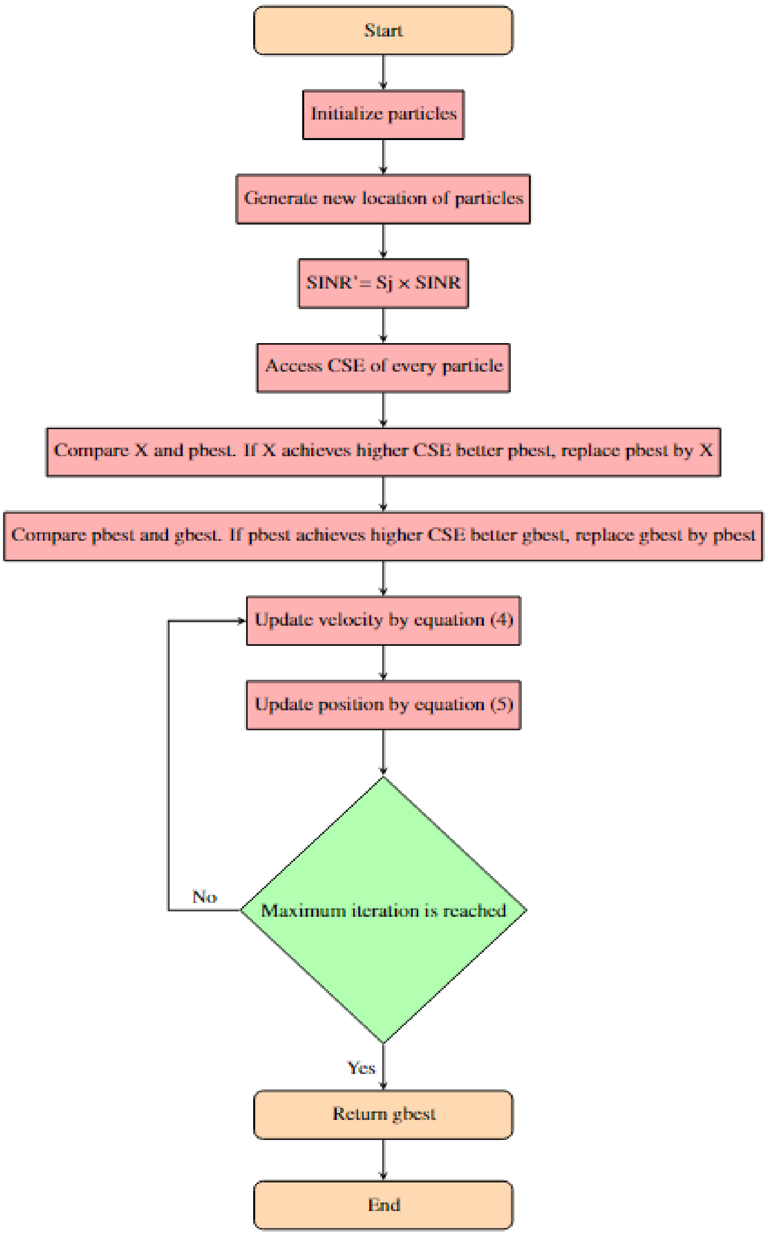


Fig. 2. The PSO approach to dynamic biasing values production.

Every particle's fitness is determined by the CSE calculation using equation (7). where S_j is the biasing value for BS j. When X achieves a higher CSE, PSO records the best particles as pbest, which is replaced by X. The PSO keeps until the maximum number of iterations is finished. The best obtained biasing values are represented by the return to gbest at the end of the PSO. The PSO finishes with return to gbest, which indicates the best got biasing values where the gbest represents the largest particle discovered to yet and by pbest [30].

5. Interference Mitigation using SDN

By using an unusual multi-layered design made up of North, East, West, and South (NEWS) bound Application Programming Interface (API) interfaces, SDN provides an overview of the interference paradigm over the whole network [7]. Wireless communication is enhanced by SDN-based interference mitigation systems with additional features like power efficiency, resource management, security, and redundancy [31]. In addition to including the research domain of next generation wireless network (NGWNs), SDN has led to a significant growth in the design and development of SDN controllers [7].

The SDN architecture suggested by the Open Network Foundation (ONF) is primary composed of three parts, namely, application layer, control layer and facilities layer. The application layer, which is the top layer in SDN architecture, includes a wide range of various business and applications [5]. SDN controller can manage the network terminal as it has the overall view of the whole system's network [5]. Furthermore, rather than depending on the supplier, the information is focused on the software. The infrastructure layer, which is at the bottom, provides services to the control layer via an open standard interface and performing data processing, forwarding, and state collecting [5]. Infrastructure layer and interface control layer utilized in southbound interface controller can help infrastructure equipment interact equipment state information acquisition [5].

The interface between the application layer and the control layer is known the north to the interface, and control layer is implemented in the API in the north. In the south, ONF has been defined as an open OpenFlow standard interface. In general, RRM can be included in the network controller. SDN decouples the control plane from data plane, enabling centralized management and dynamic resource allocation. RRM algorithms allocate RR efficiently [5].

BSs and UEs continuously send metrics to the SDN controller including signal strength, user location, traffic load (throughput, latency), and interference levels. SDN controller aggregates, processes the data and continuously monitors network conditions. Based on monitored data, the SDN controller decides how allocate resources and RRM algorithm run on the SDN controller to optimize resource distribution. The allocation decisions include determining which BSs should serve which UEs, the amount bandwidth to allocate and power levels and the SDN controller dynamically balances the load across multiple BSs to avoid congestion. The SDN controller employs RRM algorithms to minimize interference between BSs and decides on BS-UE associations.

The SDN controller continuously monitors load across BSs, if a BS becomes overloaded the controller redirects UEs to neighbouring BSs with available capacity ensures even distribution of traffic load. The SDN controller maintains a continuous feedback loop and monitoring the effects of its resource allocation decisions. Figure 3 displays utilizing RRM technology and SDN controller in the cell-less network.

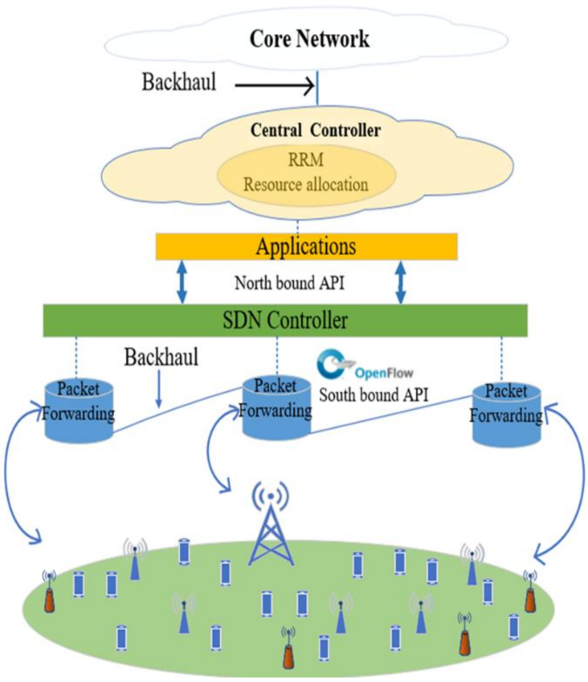


Fig. 3. Using SDN controller and RRM technology in the cell-less network.

6. Simulation Results

Based on a MATLAB simulation, the results in this study were achieved. Cellular network and a cell-less network with a total of 30 Base stations are deployed in the area: one macro Base station, three pico base stations, 14 femto base stations, and 12 Radio units are used for testing. Path loss models are used and the parameters are summarized for RUs [32], as shown in Table 1. Comparative study of cellular and cell less networks is presented.

A comparison is made between the static bias, which starts from 0 dB to 30 dB, and the dynamic bias generated by the PSO in both cellular and cell-less networks if the user receives interference from the same tier and other tiers BSs. To guarantee that the best static bias value is included in the comparison, the maximum static bias value of 30 dB is set high enough. Figure 4 displays the CSE value for the cellular network with the number of users is 1000. Figure 5 shows the CSE value for the cell-less network with the number of users is 1000. Figure 6 describes CSE value for cellular network with number of users is 500. Figure 7 explains the CSE value for cell-less network with the number of users is 500.

Figure 4 shows that when the static bias value increases from 0 dB to 20 dB, the CSE increases. After the static value reaching 30 dB the interference occurs and the CSE value decreases. Due to increased interference from neighbouring cells' signals. There is substantial interference that cuts across tiers among cells that are a part of different tiers because the cellular network utilizes competitive scheduling to provide resources for the user. Interference is received from all tiers. The strong interference that users of cell edges encounter reduce CSE. Where there is dynamic bias, the CSE value is greater than when there is static bias.

Table 1. Simulation parameters.

Parameter	Value	Parameter	Value
Bandwidth	25 MHz	**Macro path loss [33]**	128.1+37.6log10(R) R in km
Total number of RBs	125	**Pico path loss [33]**	140.7+36.7log10(R) R in Km
Tx power of Macro BS	46 dBm	**Femto path loss [33]**	127+30log10(R) R in Km
Tx power of Radio units	33 dBm	**Noise power level**	-174 dBm/Hz
Tx power of Pico BSs	30 dBm	**Scheduler**	Round robin
Tx power of Femto BSs	20 dBm	**Traffic model**	Full buffer
Carrier frequency (fc)	4 GHz	**Swarm size**	50
Radio Unit (RU) hight	15 m	**Number of iterations**	80
UE height	1.5 m	c_1	2
TTI size	1 msec	c_2	2
Shadowing std.dev	8 dB (macro),10 dB (pico) ,10 dB (femto)	w	0.9-0.4

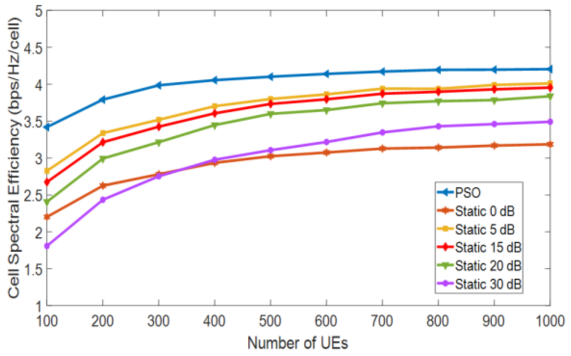


Fig. 4. CSE for different UEs in the cellular network.

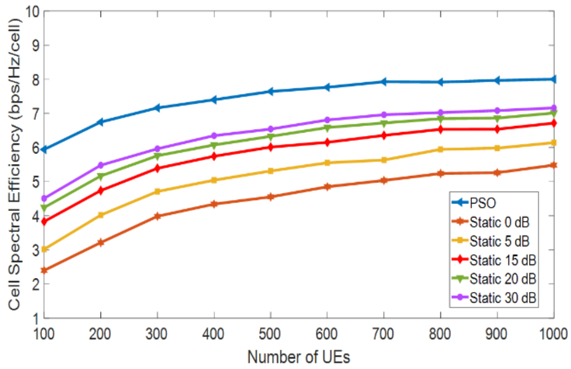


Fig. 5. CSE for different UEs in the cell-less network.

Figure 5 illustrates that the CSE value rises with the increases of the static bias value from 0 dB to 30 dB. Due to the cooperative scheduling and interference control offered by RRM, the cell-less network realizes higher improvement in network performance and system improvement by eliminating cell boundaries and giving the user more resources. Software and centralization are essential components of the cell-less network. As a result, it will deal with SDN to manage interference. The CSE value in the dynamic bias is higher than the static bias.

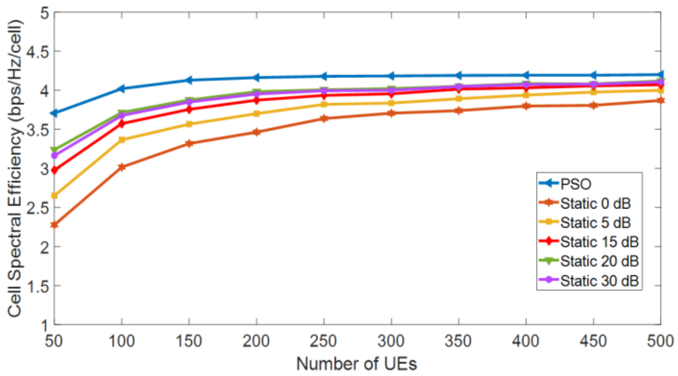


Fig. 6. CSE for different UEs in the cellular network.

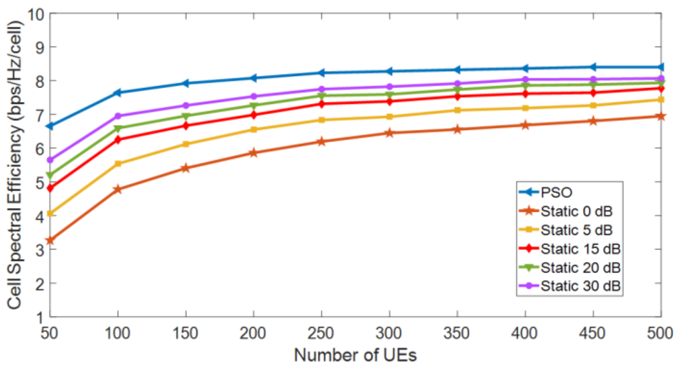


Fig. 7. CSE for different UEs in the cell-less network.

Figures 6 and 7, illustrate the CSE value will rise in both cellular and cell-less network when the reducing the number of users from 1000 to 500 this aid in mitigating interference and congestion on the cellular network. Less competition for the same bandwidth among users may result in less interference from one another and more effective utilization of the resources that are available. Fewer users mean less competition for radio resources, which leads to higher CSE and better data rates per user. However, when the static bias reaches 30 dB the interference will occur in the cellular network and the CSE will decrease. When the static bias value rises from 0 dB to 30 dB in the cell-less network, the CSE value keep rising due to using the SDN controller and cooperative RRM scheduling in the cell-less network. The CSE value in the dynamic bias is higher than the static bias.

Comparing these results that we obtained with other results in case using SDN controller and RRM technology in cell-less network. Han et al. [34] used the SDN controller in cell-less network and using Monte Carlo simulations, the results showed that the when the user terminal's SNIR threshold is set at -15 dB ~ 5 dB, the coverage probability of convergent cell-less communication networks is higher than that of conventional cellular networks. Kooshki et al. [35] proposed a cell-less RAN design and an efficient RRM algorithm for future 6G networks to improve the system capacity performance, the simulation results showed that compared to conventional cellular systems, the suggested cell-less NG RAN architecture offers a considerable increase in system capacity.

Finally, it will be feasible to improve CSE, reduce interference, lower network congestion, balance the load across all BSs, and improve the system overall by transforming the cellular network into a cell-less network.

7. Conclusion

Conventionally, Wireless system have been relied on cells where a user in cellular network is served by one BS. This traditional technique suffering from serve inter-cell interference ICI especially at the cell-edge. Therefore, it is essential to shift towards the cell-less architecture for next generation. In cell-less network, cell boundary is removed, and the user equipment communicates with one or more BSs in flexible manner. In this paper, we proposed utilized the PSO technique to generate the dynamic bias and comparison with the static bias, employs SDN technology and RRM approach to calculate the CSE when users encounter interference from the same tier and other tiers BSs in both cellular and cell-less networks.

The performance of the static bias for values starting from 0 dB to 30 dB. The simulation results illustrate that when the static bias value increases from 0 dB to 20 dB, the CSE increases. After the static value reaching 30 dB the interference happens and the CSE value decreases in the cellular network. Due to increased interference from neighbouring cells' signals. The CSE value rises with the increases of the static bias value from 0 dB to 30 dB in the cell-less., attributed to cooperative scheduling and interference reduction by RRM technology and SDN controller was utilized decouples the control plane from data plane, enabling centralized management, dynamic resource allocation, and monitoring the effects of its resource allocation decisions, reduce interference and continuously monitors network conditions. The CSE value in the cell-less network is higher than the CSE value in the cellular network and the CSE value in the dynamic bias is higher than the static bias.

Nomenclatures

c_1	Reasoning acceleration coefficients
c_2	Common acceleration coefficients
g_{ij}	Channel Gain
p_j	Transmitted Power
r_1	Uniform Random Variables
Th	Achieved Throughput
v_{id}	Particle velocity vector
w	Inertia Weight
x_{id}	Existing position of particle

Greek Symbols

γ	Attenuation Factor
σ^2	Noise Power

Abbreviations

AI	Artificial Intelligence
A-Life	Artificial Life
AP	Access Point
API	Application Programming Interface
BS	Base Station
BW	Bandwidth
CDMA	Code Division Multiple Access
CoMP	Coordinated Multipoint
CSE	Cell Spectral Efficiency
DRL	Deep Reinforcement Learning
D2D	Device-to-Device
eMBB	Enhanced mobile broadband
fc	Carrier frequency
gbest	global best particle
GSM	Global System for Mobile Communication
HetNets	Heterogeneous Networks
ICI	Inter-Cell Interference
ITS	Intelligent Transportation Systems
MILP	Mixed Integer Linear Program
MIMO	Multiple input multiple output
mMTC	Massive Machine Type Communication
NEWS	of North, East, West, and South
NGWNs	Next Generation Wireless Networks
ONF	Open Network Foundation
pbest	Personal Best Position
PSO	Particle Swarm Optimization
QoS	Quality of Service
RBs	Resource Blocks
RM	Resource Management
RR	Radio Resources
RRM	Radio Resource Management
RU	Radio Unit
SDN	Software Defined Networking
SE	spectral efficiency
SINR	Signal-to-noise plus interference ratio
SVM	Support Vector Machine
TSB	Truncated Shannon Bound
TTI	Transmission Time Interval
UDN	Ultra-Dense Network
UE	User equipment
URLLC	Ultra-Reliable Low Latency Communication
URV	Uniform random variables
WCDMA	Wideband Code Division Multiple Access

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