



# Multivariate clustering for maximizing the small cell users' performance based on the dynamic interference alignment

Prabakar Dakshinamoorthy<sup>1</sup> · Saminadan Vaitilingam<sup>2</sup> · Ramesh Sundar<sup>3</sup>

Accepted: 21 February 2023 / Published online: 11 April 2023

© The Author(s), under exclusive licence to Springer Science+Business Media, LLC, part of Springer Nature 2023, corrected publication 2023

## Abstract

Interference alignment (IA) ideas have been used into wireless communication in recent years to increase network users' capacity, sum rate, and spectral efficiency. This manuscript presents a multi-variate clustering (MC) for small-cell user communications through dynamic interference alignment (DIA). The clustering and interference alignment process focuses on retaining cluster stability and communication reliability by mitigating interference that is both intra and inter-cluster. The stability of the cluster is evaluated using the quality factor that is useful in mitigating intrauser interference. The inter-user interference is thwarted by classifying the transmitting signal based on time sequence and processing it through an appropriate cancellation matrix and rank-based analysis. Regardless of the user and cell density, the pre-coding process is based on this rank-based examination of the obtained power. The proposed MC-DIA is capable of handling both intra and inter-cluster interference for the allocated channels in the small cell scenarios. Experimentation results showed that the MC-DIA achieved a spectral efficiency of 84%. The proposed scheme performances are verified utilizing the simulation for metrics sum rate, spectral efficiency, and average degree of freedom (DoF).

**Keywords** Clustering · Interference alignment · Quality of cluster · Rank assessment · Small cell

## 1 Introduction

Wireless communication serves as the medium for information exchange between different users separated by a prominent geographical distance. Heterogeneous devices exploit diverse information and communication technologies for pervasive resource allocation and access between users. Interference is a prominent issue in a heterogeneous environment that degrades the quality of service (QoS). Wireless communication adopts either time or frequency and space factors for resource accessibility and information

exchange [1]. The communication channel occupied by a device is distorted due to the heterogeneous network nature in terms of time, frequency, or space factor [2]. Among these issues, interference is a renowned issue that needs to be mitigated to improve the design and modeling of heterogeneous communication networks.

In a heterogeneous wireless network, the users are grouped into small or large cells depending on the spectrum utilization and transmission time [2, 3]. More specifically, IA is designed for small cells; to mitigate the impact of both intra and inter-cluster interference. IA is designed based on time, frequency, or space factors along with classification and mitigation process. Arrangement of signal vectors with respect to the transmitter–receiver antenna pair in either of the orientation helps to reduce the interference. Classification of signal vectors requires a level of estimation and differentiation with respect to the time factor [4].

Signal classification and estimation solutions are restricted due to the resource-constraint nature of the communicating devices and the service utilization features. Received signal strength (RSS) assists in identifying a reliable neighbor in a communication

✉ Prabakar Dakshinamoorthy  
prabakar.ece@gmail.com

<sup>1</sup> Department of Data Science and Business Systems, School of Computing, College of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur, Chengalpattu, India

<sup>2</sup> Department of Electronics and Communication Engineering, Puducherry Technological University, Puducherry, India

<sup>3</sup> Department of Artificial Intelligence and Machine Learning, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, Tamil Nadu, India

environment with the distance consideration. The level of interference varies with the change in signal intensity noted at end of the receiver [5]. The variations in signal-to-noise ratio (SNR) levels also influence the interference levels besides channel sharing, inter-cell interference, etc. Interference alignment without the impact of noise requires a less complex computation process in specific classification and suppressing methods [6]. Channel state-based pre-coding techniques are commonly adapted for their less complex nature in interference alignment balancing transmitter–receiver communication intervals [7]. The complexity in user management and interference alignment is commonly addressed through the conventional clustering process. Clustering provides integrated solutions for IA and cell management reducing communication overhead and computation complexity. The physical factors such as user density, spectrum allocation and size of the cell are handled thoroughly through cluster-based communication [7, 8].

In this paper, a cluster-based dynamic IA is introduced for enhancing the small cell users' performances in the heterogeneous environment. The proposed method operates independently for a stabilized cluster formation and dynamic interference mitigation in a Heterogeneous networks (HetNet) scenario. It exploits the multi-attribute clustering and rank-based computation analysis paradigms for enhancing small cell users' performance. The wireless receivers and transmitters are used to provide network coverage within the small area. Joint cluster management and IA features are granted in this proposed method. The manuscript makes the following contributions:

- (i) Improve the performance of small cell users by designing the multi-variate clustering with dynamic IA (MC-DIA).
- (ii) Designing a stable clustering process that retains the quality of communication over the varying transmit SNR and number of cells.
- (iii) Introducing a novel dynamic IA scheme for achieving a better degree of freedom to maximize the small cell users' sum rate.
- (iv) The proposed strategy is compared to current methods using various parameters for confirming its reliability based on spectral efficiency and sum rate.

The remainder of this article is organised as follows: Sect. 2 describes the literature review and Sect. 3 describes the proposed MC-DIA model technique. The result part of the proposed MC-DIA is established in Sect. 4 which is compared with different methods and various performance metrics. Finally, Sect. 5 explains the concluding part.

## 2 Literature review

The distributed joint interference management (DJIM) method between cooperative small cells is proposed by Xiao et al. [9]. This method improves the utilization of the network by examining Orthogonal Frequency Division Multiple Access (OFDMA), IA, Power control and Time Division Multiple Access (TDMA). A partial interference alignment method for heterogeneous down-link communications for cellular networks was presented by Wang et al. [10]. The sub-space for a received signal through complex partial interference alignment and communication proportions was selected by the proposed method. This helps to mitigate the tradeoff between macro and micro cell users. To increase the rate mitigation of complex IA and soft partial IA, every antenna direction is considered for extracting useful signals. This method improves the sum rate and system capacity.

In [11], Wang et al. proposed an integer linear programming (ILP) based IA method for small cell networks. Interference alignment feasibility in a full duplex method in a small cell system is estimated on the basis of interference signals. The output of the proposed method improves the sum rate under less interference.

Minimized spectrum consumption clustering (MSCC) was evaluated by Zhou et al. [12] for the IA in full duplex small-cell communications. Along with MSCC, the interference leakage-based clustering approach is designed to reduce the complexity of clustering. The complexity of resource sharing between the common clusters is reduced in this method. The total rate and spectral efficiency of the users are boosted as a result.

Zhou et al. [13] developed the Average Effective Degree of Freedom (AEDOF) approach, to enhance the Degree of Freedom (DoF) in small cells together with IA. Additionally, the proposed model reduces the run time difficulties, by generating graph-based clusters.

Jang and Yoo [14] proposed a Q-learning-based interference control and transmission-aiding method for cognitive radio users. This learning-assisted communication model achieves a high detection ratio with less interference.

Joint interference alignment and precoding technique for multi-input multi output (MIMO) multiuser system is designed by Li and Li [15]. The Grassmannian conjugacy gradient algorithm (GCGA) is employed for interference alignment and precoding in the considered communication system. This joint optimization model improves the sum rate with less interference through the precoding and post-processing matrix computations.

Through device-to-device (D2D) communication, Zeng et al. [16] introduced an interference alignment (IA)

**Table 1** Summary of various research works

References	Technique	Parameters	Advantages	Limitations
Xiao et al. [9]	distributed joint interference management (DJIM)	Degree of freedom, throughput	less degree of freedom	Less accuracy
Wang et al. [10]	interference alignment method	sum rate and system capacity	improves sum rate and system capacity	Less performance
Wang et al. [11]	integer linear programming (ILP) based IA method	Sum rate, accuracy	improves the sum rate under less interference	Unable to cluster the tiny cell networks with FD
Zhou et al. [12]	Minimized spectrum consumption clustering (MSCC)	Spectral efficiency as well as the total rate	Clustering complexity is reduced	Intercluster interference problems
Zhou et al. [13]	Average effective degree of Freedom (AEDOF)	degree of freedom (DoF)	reduces the run time difficulties	Failed to progress the maximal number of the satisfactory users
Jang and Yoo [14]	Q-learning-based interference control and transmission-aiding method	sum rate and system capacity	high detection ratio	The system did not sense the channel continuously
Li and Li [15]	Grassnabian conjugacy gradient algorithm (GCGA)	sum rate	sum rate with less interference	Failed to enhance the convergence performance
Zeng et al. [16]	interference alignment (IA) technique	Degree of freedom, throughput	minimized channel state information	A non-square channel matrix was not employed in this paper
Ko et al. [17]	dynamic time division duplex (TDD)	Recall, throughput, F1-score	System capacity is enhanced	Higher cost
Arzykulov et al. [18]	IA	Accuracy, precision	High performance	Less efficient
Mohammad Ghasemi et al. [19]	distributed IA	Sensitivity, sum rate	Higher accuracy	Robust designs were not considered
Liu et al. [20]	Generalized eigenvalue decomposition (GEVD)	Degree of freedom, throughput	High performance	Lesser accuracy

technique for the MIMO heterogeneous networks downlink. The reduced channel state information (CSI) was used in the DaIA method to control co-tier interference and inter-tier interference. The results of this experiment showed that the approach outperformed the other conventional approaches. But, a non-square channel matrix was not employed in this paper.

Distributed IA for multi-antenna cellular networks using dynamic Time Division Duplex (TDD) was covered by Ko et al. [17]. Mobile station-to-mobile station (MS–MS) and base station-to-base station (BS-BS) interferences were introduced by the dynamic TDD. The results demonstrated that the scheme outperformed when compared to other approaches.

Using the IA, Arzykulov et al. [18] evaluated the capabilities of the wireless-powered cognitive relay network. The performance of the optimal network was acquired by computing the optimal energy of power splitting and time switching coefficients. For the time-switching relaying (TSR) and power-splitting relaying (PSR) protocols, the beam-forming matrices were used with imperfect and perfect channel state information.

Mohammad Ghasemi et al. [19] formulated the distributed IA with cellular networks based on large-scale antennas. The sensitivity was minimized by selecting the CSI part for the feedback. The simulation results revealed that the scheme outperformed both conventional and improved channel feedback quantization methods. In order to reduce the number of transmit antennas needed at the pico BS, W. Liu et al. [20] suggested the advanced generalised eigenvalue decomposition (GEVD) on grouping method assisted IA scheme. When compared to the basic grouping approach aided IA, this method achieves the highest total obtainable DoF. The summary of works in the literature is shown in Table 1.

### 3 Proposed methodology

This manuscript deals with cluster-assisted interference alignment (CIA) with smaller cell networks. The CIA process comprises two major phases namely dynamic interference alignment and multi-variate clustering. Interference alignment relies on the attributes of the cluster head for mitigating crossovers during communication. A

crossover is considered as interference caused due to internal cluster member or inter-cluster member. Therefore, clustering is designed to benefit interference alignment despite the dynamic member changes in small cells.

### 3.1 System model

Two different types of superimposed networks (ie) the macro network and the small cell network are included in the system model. In macro network, various macro cells in the base station are used to provide network coverage [21]. Only low-frequency bands employing legacy standards are used to run the macro cells. In small cell network, several small cells are utilized for providing the throughput and localized throughput which are operated within the high-frequency bands. A backhaul link connects each small cell to the macro cell. This system model consists of two serving points: a U-plane and C-plane. Small cells are in charge of U-plane connectivity, whereas the macro cell manages C-plane connectivity. The user equipment (UE) has dual connectivity to both small cells and macro cells. For configuration, the small cell is indirectly contacted with the core network (CN) to locally handle the baseband processing data and also exchange the low throughput signaling information through the backhaul link. The user data of a single Internet protocol (IP) is transferred through various U-plane connectivities from both small cells and macro cells. Figure 1 provides a description of the system model.

#### 3.1.1 UE connectivity modes

The single and dual connectivity modes are the two UE connectivity modes. The connections of the C-plane band U-plane in single connectivity modes are maintained by the macro cell and the C-plane connection in dual connectivity

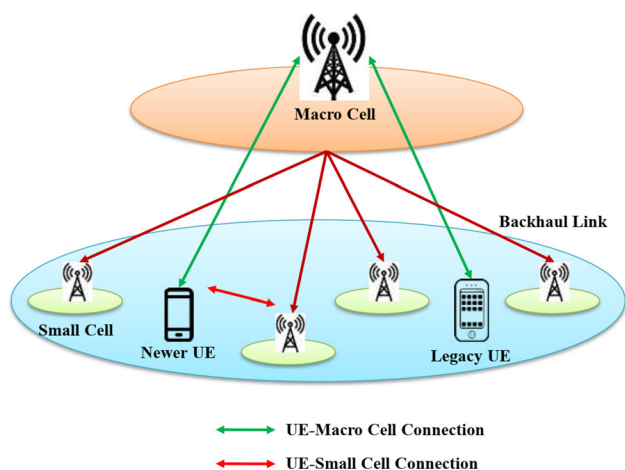


Fig. 1 System model

mode is maintained by the macro cell as well as the U-plane connection by the small cell. The single and dual connectivity modes are supported by the new UE and the legacy UE is supported only for the single mode. The connectivity of the single UE to the small cells is a complex task because the PCC cells cannot shift the specific signal. However, this method is highly applicable for projected network signals and huge link failures due to repeated handover procedures which is essential for the fast-moving UE. In this small cells are required for handling the connection made in the macro cell thus it permits the macro-assisted UE small cell connection. Thus it determines that the macro cell connection is significant to make the connection with the small cell. The UE intersects the small cell and macro cell concurrently. In this approach, the words state and mode are utilized alternately.

#### 3.1.2 Assumptions

The ON, OFF, and sleep are the three small cell states.

- The ON state requires a huge amount of energy in which the small cells are operational. The small cells are determined as stand-by-mode in the sleep state in which they could not provide any user and utilize a minimum amount of energy.
- The energy required for the sleep state is insignificant however it is essential to activate the small cell as soon as possible.
- But in the OFF state, the cells are deactivated. In the former state, the small cell utilized only the least amount of energy when related to the ON or sleep state.
- While in recent technological advancements, it takes a huge time to transmit the cell from the OFF to ON state.

However, the increase in transmitting time in the ON and OFF state will restrict the network and minimize the traffic by implementing the QoS in UE. But in some conversions, it is not possible due to variations happened in the user position and traffic. The main aim is to implement the scheme in normal network conditions and the results revealed that it focused on the transition among ON and sleep state as it conserves energy.

### 3.2 Multi-variate clustering with dynamic interference alignment (MC-DIA)

#### 3.2.1 Multi-variate clustering (MC)

LAP exploited in the communication model serves the purpose of cluster head (CH) in small cells. The CH is responsible for achieving a better sum rate ( $S_r$ ) with high quality ( $Q$ ).

Aligning interference and ensuring error-less transmission to the MBS over the allocated channel determines  $S_r$  and  $Q$  of a small cell cluster [22]. On the other hand, the quality of a cluster is influenced by the density of users, RSS and  $s_r$  due to the intrinsic characteristics of the users. The network requires evaluating the updated topology as well as deactivating or activating the links for acquiring the updated topology in the topology adaption. User characteristics such as mobility, Topology adaption, channel overlapping, and handoff influence the  $s_r$  and RSS of the CH and its quality. Therefore, the objective of a LAP acting as a CH is given by (1)

$$\tau(CH) = \left\{ \begin{array}{l} \arg \max_{c \in CH} (S_r) \forall \sum_{i=1}^K \sum_{j=1}^c \omega_{1j} \\ \arg \max_{i=1 \text{ to } k} (Q) \forall \sum_{j=1}^x \omega_{2j} \end{array} \right\} \quad (1)$$

Here,  $\tau(CH)$  is the objective function that is expected to be high for all “x” data transmissions. The variables  $\omega_1$  and  $\omega_2$  represent the clustering metrics.  $(\alpha_i)$ ,  $(\rho_n)$  are denoted as clustering interference and clustering density respectively. The clustering interference and clustering density of a CH in a small cell are estimated using (2) as

$$\alpha_i = \frac{\sum_i L(dist) + p_{li} \log\left(\frac{dist}{dist_0}\right) \forall c}{L(dist) + p_{li} \log\left(\frac{dist}{dist_0}\right)} \quad (2)$$

$$\rho_n = \frac{-|x_m - \hat{x}_m|^2}{\sigma}$$

where  $L(dist)$  is the “d” loss observed at a distance “dist”,  $p_l$  is the power loss, and  $dist_0$  is the reference distance. Also,  $(x_m, \hat{x}_m)$  denotes the position co-ordinate reference of the  $m^{th}$  user among the available density  $\sigma$ . The CH is elected by identifying the user with  $\max\{\omega\}$ , Where  $\omega$  is the weight factor that determines the CH and  $\omega = \omega_1 + \omega_2$  as estimated by Eq. (2). Weight-based CH selection is a prominent phenomenon where in the  $\omega_1$  and  $\omega_2$  are subject to change due to which Eq. (1) cannot be satisfied at instances. Therefore, the independent metrics of  $\omega_1$  and  $\omega_2$  are analyzed with respect to the received signal strength  $R_s$  observed.

$$R_s = p_t + 10\beta \log_{10}\left(\frac{dist}{dist_0}\right) + \gamma \quad (3)$$

From the above equation, transmit power is represented by  $p_t$ , noise factor and path loss exponent is described by  $\gamma$  and  $\beta$  respectively. Metrics  $\omega_1$  and  $\omega_2$  are analyzed for their coherency with the measured RSS. For this purpose, analysis matrix of both the metric is constructed to identify the balanced condition to satisfy (1). The next CH is selected based on this satisfying condition that is retained by a neighboring LAP at any time interval.

$$\omega_1 = \begin{bmatrix} \omega_{11} & \omega_{12} & \cdots & \omega_{1c} \\ \omega_{21} & \omega_{22} & \cdots & \omega_{2c} \\ \vdots & \vdots & & \vdots \\ \omega_{K1} & \omega_{K2} & \cdots & \omega_{Kc} \end{bmatrix} \quad \text{and} \quad \omega_1 = \begin{bmatrix} \omega_1 \\ \omega_2 \\ \vdots \\ \omega_x \end{bmatrix} \times [t_1 \quad t_2 \quad \dots \quad t_x] \quad (4)$$

where  $t_x$  is the transmit time and the synchronization  $Q$  is estimated at the same time. To avoid self-interference,  $\omega_{11} \quad \omega_{12} \quad \dots \quad \omega_{Kc}$  entries in  $\omega_1$  the matrix are eliminated to augment organized transmission such that  $\omega_{Kc} + \omega_x \times t_x = \max\{S_r\}$ . This is verified for all  $t_x$  in accordance with the  $Q$  update. The probability of the next CH selection ( $\rho_{CH}$ ) is computed using Eq. (5)

$$\rho_{CH} = \arg \max_n \frac{\omega_{i,j}}{\sigma} \quad (5)$$

In Eq. (5), the probability factor determines the need for selecting a CH on the basis of RSS. For estimating this need,  $\rho_i$  and  $\rho_n$  metrics  $\omega_1$  and  $\omega_2$  is correlated with the rate of  $S_r$  for the observed RSS. The elements of the  $\omega_1$  and  $\omega_2$  matrices are divided to represent  $\omega_{Kc} + \omega_x \times t_x = \arg \max\{S_r\}$  such that the elements are

$$\sum_{i,j \in \sigma} \omega_{i,j} = \sum_{i=1}^c \sum_{n_1, n_2, \dots, n_l} (\omega_{ln} + \omega_l) \quad (6)$$

The divided elements as per Eq. (6) have to satisfy  $\omega_{Kc} + \omega_x \times t_x = \max\{S_r\}$ . The divided elements with self-interference cancellation form the analysis matrix for the first condition evaluation [ $\arg \max\{S_r\}$ ]. This matrix is represented as

$$\omega_1 + \omega_2 = \arg \max(S_r) \forall \sum_{i=1}^K \sum_{j=1}^c \omega_{ij} \begin{bmatrix} 0 & \omega_{12} & \cdots & \omega_{1c} \\ \omega_{21} & 0 & \cdots & \omega_{2c} \\ \vdots & \vdots & & \vdots \\ \omega_{K1} & \omega_{K2} & \cdots & 0 \end{bmatrix} \begin{bmatrix} \omega_1 \\ \omega_2 \\ \vdots \\ \omega_x \end{bmatrix} \times [t_1 \quad t_2 \quad \dots \quad t_x] = [\omega_{ij}] = [\omega_{ln}] + [\omega_l] \quad (7)$$

For simplicity, the RHS of Eq. (7) (i.e.,  $[\omega_{ln}] + [\omega_l]$ ) is equated with  $Q$  and self-canceled metrics. The  $Q$  cluster satisfying Eq. (7) and partial Eq. (1) are computed as

$$Q = \frac{1}{2\mu} \sum_{i,j} \left( \sigma_i - \frac{\mu_{CH_i}}{2\mu} \right) \rho(i,j), \quad (8) = \sum_{i=1}^c \left[ \frac{\sigma_i}{\mu} - \left( \frac{\mu_{CH_i}}{2\mu} \right)^2 \right]$$

where  $\mu$  represents the number of transmitting antennas and  $\mu \in n$ ,  $\mu_{CH}$  denotes transmitting links associated with the CH and  $\rho(i,j) = 1$ , if the CH/LAP is connected to the member with a transmission links. The estimated  $Q$  must



be high for each composite output of  $\omega_{kc} + \omega_x \times t_k$  such that  $\omega_{kc}$  and  $\omega_x \in [\omega_{ij}]$ . The set of users available for the next  $\rho_{CH}$  is defined as

$$\begin{aligned} \rho_{n-CH} &= \{\rho_1, \rho_2, \dots, \rho_{n-1}, C_1, C_2, \dots, C_n - 1\}, \\ \rho_{n-CH} &= \max_{c \in n} RSS_C \forall n \text{ in cluster and } \omega_1 + \omega_2 = \omega_{ij} = \max\{S_r\} \end{aligned} \tag{9}$$

Based on Eqs. (8) and (9) the matrix representation in Eq. (7) is modified as

$$\begin{aligned} &\begin{bmatrix} 0 & \omega_{12} & \dots & \omega_{1c} \\ \omega_{21} & 0 & \dots & \omega_{2c} \\ \vdots & \vdots & \ddots & \vdots \\ \omega_{K1} & \omega_{K2} & \dots & 0 \end{bmatrix} + \sum_{i=1}^x \omega_i t_i \\ &= \sum_{i=1}^n \sum_{j=1}^c \omega_{ij} + \omega_j, \forall \tau(CH) \text{ and } \arg \max_c(Q) \end{aligned} \tag{10}$$

Until interference occurs, Left Hand Side (LHS) of the above equation must meet both restrictions. Before the interference estimation,  $\gamma$  estimation is mandatory to reduce the internal drawbacks of the cluster. If  $\gamma = 0$  (ideal case), then  $RSS$  is maximum. In this case, the LHS of Eq. (10) satisfies  $\max(\omega_{ij} + \omega_j)$  and  $Q$  is high. Contrarily, this cannot be retained throughout  $t_x$ . Therefore some  $(\omega_{ij} + \omega_j)$  is compromised at  $t_x$  for the transmitted  $d$ . The specific element that generates less  $(\omega_{ij} + \omega_j)$  is independently segregated from the matrix representation of Eq. (7).

The updated matrix is represented as

$$\begin{aligned} &\begin{bmatrix} 0 & \Delta\omega_{12} & \dots & \omega_{1c} \\ \Delta\omega_{21} & 0 & \dots & \omega_{2c} \\ \vdots & \vdots & \ddots & \vdots \\ \Delta\omega_{K1} & \Delta\omega_{K2} & \dots & 0 \end{bmatrix} + \sum_{i=1, x \neq c}^x \omega_i t_i \\ &= \sum_{i=1}^c \min\{Q_i\} + \max\{L(dist)_i\} \end{aligned} \tag{11}$$

In (11), minimum and maximum values of  $Q$  and  $L(dist)$  in any  $i$  is required.

Independently,

$$[\omega_{ij}] + \sum_{i=1}^x \omega_i t_i \sum_{j=1}^c Q_j + L(dist)_j = \Delta\omega_{ij} = \forall c \in n \tag{12}$$

The independent case analysis follows for different variations  $(\omega_1 + \omega_2)$ . A conventional process  $\omega_{ij} = \omega_{ij}\rho_n + \omega_j\rho_i$  is computed for selecting a CH. The LAP is selected as a CH for achieving better regulated  $d$  exchange to the  $MBS$  in the allocated  $c$ . The final clustering process satisfies the following constraint for all the  $n$  in the range of a LAP,

$$\begin{aligned} &\max \sum_{i=1}^K \sum_{j=1}^n \omega_{ij} \rho_{n \rightarrow n+1} \\ &\cap \min \sum_{j=1}^c \rho_j, \forall n \in \text{cluster and } n \neq \rho_{CH} \end{aligned} \tag{13}$$

The above condition is satisfied for all  $dist(CH, n) < R(CH)$  or  $R(n)$ ,  $R$  in the range of  $CH$  for the user with  $n_{th}$  an antenna. The formed cluster as per Eq. (13) satisfying Eq. (1) by eliminating Eq. (11) independent elements remains the same for all  $t_x$  satisfying  $\max\{Q\}$ . In any  $t_x$ , if  $Q$  is observed to be less than the previous time  $t_{x-1}$ ,  $[\omega_{ij}] - [\Delta\omega_{ij}]$  is eliminated and the next maximum  $\{\omega_{ij}\}$  user is elected as LAP. The LAP is selected from the available set of local access points communicating to the users. After the clustering process, dynamic interference alignment is focused.

### 3.2.2 Dynamic interference alignment (DIA)

In the dynamic IA, the changes in cluster members and  $\rho_n$  are accounted for by suppressing interference across  $c$ . The objective in IA is to maximize the degree of freedom ( $\phi^z$ ) to achieve better reliability in signal transmission. If  $T^z$  is used to denote the transmitted signal, then it is given by the following equation.

$$T^z = \sum_{i=1}^{\phi^z} A^z \tag{14}$$

Here,  $A^z$  is the product matrix representation,  $A^z = T^z \times \phi^z$  in transmission space.

$$\text{Let } R_x^\infty = R^z \Gamma^z \phi^z \tag{15}$$

where  $\Gamma^z$  is the matrix representation of the received signal  $R^z$  at the time  $t_x$  measured using  $p_t$ ,  $dist$ , and  $dist_0$ . In other words, the matrix is represented using the  $RSS$  observed in this signal space for its  $\phi^z$ .

The analysis for IA in order to achieve high  $\phi^z$  must suppress interference at its least possible signal representation. A communicating signal is represented using the antennas of the transmitter and receiver. The signal matrix  $A^z$  representation must co-exist with an interference mitigating matrix with respect to  $\bar{G}_a$ . Therefore, a pre-coding matrix  $B_i^c$  is exploited to verify the independency of  $\Gamma^z$  from  $\gamma$  and other interference. The least requirement of IA in a transmitter–receiver pair with  $n$  antennas is

$$(B_i^c) A^z C_i^c = 0, \text{ if } c \in n, i \in c, \forall \Delta\omega_{ij} = [\omega_{ij}] + \sum \omega_i t_i \tag{16}$$

In Eq. (16) the cancellation matrix  $C_i^c$  is used along with  $B_i^c$  for evading interference. The process of interference alignment follows rank-based estimation to maximize  $\phi^z$ .

The cluster members satisfying  $\max\{\omega_{ij}\}$  participate in concurrent transmission through LAP. In such cases, the primary task is to suppress local interference. Local interference is canceled by computing the concurrent communication matrix of all the cluster members in  $t_x$ :

$$y_i^{c,n} = \theta_1^K \theta_2^{t_x} (B_i^c) A^z C_i^c + \sum_{i \in c} \theta_1^i \theta_2^{t_x} \cdot B_i^c A_i^z \varphi_i^c + \sum_{j \in t_x} \theta_1^k \theta_2^j \cdot B_j^c A_j^z (1 - \gamma_i) \tag{17}$$

where  $y_i^{c,n}$  is the expected concurrent transmission signal. In other words,  $y_i^{c,n}$  is the sum of all  $T^z$  with  $\gamma$  in each  $t_x$ . Therefore, the signal represented in Eq. (17) is received by the end user as  $R_x^\infty$ . Now, the achievable sum rate ( $\hat{S}_r$ ) is expressed as;

$$\hat{S}_r = \log 1 + \theta_1^K \theta_2^{t_x} p_t \frac{B_i^c A_i^z \varphi_i^z (1 - \gamma_i) R_x^z}{(B_i^c) \gamma_i [C_i^c y_i^{c,n} + y_i]} \tag{18}$$

The above sum rate is the outcome of all the  $y_i^{c,n}$  transmitted at  $t_x$  and observed at the receiver end. The sum rate as computed in Eq. (18) is a joint estimation of the sum rate of all the  $m$  antennas experiencing  $\gamma$ . This reduces the rate of throughput experienced. Therefore, interval IA is prominent in achieving maximum ( $\hat{S}_r$ ). The difference in sum rate (ideal and computed) (i.e.) ( $\hat{S}_r \sim S_r$ ) is the less in communication due to the  $y_i^{c,n}$ . The objective of achieving high throughput is given as

$$\arg_{\theta_1^K} \max_{\theta_2^j} \sum_{i \in t_x} \sum_{m \in n} \sum_{e \in c} R_i^z(m, e) = \sum_{i \in t_x} \sum_{m \in n} \sum_{e \in c} \hat{S}_{ri}(m, e) \tag{19}$$

The above throughput  $R_i^z$  for all  $(m, e)$  is achieved in effect provided the IA condition satisfies  $n = 2 \times T - 1$ , where  $T$  the communicating user terminals are.

Therefore, a joint IA considering the dynamicity of  $T$  and  $y_i^{c,n}$  is accounted for through rank-based operations. Before the operations of rank-based IA, the dynamicity of the cluster member is classified by segregating them  $y_i^{c,n}$  based on  $t_x$ . The pre-coding steps followed for classifying the signal are derived as follows

$$\max_{S_r} \sum_{m \in n} \sum_{e \in c} R^z(m, e) = \sum_{i \in t_x} \sum_{m \in n} \sum_{e \in c} \hat{S}_{ri}(m, e) \pm \Delta \omega_{ij} \tag{20}$$

$$\sum_{e \in c} \theta_2^e B_e^c = 1, \text{ if } (\hat{S}_{ri} \sim S_r) = 0$$

From Eq. (20), the transmitted signal  $y_i^{c,n}$  in  $t_x$  requires the cooperation of the other entire cluster member for  $t_x$ . This cooperative communication is scheduled into slotted  $t_x$  for all  $\Delta \omega_{ij}$  with high  $Q$ . The transmitting  $y_i^{c,n}$  is then classified as

$$\max_{S_r} \sum_{m \in n} \sum_{e \in c} R^z(m, e) = B_i^c C_i^c T^z = \varphi^z, \tag{21}$$

$$T^z = y_i^{c,n} - \gamma, \text{ if } \varphi^z = 0 \& t_x \neq 0,$$

$$T^z = y_{i+1}^{c,n} - \gamma, \text{ if } \varphi^z = 0 \& t_{x+1} \neq 0$$

The least possible classification of  $T^z$  is with respect to

$t_x$  and  $t_{x+1} \forall \varphi^z = 0$ . On the other hand,  $\varphi^z = 0$  either  $t_x$  or  $t_{x+1}$ , if it is zero in both in transmission, then IA is not performed. Therefore, IA is performed in the sequence of  $\min\{\varphi^z\} \forall t_x$ . The achievable DoF is  $(C_i^c R^\infty + B_i^c + E^z)$ , where,  $E^z \sim (0, T_m^z)$ .

Other than using a noise rate, the identity matrix  $I_m^z$ , where the presence of  $y_i^{c,n}$  in  $T^z$  with  $\max\{Q \cap \hat{S}_r\}$  it  $t_x$  is estimated. Now, the rank process is initiated for mitigating interference in  $c \forall n$ , as

$$\text{rank}(C_i^c B_i^c R^\infty) = \varphi^z, \forall E^z = 0 \tag{22}$$

$$C_i^c B_i^c I_m^z \neq 0, \forall c \in n \text{ in } t_x$$

and

$$\text{rank}(C_i^c y_i^{c,n}) - E^z = \varphi^z, \forall E^z \neq 0 \ t_x \neq t_{x+1} \tag{23}$$

$$C_i^c y_i^{c,n} I_m^z \leq 1, \forall c \text{ in } t_{x+1}$$

In Eqs. (22) and (23), the rank-based interference

alignment is processed for two different intervals  $t_x$  and  $t_{x+1}$ . The case of nominal transmission is illustrated in Eq. (22) and the less  $\varphi^z$  condition is expressed in Eq. (23). This can be exchanged at different time intervals  $t_x$  and  $t_{x+1}$  where  $I_m^z \leq 1$ . The two cases of IA with respect to  $t_x$  and  $t_{x+1}$  is illustrated in Fig. 2(a) and (b) respectively. The degree of freedom required in the conventional IA is high that increasing the signaling overhead.

Different from the existing methods, in MC-DIA, the signaling overhead is confined to the active users in the cell. The path loss probability and the rate of power loss ensure the participation of the user in communication. The user's density is influenced by the sum rates through the enhancement of the interference level. The interference level is reduced by the pre-coding process between the cell and user levels. Therefore, the first step of maximizing the sum rate is induced by self-interference cancellation followed by IA and hence a higher degree of freedom.

The pseudocode of dynamic interference alignment is described in algorithm 1.

**Algorithm 1:** Pseudocode of dynamic interference alignment

```

1) Start
2) Parameter initialization
3) Fitness function evaluation for maximizing the degree of freedom ( $\phi^\alpha$ )
4) Evaluate transmitted signal ( $T^\alpha$ ) using equation (14)
5) Evaluate received signal ( $R^\alpha$ ) using equation (15)
6) Calculate interference alignment using equation (16)
7) Calculate concurrent transmission signal ( $y_i^{c,n}$ ) by equation (17)
8) Evaluate sum rate and threshold value by using equations (18) and (19) respectively
9) Perform signal classification using (20)
10) if
     $\phi^\alpha = 0$  at both  $t_x$  and  $t_{x+1}$ 
        IA is performed
    Else
        IA is not performed
    Endif
11) Perform rank-based interference alignment using equations (22) and (23)
12) Better reliability in signal transmission
13) End

```

## 4 Simulation results

The proposed MC-DIA performance is evaluated by utilizing the MATLAB simulations in a network of size  $0.5 \text{ km} \times 0.5 \text{ km}$  with a transmit power of 10dBm for small cell users. The network is segregated into clusters of varying sizes as illustrated in Fig. 1. The communications are directed to the MBS through the LAP. In Table 2, the detailed simulation parameter and its values are presented. The proposed approach's variable description is shown in Table 3.

The proposed MC-DIA is evaluated utilizing the parameters like spectral efficiency, sum rate and average DoF. A comparative analysis using the above metrics is performed between the proposed scheme and the existing DJIM [9] and MSCC [12].

### 4.1 Sum rate analysis

When compared to previous approaches, the suggested MC-total DIA's rate per cell is relatively high. This is initiated by optimizing the stability of the cluster on estimating  $Q$ . It helps to suppress the internal losses due to overlapping channels.

Similarly,  $\hat{S}_n(m, e) \pm \Delta\omega_{ij}$  approximates the data stream received in the MBS achieving a better sum rate. Another

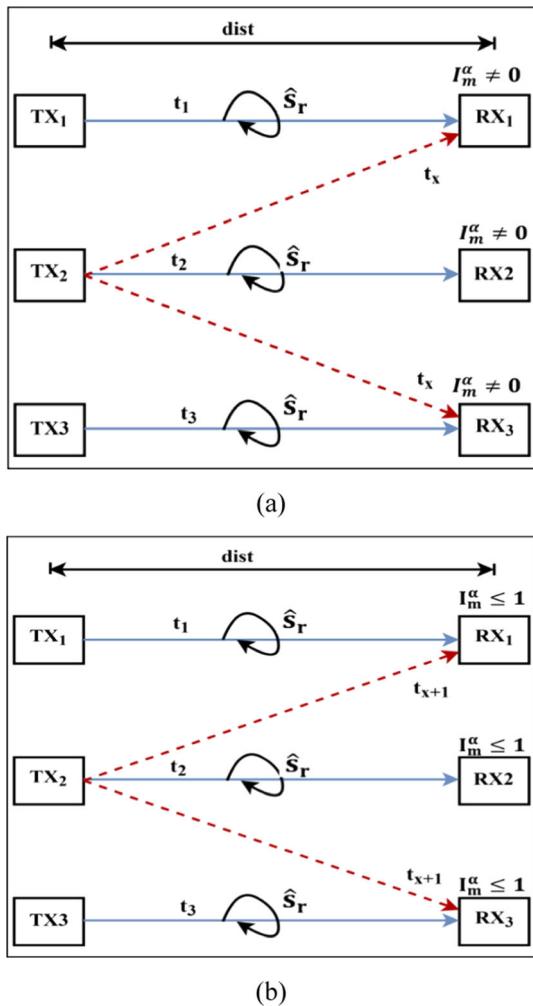
attuning factor for the sum rate is its  $\phi^\alpha$  maximization and  $(\theta_1^K \theta_2^{t_x})$  is the balancing metrics with respect to  $c$  and transmits time respectively. These factors are focused to estimate noise as  $\gamma$  or  $(1 - \gamma)$  depending on the  $t_x$ . For comparative analysis, three methods such as DJIM, MSCC and proposed MC-DIA are utilized. Figure 3 compares the results, showing that as the number of cells increases, the sum rate also increases. In each cell, the proposed MC-DIA method has a high sum rate of 28 Mbps compared to other methods.

The classification of signals on the basis of  $t_x$  and  $E^\alpha$  provides a clear vision for IA retaining  $Q$ . The Sum Rate Analysis of MC-DIA is therefore higher than that of the other methods, as illustrated in Fig. 4. For comparative analysis, three methods such as DJIM, MSCC and proposed MC-DIA are utilized. Figure 4 shows the sum rate of transmitting SNR and when the transmit SNR rate is increased the sum rate also increased simultaneously. The proposed MC-DIA method attained a high sum rate of 48 Mbps.

### 4.2 Analysis of spectral efficiency

The observed spectral efficacy is compared among the proposed methods and existing for varying the cell density is illustrated in Fig. 5. Irrespective of the cells in the network, the stability of the cluster is retained by verifying  $Q$





**Fig. 2** Cases **a** Case of IA with respect to  $t_x$ , **b** Case of IA with respect to  $t_{x+1}$

**Table 2** Simulation parameter and values

Parameter	Value
Network region	0.5 km × 0.5 km
No. of small cells	50
Path loss design	Rayleigh Fading
Bandwidth rate	180 kHz
Path LOSS FACTor	3.76
Macro base station (MBS)	2
Users	200
MBS transmit power	45 dBm
Noise power	$10^{-7}$

over the  $t_x$ . The internal interference issues are suppressed by retaining and changing the members based on  $Q$  factors. Externally, the alignment required signal  $y_i^{c,n}$  is classified on the basis of  $E^z = 0$  and  $E^z \neq 0 \forall I_m^z$ .

The classification of signals on the basis of  $t_x$  and  $E^z$  provides a clear vision for IA retaining  $Q$ . Therefore, the

**Table 3** Variable description

Variables	Variables description
$(S_r)$	Sum rate
$(Q)$	Quality
$\omega_1, \omega_2$	Clustering metrics
$(\rho_i)$	Clustering interference
$(\rho_n)$	Clustering density
$(x_m, \hat{x}_m)$	Position co-ordinate reference
$\omega$	Weight factor
$p_l$	Power loss
$\beta$	Path loss exponent
$t_x$	Transmit time
$\mu$	Transmitting antennas
$\mu_{CH}$	Transmitting links associated with the CH
$\Gamma^z$	Matrix representation of the received signal
$C_i^c$	Cancellation matrix
$y_i^{c,n}$	Expected concurrent transmission signal
$I_m^z$	Identity matrix
$A^z$	Signal matrix
$\tau$	Objective function
$L$	Loss observed
$\sigma$	Available density
$p_t$	Transmit power
$R$	Range of CH
$\phi^z$	Degree of freedom
$T^z$	Transmitted signal
$R^z$	Received signal

received signal  $R^z$  is observed with high  $\hat{S}_r$  utilizing the allocated spectral efficiency. Hence, the spectral efficiency of MC-DIA is high compared to the other method.

### 4.3 Degree of freedom analysis

A comparative analysis of the average DoF between the proposed scheme and the existing methods is presented in Fig. 6. DoF maximization in the proposed MC-DIA is carried out for both transmission intervals  $C_i^c, y_i^{c,n} \cdot I_m^z \leq 1$ . The initial transmission follows  $\max\{\phi^z\}$  suppressing the interference over  $c$ . In the later part,  $rank(C_i^c, \Delta_i^c, R^\infty) = \max\{\phi^z\}, \forall E^z = 0$  in  $t_x$  and  $rank(C_i^c, y_i^{c,n}) - E^z = \max\{\phi^z\} \forall E^z \neq 0$ , in  $t_{x+1}$ . Therefore, in both cases, IA and noise suppression are augmented for extracting  $R^\infty$  from  $y_i^{c,n}$  with the consideration  $\Delta\omega_{ij}$  and  $\hat{S}_r$ .

A comparison of the average Degree of Freedom (DoF) between the proposed scheme and the existing methods is presented in Fig. 7 for varying SINR (dB). The proposed MC-DIA achieves better DoF when compared with existing methods. From the above diagram, at an SINR of

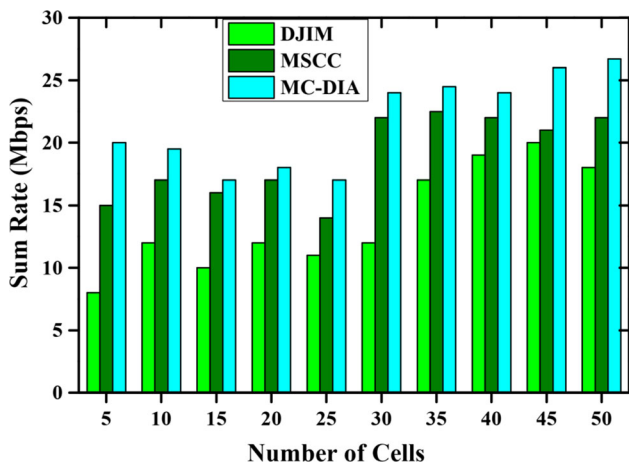


Fig. 3 Sum rate versus number of cells

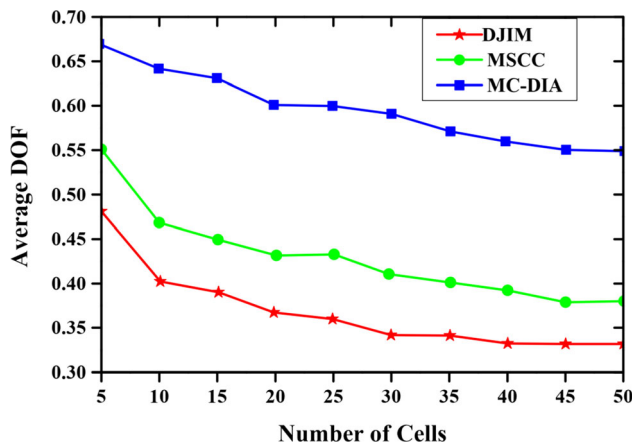


Fig. 6 Average DoF versus number of cells

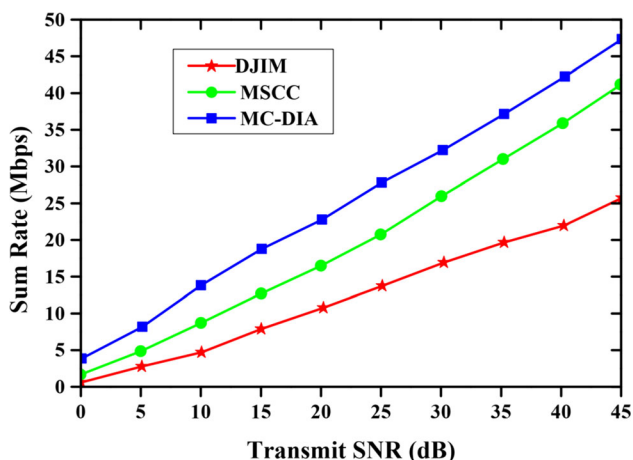


Fig. 4 Sum rate versus transmit SNR

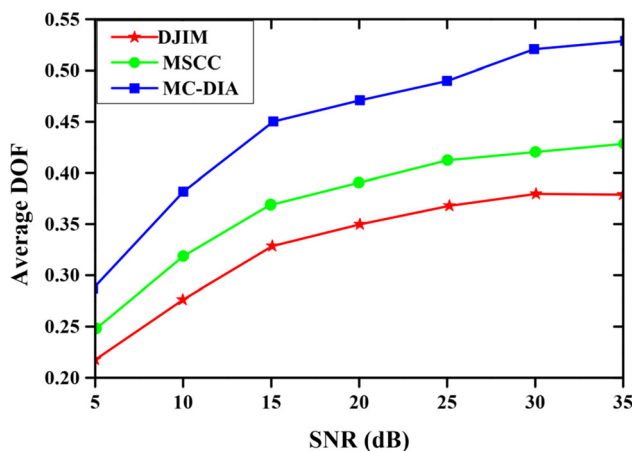


Fig. 7 Average DoF versus SINR

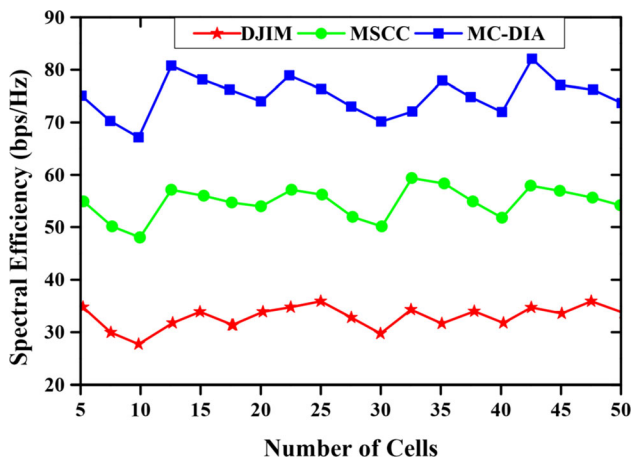


Fig. 5 Spectrum efficiency versus number of cells

35 dB, the proposed technique achieved a 0.55 average DoF. As per the comparison made, the proposed method obtained enhanced DoF.

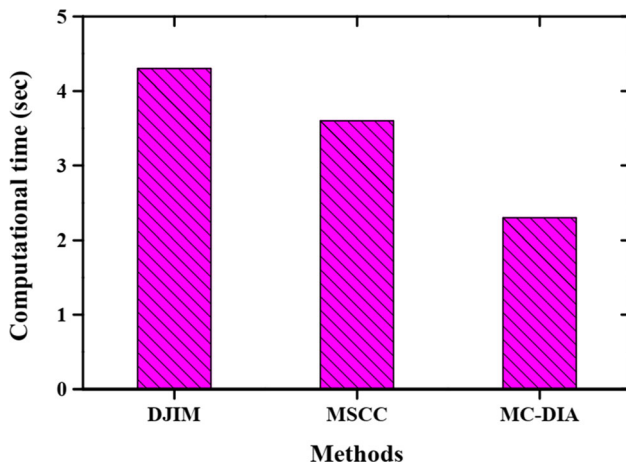
Figure 8 represents the computational time of different methods such as DJIM, MSCC and proposed MC-DIA. From the comparative analysis, the proposed MC-DIA method attained a computational time of 2.3 s. The proposed MC-DIA method has very low computational time compared to other state-of-art methods. Comparative studies of the above results are discussed in Table 4.

### 5 Conclusion

As a way to improve the performance of smaller cell users in a heterogeneous environment, this research discusses multi-variate clustering with a dynamic interference alignment mechanism. Multi-variate clustering and dynamic interference alignment are addressed jointly for suppressing inter and intra-cluster interference and DoF maximization. Quality-based cluster assessment and rank-based IA serve the purpose of maximizing the sum rate and reducing the interference rate achieving a high DoF.

**Table 4** Comparative Analysis

Metrics	DJIM	MSCC	MC-DIA
Sum rate (Mbps) at SNR = 45 dB	26.5	41.6	46.1
Sum rate (Mbps) (Number of cells = 50)	18.2	22.5	24.3
Spectral efficiency (bps/Hz) (Number of cells = 50)	34	53	75
Average DoF (Number of cells = 50)	0.33	0.38	0.54
Average DoF at SINR = 35 dB	0.37	0.42	0.55
Computational time (seconds)	4.4	3.8	2.3
Packet size (second)	100	220	300

**Fig. 8** Comparative analysis of computational time

Experimentation results showed that the MC-DIA achieved a spectral efficiency of 84%. Thus by increasing the sum rate, spectral efficiency and DoF, the results demonstrated the consistency of the suggested system. In future, this research will be directed to enhance the clustering technique with respect to memory space and time thereby evaluating huge datasets containing diverse data forms.

**Funding** None.

**Data availability statement** Data sharing is not applicable to this article as no new data were created or analyzed in this study.

**Code availability** Not applicable.

## Declarations

**Conflict of interest** The authors declare that they have no conflict of interest.

**Consent to participate** Not applicable.

**Consent for publication** Not applicable.

**Human and animal rights** This article does not contain any studies with human or animal subjects performed by any of the authors.

**Informed consent** Informed consent was obtained from all individual participants included in the study.

## References

- Hajiakhondi-Meybodi, Z., Mohammadi, A., Abouei, J., Hou, M., & Plataniotis, K. N. (2021). Joint transmission scheme and coded content placement in cluster-centric UAV-aided cellular networks. *IEEE Internet of Things Journal*, 9(13), 11098–11114.
- Ashtari, S., Zhou, I., Abolhasan, M., Shariati, N., Lipman, J., & Ni, W. (2022). Knowledge-defined networking: Applications, challenges and future *IEEE Transactions on Mobile Computing. Array*, p. 100136.
- Pratap, A., & Das, S.K. (2021). Stable matching based resource allocation for service provider's revenue maximization in 5G networks. *IEEE*
- Wang, L., & Liang, Q. (2018). Partial interference alignment for heterogeneous cellular networks. *IEEE Access*, 6, 22592–22601.
- Adnan-Qidan, A., Morales-Céspedes, M., & Armada, A. G. (2020). Load balancing in hybrid VLC and RF networks based on blind interference alignment. *IEEE Access*, 8, 72512–72527.
- Qamar, F., Hindia, M. H. D., Dimiyati, K., Noordin, K. A., & Amiri, I. S. (2019). Interference management issues for the future 5G network: A review. *Telecommunication Systems*, 71(4), 627–643.
- Rihan, M., & Huang, L. (2018). Optimum co-design of spectrum sharing between MIMO radar and MIMO communication systems: An interference alignment approach. *IEEE Transactions on Vehicular Technology*, 67(12), 11667–11680.
- Ghosh, S., & De, D. (2020). Weighted majority cooperative game based dynamic small cell clustering and resource allocation for 5G green mobile network. *Wireless Personal Communications*, 111(3), 1391–1411.
- Nasser, A., Muta, O., Elsabrouty, M., & Gacanian, H. (2019). Interference mitigation and power allocation scheme for downlink MIMO-NOMA HetNet. *IEEE Transactions on Vehicular Technology*, 68(7), 6805–6816.
- Hossain, M.D., Huynh, L.N., Sultana, T., Nguyen, T.D., Park, J.H., Hong, C.S., & Huh, E.N. (2020). Collaborative task offloading for overloaded mobile edge computing in small-cell networks. In *2020 International Conference on Information Networking (ICOIN)* (pp. 717–722). IEEE.
- Wang, K., Yu, F. R., Wang, L., Li, J., Zhao, N., Guan, Q., Li, B., & Wu, Q. (2019). Interference alignment with adaptive power allocation in full-duplex-enabled small cell networks. *IEEE Transactions on Vehicular Technology*, 68(3), 3010–3015.
- Zhou, M., Li, H., Zhao, N., Zhang, S., & Yu, F. R. (2019). Feasibility analysis and clustering for interference alignment in full-duplex-based small cell networks. *IEEE Transactions on Communications*, 67(1), 807–819.

13. Zhou, M., Li, H., Li, J., & Wang, K. (2017). Average effective degrees of freedom (AEDoF) maximization with interference alignment in small cell networks. *Wireless Networks*, 24(3), 981–991.
14. Jang, S. J., & Yoo, S.-J. (2018). Q-learning-based dynamic joint control of interference and transmission opportunities for cognitive radio. *EURASIP Journal on Wireless Communications and Networking*, 2018(1), 1–24.
15. Li, T., & Li, F. (2018). Joint interference alignment precoding based on the optimization algorithm on the Grassmannian manifold. *AEU - International Journal of Electronics and Communications*, 84, 300–306.
16. Zeng, S., Wang, C., Qin, C., & Wang, W. (2018). Interference alignment assisted by D2D communication for the downlink of MIMO heterogeneous networks. *IEEE Access*, 6, 24757–24766.
17. Ko, K. S., Jung, B. C., & Hoh, M. (2018). Distributed interference alignment for multi-antenna cellular networks with dynamic time division duplex. *IEEE Communications Letters*, 22(4), 792–795.
18. Arzykulov, S., Nauryzbayev, G., Tsiftsis, T. A., & Abdallah, M. (2018). On the performance of wireless powered cognitive relay network with interference alignment. *IEEE Transactions on Communications*, 66(9), 3825–3836.
19. Mohammad-Ghasemi, H., Sabahi, M. F., & Forouzan, A. R. (2019). Limited feedback distributed interference alignment in cellular networks with large scale antennas. *AEU-International Journal of Electronics and Communications*, 110, 152875.
20. Liu, W., Tian, L., & Sun, J. (2020). Interference alignment for MIMO downlink heterogeneous networks. *IEEE Access*, 8, 35090–35104.
21. Teron, E., Agyapong, P. K., & Dekorsy, A. (2015). Performance evaluation of macro-assisted small cell energy savings schemes. *EURASIP Journal on Wireless Communications and Networking*, 2015(1), 1–23.
22. Prabakar, D., & Saminadan, V. (2020). Improving Spectral Efficiency of Small Cells with Multi-Variant Clustering and Interference Alignment. *Journal of Computational and Theoretical Nanoscience*, 17(5), 2203–2206.

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.



**Prabakar Dakshinamoorthy** received his B.E. degree in Electronics and Communication Engineering from Anna University, Chennai in 2007 and M.Tech. degree in Wireless Communication from Pondicherry University, Puducherry in 2009. He is having eight years of teaching experience. He is currently pursuing his Ph.D. degree in Department of Electronics and Communication Engineering at Pondicherry Engineering College. His area

of research includes, Interference Mitigation, Heterogeneous

Networks, MIMO Communication, Device to Device Communications, and Wireless Communications.



**Saminadan Vaitilingam** received his B.Tech. and M.Tech. degrees in Electronics and Communication Engineering from Pondicherry University, Puducherry in 1992 and 1994 respectively and Ph.D. degree in Electronics and Communication Engineering from Anna University, Chennai in 2006. He is currently working as a Professor in Department of Electronics and Communication Engineering at Pondicherry Engineering College, Puducherry. He has more than 20 years of Teaching and Research experience. He has more than 40 Research Publications in reputed journal and conferences. His area of research includes Optical Networks, Wireless Communication and VLSI design.



**Ramesh Sundar** obtained B.E. degree in Electronics and communication from Periyar University Salem, India in 2004. He obtained his M.E degree in Applied Electronics from Anna University Chennai, India in 2006. He is Completed his Ph.D. Degree from Sathyabama University, Chennai -119. in the field of Wireless Communication. He is currently working as an Associate professor in Vignan's Foundation for Science Technology and Research,

Guntur, Andhra Pradesh, India. His research interest includes Wireless Communication, Signal Processing, Artificial Intelligence.