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ORIGINAL RESEARCH

MMC-DIA: multi-metric clustering with differential interference alignment for improving small cell performance

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Abstract

Interference in small cells occurs due to the interoperability of different wireless communication technologies. Uncontrolled interference defaces the increasing user density and subscriber services. Therefore, interference management is mandatory to balance user service and performance enhancements. In this paper, multi-metric clustering with differential interference alignment (MMC-DIA) for leveraging the performance of small cell users is presented. This proposed technique operates in two phases namely clustering and differential interference alignment. In the clustering process, sum-rate maximization objective based grouping of small cell users is performed to retain the efficiency of communication. In a differential IA phase, the transmitted signal is analyzed for its first and second order of assessment on the basis of transmitter–receiver communication interval. Pre-coding and cancellation matrix over the signal vectors are imposed in the periodic time intervals for improving the degree of freedom (DoF) and thereby retaining the efficiency of the system. This is applicable for both the first and second order signal derivatives to handle inter and intra cluster interference along with the objective satisfaction. The performance of the proposed technique is compared for sum-rate, spectral efficiency, and DoF with the existing methods and non-clustering method respectively. From the comparative analysis, the proposed MMC-DIA is found to improve spectral efficiency and sum rate by 6.84% and 11.18% respectively. Similarly, with respect to the varying transmit power, the proposed MMC-DIA achieves 5.85% and 6.292% better spectral efficiency and sum rate.

Keywords Clustering · Differential optimization problem · Interference alignment · Rate loss · Small cell

1 Introduction

Communication Networks rely on wireless physical medium for information exchange between different devices. The wireless communication medium is responsible for scaling devices and distance in a flexible manner (Zeng et al. 2018; Wang et al. 2018). The role of information and communication technologies (ICT) in this process is prominent in handling connectivity and information sharing between the devices. As the platform is interoperable, incorporation of diverse ICT is feasible in this environment (Xu et al. 2018; Wang et al. 2020). Resource sharing and allocation are the contributing features in the shared platform for retaining the communication and resource sharing nature of the network and devices. Shared resource utilization is a common process through shared wireless channels. In such cases, interference is a notable dispute as it impacts the quality of service (QoS) of the users (Jiang et al. 2018). In multi-input multi-output (MIMO) environments, managing the antennas and receiver is a complex task as the overlapping and overhearing interferences are common in the shared medium. This is because of the mode of operation of the wireless communication; either time or space dependent. The heterogeneous characteristics of the devices and the communicating channel influences the QoS of the users as in time, spectrum or frequency domains (Hu et al. 2018).

Interference Alignment (IA) is one of the considerable factors impacting the QoS and resource allocation of the heterogeneous communication environment (Rihan and Huang 2018). IA suppressing and mitigating techniques are augmented with the resource allocation and service handling features of the communication networks, for suppressing cancellation errors and to grant achievable sum-rate (Dai

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et al. 2018). A heterogeneous communication network is packed with small and large cells under the synchronization of micro and macro base stations. The operations of the users in such environment are synchronized and to improve the service quality along with interference suppression (Jang 2018). Both internal and external interference in resource allocation and sharing is mitigated through reliable IA methods. The design of IA techniques is modeled on the basis of time, space, or frequency in accordance with the synchronization of transmitter–receiver pair. The orientation and physical design of the antennas are the density of the users in the communication region is the considerable factors in designing reliable IA solutions (Hu et al. 2018; Jang 2018; Hao et al. 2017).

IA features rely on some basic entities such as distance, received signal strength (RSS), density, etc. for addressing different issues in allocation. The impact of interference cannot be predicted fore-hand as the communication features vary with the representation and orientation of the device (Hao and Yang 2017). Signal strength observed in the receiver antenna determines the level of interference in the transmitted signal. IA solutions are confined with this factor along with the noise impulse between the communicating antenna pairs. In addition to this consideration, IA solutions must ensure less complex and deviation-free validations for improving the rate of allocation and interference suppression (Rihan and Huang 2018; Hao and Yang 2017; Oguejiofor et al. 2018). Pre-coding and cancellation matrix based solutions are prominent using the vector representation of the transmitted signals. Cluster-based solutions are emerging in IA optimization and handling by adapting to the density and communication features of the users and region. Another consideration is the communication intervals in which the alignment is performed. A best-fit clustering synchronizes end-user communication along with cell management and better IA. Cluster-dependent IA solutions are reliable by considering the physical and communication features of the devices and synchronizing the transmitter–receiver antenna pairs (Oguejiofor et al. 2018; Yu et al. 2020). The contributions of the paper are as follows:

(i) Introducing a multi-metric clustering technique with differential interference alignment for leveraging the performance of small cell heterogeneous communication network users.
(ii) Improving the performance of the small cell users by maximizing the objective of sum rate by achieving optimal interference alignment using multi-conditional analysis and stabilized cluster coalition process.
(iii) Performing a comparative analysis with different metrics for verifying the reliability of the proposed method.

The organization of the paper is given as: Sect. 2 describes the works related to IA, clustering, and performance enhancement of the small cell heterogeneous users in a brief manner. In Sect. 3, the proposed technique along with its clustering and differential IA is discussed with computational models. Section 4 presents the comparative study of the proposed technique with the existing methods and the clustering and non-clustering based approaches and the paper is concluded in Sect. 5.

2 Related works

In this section, the clustering with IA and other IA techniques from the existing works are discussed along with their contributions.

2.1 Clustering

Wang et al. (2019a, b, c) proposed a multiple kernel clustering algorithm for mitigating the local kernel alignment issues in clustering. Weight-based estimation is used for verifying the contributions of the local kernel alignments to improve the performance of the clustering process. The performance of the kernels is assessed using the previously assigned weights. A three-series validation algorithm reduces the issues in kernel alignment for leveraging the outcome of the clusters. This method is suitable for low level kernel samples as it increases the computation time for large data kernels.

Affinity propagation-based self-adaptive (APSA) is designed by Wang et al. (2019a, b, c) mitigating the convergence issues in conventional clustering methods in wireless sensor networks. Performance dependent clustering through K-medoids and topology are the considerable factors in creating optimal clusters. Wang et al. (2018) provided clustering solution with mobile data aggregation for wireless sensor networks. This is named as asynchronous clustering and mobile data gathering based on timer mechanism (ACMDGTM) that aids better packet delivery and conserves energy.

. Clustering based resource allocation with IA is introduced by Zhang et al. (2019). This method is introduced to maximize the small cell data transmission streams of heterogeneous networks. In particular the proposal in this work focuses on reducing the co-tier interference using perfect channel state information. Based on the information, the sub-channel allocations take place. The proposed algorithm reduces the computational complexity by achieving high level of optimality.

Average effective degrees of freedom (AEDoF) is presented by Zhou et al. (2018) for addressing the tradeoff issues between multiplexing gain and overhead in small cell networks. In this proposal the channel state information overhead is addressed using graph-dependent clustering algorithm. This algorithm significantly reduces the complexity of the maximization problem, and improves spectral efficiency compared to the other clustering methods.

2.2 Interference alignment

Li et al. (2018) introduced feasibility aware-partial interference alignment (FA-PIA) to improve the throughput and energy management of 5G wireless network. Asymmetric interference management through interference mitigation helps to maximize the DoF in the heterogeneous communication infrastructure. The proposed IA consists of three steps namely interference selection using transfer tree, partial IA through minimum interference leakage estimation, and recursive power optimization for residual interference handling. The interference links are classified on the basis of pressure transfer tree based IA constraint estimation.

Different from the above, a partial interference alignment technique for downlink transmissions in heterogeneous communication networks is introduced by Wang and Liang (2018). The tradeoff between the different levels of users is suppressed by selecting appropriate subspaces to mitigate the impact of hard IA. Using singular value distribution of the channel matrix, the transmit dimensions and the conditions are addressed in this method.

Relay-dependent communication proposed by Dao et al. (2019) is aided for thwarting inter-cell interference (ICI) in 5G heterogeneous networks. This proposal addresses resource availability and allocations issues in the heterogeneous environment. Resource availability maximization (RAmax), relay connected pico eNodeB, and relay-Internet of Things (reIoT) functions are jointly used for improving the channel quality so as to improve the network throughput.

Liu et al. (2017) designed feedback concentration based IA (FCIA) for D2D communication in order to improve its sum rate. Based on the global channel state information, the proposed algorithm estimates the precoding matrix for reducing interference along with transmission coordination. In this design the forward and backward pilot exchange between the transmitter and receiver is used for estimating the channel state information. Such estimation improves the classification of precoding matrix for IA. This method is effective in reducing the overhead in IA and also improves device discovery time.

Joint interference management (JIM) is introduced by Xiao et al. (2018) for ultra-dense small cell networks. This management method is based on overlapping coalition formation game (OCFG) for assessing the cooperative communication nature of the devices. IA is mitigated by making autonomous coalition decisions over the self-organizing interactions of the small cells. This method achieves reliable tradeoff between the cost and advantages of the joint management system, to improve the throughput of the small cell networks.

Zhou et al. (2017) analyzed the practicable conditions for IA in small cell networks. The IA conditions in full-duplex communication mode are predicted using Bezout's theorem. The authors concluded that the density of user antennas confines the performance of the IA. The authors also suggested that implication of opportunistic full-duplex modes could achieve better DoF.

Mohammad Ghasemi et al. (2019) proposed an IA with less feedback information for large-scale antennas in cellular networks. Using low-rank matrix approximation theory, this IA method estimates the perfect and imperfect channel state information for improving the performance of the cellular networks. With the help of covariance and precoder matrix, the interference in non-uniform channels is suppressed. This method achieves better sum-rate for varying antennas and feedback approximations.

Li and Li (2018) discussed the impact of Grassmannian Conjugacy gradiant algorithm for joint interference alignment precoding (GCGA-JIAP) in multi-user MIMO systems. This algorithm optimizes the Euclidean space for reducing the computational cost with the knowledge of the degeneration dimensions. This method achieves the iterate convergence to improve the sum-rate of the MIMO users.

Linear Finite State Markov Chain (LFSMC) is proposed by Shi et al. (2018) is exploited for IA in cognitive radio networks. This method relies on the perfect channel state information in a multi-user environment for balancing between the transmitters and receivers in a reliable manner. The impact of imperfect channel state information is reduced using predictors based on simplified LFSMC. This method achieves better spectral efficiency with less prediction error. The disagreement of this method is the adaptation of simplified LFMSC that is congruent with the application scenario. This results in paused sum rate due to finite state decisions during IA.

A stochastic geometric based IA is introduced by Luo et al. (2017) for two-tier heterogeneous wireless networks. In this method, the upper bound of the IA streams is first identified to identify the tradeoff between signal-to-interference ratio and multiplex gain. In this approach, the precise estimation of upper bound conditions are identified in fore-hand for effective IA. Throughput in the consecutive sequences is maximized by mitigating the tradeoff between SINR and multiplexing gain, respectively. This geometry model is reliable over cross-tier and inter-cluster interferences and also maximizes throughput with less path-loss.

Grouping based IA approach for heterogeneous network is proposed by Qin et al. (2017). Grouping based two-stage distributed IA (GTDIA) is reliable in grouping pico and macro users to classify and identify the interference between them. In this method beamforming matrix is used for cancelling interference between the layers. The reciprocity in time-division duplex system issues is also addressed in the distributed IA to improve the sum rate of the heterogeneous network users.

Zhang et al. (2017) introduced centralized efficient sub-channel allocation scheme for quality of service based IA in dense small cell networks. Combinatorial optimization problem is formulated for graph partitioning and cluster based sub-channel allocation. This reduces the computational complexity of the proposed method in both perfect and imperfect channel state information conditions.

Ma et al. (2016) proposed two-stage precoding based IA for multi-cell MIMO communication. The complexity in channel estimation using frequency division duplexing (FDD) and feedback mechanism is reduced in this method. The overhead in channel estimation and FDD is reduced using the two-stage precoding process. This method jointly achieves less interference rate and also maximizes the data rate of the end-users in a reliable manner. This method is confined to limited user support besides multi-antenna support, due to intra-cell interference issues.

The fore-discussed methods perform reliable IA solutions based on external infrastructure units such as relays (Dao et al. 2019) or improve the resource allocation based on the density and efficiency of first order transmitted signals (Xiao et al. 2018; Zhang et al. 2019, 2017). These methods improve the resource utilization along with the interference prediction and alignment at fixed cell structures and consistent transmit power. This is feasible if the transmitter–receiver antenna pairs are synchronized in the same time interval. Therefore, the alignment vectors used in these scenarios are valid for fixed time intervals and hence the resource allocation and coalition can alone prevent interference (Zhang et al. 2019; Wang and Liang 2018; Qin et al. 2017). Different from these methods, the proposed method assesses the transmitted signal in its first and second order of derivatives, increasing the chances for IA in any time interval. This helps to retain the performance of the transmitter–receiver pairs in both synchronized and un-synchronized communication interval.

3 Proposed interference alignment method

3.1 System model

The 5G communication network consists of different sets of device including macro and small cell users. Let k represent the small cells in this 5G environment. The density of n users varies with the available cells, where the users employ independent antennas for communication. The data exchanged between the users is denoted as d and it varies with communication time intervals. For each interval, the users are allocated with individual and different time slots. The span of the communication slot is not the same for all the n users. A local base station (LBS) is responsible for organizing the communications of the small cell users. The LBSs are connected to the macro base station (MBS) that acts as a service provider/primary user. In Fig. 1, the system model is presented.

In the above system model, the local base station is capable of forming small clusters with the available devices. The data exchange d is facilitated using the LBS at a low level and the further exchange of data is preceded using the MBS. The number of devices in a small cell varies depending on the mobility and availability of the users. The cluster is formed using different LBS to thwart the impact of interference. Data rate loss and density of the users are the initial conditions in forming a cluster using LBS.

3.2 Methodology

The proposed clustering assisted IA is defined into two phases namely cluster formation and interference alignment. The phases are independently modeled to reduce the computation and signal processing complexities in 5G communications. Contrarily, the functions of the independent phases are jointly used to suppress communication issues.

3.2.1 Multi-metric clustering process

The multi-metric clustering process is used to determine stability of the grouped users in maximizing sum-rate (S_r) is performed as a linear optimization based on weight factor of different metrics. The considered metrics for clustering are:S_r, rate loss (R_l) and density (ρ_n). Therefore, the objective of a $LBS(O)$ is given as

$$O(CH) = \left. \begin{array}{c} \operatorname{argmax} \sum_{i=1}^{c} S_{r_i} \\ and \\ \operatorname{argmax} \sum_{j=1}^{m} R_{l_j}, j \in m \end{array} \right\} \quad (1)$$

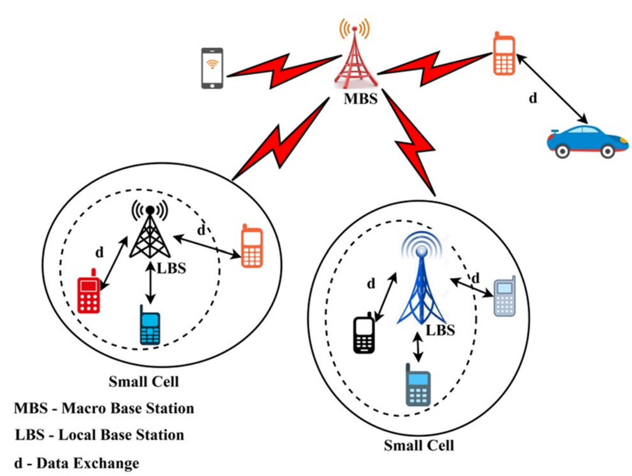

Fig. 1 System model

In the above equation $O(CH)$ is the objective of the LBS candidate that is to be fulfilled. The condition of the objective is defined for all the C clusters and m transmissions. From Eq. (1) the role of clusters in accordance to the rate loss is accounted to provide a stable clustering instance. The density of the users impacts the minimization of R_l and thus it is reflected in the S_r maximization objective. The communications links between n and LBS vary with ρ_n and time. Therefore a stable/constant set of neighbors is not ensured in the view of achieving $\max\{S_r\}$ for all i. The rate loss between an i^{th} user and $j^{th} LBS$ is computed as

$$R_{l_{(i,j)}} = \begin{cases} \tau_{ji} + \tau_{ij}, & if\ i \neq j \\ 0, & otherwise \end{cases} \tag{2}$$

Here

$$\tau_{ij} = log_2\left(1 + \frac{\gamma_{ij} \cdot p_j}{p_n}\right) - log_2\left(1 + \frac{\gamma_{ij} p_j}{p_n + \gamma_{ij} p_i}\right) \tag{3}$$

where, γ_{ij} is the path loss observed between i and j, p_j is the transmit power of LBS, p_n is the total transmit power. With respect to the Eq. (3), the actual S_r is computed using Eq. (4) as

$$\left.\begin{array}{l} S_r = log_2\left(1 + \frac{p_j \gamma_{ij} |u_j H_{ij} v_j|^2}{\hat{I}_j + \underline{I}_j + p_n}\right) \\ \quad where, \\ \hat{I}_j = \gamma_{ij} p_i |u_j H_{ij} v_j|^2, i \in c \\ \underline{I}_j = \gamma_{ij} p_j |u_j H_{ji} v_j|^2, j \notin c \end{array}\right\} \tag{4}$$

In Eq. (4) the sum-rate achieves with inter and intra ($\underline{I}_j and \hat{I}_j$) cluster R_l observed in m. The clustering constraints are re-defined such that $\min\left\{R_{lj}\right\}, j \in C$ is true for all $O(CH)$ lies in $\left[S_r + R_{l(i,j)}\right]$ and S_r. This means the clustering LBS must satisfy the constraint of achieving high S_r other than the expected sum-rate ($\hat{S}_r$) provided the received signal strength (RSS) is high. The problem of retaining cluster stability is solved as a linear optimization between S_r and R_l irrespective of the distance (d) and p_n of n. This optimization of the independent metrics is processed in a joint manner such that $\hat{S}_r = S_r - R_l$.

Let X and Y represent the individual matrices of S_r and R_l such that $\alpha_1 X + (-\alpha_2) Y \leq \hat{S}_r$ or $\alpha_1 X - \alpha_2 Y \leq \hat{S}_r$ is the stabilizing constraint for the cluster. Here,α_1 and α_2 are the balancing co-efficient for $\hat{S}_r$ and R_l with respect to ρ_n. Therefore, the matrix of X and Y is represented as

$$\hat{S}_r = \alpha_1 \begin{bmatrix} x_{11} & x_{12} \dots & x_{1c} \\ x_{21} & & \\ \vdots & x_{22} \dots & x_{2c} \\ x_{m1} & x_{m2} \dots & x_{mc} \end{bmatrix} - \alpha_2 \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}, \{x_{11}, x_{12}, \dots x_{mo}\} \in X\, and\, y_1, y_2, \dots y_c\} \in Y \tag{5}$$

The matrix representation of $\hat{S}_r$ as in Eq. (5) is used for estimating the stability of the cluster. Considering the fact that S_r and R_l are inversely proportional and ρ_n varies with time, α_2 is modeled as transmit for different m as $\{t_1, t_2, \dots t_m\} \in t_t$. Similarly, to prevent self-interference the cases where $m = c$ are mitigated Eq. (5) and therefore

$$\hat{S}_r = \alpha_1 \begin{bmatrix} 0 & x_{12} \dots & x_{1c} \\ x_{21} & 0 \dots & x_{2c} \\ \vdots & & \\ x_{m1} & x_{m2} \dots & x_{mc} \end{bmatrix} - \begin{bmatrix} \frac{1}{t_1} \\ \frac{1}{t_2} \\ \vdots \\ \frac{1}{t_n} \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \tag{6}$$

This sum-rate achieved in Eq. (6) permits self-interference cancelled $\hat{S}_r$ observed in the receiver end. The changes in ρ_n and $m = c$ conditions are validated for mitigating this clause. Therefore, the available ρ_n and t_t are impacting factors of $\hat{S}_r$. The factor α_1 must also be modeled with respect to time but this leads to the distortion is channel and transmission allocation time. Therefore,α_1 is accounted with respect to ρ_n and therefore, the overall S_r of all n in t_t is estimated for a selected LBS. An odd condition of α_1 and α_2 is the distribution of weights $\in$ [0,1] provided $\alpha_1 > \alpha_2$ in all m. If α_1 is found to be equal or less than α_2, the LBA is replaced with the next possible neighbor. This conditional verification is used group. As mentioned earlier, the sum rate is achieved between $[S_r - R_{l_{(i,j)}}]$ and S_r in all m. The objective of CH selection is then redefined as

$$\sum_{j \in c} \sum_{i \in n} |\sqrt{\gamma_{ij}} H_{ij} v_i - O_j H_{ij} \sqrt{\gamma_{ij}} H_{ij} v_i|^2 \tag{7}$$

The variable O_j is the orthogonal representation of the transmitted signal. Here,$O_j . H_{ij} = \underline{I}_j - 1$, if $|u_j|^2 = 1$ else $O_j . H_{ij} = \hat{I}_j - 1$, if $|v_j|^2 = 1$. The transmitter and receiver signal (i.e.) u_j and v_j are not always unity for the fading factor H_{ij} observed. Now, using the above conditions, the $\hat{S}_r$ in the receiver end is thus classified as

$$\hat{S}_r = \begin{cases} S_r, & if\ |u_j|^2 = 1 \\ S_r - R_{l_{(i,j)}}, & if\ |v_j|^2 = 1 \end{cases} \tag{8}$$

Resolving Eq. (8) from two different perspectives, the conditions for a stable clustering is derived as

$$\left.\begin{array}{l} \begin{bmatrix} 0 & x_{12} & \dots & x_{1c} \\ x_{21} & 0 & \dots & x_{2c} \\ \vdots & & & \\ x_{m1} & x_{m2} & \dots & x_{mc} \end{bmatrix} \times \rho_n = \left[\gamma_{ij} p_j |u_j H_{ij} v_j|^2\right] d \\ \begin{bmatrix} 0 & x_{12} & \dots & x_{1c} \\ x_{21} & 0 & \dots & x_{2c} \\ \vdots & & & \\ x_{m1} & x_{m2} & \dots & x_{mc} \end{bmatrix} \rho_n - \begin{bmatrix} y_1/t_1 \\ y_2/t_2 \\ \vdots \\ y_m/t_m \end{bmatrix} - d\left[\left[\gamma_{ij} p_i |u_j H_{ij} v_i|^2\right]\right. \end{array}\right\} \tag{9}$$

With respect to the self-interference cancellation within the cluster, the sum-rate relies on ρ_n and S_r for all the 'm' transmissions. On the other hand, if there is inter and intra cluster interference, then the (y_m/t_m) determines the rate of S_r. Therefore, the selected LBS as a CH must balance between these two spans. This is the achievable sum-rate augmented for all $|u_j|^2 = 1$ and $|v_j|^2 = 1$ condition ensuring the transmitted signal ($T^\propto$) is received with better strength in the receiver end. There are two stability analysis cases with respect to $|u_j|$ and $|v_j|$ that are discussed as follows:

Case 1: The transmitted signal $T^\propto$ vectors $u_j > v_j$ are not equal.

Analysis 1: In this case either $u_j > v_j$ and $u_j < v_j$ is the achievable condition. Obviously, $u_j < v_j$ is not a valid condition and hence this is not accounted. Contrarily, the normalization is $u_j > v_j$ where the sum-rate objective as in Eq. (1) is achieved for all $|u_j|^2 = 1$. This is concluded for the users within C as the self-interference is cancelled through the linear representation. The linear representation models time slot allocation in an independent manner. The objective in Eq. (1) holds unless $R_l = 0$ inside and outside the cluster. The changes in time slot allocation (i.e.) t_t results in $R_l \neq 0$ condition.

The overlapping t_t allocation also causes losses in transmission and therefore $|v_j|^2 \neq 1$ for all $|u_j|^2 = 1$. In this case, $\gamma_{ij} p_i u_j |H_{ij} v_j|^2 d$ is the achievable S_r. Therefore, the S_r is computable for the alternating (discrete) $T^\propto$ such that Eq. (9) is the final S_r. This S_r is estimated for all m and if $\max\{S_r\}$ in any m determines the stability of the cluster. On the other hand, if $\max\{S_r\} < \left[S_r - R_{l(i,j)}\right]$ of any t_t, then the CH has to replace with new LBS.

Case 2: The transmitting and receiving vectors are same (i.e.) $\left|u_j\right| = |v_j|$.

Analysis 2: In this analysis, the transmitted signal is received without distortion, providing an ideal case. For a limited number of users sharing the common radio range, the above is feasible where, R_l is very less and hence it is negligible and therefore, from Eq. (9),$p_i = p_j$ in all t_t. Solving Eq. (9) further, the resultant of the linear representation in $y_m = 0$ and therefore,$\alpha_1 X \leq \widehat{S}_r$. As this case is an ideal transmission scenario and $p_i = p_j$,$\widehat{S}_r = \alpha_1 X$. From this point, though $\left|u_j\right|$ and $|v_j|$ are equal, S_r relies on the density of the users.

From both the case of analysis, the CH candidates are listed as $\max\{S_{r_i}\}, i \in C$ and $\min\left\{R_{l_j}\right\}, j \in m$. The LBS satisfying the above condition is capable of forming a group with the neighbors that satisfies case 2 and then case 1 is verified for all small cell clusters. This verification follows Eq. (9) provided, the CH satisfies Eq. (7). The need for next CH (i.e.) change of CH is achieved, if $argmax\left\{\frac{\sum_m \alpha_2}{\rho_n}\right\}$ is observed for any LBS.

3.2.2 Differentiated interference alignment

In differentiated IA, the process of signal classification and interference suppression is performed in a differential manner. The classified received signal is analyzed for its second order derivative until the IA is made. In this case, IA is achieved if $d \leq \frac{n_t + n_r}{n+1}$, where n_t and n_r area the transmitter and receiver antennas. The received signal $1/r$ is denoted using Eq. (10) as

$$\Gamma_r = \sum_{i=1}^{C} d_i v_i H_{ii} O^{T_i d_i} + \sum_{j+1} v_i H_{ij} u_j + \eta_o \tag{10}$$

where, $O^{T_i d_i}$ is the transmitted signal and H_{ii}, H_{ij} are used to represent the channel fading factor of the i^{th} n_t and j^{th} n_r respectively. The variable η_o is used to denote the white noise observed in the transmission process. The transmitted signal (Γ_t) is analyzed with the cancellation and pre-coding matric ($\mathbb{C}_i and \Delta_j$). With respect to $\mathbb{C}_i$, the received signal is classified as

$$\bar{\Gamma}_r = \sum_{i=1}^{c} d_i v_i \frac{H_{ii}}{\mathbb{C}_i} + d_i v_i \frac{O^{T_i d_i}}{\mathbb{C}_i} + d(u_i + v_j) \tag{11}$$

In Eq. (11) the second order derivative of the Γ_r is extracted for maximum IA. Therefore, the Δ_j matrix is augmented for Eq. (11)$d_i v_i \frac{H_{ii}}{\mathbb{C}_i} + d_i v_i \frac{O^{T_i d_i}}{\mathbb{C}_i}$ to extract the actual signal. The signal-to-noise ratio in Γ_r is computed using Eq. (12)

$$SNR_r = \frac{(d_i)^H H_{ii} t_i (t_j) H_{ii}^H d_i}{(d_i)^H \tau_{ij} d_j} \tag{12}$$

where τ_{ij} is the noise plus interference observed in $\bar{\Gamma}_r$. This noise plus interference is not assured in Γ_r as the pre-coding and cancellation matrices are induced in all m transmissions. Therefore,

$$\tau_{ij} = \begin{Bmatrix} \sum_{i=1}^{C} \sum_{j=1}^{m} H_{ji} t_j (t_i)^H (H_{ji})^H - H_{jj} t_j^i (t_j^i)^H + \rho_n \left(\bar{I}_j - 1 \right), if \left| u_j \right|^2 = 1 \\ = \sum_{i=1}^{C} \sum_{j=1}^{m} H_{ji} t_j (t_i)^H (H_{ji})^H - H_{jj} t_j^i (t_j^i)^H (H_{jj})^H + \rho_n \left(\hat{I}_j - 1 \right), if \left| v_j \right|^2 = 1 \end{Bmatrix} \tag{13}$$

The cancellation and pre-coding matrix operations are performed on the second order $\bar{\Gamma}_r$ for segregating interference for suppression. The Γ_r is differentiated as two segments for differential analysis (i.e.) $d_i v_i \frac{H_{ii}}{\mathbb{C}_i}$ and $d_i v_i \frac{O^{T_i d_i}}{\mathbb{C}_i}$ for Δ_j analysis. In both the cases, the condition for achieving optimal IA is $d \le \frac{n_t + n_r}{n+1}$. This means, the data stream must be less than the communicating pair of transmitters and receivers.

Now, the sum-rate condition is equated for the different segments of Eq. (11). IF the IA is achieved given the above condition, then S_r is high. The verification of the above segments with the X and Y in Eq. (6) is equated as

$$\left.\begin{array}{l} \gamma_{ij} p_j |u_j H_{ji} v_j|^2 d = d_i v_i \frac{H_{ii}}{\mathbb{C}_i}, |u_i| = |v_j| \\ \gamma_{ij} p_j |u_j H_{ji} v_j|^2 d = d_i v_i \frac{H_{ii}}{\mathbb{C}_i}, -\frac{R_{l(i,j)}}{t_i}, if |u_i| > |v_j \end{array}\right\} \tag{14a}$$

Similarly,

$$\left.\begin{array}{l} d_i v_i O^{T_i d_i}.\Delta_j = \gamma_{ij} p_j |u_j H_{ji} v_j|^2 d, if |u_i| = |v_j \\ d_i v_i O^{T_i d_i}.\Delta_j - \frac{R_{l(i,j)}}{t_i} = \gamma_{ij} p_j |u_j H_{ji} v_j|^2 d, if |u_i| > |v_j \end{array}\right\} \tag{14b}$$

The case presented in Eqs. 14(a) and 14(b) is differentiated with the $\begin{bmatrix} 0 & x_{12} & \dots & x_{1c} \\ x_{21} & 0 & \dots & x_{2c} \\ \vdots & & & \\ x_{m1} & x_{m2} & \dots & x_{mc} \end{bmatrix}$ matrix along with R_l estimation for the three cases. Therefore, the received signal is analyzed for the following cases to verify if the IA condition is satisfied. On the other hand, the IA condition achieved describes the DOF achieved by the small cell users for maximizing S_r. The above representations are categorized into three cases as follows. In all the three cases, rank based IA is employed for achieving maximum DOF and sum rate, satisfying the previously mentioned condition.

Case 1: In this case, $d_i v_i \frac{H_{ii}}{\mathbb{C}_i}$ and $d_i v_i H_{jj} \Delta_j$ without $R_{l_{(i,j)}}$ is considered.

Analysis 1: In this case, there is no external interference and hence, $\mathbb{C}_i = 1$ is the unit matrix for v_i. Therefore, the achievable sum-rate is $d_i v_i H_{jj}$ [as Δ_j =1] such that the vector representation of $n_t > d$. If $n_t > d$, then $\left(n_t + n_r\right) > d$, satisfying the IA condition. Therefore,$rank(d_i v_i H_{ii}) = \emptyset$, provided $\mathbb{C}_i = \Delta_j = 1$ is the rank based condition in IA, for this case (see Fig. 2).

Case 2: Considering the Eq. 14(a) (i.e.) $d_i v_i \frac{H_{ii}}{\mathbb{C}_i} - \frac{R_{l(i,j)}}{t_i}$ is the achievable sum-rate.

Analysis 2: Here, the cancellation matrix for the self-interference mitigated X requires an augmented $\bar{\Gamma}_r$ for maximizing $\emptyset$. Therefore,

$$\max\left\{S_r\right\} = \bar{\Gamma}_r.\frac{T_i}{\mathbb{C}_i}.H_{ii}(t_i)^H = \emptyset, in\ all\ m \tag{15}$$

Such that

$$rank(d_i v_i \frac{H_{ii}}{\mathbb{C}_i}.\mathbb{C}_i) = \bar{\Gamma}_r - R_{l_{(i,j)}} = \emptyset \tag{16}$$

Is the DOF maximizing procedure.

In this case, $\Delta_j = 1$ whereas $\mathbb{C}_i$ is not unity, so as to achieve $\max\left\{S_r\right\}$ in all the m transmissions (Fig. 3).

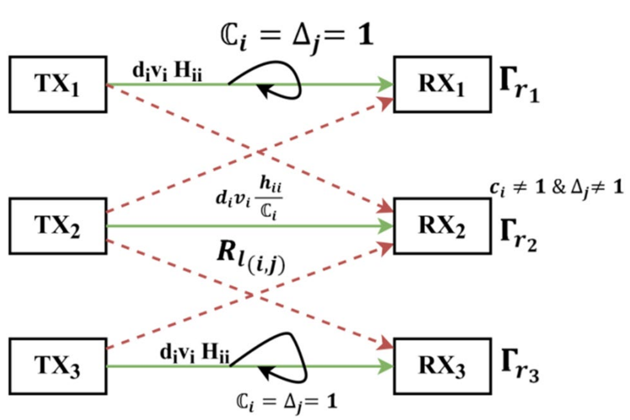

Fig. 2 $\mathbb{C}_i = \Delta_j = 1$

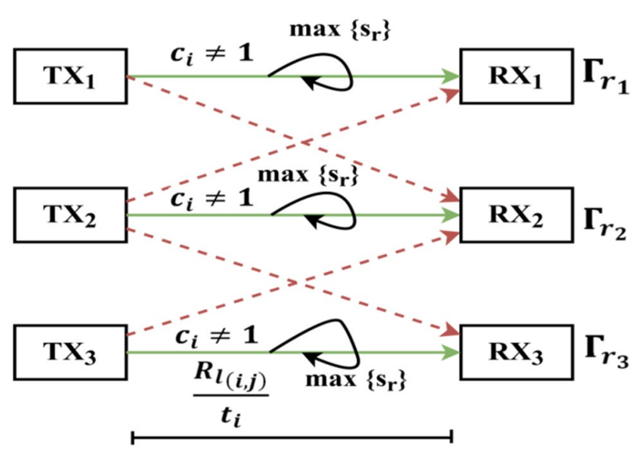

Fig. 3 $\Delta_j = 1$

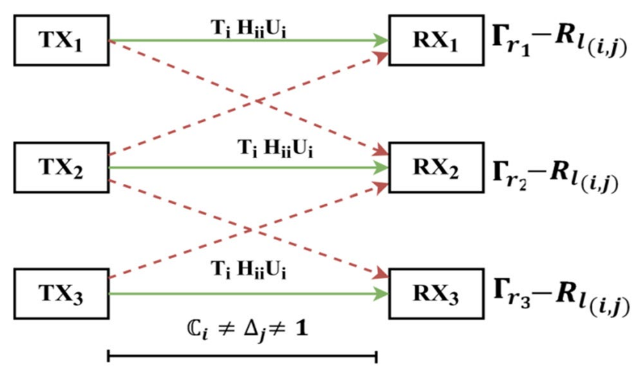

Fig. 4 $\Delta_j \neq 1, \mathbb{C}_i \neq 1$

Table 1 Simulation parameters and values

Simulation parameter	Values
Network region	500 m × 500 m
Cell count	50
Path loss model	Rayleigh Fading
Bandwidth	180 kHz
Path loss factor	3.76
MBS	8
Users	200
Noise power	10^{-7}

Case 3: $d_i v_i O^{T_i d_i}.\Delta_j - \frac{R_{l_{(i,j)}}}{t_i}$ is the consideration for estimating the sum rate in the received signal.

Analysis 3: The IA condition for maximizing DOF relies on the estimation of transmission loss in the Γ_r, the difference in Γ is the expected $R_{l_{(i,j)}}$. If the loss is high than the difference, as estimated using the interference precoding matrix of $|u_i|$, then the transmission is halted. This is because, the received Γ_r is interference and a new channel is to be selected for reducing further interference and maximizing $\varnothing$. Therefore, the rank process is modified as

$$rank\left(T_i \frac{H_{ii}}{u_i} \frac{\Delta_j}{\mathbb{C}_i}\right) = \Gamma_r - R_{l_{(i,j)}} = \varnothing \tag{17}$$

Is the maximum DOF condition. Therefore, the SNR analysis for all the three cases relies on the rank process in Eq. (16) and (17) (Fig. 4).

In case 1, $rank\left(T_i H_{ii} u_i\right) = \varnothing$ as there is no need for Δ_j and $\mathbb{C}_i$. On the other hand, though case 3 relies on Γ_r for rank estimation and $\Delta_j \neq 1, \mathbb{C}_i \neq 1$ is the required condition for achieving maximum DOF.

4 Performance analyses

The proposed MMC-DIA technique is assessed for its performance using the simulations performed using MATLAB tool. In a network of 0.5 km × 0.5 km dimension, 50 cells are deployed with varying user densities. Each cell is allocated with a local base station and the macro base station consolidates the communication of LBS. The transmit power of the MBS is 50dBm. The network setup resembles the structure presented in Fig. 1. In Table 1, the detailed simulation parameters are presented.

The comparative analysis of the proposed technique is performed using the metrics sum-rate, spectral efficiency, and DoF. This comparison is performed as the study between the existing methods and with non-clustering instance. For the comparative study with the existing methods, the existing methods LFSMC (Shi et al. 2018), JIM (Xiao et al. 2018), and FA-PIA (Li et al. 2018) are considered.

4.1 Impact of number of cells

The varying number of cells accommodates multiple densities of users in the communication region. The rate of interference in d varies with the channel utilization and time synchronization between the LBS and the end-user devices. Therefore, the varying density of cell does not guarantee fixed interference and hence the alignment is to be performed in an adaptive manner. The sum rate and spectral efficiency with respect to the varying cells is presented in Figs. 5 and 6.

The cluster based arrangement groups the available users to be restricted to the LBS, preventing unsynchronized channel access. Therefore, the rate of interference due to independent utilization is confined in the proposed technique. Besides the probability of clustering is high as different metrics are analyzed for forming the joint communication architecture. The Γ_r at different cases analyzing the least feasible constraints for path-loss and overlapping interference. Based on the availability of channel, the sum rate is achieved as per the objective in Eq. (1) where in the achievable rate as per the three cases is bound to $\left[\Gamma_r - R_{l(i,j)}, \Gamma_r\right]$. This is verified by validating the differential alignment in both the clustering and all the analysis cases. Thus, the sum rate is maximized by suppressing the interference in the proposed technique (see Fig. 5).

The spectral efficiency of the proposed technique is improved by assigning appropriate verification cases for

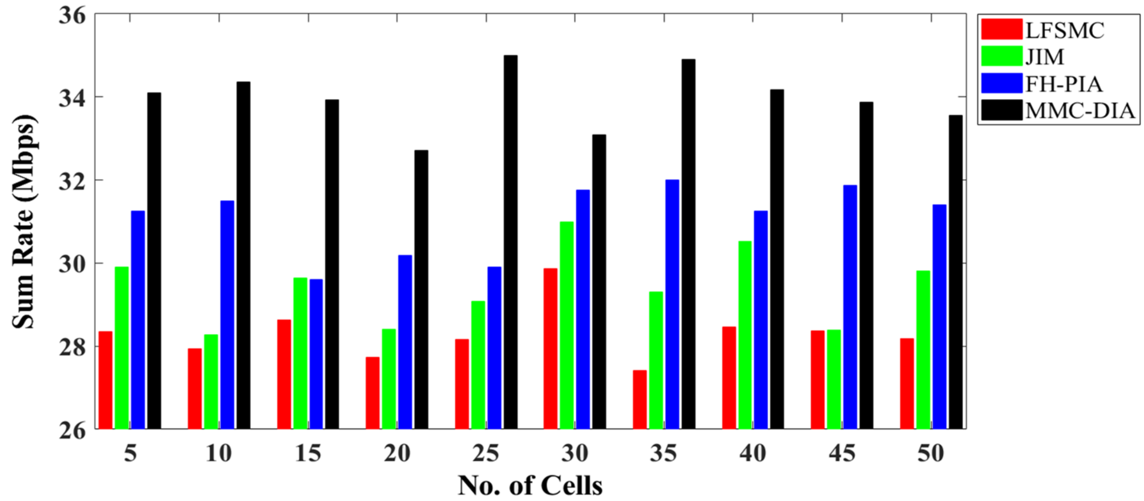

Fig. 5 Sum rate versus cells

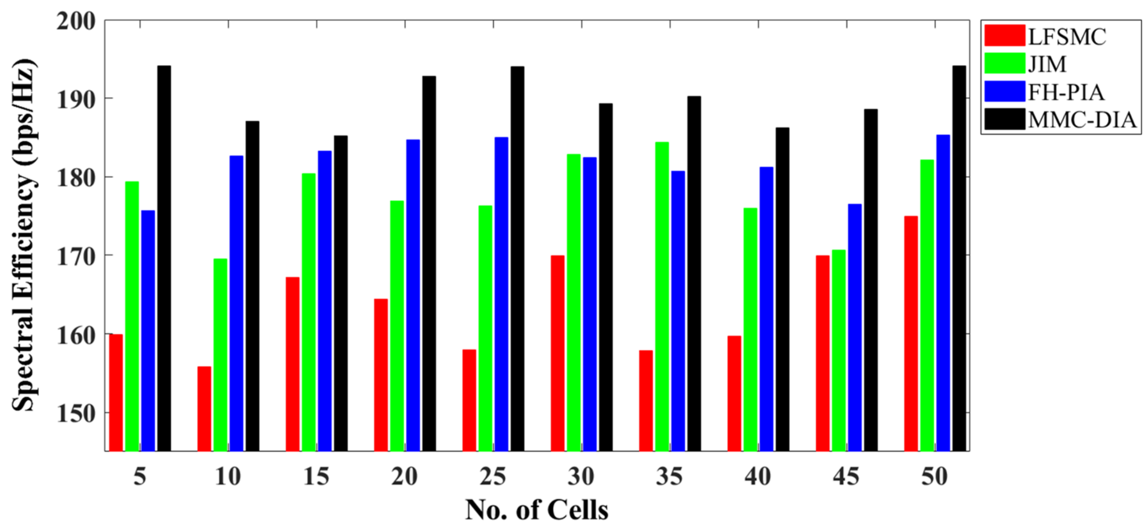

Fig. 6 Spectral efficiency versus cells

Table 2 Comparative analysis with respect to varying cells

Metrics	LFSMC	JIM	FA-PIA	MMC-DIA
Spectral efficiency (bps/Hz)	174.93	182.14	185.33	194.07
Sum rate (Mbps)	28.19	29.82	31.41	33.56

the different segments of X and Y as per Eq. (6). The verifications performed using Eq. (14a) and (14b) is resolved for R_l estimation to verify the condition of $d \leq \frac{n_t+n_r}{n+1}$ is satisfied. As the SNR_r is achieved in a optimal manner for both the first order Γ_r and second order $\bar{\Gamma}_r$, $d_i v_i\left(\frac{H_{ii}}{\mathbb{C}_i} + \frac{O^{T_i d_i}}{\mathbb{C}_i}\right)$ is the maximum efficiency achieved is this method. The impact of pre-coding and cancellation vectors over Γ_r and $\bar{\Gamma}_r$ based on the three cases (as suitable) is imposed to maximize the spectral efficiency (see Fig. 6). In Table 2, the results of the above comparison are tabulated.

In both the sum-rate and spectral efficiency detainment, the Γ_r and $\bar{\Gamma}_r$ as classified on the basis of R_l is imposed with τ_{ij}, $H_{ii}\Delta_i$ and $\mathbb{C}_i$ verification, for each cell in an adaptive manner. Therefore, the impact of varying cell density holds less impact of R_l over Γ_r and Γ_r achieving better efficiency.

4.2 Impact of varying transmit power

The impact of varying transmit power at the MBS achieves high sum-rate in a view to maximizing the efficiency of the

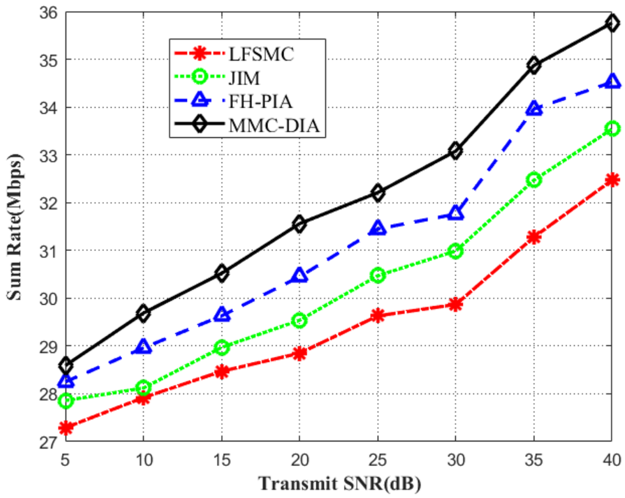

Fig. 7 Sum rate versus transmit SNR

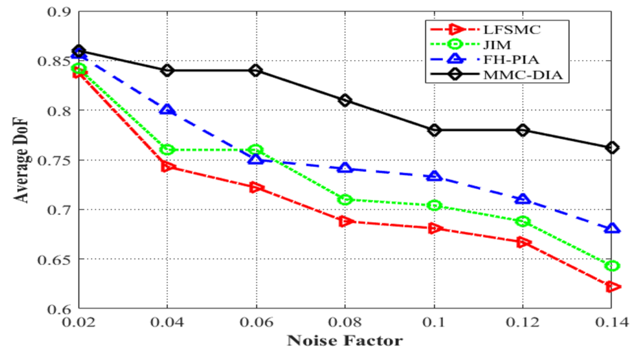

Fig. 9 Average DoF versus noise factor

Table 3 Comparative results with respect to varying transmit SNR

Transmit SNR	LFSMC	JIM	FA-PIA	MMC-DIA
Spectral efficiency (bps/Hz)	179.67	189.04	191.89	198.47
Sum rate (Mbps)	32.47	33.54	34.52	35.76

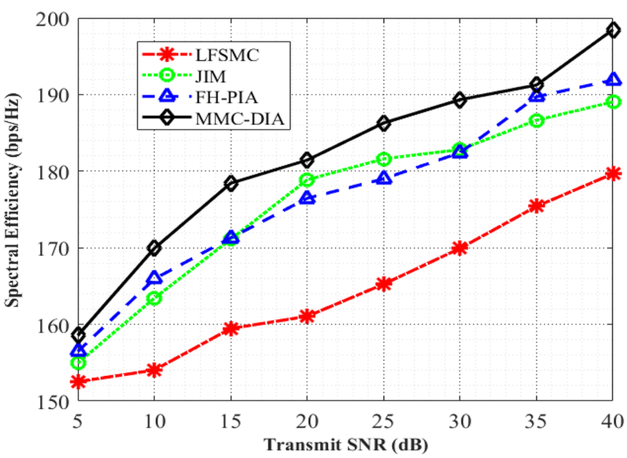

Fig. 8 Spectral efficiency versus transmit SNR

network. The transmit power allocation requires free-flow of channels causing overlapping and hence the interference is increased. Therefore, the R_l impacts both spectral efficiency and sum rate that is to be suppressed to retain the efficiency of the exchange. In Figs. 7 and 8 the sum-rate and spectral efficiency of the network is presented as a comparison for the varying transmit power.

In order to retain the sum rate, the differential case of $R_{l(i,j)}$ and $-\frac{R_{l(i,j)}}{t_i}$ cases are validated for $\Gamma_r and \Gamma_r$ at different transmit power intervals. The changes in transmit power with respect to R_l and t_i for estimation of $\varnothing$ in all the three cases helps to maximize the sum rate. The objective of Eq. (1) for LBS is retained in Γ_r or at-most in the Γ_r of the entire transmitted signal. This helps to retain the S_r irrespective R_l due to different channel availability conditions. Besides, this is achieved by segmenting X and Y as in Eq. (14a) and (14b) respectively. The matrix based correlation and interference suppression for validating Γ_r and Γ_r in $\frac{1}{r}$ helps to achieve maximum S_r.

The SNR_r of the varying transmit power at the LBS is analyzed in the first and second order derivatives ofΓ_r. The classification of Γ_r on the basis of $d_i v_i \frac{H_{ii}}{\mathbb{C}_i}, d_i v_i \frac{oT_i d_i}{\mathbb{C}_i}$ for analyzing Δ_j helps to estimate the rank for achieving$\varnothing$. Besides,τ_{ij} based classification of Γ_r helps to verify if $\Delta_j = \mathbb{C}_i = 1$ or$\Delta_j \neq 1, \mathbb{C} \neq 1$, or either of the cases. This verification retains the pre-coding and cancellation matrix to verify if $d \leq \frac{n_t+n_r}{n+1}$ for the consideration of $R_{l(i,j)}$ or$-\frac{R_{l(i,j)}}{t_i}$. This process is unanimously adapted for all any number of clusters with varying transmit power, retain the spectral efficiency.

4.3 Average DoF

In Fig. 9, the DoF with respect to the noise factor is compared between the existing and proposed methods. The impact of R_l or $-\frac{R_l}{t_i}$ is balanced by maximizing $\varnothing$ at each d exchange with the knowledge of τ_{ij}. The covariance and pre-coding matrix estimations on the cancellation and IA for the varying cells and transmit power is adopted for Γ_r. This Γ_r is classified from Γ_r due to the influence of R_l. If the condition of $(n_t + n_r) > d$ is not satisfied, then matrix based analysis and IA is performed for maximizing the DoF.

In all the three cases of analysis, the criterion of $\mathbb{C}_i = \Delta_j = 1, \Delta_j = 1$ and $\mathbb{C}_i \neq 1$, rank$\left(T_i \frac{H_{ii}}{u_i} \frac{\Delta_j}{\mathbb{C}_i}\right)$ is the validat-

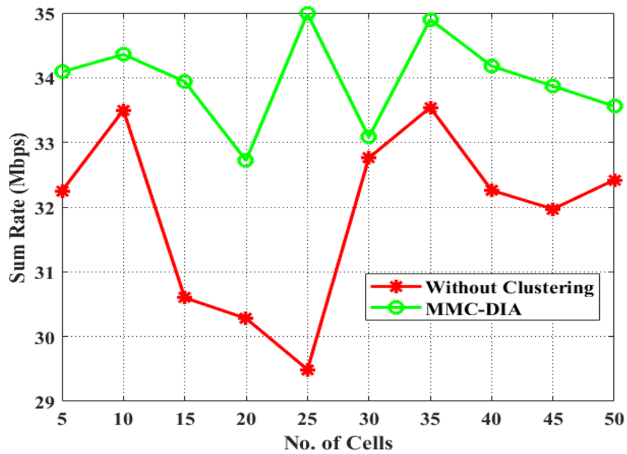

Fig. 10 Sum rate versus cells

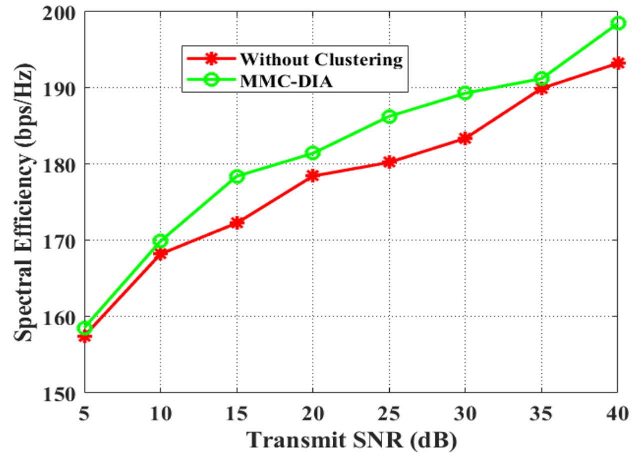

Fig. 13 Spectral efficiency versus transmit SNR

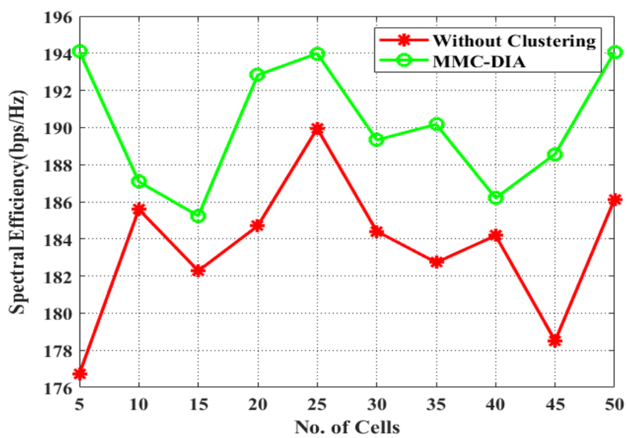

Fig. 11 Spectral efficiency versus cells

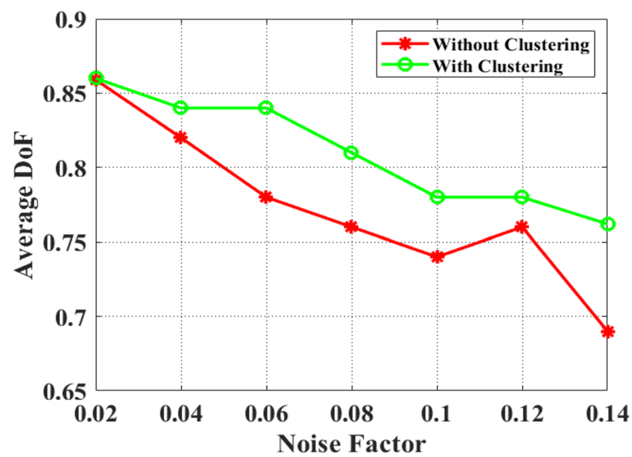

Fig. 14 Average DoF versus noise factor

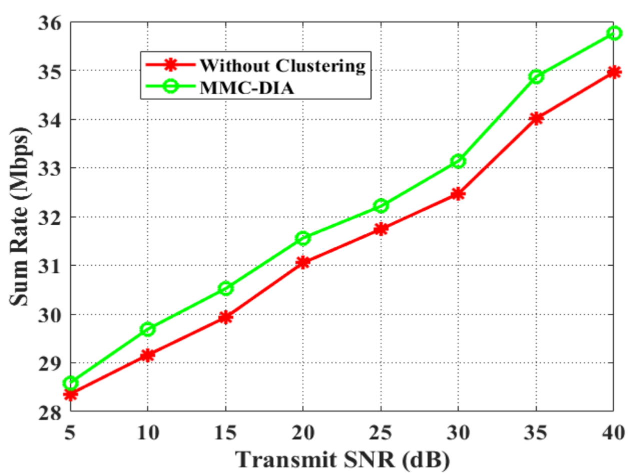

Fig. 12 Sum rate versus transmit SNR

ing conditions for maximizing $\varnothing$ in the proposed technique. In Table 3 the comparative analysis of the above with respect to the varying transmit SNR is presented.

4.4 Comparative analysis with respect to clustering

In Figs. 10, 11, 12, 13 and 14 the above metrics are compared between the methods with clustering and without clustering, respectively. The advantages of clustering in maximizing the sum rate and spectral efficiency along with the DoF for the varying cells and transmit power are discussed in this section. In a clustering method, the objective of maximizing S_r with respect to R_l and τ_{ij} suppression is performed for both Γ_r and Γ_r at different instances of time.

This classification is performed by assigning appropriate channels for relaying d such that path-loss and interference due to overlapping channels and errorneous

Table 4 Comparative analysis between clustering and without clustering

Metrics	Variable	Without clustering	MMC-DIA
Spectral efficiency (bps/Hz)	No. of cells	186.14	194.07
Sum rate (Mbps)		32.42	33.56
Spectral efficiency (bps/Hz)	Transmit SNR	193.25	198.47
Sum rate (Mbps)		34.96	35.75

transmissions are suppressed. The differentiation of $\widehat{I}_j$ and I_j as in Eq. (4) validates the efficiency as $\left[S_r + R_l\right]$ at the initial state. The independent segregation of $\widehat{S}_r$ on the basis of X and Y and $\left(\frac{y_m}{t_m}\right)$ based S_r retainment are the feasible conditions for achieving better efficiency. On the other hand, the clustering is performed by retaining the possible conditions each as $u_j > v_j$ and $\left|u_i\right| = \left|v_j\right|$ to achieve the fore-discussed efficiency. The CH selects as per $argmax\left\{\frac{\sum_m \alpha_2}{\rho_m}\right\}$ retain the efficiency of the LBS. In a non-clustering method, the efficiency though retained at the initial state, is not sustained throughout due to the varying unsynchronized d in the communication interval. This does not ensure reliable access to resources and cannot ensure better DoF. In Table 4, the above comparative results are tabulated.

5 Conclusion

This paper introduces multi-metric clustering with differential interference alignment for small cell users in a heterogeneous communication environment. The proposed method performs clustering and interference alignment in an independent manner in order to achieve maximum sum rate along with spectral efficiency. The proposed method employs precise pre-coding and covariance matrix operations over the signal vector at regular communication intervals between the transmitter and receiver pair to classify the first and second order of the transmitted signals. This helps to reduce the impact of inter and intra cluster interference by maximizing the degree of freedom between the connected transmitter and receiver pairs. The performance assessment of the proposed technique shows that it is capable of maximizing spectral efficiency and sum rate along with DoF irrespective of the varying cell size and transmit power. It is also seen that the proposed clustering based technique leverage the performance of the small cell users other than a network without clustering. In the future the proposed method is planned to be incorporated for dynamic heterogeneous environment to measure and address the impact of timed-events and interference.

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