

RESEARCH ARTICLE

A Novel Multiple Access Scheme for 6G Assisted Massive Machine Type Communication

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ABSTRACT The diverse Internet-of-things (IoT) applications involve massive machine type communication (mMTC) with large number of communicating nodes. The energy and resource overhead owing to shorter battery lives and limited network resources are the main challenges of mMTC in IoT. To support this massive random access and to overcome these challenges, future wireless networks are envisioned with collision resolution capabilities, reduced latency and ultra-high reliability. This paper presents a novel scheme for 6G assisted massive machine type communication (mMTC) with collision resolution capabilities and reduced latency. A cell-free network model is proposed in which the communication of mMTC devices is assisted through access points (APs) cooperation. The performance of proposed network is evaluated for achieved signal-to-noise ratio (SNR) and accuracy of node detection for different node locations, fading parameters and cell-areas. With increase in cell area and shadow fading, the SNR achieved by active nodes decreases. Further, an algorithm is proposed in the paper that makes AP clusters for serving the communicating nodes. The tendency of network for successful node detection is determined for different cluster sizes with different activation probabilities. In the end, the proposed algorithm is compared with two other schemes, namely, random clustering scheme and nearest-neighbour clustering scheme. It is found that the proposed approach achieves best performance in the detection of active communicating nodes in the system model with 9.09% improvement as compared to random scheme and 1.1% as compared to nearest-neighbour scheme.

INDEX TERMS 6G, cell-free massive MIMO, collision resolution, massive machine type communication, miss rate.

I. INTRODUCTION

To support the massive machine type communication (mMTC) for internet-of-things (IoT) services, future wireless networks especially beyond 5G and 6G networks are envisioned [1]. These networks aim to handle the extreme data traffic while offering ultra reliable and low latency communication capabilities [2]. It is expected that mMTC serves millions of active IoT nodes per square kilometer [3]. With

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large number of devices, lies the challenge of managing them with efficient allocation of time and frequency resources. The energy overhead owing to the short battery lives of these mMTC devices is another challenge [4]. Multiple devices communicating at the same time led to collisions at the base station. The collision resolution delays the packet transmission or data payload of devices and led to increased latency [5]. The massive access is well supported by massive multiple-input multiple-output (mMIMO) technology with large number of antennas at the base station [6], [7]. These large number of antennas offers spatial degrees of

freedom which the devices can exploit to transmit simultaneously [8]. The literature includes conventional approaches for grant-based random access where devices with same pilot sequences collide at the base station and there is conflict in grant of resources [9]. These are followed by increased latency and signalling overhead. To overcome these challenges, grant-free approaches has taken control over the last few years. The use of unique non-orthogonal signature sequences allows the user nodes to transmit the data payload simultaneously without colliding. From the received signals information, the identification of active nodes is also made possible. But it comes at the cost of increased interference in the signals received at the base station. The user detection approaches based on compressive sensing (CS) [10], [11], CS-based approximate message passing (AMP) [12], [13], covariance-based approach [14] and deep-learning enabled approaches [15], [16] are explored in literature. For example, [17] highlights a covariance-based approach for massive random access which is based on phase transition. It evaluates the probability of detection error based on phase transition in a mMIMO scenario. [18] proposes a low-complexity algorithm that jointly detects users and data based on covariance approach. The massive access in mMTC scenario with large number of devices is supported by beyond 5G and 6G networks with promising technologies like millimeter wave (mmWave), heterogenous networks (HetNets), multiple antenna technologies including mMIMO and cell-free mMIMO. High data rates can be achieved per node by the densification of cells but it comes at the cost of increased intercell interference when the cell density is less than a critical threshold [19]. mmwave technology offers large bandwidth but it comes at the cost of increased signalling overhead and reduced coherence time [20], [21], [22]. mMIMO communication system offers huge data rates but suffer from traffic congestion at the cell-boundaries [23], [24]. The low signal strength at the cell edges led to subsequent call drops. Cell-free mMIMO is a promising approach in which there are no cell boundaries and density of access points (APs) is increased by deploying large number of APs in a given coverage area [25], [26]. Through AP cooperation, mMTC is supported by cell-free networks with sufficiently good 95% likely performance, which is performance attained by 95% of the nodes in the cell-free network is optimum [27], [28]. The cell-free mMIMO system is also compared with conventional co-located mMIMO systems for performance analysis with parameters like spectral efficiency in [29] and energy efficiency in [30] and [31]. Also, [32] compares the co-located mMIMO system and cell-free system for massive connectivity. In IoT networks, due to large number of IoT nodes, the detection of IoT events or nodes is explored in [33] and [34]. Reference [33] uses machine learning based approach to detect the nodes amid network traffic for better network performance while [34] makes use of hybrid grant random access for collision resolution at the base station. [35] extracts useful information about the active nodes from the network traffic involving massive number of IoT

nodes. The network traffic is often encrypted for different IoT applications. To meet the requirements of low latency in mMTC scenario with large number of IoT nodes, [36] proposes a packet-asynchronous approach to support massive access and reduce delays as compared to packet-synchronous approach [37]. [38] prioritizes the MTC devices for access based on access class barring (ACB) approach. This results in reduced congestion at the base station. [39] proposes a multiple access scheme based on rate splitting which aims to enhance the performance of cell-free mMIMO systems. This is combined with precoder design and power control for efficient system gain. [40] addresses the problem of using limited pilot sequences in a cell-free mMIMO system by proposing a pilot assignment scheme for multiple access. In this paper, a novel scheme for 6G enabled mMTC is proposed that supports multiple access and improves the system performance through AP cooperation. Each IoT node is identified using information from clusters of APs which are designed using the proposed clustering algorithm. The performance of network is evaluated for various performance parameters like SNR achieved and accuracy of detection.

A. CONTRIBUTIONS AND OUTCOMES

The major limitation of mMTC in the random massive access scenario is the increased latency due to collisions and access failures. This led to increased energy consumption of the mMTC devices, sensor nodes and IoT nodes which need to be active for longer periods of time to support their packet transmission. Thus, energy aware solutions are needed which resolve the collisions and keep the battery lives of the active devices as long as possible. This paper proposes an intelligent network solution which aims to detect active users, resolve collisions and provided extended network coverage. The novel contributions of the paper are

- To support the mMTC, a 6G assisted cell-free mMIMO network is investigated in which a large number of APs serve the massive number of devices.
- For detection of active nodes, covariance based maximum-likelihood approach is utilised such that the probability of missed detection and false alarm rate is reduced.
- A novel clustering algorithm is proposed which makes clusters of APs based on minimum interference criteria. It offers computationally efficient method of activity detection using information from cluster of APs against all APs.
- The proposed 6G enabled cell-free approach for mMTC is evaluated for performance in terms of achieved SNR and accuracy of active node detection for different cluster sizes.
- The performance analysis is carried out for the mMTC scenario with different node locations, cell area and shadow fading effects. Also, comparison with a conventional model with a single base station having multiple co-located antenna arrays is highlighted.

- In the end, the proposed algorithm is compared with two other algorithms, namely random scheme and nearest-neighbour scheme.

II. SYSTEM MODEL

Consider a network model that supports mMTC with large number of IoT devices, sensor nodes and mobile terminals. These massive devices are being served by a large number of APs distributed arbitrarily in the network (Fig. 1). Let us suppose that to support K mMTC devices, L APs are deployed each having N number of antennas. All the mMTC devices have single antenna. There is a central server known as central processing unit (CPU) that connects all the APs via fronthaul. All the communicating nodes and the APs are well separated in the coverage area so independent channels are assumed between the node and the APs. Negligible height difference is considered between location of sensor node and the serving AP. At any instant of time, only fraction of devices are active. The probability that a device is active is denoted by activation probability Λ and it is taken as $\Lambda \ll 1$. The channel gains between the communicating devices and the APs are denoted as

$$h_{lkn} = \sqrt{\beta_{lk}} g_{lkn} \tag{1}$$

Here, g_{lkn} is the small-scale fading coefficient with mean zero and unity variance while β_{lk} is the large-scale fading coefficient given by [41]

$$\beta_{lk}[dB] = -30.5 - 36.7 \log_{10}\left(\frac{d_{lk}}{1m}\right) + S_{lk} \tag{2}$$

S_{lk} is the shadow-fading with mean zero and variance σ_{sh}^2 and d_{lk} is the distance between node k and AP l .

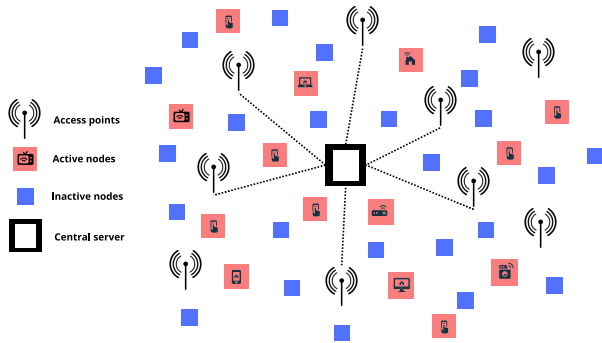


FIGURE 1. Proposed network design in which a large number of mMTC devices are being served through AP cooperation.

The block fading model is considered to support massive random access of mMTC devices where the channel remains constant for each coherence interval denoted by T_c . The number of symbols in each coherence block is denoted by τ_c . To support the sporadic nature of massive traffic, unique non-orthogonal pilot signature sequence with length P_L is used such that $P_L \leq \tau_c$.

Suppose Q denote a set of signature sequences of all the K devices such that $Q = [q_1, q_2, \dots, q_K]$ with dimensions

$P_L \times K$. And, $\rho = (\rho_1, \rho_2, \dots, \rho_K)$ defines the activity of K sensor nodes which are active at any instant, $\rho_k = 1$ implies a node is active and $\rho_k = 0$ indicates an inactive node. The active node k transmits the signature sequence q_k with power p_k to the APs such that the received signal is

$$y_{ln} = \sum_{k=1}^K \rho_k \sqrt{p_k} h_{lkn} q_k + z_{ln} \tag{3}$$

where h_{lkn} are the channel coefficients between n^{th} antenna of AP l and user node k and $h_{ln} = [h_{ln1}, h_{ln2}, \dots, h_{lnK}]^T$ is the channel vector at the n^{th} antenna of l^{th} AP from all the K nodes. z_{ln} is the independent noise vector. Equ. (3) can be written as

$$y_{ln} = QD_{\rho} \sqrt{D_p} h_{ln} + z_{ln} \tag{4}$$

with $D_p = \text{diag}(p_1, p_2, \dots, p_K)$ and $D_{\rho} = \text{diag}(\rho)$ The collective signal received at the l^{th} AP from all the K sensor nodes is given as

$$Y_l = QD_{\rho} \sqrt{D_p} H_l + Z_l \tag{5}$$

Here, H_l is the channel matrix between the K nodes and the l^{th} AP and Z_l is the noise matrix. The signal can be expanded as follows

$$Y = \begin{bmatrix} Y_1 \\ \vdots \\ Y_L \end{bmatrix} = \begin{bmatrix} QD_{\rho} \sqrt{D_p} H_1 \\ \vdots \\ QD_{\rho} \sqrt{D_p} H_L \end{bmatrix} + Z \tag{6}$$

The overall signal Y has independent columns which are distributed with covariance matrix \mathcal{L} given as

$$\mathcal{L} = \begin{pmatrix} QD_{\beta_1} D_{\mu} Q^H & \cdots & 0_{P_L} \\ \vdots & \ddots & \vdots \\ 0_{P_L} & \cdots & QD_{\beta_L} D_{\mu} Q^H \end{pmatrix} + \sigma^2 I_{LP_L} \tag{7}$$

Here, β_l denotes the large-scale fading coefficients from all the K nodes to the l^{th} AP and D_{β_l} is the diagonal matrix with β_l as the diagonal entries. D_{μ} is the diagonal matrix with μ given by $\mu = (\rho_1 p_1, \rho_2 p_2, \dots, \rho_K p_K)$. The covariance matrix \mathcal{L} has block-diagonal structure that is utilised to obtain the likelihood of Y given μ as

$$p(Y|y) = \prod_{l=1}^L \frac{1}{|\pi \mathcal{L}_l|^N} \exp\left(-\text{Tr}\left(\mathcal{L}_l^{-1} Y_l Y_l^H\right)\right) \tag{8}$$

with $\mathcal{L}_l = QD_{\beta_l} D_{\mu} Q^H$. By maximizing $p(Y|y)$ and minimizing $-\log(p(Y|y))$, the maximum-likelihood estimate of μ is given as

$$\mu^* = \arg \min_{\mu} \sum_{l=1}^L \log |\mathcal{L}_l| + \text{Tr}\left(\mathcal{L}_l^{-1} \frac{Y_l Y_l^H}{N}\right) \tag{9}$$

subject to $\mu \geq 0_K$. All the received signals at the APs are passed to the CPU and using the information at multiple APs, the node activity is detected.

III. ACTIVITY DETECTION AND COLLISION RESOLUTION

In the mMTC scenario, the massive random access led to collision at the serving APs which result in access failure and increased latency. The overhead incurred due to access failure increases the time duration in which the node has to remain active. This results in increased energy consumption due to shorter battery lives of the mMTC devices. Thus, collision resolution is a challenge in mMTC communication. To resolve collisions at the APs, it is very important to have prior knowledge of the communicating nodes in order to avoid delays. The active nodes need to be detected in order to resolve collisions and to obtain the channel estimates too. Most of the existing literature provides activity detection for co-located systems [42]. Very few papers have considered activity detection for cell-free networks. In [43], the active users are detected by decoding the information from all the APs. This has the drawback of high computational complexity which is overcome in [44] where one master AP is selected for each node. The master AP conveys the information about user activity to all other nodes thereby enhancing the network computational efficiency. But it comes at the cost of low performance with more probability of missed detection. In this paper, as a trade-off between complexity and performance, a clustering based approach is utilised for activity detection. Against all APs or one master AP, a cluster of APs are assigned to each communicating node based on favourable propagation or good channel conditions as the criteria.

In this section, for the proposed cell-free system model in section 2, the activity detection is performed using the information obtained at the serving AP clusters.

Let K_A define the set of active nodes such that $K_A = \{k : \rho_k = 1\}$ while the estimate of set of active users is denoted by \hat{K}_A such that $\hat{K}_A = \{k : \hat{\rho}_k = 1 \forall k \in [1, K]\}$. where $\hat{\rho}_k$ defines the estimate of activity of each node k as

$$\hat{\rho}_k = \begin{cases} 1, & \text{if } \mu_k^* > \mu_k^{th} \\ 0, & \text{otherwise} \end{cases} \quad (10)$$

with μ_k^{th} being the chosen threshold for desired performance in terms of probability of missed detection and false alarm rate.

Using the block diagonal structure of covariance matrix \mathcal{L} , let us define the cost function as [45]

$$f(\mu^*) = \sum_{l=1}^L \log |\mathcal{L}_l| + \text{Tr} \left(\mathcal{L}_l^{-1} \frac{Y_l Y_l^{-1}}{N} \right) \quad (11)$$

Also,

$$f(\mu) = \sum_{l=1}^L f^l(\mu) \quad (12)$$

where

$$f^l(\mu) = \log |\mathcal{L}_l| + \text{Tr} \left(\mathcal{L}_l^{-1} \frac{Y_l Y_l^{-1}}{N} \right) \quad (13)$$

is the cost function of l^{th} block.

$$\mathcal{L}_l(\mu) = QD\beta_l D_\mu Q^H + \sigma^2 I_{P_L} \quad (14)$$

$$= \sum_{k=1}^K \mu_k \beta_{lk} q_k q_k^H + \sigma^2 I_{P_L} \quad (15)$$

The overall maximum-likelihood cost function for node k is given as

$$f_k(d) = \sum_{l=1}^L \left(\log \left(1 + d \beta_{lk} q_k^H \mathcal{L}_l^{-1} q_k \right) - d \beta_{lk} \frac{q_k^H \mathcal{L}_l^{-1} \mathcal{L}_{Y_l} \mathcal{L}_l^{-1} q_k}{1 + d \beta_{lk} q_k^H \mathcal{L}_l^{-1} q_k} \right) \quad (16)$$

The cost function can be modified according to the AP clusters to detect the active users nodes. For example, for a cluster C_k of APs for node k , the cost function can be modified as

$$f_k(d) = \sum_{l \in C_k} \left(\log \left(1 + d \beta_{lk} q_k^H \mathcal{L}_l^{-1} q_k \right) - d \beta_{lk} \frac{q_k^H \mathcal{L}_l^{-1} \mathcal{L}_{Y_l} \mathcal{L}_l^{-1} q_k}{1 + d \beta_{lk} q_k^H \mathcal{L}_l^{-1} q_k} \right) \quad (17)$$

Taking derivative of equ. (17) and equating it to zero will give the minimizer of $f_k(d)$ as d^* which is equivalent to μ_k^* in equ. (10).

The probability of missed detection and probability of false alarm can be obtained as follows

$$Pr_{MD} = 1 - E \left\{ \frac{|K_A \cap \hat{K}_A|}{|K_A|} \right\} \quad (18)$$

$$Pr_{FA} = E \left\{ \frac{|\hat{K}_A \setminus K_A|}{K - |K_A|} \right\} \quad (19)$$

IV. AP CLUSTERING

The proposed network model contains a large number of APs which assist the communication of the active nodes distributed arbitrarily in the given network area. As discussed in section 3, the received signals at the APs are sent to the CPU which detects the active nodes for resource grant and collision resolution. This results in a network which has low latency and low signalling overhead due to limited access failures. This section presents that making clusters of APs for serving a particular node in the cell-free communication scenario results in increased performance. In spite of all APs, few APs are associated with a particular sensor node and the information about that node is passed to the other nodes. This is computationally less complex as compared to when all APs contribute to the identification of active nodes.

A. CLUSTERING ALGORITHMS

In this section, the clustering algorithms are introduced through which clusters of APs are formed. Let us suppose C_1, C_2, \dots, C_K are the K clusters corresponding to the K

sensor nodes. Three approaches to clustering are defined namely Random clustering, Nearest-neighbour clustering and proposed clustering.

Random Clustering- In this type of clustering technique, clusters of APs are formed for each sensor node randomly. In other words, the APs are randomly picked to serve a particular user node.

Nearest-neighbour Clustering- In this type of clustering technique, the APs which are close to the active communicating nodes are selected. The APs with the least distance to the user node are added to the AP cluster for that node. This is denoted by $l \leftarrow \arg \min_{l \in \{1, \dots, L\}} d_{kl}$.

Proposed Clustering- In this, a clustering algorithm is proposed which aims to enhance the system performance for the considered cell-free network model. For every node in the communication scenario, a cluster of APs are formed in which the APs are selected using the minimum interference criteria. As discussed in section 2, unique non-orthogonal pilot signature sequences are used in order to manage the collisions in massive random access involving huge number of connected devices. The proposed algorithm makes use of unique pilot sequence q_k assigned to each node k . Algorithm 1 gives the steps involved in the proposed clustering algorithm. A node k transmits the pilot sequence q_k to all the APs and the AP l at which the pilot interference is minimum is selected and added in the cluster set for that particular node. It is based on the criteria that any node k will transmit to a particular AP l with minimum interference if it has good channel to it. This is repeated for all the nodes till all clusters sets are obtained. The proposed algorithm is also elaborated with the help of flowchart as shown in fig. 2.

Proposed Algorithm

- Input:** L, Q, K
Output: C_1, C_2, \dots, C_K
- 1: Initialize $C_1 = C_2 = \dots, C_K = \{\phi\}$.
 - 2: Allocate the unique signature sequences to all the K sensor nodes.
 - 3: Evaluate the channel gains between the nodes and the APs.
 - 4: Select the AP l to which node k assigned with q_k transmits with minimum interference
 $l \leftarrow \arg \min_{q_k \in \{Q\}} \sum_{l=1}^L h_{kl}$
 - 5: Add the selected AP to the k^{th} node cluster C_k $C_k = C_k \cup \{l\}$
 - 6: Repeat steps 1-5 for every node k
 - 7: **return** C_k

V. RESULTS AND DISCUSSION

Here, the proposed network is modelled in MATLAB and the simulation results are presented to evaluate its performance for various performance parameters. It is considered that a wrap around square area supports 400 mMTC devices which are served by a pool of APs randomly distributed in that area. At any instant, only few nodes are active with the probability

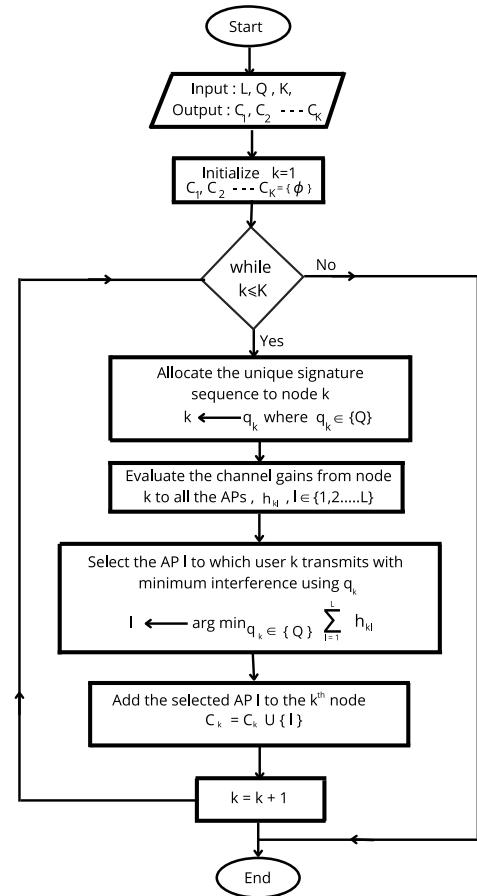


FIGURE 2. Flowchart of the proposed algorithm.

of activation being $\epsilon < 1$. The number of realizations are 10^4 for each simulation setup. For comparison, a conventional network is considered in which the communicating nodes are served by a single base station (BS) at the center equipped with co-located antenna arrays. The parameters used for simulation are given below in Table 1.

The proposed communication network is compared with another conventional network which uses co-located antenna arrays at the centre of the coverage area in fig. 3. The SNR achieved by each active device is plotted for different node locations for different coverage areas. When same number of APs are distributed in a compact area, there is a high possibility that each device is surrounded by one of the APs with good channel conditions and thus achieves improved SNR. Thus, in both the models, achieved SNR is less in large coverage area. The proposed model considers a pool of APs randomly distributed in the service area whereas in conventional model a co-located antenna array base station is located at the centre. It is clear from fig. 3 that SNR achieved by the active devices located adjacent to the serving APs is more compared to the active users located at the edges. It is shown that there is an improvement of 20dB in achieved SNR by 95% of the active nodes with the proposed approach as compared to conventional approach.

TABLE 1. Simulation parameters.

Parameters	Value	Parameters	Value
N	2	P_L	40
M	20 – 25	τ_c	200
K	400	p_k	200 mW
B	20MHz	σ^2	-109 dBm
B_c	200kHz	T_c	1ms

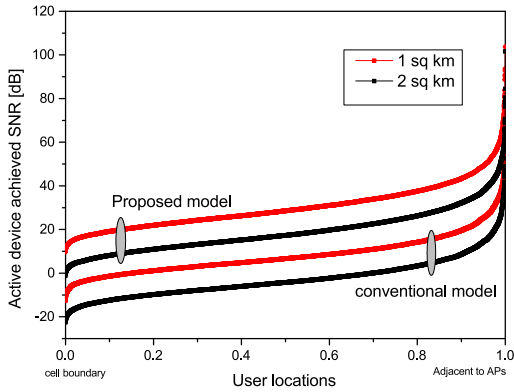


FIGURE 3. SNR achieved by each active node as a function of nodes locations.

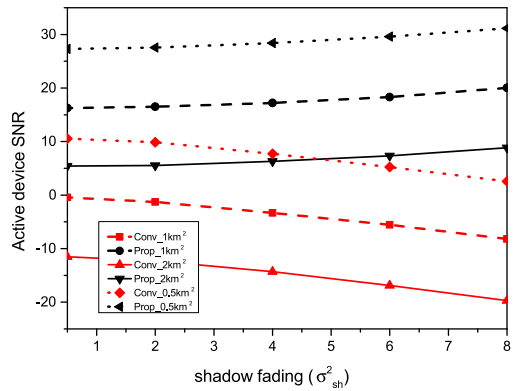


FIGURE 4. Achieved SNR vs shadow fading for different coverage areas.

The effect of large scale fading on the propagation characteristics of the proposed and conventional network models is depicted in fig. 4 with achieved SNR as a function of shadow fading. The robustness of a network to shadowing effects is depicted in fig. 4 for different cell areas. It is clear from fig. 4 that proposed model is more prone to shadow fading such that the SNR achieved by active nodes increases with shadow fading. This is in contrast to the performance of conventional model with shadow fading. Also, at large areas, the AP density is less and thus the achieved SNR is less compared to smaller areas.

In the proposed network scenario it is assumed that there are large number of mMTC nodes and only few are active at any instant. The probability that a device is active is denoted by the activation probability Λ . The probability of missed detection is plotted with varying values of Λ in fig. 5. When

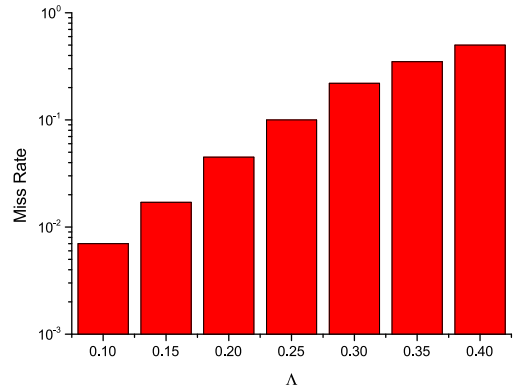


FIGURE 5. Missed detection rate for different node activation probability.

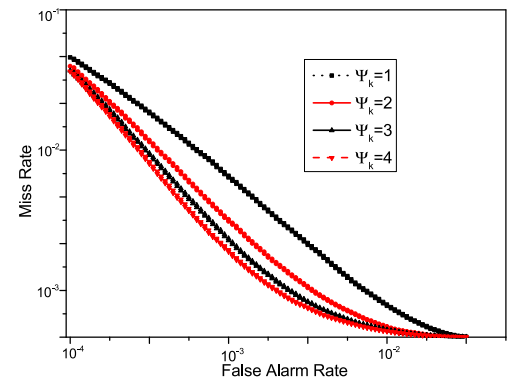


FIGURE 6. Missed detection rate for different false alarm rate with the proposed scheme with different cluster sizes.

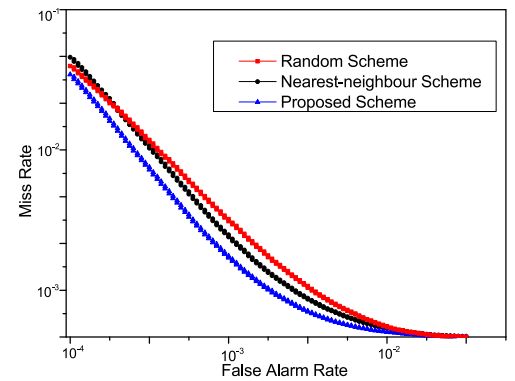


FIGURE 7. Comparison of different schemes for missed detection rate with cluster size 4.

the activation probability is 0.10, the miss rate or probability of missed detection is 7×10^{-3} while it is 0.5 at $\Lambda = 0.40$. Thus, with more the number of active nodes, more is the probability of missed detection. As mentioned in previous section, the proposed algorithm creates AP clusters for serving sensor nodes. The cluster size refers to the number of APs in the cluster which is chosen to serve a particular node against all APs serving an active node. The miss rate is plotted as a function of false alarm rate in fig. 6 for different cluster sizes. For a particular false rate, there is high chance that active nodes are detected with fair performance when the cluster size

is more, which means when there are more number of serving APs in a cluster. When there is only one AP in the cluster as in conventional approach, the ratio of non-detected devices to the total active devices is more suggesting that probability of missed detection is high. At 10^{-3} probability of false alarm, there is 14.7% improvement in the detection of active nodes when the cluster size is 4 against the cluster size 1. The proposed communication model has witnessed performance improvement with clustering approach. Fig. 7 gives the comparison of clustering schemes discussed in the paper, namely random clustering, nearest-neighbour clustering and proposed clustering scheme. It is clear from the figure that the proposed scheme gives lowest probability of missed detection. In other words, the proposed approach achieves best performance in the detection of active communicating nodes in the system model with 9.09% improvement as compared to random scheme and 1.1% as compared to nearest-neighbour scheme.

VI. CONCLUSION

mMTC in IoT services involve massive number of connected nodes and the huge amount of data traffic. This multiple random access leads to collisions, access failures, delay in resource grants and thus increases the average latency. Subsequently, these delays led to an increase in the energy consumption of mMTC devices. To overcome these challenges, this paper presents a novel scheme that supports this massive access in future 6G enabled mMTC. A network model is proposed in which these large number of IoT devices are supported by large number of APs deployed within the network area. By means of AP cooperation, the communicating nodes are identified and the performance of the network is evaluated for SNR achieved for different cell areas, shadow fading and node locations. An improvement of 20dB in achieved SNR is observed by 95% of the active nodes with the proposed approach as compared to conventional approach. It is also found that proposed approach is more robust to shadow fading and with increase in AP density, the achieved SNR improves. Further, an algorithm is proposed to make AP clusters whose performance is also evaluated for accuracy of node detection with different cluster sizes. It is observed that at a particular probability of false detection, 10^{-3} , there is 14.7% improvement in the detection of active nodes for larger cluster sizes. On comparison with other schemes, it is inferred that proposed algorithm offers an improvement of 9.09% over random clustering and 1.1% over nearest-neighbour clustering in the detection of active nodes to support multiple access.

REFERENCES

- [1] M. Mohammadkarimi, O. A. Dobre, and M. Z. Win, "Massive uncoordinated multiple access for beyond 5G," *IEEE Trans. Wireless Commun.*, vol. 21, no. 5, pp. 2969–2986, May 2022.
- [2] B.-H. Lee, H.-S. Lee, S. Moon, and J.-W. Lee, "Enhanced random access for massive-machine-type communications," *IEEE Internet Things J.*, vol. 8, no. 8, pp. 7046–7064, Apr. 2021.
- [3] J. Choi, J. Ding, N.-P. Le, and Z. Ding, "Grant-free random access in machine-type communication: Approaches and challenges," *IEEE Wireless Commun.*, vol. 29, no. 1, pp. 151–158, Feb. 2022.
- [4] L. Qiao, J. Zhang, Z. Gao, D. W. K. Ng, M. D. Renzo, and M.-S. Alouini, "Massive access in media modulation based massive machine-type communications," *IEEE Trans. Wireless Commun.*, vol. 21, no. 1, pp. 339–356, Jan. 2022.
- [5] Y. He and G. Ren, "Cluster-aided collision resolution random access in distributed massive MIMO systems," *IEEE Internet Things J.*, vol. 9, no. 13, pp. 11453–11463, Jul. 2022.
- [6] E. Björnson, E. de Carvalho, E. G. Larsson, J. H. Sørensen, and P. Popovski, "A random access protocol for pilot allocation in crowded massive MIMO systems," *IEEE Trans. Wireless Commun.*, vol. 16, no. 4, pp. 2220–2234, Apr. 2017.
- [7] J. C. Marinello, T. Abrão, R. D. Souza, E. de Carvalho, and P. Popovski, "Achieving fair random access performance in massive MIMO crowded machine-type networks," *IEEE Wireless Commun. Lett.*, vol. 9, no. 4, pp. 503–507, Apr. 2020.
- [8] E. De Carvalho, E. Björnson, J. H. Sørensen, E. G. Larsson, and P. Popovski, "Random pilot and data access in massive MIMO for machine-type communications," *IEEE Trans. Wireless Commun.*, vol. 16, no. 12, pp. 7703–7717, Dec. 2017.
- [9] E. Björnson, E. de Carvalho, E. G. Larsson, and P. Popovski, "Random access protocol for massive MIMO: Strongest-user collision resolution (SUCR)," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2016, pp. 1–6.
- [10] K. Senel and E. G. Larsson, "Grant-free massive MTC-enabled massive MIMO: A compressive sensing approach," *IEEE Trans. Commun.*, vol. 66, no. 12, pp. 6164–6175, Dec. 2018.
- [11] V. Shyianov, F. Bellili, A. Mezghani, and E. Hossain, "Massive unsourced random access based on uncoupled compressive sensing: Another blessing of massive MIMO," *IEEE J. Sel. Areas Commun.*, vol. 39, no. 3, pp. 820–834, Mar. 2021.
- [12] K. Senel and E. G. Larsson, "Device activity and embedded information bit detection using AMP in massive MIMO," in *Proc. IEEE Globecom Workshops (GC Wkshps)*, Dec. 2017, pp. 1–6.
- [13] X. Lin, L. Kuang, Z. Ni, C. Jiang, and S. Wu, "Approximate message passing-based detection for asynchronous NOMA," *IEEE Commun. Lett.*, vol. 24, no. 3, pp. 534–538, Mar. 2020.
- [14] Z. Chen, F. Sohrabi, Y.-F. Liu, and W. Yu, "Covariance based joint activity and data detection for massive random access with massive MIMO," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2019, pp. 1–6.
- [15] Y. Bai, B. Ai, and W. Chen, "Deep learning based fast multiuser detection for massive machine-type communication," in *Proc. IEEE 90th Veh. Technol. Conf. (VTC-Fall)*, Sep. 2019, pp. 1–5.
- [16] Z. Zhang, Y. Li, C. Huang, Q. Guo, C. Yuen, and Y. L. Guan, "DNN-aided block sparse Bayesian learning for user activity detection and channel estimation in grant-free non-orthogonal random access," *IEEE Trans. Veh. Technol.*, vol. 68, no. 12, pp. 12000–12012, Dec. 2019.
- [17] Z. Chen, F. Sohrabi, Y.-F. Liu, and W. Yu, "Phase transition analysis for covariance-based massive random access with massive MIMO," *IEEE Trans. Inf. Theory*, vol. 68, no. 3, pp. 1696–1715, Mar. 2022.
- [18] Z. Wang, Z. Chen, Y.-F. Liu, F. Sohrab, and W. Yu, "An efficient active set algorithm for covariance based joint data and activity detection for massive random access with massive MIMO," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, Jun. 2021, pp. 4840–4844.
- [19] Q. Zhang, H. H. Yang, T. Q. S. Quek, and J. Lee, "Heterogeneous cellular networks with LoS and NLoS transmissions—The role of massive MIMO and small cells," *IEEE Trans. Wireless Commun.*, vol. 16, no. 12, pp. 7996–8010, Dec. 2017.
- [20] I. K. Jain, R. Kumar, and S. S. Panwar, "The impact of mobile blockers on millimeter wave cellular systems," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 4, pp. 854–868, Apr. 2019.
- [21] J. Zhang, L. Dai, X. Li, Y. Liu, and L. Hanzo, "On low-resolution ADCs in practical 5G millimeter-wave massive MIMO systems," *IEEE Commun. Mag.*, vol. 56, no. 7, pp. 205–211, Jul. 2018.
- [22] W. Hong, Z. H. Jiang, C. Yu, D. Hou, H. Wang, C. Guo, Y. L. Hu Kuai, Y. Yu, Z. Jiang, Z. Chen, J. Chen, Z. Yu, J. Zhai, N. Zhang, L. Tian, F. Wu, G. Yang, Z.-C. Hao, and J. Y. Zhou, "The role of millimeter-wave technologies in 5G/6G wireless communications," *IEEE J. Microw.*, vol. 1, no. 1, pp. 101–122, Jan. 2021.
- [23] L. Sanguinetti, E. Björnson, and J. Hoydis, "Toward massive MIMO 2.0: Understanding spatial correlation, interference suppression, and pilot contamination," *IEEE Trans. Commun.*, vol. 68, no. 1, pp. 232–257, Jan. 2020.
- [24] E. Björnson, L. Sanguinetti, H. Wymeersch, J. Hoydis, and T. L. Marzetta, "Massive MIMO is a reality—What is next: Five promising research directions for antenna arrays," *Digit. Signal Process.*, vol. 94, pp. 3–20, Nov. 2019.

- [25] T. C. Mai, H. Q. Ngo, and T. Q. Duong, "Downlink spectral efficiency of cell-free massive MIMO systems with multi-antenna users," *IEEE Trans. Commun.*, vol. 68, no. 8, pp. 4803–4815, Aug. 2020.
- [26] H. Q. Ngo, A. Ashikhmin, H. Yang, E. G. Larsson, and T. L. Marzetta, "Cell-free massive MIMO versus small cells," *IEEE Trans. Wireless Commun.*, vol. 16, no. 3, pp. 1834–1850, Mar. 2017.
- [27] Ö. T. Demir, E. Björnson, and L. Sanguinetti, "Foundations of user-centric cell-free massive MIMO," *Found. Trends Signal Process.*, vol. 14, nos. 3–4, pp. 162–472, 2021.
- [28] E. Björnson and L. Sanguinetti, "A new look at cell-free massive MIMO: Making it practical with dynamic cooperation," in *Proc. IEEE 30th Annu. Int. Symp. Pers., Indoor Mobile Radio Commun. (PIMRC)*, Sep. 2019, pp. 1–6.
- [29] A. Burr, S. Islam, J. Zhao, and M. Bashar, "Cell-free massive MIMO with multi-antenna access points and user terminals," in *Proc. 54th Asilomar Conf. Signals, Syst., Comput.*, Nov. 2020, pp. 821–825.
- [30] H. Yang and T. L. Marzetta, "Energy efficiency of massive MIMO: Cell-free vs. cellular," in *Proc. IEEE 87th Veh. Technol. Conf. (VTC Spring)*, Jun. 2018, pp. 1–5.
- [31] H. Q. Ngo, L.-N. Tran, T. Q. Duong, M. Matthaiou, and E. G. Larsson, "On the total energy efficiency of cell-free massive MIMO," *IEEE Trans. Green Commun. Netw.*, vol. 2, no. 1, pp. 25–39, Mar. 2018.
- [32] H. Wang, J. Wang, and J. Fang, "Grant-free massive connectivity in massive MIMO systems: Collocated versus cell-free," *IEEE Wireless Commun. Lett.*, vol. 10, no. 3, pp. 634–638, Mar. 2021.
- [33] G. Xue, Y. Wan, X. Lin, K. Xu, and F. Wang, "An effective machine learning based algorithm for inferring user activities from IoT device events," *IEEE J. Sel. Areas Commun.*, vol. 40, no. 9, pp. 2733–2745, Sep. 2022.
- [34] Q. Zhang, S. Jin, and H. Zhu, "A hybrid-grant random access scheme in massive MIMO systems for IoT," *IEEE Access*, vol. 8, pp. 88487–88497, 2020.
- [35] Y. Wan, K. Xu, F. Wang, and G. Xue, "IoT Athena: Unveiling IoT device activities from network traffic," *IEEE Trans. Wireless Commun.*, vol. 21, no. 1, pp. 651–664, Jan. 2022.
- [36] W. Zhang, J. Li, X. Zhang, and S. Zhou, "A joint user activity detection and channel estimation scheme for packet-asynchronous grant-free access," *IEEE Wireless Commun. Lett.*, vol. 11, no. 2, pp. 338–342, Feb. 2022.
- [37] W. Zhang, S. Zhou, and X. Zhang, "An asynchronous grant-free multiple access scheme with rateless codes for URLLC," in *Proc. IEEE 92nd Veh. Technol. Conf. (VTC-Fall)*, Nov. 2020, pp. 1–5.
- [38] M. R. Chowdhury and S. De, "Delay-aware priority access classification for massive machine-type communication," *IEEE Trans. Veh. Technol.*, vol. 70, no. 12, pp. 13238–13254, Dec. 2021.
- [39] A. Mishra, Y. Mao, L. Sanguinetti, and B. Clerckx, "Rate-splitting assisted massive machine-type communications in cell-free massive MIMO," *IEEE Commun. Lett.*, vol. 26, no. 6, pp. 1358–1362, Jun. 2022.
- [40] M. Sarker and A. O. Fapojuwo, "Granting massive access by adaptive pilot assignment scheme for scalable cell-free massive MIMO systems," in *Proc. IEEE 93rd Veh. Technol. Conf. (VTC-Spring)*, Apr. 2021, pp. 1–5.
- [41] *Further Advancements for E-Ultra Physical Layer Aspects (Release 9)*, document 3GPP TS 36.814, 3GPP, 2017.
- [42] Z. Chen, F. Sohrabi, and W. Yu, "Sparse activity detection in multi-cell massive MIMO exploiting channel large-scale fading," *IEEE Trans. Signal Process.*, vol. 69, pp. 3768–3781, 2021.
- [43] A. Fengler, "Sparse recovery based grant-free random access for massive machine-type communication," Tech. Univ. Berlin, Berlin, Germany, Tech. Rep., Mar. 2021.
- [44] U. K. Ganesan, E. Björnson, and E. G. Larsson, "An algorithm for grant-free random access in cell-free massive MIMO," in *Proc. IEEE 21st Int. Workshop Signal Process. Adv. Wireless Commun. (SPAWC)*, May 2020, pp. 1–5.
- [45] U. K. Ganesan, E. Björnson, and E. G. Larsson, "Clustering-based activity detection algorithms for grant-free random access in cell-free massive MIMO," *IEEE Trans. Commun.*, vol. 69, no. 11, pp. 7520–7530, Nov. 2021.



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