Secure Factory Automation Using IoT-Based Clustered PD-NOMA

Dr Naureen Farhan
Department of Computing and Emerging Technologies
Ravensbourne University London
England, United Kingdom
n.farhan@rave.ac.uk

Engr. Aisha Danish
PhD Scholar Department of Computer Science
Bahria University Karachi Campus
Karachi, Pakistan
aishadanish.bukc@bahria.edu.pk

***Abstract*—— Factory automation increasingly relies on IoTs to achieve security through continuous monitoring and control. However, the rapid expansion of connectivity increases security risks. Identifying these challenges requires a tactical approach, such as implementing secure infrastructure to enhance data security and employing distributed control methods to locate controllers closer to the machines they supervise, thus minimising the centralised vulnerabilities. Wearable IoT devices are increasingly integrated into industrial operations, working with human operators to enhance task efficiency. Adopting 5G technology presents a promising solution, including low latency, high scalability, and improved energy efficiency. In this research, the proposed clustering method of 5G in Industrial IoT (IIoT) is intended to reduce radio resource delay and improve the security and data rate more effectively. The proposed hybrid clustering method with PD-NOMA reduces the radio resource delay by improving the real-time data transmission and throughput, and security by applying localised clustering. This study proposes a 5G based clustering approach for IIoT to reduce radio resource delays and increase secure data transmissions by minimising interference. The results show several connected nodes and a significant increase in data rate and coverage probability. This work highlights the importance of secure and efficient communication in advancing IIoT technologies.**

***Index Terms*—Power Domain - Non Orthogonal Multiple Access (PD-NOMA), Small cell Base Station (SBS), Internet of Things (IoT), High Power Wireless Access (HPWA), Low Power Wireless Access (LPWA)**

I. Introduction

With globalisation and the era of rapidly evolving technology, the need for secure, flexible digital systems keeps growing. The primary objective of Industry 4.0 is for companies to reduce their dependence on human labour, increase profit margins, enhance production efficiency, and automate as many business functions as possible. Additionally, businesses must be able to quickly adapt to changing customer needs while enabling machines to learn and make autonomous decisions over time. This growing emphasis on automation has increased the need for the Industrial Internet of Things (IIoT) and 5G technologies. An analysis of the literature indicates that to achieve the basic requirements for Industry 4.0 or IIoT, an efficient network architecture under 5G heterogeneous connectivity is crucial [1, 2]. The signal transmissions are deteriorated due to the increased variation of base station power levels and massive density within the heterogeneous network. The researchers devised multiple methods to improve the performance of 5G HetNet, including radio resource management, one of the most promising solutions to improve the data rates [19, 20]. Considering IIoT, high throughput and reliability with ultra-low latency are crucial.

A. Challenges and Motivation

5G networks are highly susceptible to signal degradation due to physical obstructions and require a clear line-of-sight or dense deployment of small cell base stations, which could bring more challenges to Industry 4.0. Also, the integration complexity in the existing IIoT primarily relies on protocols and the hardware, which is incompatible with 5G. Therefore, IIoT has emphasised the need for seamless connectivity, real-time decision-making, and high-performance computing in industrial environments. One of the key challenges in IIoT implementation is network congestion and resource management. The exponential increase in connected devices leads to excessive data traffic, causing delays and affecting real-time applications. This is particularly problematic for time-sensitive industrial processes that require ultra-low latency communication. Another major challenge is interoperability and scalability. IIoT systems integrate multiple devices from various manufacturers, each with different communication protocols and data formats. Ensuring seamless interaction between these heterogeneous devices is a significant problem in large-scale industrial automation. To address these issues, 5G technology presents a viable solution by offering enhanced mobile broadband (eMBB), ultra-reliable low-latency communication (URLLC), and massive machine-type communication (mMTC). However, efficient resource allocation strategies are needed to maximize the potential of 5G in industrial applications. The existing approaches often fail to adapt dynamically to varying network conditions, leading to suboptimal performance. This highlights the need for an efficient clustering mechanism to enhance network performance while maintaining low latency and high reliability.

B. Contribution

This research presents an optimised clustering method to improve the efficiency of 5G-based IIoT networks, particularly in radio resource management and data transmission. The key contributions of this work include an adaptive clustering algorithm for 5G enabled IIoT networks to reduce radio resource delays and improve data rates, improved coverage and throughput by minimising interference in HetNets, and demonstrating improved performance metrics, including reduced end-to-end delay in comparison to flat networks and existing clustered networks. By tackling the critical security challenges outlined above, this research proposes a scalable and resilient solution for securing 5G enabled IIoT environments, improving industrial automation and securing innovative manufacturing processes against the emerging threats and existing vulnerabilities.

The rest of the article is organised as follows. In section 2, the existing work performed in the relevant research is discussed and analysed. Section 3 outlines the relationship between the Internet of Things (IoT) and the 5G heterogeneous networks and the significance of industrial IoT. The importance and the need for clustering techniques to achieve improved radio resource management and overall improved network performance are explained in Section 4. Section 5 describes the proposed clustering methodology to be implemented over the IIoT environment to enhance the IIoT network performance. The results are discussed in Section 6, and the conclusion is given in Section 7 of the paper.

II. Related Work

Extensive research has been carried out to turn the concept of a smart city into reality. The latency would be negligible, and an extensively seamless connected environment could be achieved with considerably high data rates. Various approaches have been explored in the existing literature to construct a robust 5G heterogeneous network using multiple techniques. Many studies have focused on improving radio resource management or enhancing the existing methods to achieve the potential objectives of 5G HetNet.

Deep learning and neural networks have been recognised as practical techniques for vehicular networks, especially compared to stationary randomly deployed nodes. These techniques improved radio resource management by optimising network performance and reducing latency in dynamic vehicular environments [4]. Furthermore, neural network-based methods were applied to enhance 5G small cell selection, demonstrating improved connectivity and network efficiency in Internet of Vehicles (IoV) applications [5]. The application of deep learning techniques to improve radio resource management in 5G HetNet is discussed in [21, 22]. Agarwal et al. [21] demonstrated the role of AI-driven approaches for network optimisation by conducting a detailed survey of existing solutions, emerging trends, and key issues faced by radio resource management within 5G HetNet. Iqbal et al. [22] further explore an optimal learning paradigm combined with clustering techniques to enhance resource allocation efficiency, reduce latency, and improve network reliability in dynamic 5G contexts.

Clustering can be executed using both supervised and unsupervised machine learning approaches. Clustering performed as an unsupervised machine learning approach is assumed to be more suitable for the 5G heterogeneous networks since these networks involve the random deployment of base stations, which can be more effectively managed with such techniques [2]. Additionally, deep learning techniques are more appropriate for predicting the location of small cell base stations to be deployed [4, 6], as in these techniques, the data must be trained and requires a massive amount of real-time information to get better results. Although deep learning is a trending research focus, its suitability is more pronounced in vehicular networks and device-to-device (D2D) communication rather than general 5G HetNet applications.

Moreover, switching (On/Off) methods in the network are also in demand to prolong the lifetime of nodes by preserving the energy levels of the base stations and providing uninterrupted, seamless connectivity for the connected nodes. These techniques enhance network performance by regulating power levels according to network demands, making network elements inactive when not required, thus conserving energy. Switching techniques are more commonly used with green networks and function as energy efficient methods [7]. A review of state-of-the-art 5G architecture within the Internet of Things (IoT) context and significant challenges are presented in [3]. In [32], the author integrates the blockchain with software-defined networking (SDN) to improve energy efficiency and security in IoT networks. The author proposes a cluster-based routing protocol with a private and public blockchain for secure Peer-to-Peer(P2P) communication and achieved improved network performance in terms of throughput and energy consumption. Moreover, in [33], the LEACH and LEACH-C protocols are implemented to improve the energy efficiency and network lifespan in flying ad hoc networks. An optimized clustering algorithm with a novel threshold function is proposed to strengthen cluster head (CH) selection, reduce energy consumption, and enhance data transmission efficiency. The research in [34] provides a taxonomy of analytical systems and analyses the key data mining techniques like classification, clustering, and prediction to enhance smart city infrastructure sustainability. The study explores the role of big data in 5 G-enabled Iot and industrial Iot within smart cities, highlighting its significance in optimising network operations and improving urban connectivity. Existing studies have typically utilised centralised or distributed clustering, each with limitations. To overcome these challenges, this study applies hybrid clustering, as proposed in [1,18] and applies it to a 5G Industrial IoT (IIoT) infrastructure using the algorithm introduced initially in [1,18]. Existing hybrid clustering methods have not been extensively applied or optimised for heterogeneous 5G enabled IIoT environments. Our study adapts and fine-tunes the clustering model to address the unique challenges posed by industrial networks, such as high device density, interference, and ultra-reliable low-latency communication (URLLC) requirements.

III. 5G Industrial IoTs(IIoTs)

As discussed in [6], the growth of IoT devices has increased tremendously. In industries, it is referred to as the IIoT, in which the coverage and energy efficiency increase are the primary concerns. These systems require an increased number of resources to achieve a greater lifetime. If the number of resources is limited, there is a high possibility that the access points/base stations will be deprived of required energy levels and, as a result, will reduce the overall network lifetime. However, there is more energy consumption due to the massively deployed sensors and devices in a 5G network. One of the potential challenges for recent 5G communications and edge trends is the co-existence of 5G IIoT devices. In an IIoT environment, several sub-IIoT systems exist, and the efficient performance of such heterogeneous networks is required. The seamless communication and interaction between the sub-IoT systems is a significant challenge to be achieved. Furthermore, the interference caused by the heterogeneous subsystems is another major challenge. The subsystems frequently operate in an environment with a dense and compact deployment of nodes. Therefore, the IoT operation of subsystems can lead to increased interference with significantly increased delay within the network.

In 5G heterogeneous networks, achieving a high data rate is an essential challenge for IIoT. Industry 4.0 is the 4th revolution in industrial automation; it demands seamless connectivity with a reduced delay between machine–to–machine and human-machine communications. To achieve the required goal of massive connectivity for Industry 4.0, 5G small cells are in demand, and with the dense deployment of 5G small cells, the enhanced IoT coverage area can be achieved. Also, the 5G small cell base stations are a low-cost solution to improve the network coverage and throughput. Also, by introducing the SBSs, the overloaded macro base stations can offload the data traffic to these SBSs. To achieve massive connectivity, the required goals of ultra-high reliability, increased throughput, and reduced latency must be achieved with improved capacity and network coverage in IoT environments [10]. 5G small cells are being deployed to serve users with high data rates in dense IoT networks, such as event centres, shopping malls, homes, businesses, and industrial buildings. Overall, the 5G small cells play a significant role in structuring and developing the concept of smart cities [3]. According to [6], industrial automation requires highly accurate estimation to preserve the system's energy. This requires an adaptive resource allocation strategy and an on demand information system design. For green communications in industrial IoT, cooperative caching and power optimization under 5G networks are deployed [11], and relays have been used to achieve better data transmission within the IoT network environment. Similarly, heterogeneous networks are used to achieve enhanced energy efficiency.

The Internet of Things (IoT) contributes to the industrial revolution through smart tracking that indicates any changes made to the procurement plan. Digital factories can also be achieved by enhancing and streamlining the line of command in the work units. According to the analysis performed in [12, 17], the IoT and IIoT differ in the type of information being transmitted, primary usage, and connectivity issues. Figure 1 shows the Voronoi Tessellation [18] diagram of massive random deployment of nodes in a 5G heterogeneous network under the Poisson Point distribution, as considered in this work.

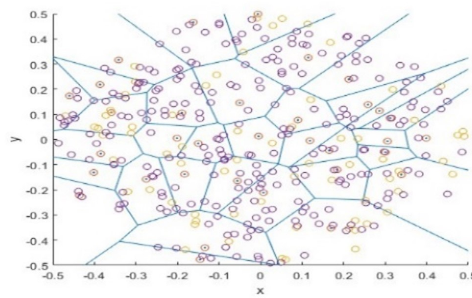

Fig. 1. Massively deployed Base Stations in a 5G Network

TABLE I
COMPARISON OF ACCESS TECHNOLOGIES

Access Technology	Connected devices	Performance	Coverage
HPWA	+2 Billion	High	High/Med
LPWA	+11 Billion	Moderate	High

Table 1 shows that the required number of connections for low-power wireless access (LPWA) is significantly higher than that of the HPWA. Also, it must be considered that the deployment of LPWA nodes is denser than the High-Power Wireless Access (HPWA) nodes. The improved performance requirement for HPWA is expected to be higher than the performance of LPWA. However, the coverage constraint can be moderate to high for the HPWA and high for the LPWA nodes. This shows that better network performance can be achieved by managing the low-power nodes more effectively with enhanced coverage and capacity for the whole system.

IV. SIGNIFICANCE OF CLUSTERING IN IMPROVING THE PERFORMANCE IN IIOT ENVIRONMENT

Machine learning techniques have been widely used within IoT systems and provide efficient solutions to IoT-based problems, such as congestion management and resource management, to reduce the impact of interference and increased delay. Because of the small cell base station's random deployment, unsupervised methods, like clustering or node localisation methods, are more suitable [22 - 23].

In [13], an analysis of the IIoT in 5G vision and design trends is discussed, with the primary focus on increasing the coverage and capacity of the system. The increased capacity can be achieved by deploying the nodes closer to each other, as shown in Figure 2. This reduced cell size can be achieved by deploying small cell base stations. In a highly dense heterogeneous environment, the load across the cell is uneven due to random deployment of small cells, IOT devices, and user equipment mobility. Therefore, unbalanced loads result in power degradation, such as throughput and handover management [24 – 25]. A cluster-based load balancing

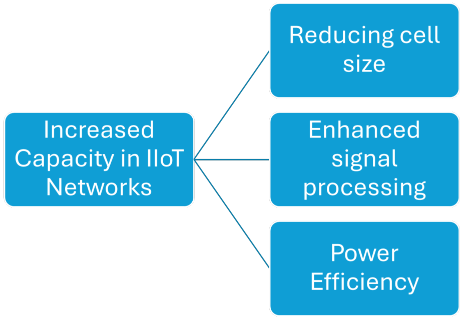

Fig. 2. Various techniques to improve the Capacity in IIoT

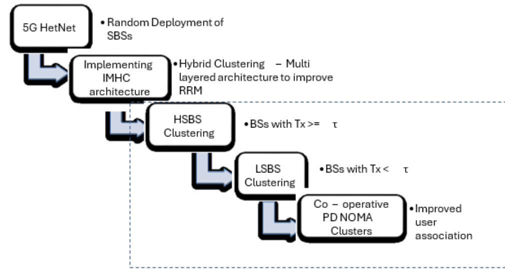

Fig. 3. Proposed Methodology of Clustered 5G Model

technique is required to resolve the uneven load issue and improve network performance. Efficient management of IOT devices can be achieved with the n-tier network architecture. In [14], the algorithm is based on load estimation calculated from the signal-to-interference and noise ratio (SINR). The algorithm considered a fixed threshold to identify overloaded cells. The load balancing algorithm estimates the load in both overloaded and neighbouring cells. Performs user equipment (UE) handovers using event-driven measurement reports from the UEs. However, several existing methods have focused on the adjacent neighbouring cells of an overloaded cell for load balancing. To cope with the dynamically changing environments, developing an IoT adaptable system is essential. IoT systems are energy controlled networks. Transmitting all the data packets to the sink node is found to be inefficient and dramatically consumes the node's energy. However, in clustering methods, the Cluster Head (CH) improves energy efficiency by collecting data from the cluster members within its vicinity and transmitting only the aggregated data to the sink node. Machine learning algorithms can help decide the number of clusters needed and the cluster-controlling layout [15 – 18]. There are various methods to improve the data rate in an IoT network, among which radio resource management using the clustered architecture is the most promising solution [1 – 2, 29 - 31]. In dense deployments, the access points will be deployed closer to each other and require robust reception of significant data rates received at user equipment or IoT devices. Another benefit of forming clusters of nodes is that the grouping can be performed based on different power levels for other purposes in multiple industry domains.

V. Proposed Clustering Technique for Robust Resource Management in IIoT

This article contributes to implementing the previously designed interference-managed clustered model over an IIoT environment, where IIoT is the additional tier added to the existing model. The multi-tier clustered network architecture comprises a macro base station (MBS) and ultra-dense randomly deployed clustered small-cell base stations (SBSs) that serve the sensors within the IoT environment. The Pico and Micro SBSs are laid as High-power Small-cell Base Stations (HSBS), and the femto BSs are considered as the Low-power Small-cell Base Stations (LSBS) distributed over a multi-tier network as given in [1, 18]. The Small Base Stations (SBSs) are positioned at the cluster's core, featuring a radius of 'r', and accommodating 'n' users within each SBS cluster [16]. Figure 3 illustrates the architecture of the proposed multi-tier clustered model. MBS will be deployed at tier-1, pico BSs at tier-2, and femto BSs at tier-3. Hence, hybrid clustering is performed at tier-2 and tier-3 to manage interference and improve the overall system throughput. PD-NOMA is implemented at the tier-2 and tier3 [18]. According to the algorithm proposed in [1], the system interference is reduced by forming clusters of the SBSs in a hybrid manner. Moreover, a power control algorithm is implemented, clustered SBSs are organized based on a set of interference thresholds and classified into two types: the LSBS and the HSBS. Therefore, these base stations will create clusters to serve their respective nodes.

Figure 4 shows the methodology for implementing the scheme to form hybrid clusters. The threshold power value is demonstrated by 'τ' in the figure, based on which the clustering decisions will be made. Upon implementing the proposed scheme, the goals of industrial IoT can be achieved, including ultra-high reliability, increased throughput, and reduced delay.

A. *Algorithm of the Proposed Scheme*

The algorithm for hybrid clustering for optimisation of the 5G IIoT network is given below:

article algorithm algpseudocode amsmath

Cluster Formation and Power Control in Heterogeneous Networks

Input: Randomly distributed nodes (Pico BS, Femto BS, Macro BS as backhaul); Power threshold (τ); Target Signal-to-Interference Ratio (SIR)

Output: Optimized cluster formation; Improved system capacity and reduced latency

Step 1: Initialize Network

Deploy nodes using Poisson point distribution Identify Macro BS as the backhaul node

Step 2: Centralized Cluster Formation (HSBSs)

Compute total interference: sum of interference from all tiers

Introduce power threshold (τ) for each Cluster Head (CH)

Select Cluster Members (CMs) based on target SIR

Step 3: Distributed Cluster Formation (LSBSs)

Identify one-hop neighbors for each LSBS Form clusters

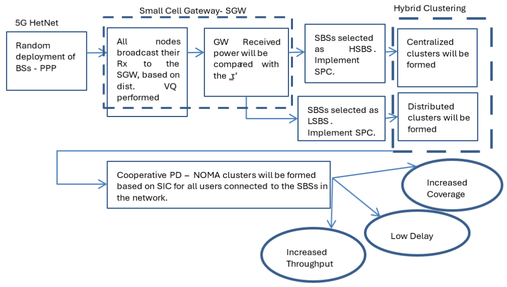

Fig. 4. Workflow of the Proposed Scheme to Achieve Improved IIOT Environment

using neighborhood-based clustering
Step 4: Implement Power Control
Adjust the transmission power of HSBSs and LSBSs
Ensure all SBSs achieve the target SIR
Step 5: Channel State Information (CSI) Exchange
Users/sensors send CSI to their respective SBS
Step 6: Channel Gain Difference Evaluation
Calculate channel gain difference for each user/sensor
Form clusters prioritizing users/sensors with maximum channel gain difference
Step 7: Final User Selection
SBS selects users/sensors with the highest channel gain difference
Optimise system capacity and minimise latency

Under the NOMA scheme, the SBSs share the 'W' bandwidth, including HSBS and LSBS users. Moreover, it is also assumed that the users/sensors associated with NOMA SBSs will have a high probability of attaching to the LSBSs [18]. Figure 4 shows the workflow of the proposed scheme. The scheme shows that by implementing the proposed solution, the performance parameters, i.e., the throughput and coverage probability, will be improved with a reduced delay factor. The proposed hybrid clustering algorithm aims to enhance the efficiency of 5G-enabled IIoT networks by addressing key challenges such as interference management, optimised resource allocation, and improved coverage probability. The algorithm strategically combines centralised and distributed clustering approaches to achieve optimal latency, data rate, and network capacity performance. The proposed hybrid clustering algorithm significantly improves over traditional clustering methods by optimising key performance metrics in 5G-based IIoT networks. It effectively reduces end-to-end latency by minimising radio resource delay, reducing up to 0.4 milliseconds even in high node density scenarios. The adaptive power control and clustering approach enhances spectral efficiency, resulting in higher data rates and improved coverage probability than conventional techniques. The algorithm also enhances network scalability through distributed clustering for LSBSs, enabling seamless integration of new devices without negatively impacting performance. Furthermore, it strengthens industrial IoT applications by ensuring high reliability and ultra-low latency communication, making it suitable for time-sensitive industrial automation and intelligent manufacturing environments. This hybrid clustering approach provides a scalable, efficient, and reliable solution by addressing critical challenges such as interference management, resource allocation, latency reduction, and coverage optimisation.

VI. Result and Discussion

The results obtained by implementing the methods described in the previous section are evaluated and explained in this section. The improved performance parameters and the respective outcomes in different scenarios are simulated using the MATLAB simulation tool. According to the previous section, the multi-level hybrid clustering technique is implemented under the PD-NOMA access model to improve the IIoT environment. To achieve better communication and reliability among the massively and closely deployed sensor nodes, efficient resource management techniques must be implemented to reduce interference. With the reduction in interference, better network performance can be achieved. The service quality of the network, as observed by the IoT nodes, is mainly affected by the performance of the underlying network. Therefore, it is essential to measure the performance of the underlying network; the performance parameters considered in this research are coverage probability, throughput, signal-to-interference ratio, and delay. High bandwidth helps the user and the IoT devices upload the requested information with reduced delay, a crucial requirement of IIoT networks. Bandwidth can be described as the available channels that help transmit data traffic within the IIoT environment, considering the Industry 4.0 era. Therefore, in an efficient network, fair bandwidth distribution holds great importance. This leads to proper interference management for increased bandwidth utilisation with a low delay factor.

A. Simulation Environment

Considering the IIoT, which includes machinery and machine-oriented software and tools, the sensor nodes must be stationary over a dense 5G network. The transmitting power of all communicating nodes will be different, leading to uneven energy consumption at all nodes. The simulation parameters are summarised in Table 2; all values are considered according to the 3GPP standards over the identically independent randomly deployed Poisson Point distribution of nodes.

B. Simulation Tool and Performance Metrics

The analysis of the methods discussed above, as well as the evaluation of results related to the Interference Managed Hybrid Clustering (IMHC) mechanism and the cooperative PD – NOMA technique, are explained in this section. Different simulation scenarios are developed to analyse network performance under various conditions. MATLAB is used to execute continuous dynamic simulations, as discrete event simulation relies on time-dependent variables. In discrete event simulation, the model involves a sequence of discrete and instantaneous events, with the system remaining constant and unchanged between events. However, in continuous dynamic

TABLE II
SIMULATION PARAMETERS

Parameter	Value
Bandwidth	10 MHz
Sub Carrier Bandwidth	5 MHz
Transmission Power of MBS	46 dBm
Transmission Power of HSBS	30 dBm
Transmission Power of LSBS	15 dBm
Channel Gain (MBS)	14 dBi
Channel Gain (SBS)	7 dBi
No. of HSBS	100
No. of LSBS	1000
No. of IoT devices	2–80
No. of sub-carriers	5
AWGN	169 dBm/Hz
Fading	Rayleigh

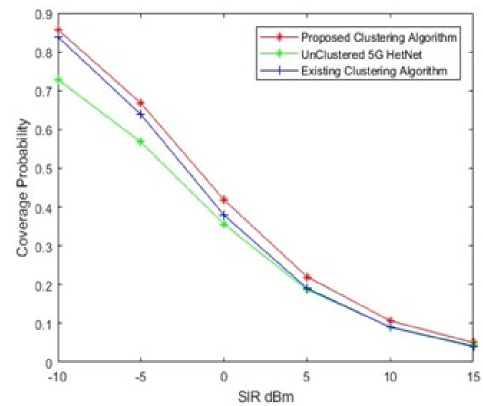

Fig. 5. Coverage Probability achieved with the Proposed secure scheme for an IIoT environment

simulation, a set of outputs is plotted on the Y-axis, and any value can be represented continually. This scheme works more continuously and involves parallel processing to keep the system more scalable and flexible. Also, it deals with the processes, conditions, and behaviours constantly depicted with changing dependent variables. The following are the parameters to evaluate efficient radio resource management in the proposed ultra-dense hybrid clustered network. The probability that a typical user can receive the signals concerning the threshold SINR, denoted as β is considered the coverage probability, i.e.

$$P_c = P(\text{SINR} \geq \beta) \tag{1}$$

In OFDMA systems, the SIR values vary radically across the cell. Transmitter xi covers the receiver yi in the referred slot if,

$$\text{SINR}_i = \frac{\dfrac{F_i}{I(|x_i - y_i|)}}{W + I_j} \geq \beta \tag{2}$$

Where, Ij is the interference and β Is the SINR threshold. Considering the coverage probability, a typical user is assumed to be within the network coverage if the received SIR exceeds the SIR threshold. β value for analysing a successful SIR reception. In a multi-tier network, the per-tier coverage probability can be given as the probability that a typical user of the same tier is within the coverage, assumed to be served by the SBS at the given tier. The total coverage probability can be defined as the per-tier coverage probability given as, Where, if A_i is the association probability.

$$P_{cj} = \sum (1\,(\text{SIR} > \beta)) \tag{3}$$

$$P_{ci} = \sum_{k=0}^{i} A_i P_{cj} \tag{4}$$

Uniform user distribution is the primary concern with the random deployment of users within a network, assuming the users are located identically independent of BSs. It has also been observed that the coverage probability decreases with the increase in the radius of the cluster around the SBS. The coverage probability (Pc) is computed based on the assumption of choosing a randomly selected user from any formed cluster. Figure 5 shows the coverage probability under the BS-user correlation, and the result achieved with IMHC [1], and cooperative clustered PD-NOMA [18] is better than the existing hybrid clustering scheme. Also, it can be deduced from the results that the coverage probability shows an improvement in behavior with the users located nearer to the SBS forming clusters under a low-interference access network. The improvement in coverage probability is achieved by controlling the transmission power at the base station, i.e., SBS. Moreover, the result shows that the coverage probability has improved by implementing the cooperative PD-NOMA, which was achieved with the existing hybrid clustering scheme and the IMHC hybrid scheme. Significant improvement can be observed with low SIR values, whereas with high SIR values, the coverage probability shows low variations. With the increase in cluster radii, a typical user can be located far from the centre of the cluster, which thus affects the association probability of the user with the SBS.

Additionally, it can be deduced from the results that the coverage probability improves with the IoT devices deployed nearer to the access points (SBSs), forming clusters with reduced interference power levels. However, the improvement is due to the interference-limited and robust IoT device association due to the PD–NOMA implementation within the proposed scheme [26 – 28]. Figure 6 shows the throughput achieved with the proposed clustering scheme. The given result shows that the throughput has improved significantly with the proposed clustering method. The improvement in throughput is due to the decline in interference, as the 5G network is mainly comprised of SBS. Therefore, by reducing the interference among the SBSs, the overall system throughput is improved significantly. Figure 7 shows the SIR achieved at the small cell base stations in a 5G heterogeneous network with the existing and proposed clustering schemes. It can be analysed

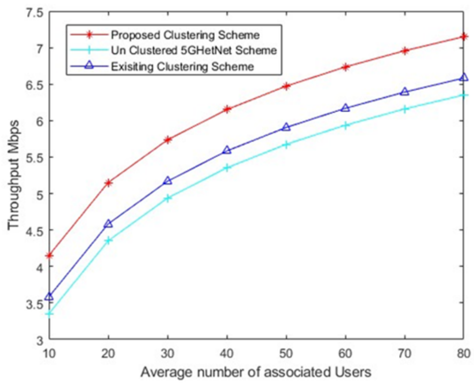

Fig. 6. Throughput achieved with the proposed clustering Scheme

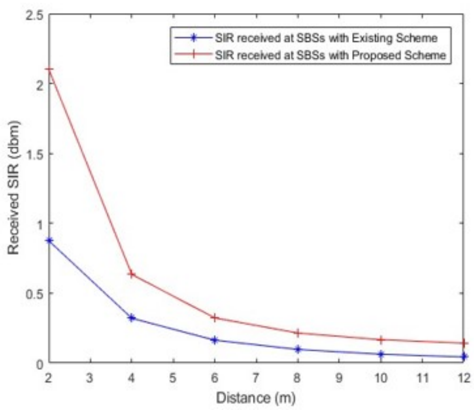

Fig. 7. Comparison of SIR received using the existing and proposed clustering schemes at SBSs

from the outcome that the SIR received with the proposed scheme has significantly improved. There are two significant reasons for this improvement in results: firstly, the hybrid clustering scheme, which is implemented, is based on the interference threshold value, and secondly, due to the inclusion of power threshold, the SBSs are managed more efficiently [1]. Secondly, with the implementation of the PD-NOMA access scheme for users/IoT devices, the interference has been reduced as PD-NOMA applies the signal to interference cancellation [18]. That has further reduced the interference at the receiving end in a massively dense network environment. Therefore, on average, the SIR for the near IoT devices has improved by almost 95% It has been enhanced by 20% for the distant IoT devices compared to the existing clustering schemes implemented for the IIoT environments.

Table 3 shows the comparative analysis of end-to-end delay, the throughput received under the proposed clustering scheme, and the existing schemes for an IIoT environment. It can be observed from the results given in the table that the end-to-end delay has reduced significantly when compared with the existing clustering scheme and the non-clustered 5G HetNet when deployed for the IIoT environment. Along with the delays, the respective throughput achieved under the same

TABLE III
COMPARISON OF AVERAGE END-TO-END DELAY AND AVERAGE THROUGHPUT

IIoTs/Cluster	Average End-to-End Delay (ms)			Average Throughput (Mbps)		
	Proposed N/W	Existing N/W	Flat N/W	Proposed N/W	Existing N/W	Flat N/W
5	0.2	0.2	0.35	4.31	3.73	3.14
10	0.25	0.3	0.39	5.31	4.73	4.14
15	0.29	0.35	0.42	5.89	5.31	4.73
20	0.35	0.38	0.46	6.31	5.73	5.14
25	0.4	0.4	0.5	6.6	6.3	5.73
30	0.45	0.49	0.53	6.72	6.5	5.9

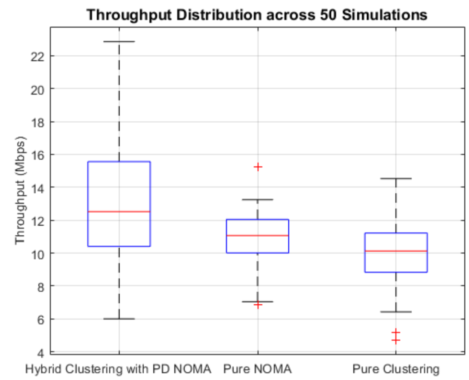

Fig. 8. Throughput distribution across 50 simulations

scenarios is also given in Table 3 and proves that the proposed scheme has improved throughput achieved with a lowered delay factor when implemented for a massively dense IIOT environment. Furthermore, it can be observed from the table that the comparative delay per cluster has also been reduced with the proposed scheme, which indicates that improved fairness is achieved with the proposed cooperative PD-NOMA clusters implemented over the IMHC hybrid clustered heterogeneous network. Figure 8 shows the statistical analysis of the throughput achieved across 50 simulations and indicates that the highest value is attained with the hybrid clustering technique with PD-NOMA calculating the mean, standard deviation, and confidence intervals for each. The results show that improved performance of a multi-tier heterogeneous network under dense deployments can be achieved first by forming efficient clusters to reduce the number of nodes per tier level and second by improving the channel access methods and considering the spectral efficiency simultaneously.

VII. CONCLUSION AND FUTURE WORK

In an ultra-dense heterogeneous network environment, it is substantial that small cell base stations must be deployed closely and randomly. The radio resources can be efficiently managed by grouping the base stations in clusters under a hybrid clustering scheme, i.e., with both centralised and distributed control, as needed per tier in each resource block. In this way, the interference reduces significantly at the SBS tiers. Also, by categorising the SBSs based on their respective received power and deploying them in a multi-tier architecture, the interference and the SBS outage ratio within a multi-tier network with BSs having various power values are reduced significantly. BSs with high-power values will cause more interference than BSs with low-power values. Therefore, the categorisation of the SBSs, as HSBS and LSBS using efficient clustering methods and implementing the power prioritisation scheme as performed with the SPC under the IMHC scheme, interference can be managed more efficiently, and improved network throughput at lower transmit power values can be achieved. Furthermore, the PD–NOMA is implemented to help achieve improved user association, and thus, robust and secure SBS-IIoT device association can be achieved. Also, the proposed solution is flexible to serve a scalable network, with significantly improved coverage probability. In the future, more work can be performed to enhance the quality of service and fairness within the densely packed networks. The future work includes considering improving the quality of service provided within the clustered network and exploring how energy efficiency can be optimised. Also, in the future, the complexity of performing clustering at multiple levels in a dense network will be evaluated and reduced by improving the given architecture (IMHC). Therefore, in the future, further work could be performed to reduce the complexity of the proposed scheme for an increased number of tiers.

REFERENCES

[1] Farhan, N. and S. Rizvi, An Interference-Managed Hybrid Clustering Algorithm to Improve System Throughput. Sensors, 2022. 22(4): p. 1598.

[2] Farhan, N., et al., Clustering Approaches for Efficient Radio Resource Management in Heterogeneous Networks. 2021.

[3] Li, S., L. Da Xu, and S. Zhao, 5G Internet of Things: A survey. Journal of Industrial Information Integration, 2018. 10: p. 1-9.

[4] Agarwal, V. and S. Sharma, Deep Learning Techniques to Improve Radio Resource Management in Vehicular Communication Network, in Sustainable Advanced Computing. 2022, Springer. p. 161-171

[5] Alablani, I.A. and M.A. Arafah, Enhancing 5G small cell selection: A neural network and IoV-based approach. Sensors, 2021. 21(19): p. 6361.

[6] Mao, W., et al., Energy-efficient industrial internet of things: overview and open issues. IEEE transactions on industrial informatics, 2021. 17(11): p. 7225-7237.

[7] Shanthamallu, U.S., et al. A brief survey of machine learning methods and their sensor and IoT applications. In 2017, the 8th International Conference on Information, Intelligence, Systems Applications (IISA). 2017. IEEE

[8] C.-K. Hsieh, K.-L. Chan, and F.-T. Chien, "Energy-Efficient Power Allocation and User Association in Heterogeneous Networks with Deep Reinforcement Learning," *Applied Sciences*, vol. 11, no. 9, p. 4135, 2021.

[9] L. N. Huynh, *et al.*, "Efficient computation offloading in multitier multi-access edge computing systems: A particle swarm optimization approach," *Applied Sciences*, vol. 10, no. 1, p. 203, 2020.

[10] M. R. Palattella, *et al.*, "Internet of Things in the 5G era: Enablers, architecture, and business models," *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 3, pp. 510–527, 2016.

[11] B. Mao, *et al.*, "AI models for green communications towards 6G," *IEEE Communications Surveys & Tutorials*, vol. 24, no. 1, pp. 210–247, 2021.

[12] S. Mumtaz, *et al.*, "Massive Internet of Things for industrial applications: Addressing wireless IIoT connectivity challenges and ecosystem fragmentation," *IEEE Industrial Electronics Magazine*, vol. 11, no. 1, pp. 28–33, 2017.

[13] A. Mahmood, *et al.*, "Industrial IoT in 5G-and-beyond networks: Vision, architecture, and design trends," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 6, pp. 4122–4137, 2021.

[14] M. M. Hasan and S. Kwon, "Cluster-based load balancing algorithm for ultra-dense heterogeneous networks," *IEEE Access*, vol. 8, pp. 2153–2162, 2019.

[15] A. Khattab and N. Youssry, "Machine learning for IoT systems," *Internet of Things (IoT)*, pp. 105–127, 2020.

[16] K. Hoque, M. B. Hossain, A. Sami, D. Das, A. Kadir, and M. A. Rahman, "Technological trends in 5G networks for IoT-enabled competent healthcare: A review," *International Journal of Science and Research Archive*, vol. 12, no. 2, pp. 1399–1410, 2024.

[17] J. Yang, Y. Liu, and P. L. Morgan, "Human-machine interaction towards Industry 5.0: Human-centric smart manufacturing," *Digital Engineering*, p. 100013, 2024.

[18] N. Hasan, S. Rizvi, and A. Shabbir, "A Clustered PD-NOMA in an Ultra-Dense Heterogeneous Network with Improved System Capacity and Throughput," *Applied Sciences*, vol. 12, no. 10, p. 5206, 2022.

[19] A. Slalmi, R. Saadane, A. Chehri, and H. Kharraz, "How will 5G transform industrial IoT: Latency and reliability analysis," in *Human Centred Intelligent Systems: Proceedings of KES-HCIS 2020 Conference*, Springer Singapore, pp. 335–345, 2021.

[20] S. Shukla, *et al.*, "Improving latency in Internet-of-Things and cloud computing for real-time data transmission: a systematic literature review (SLR)," *Cluster Computing*, pp. 1–24, 2023.

[21] B. Agarwal, M. A. Togou, M. Marco, and G. M. Muntean, "A comprehensive survey on radio resource management in 5G HetNets: Current solutions, future trends and open issues," *IEEE Communications Surveys & Tutorials*, vol. 24, no. 4, pp. 2495–2534, 2022.

[22] M. U. Iqbal, *et al.*, "Optimal learning paradigm and clustering for effective radio resource management in 5G HetNets," *IEEE Access*, vol. 11, pp. 41264–41280, 2023.

[23] K. Nuanyai, P. Tarbut, and S. Chantaraskul, "Cell-Edge User Satisfaction-Based Dynamic CoMP Clustering with Load Awareness in Ultra-Dense Networks," *International Journal of Networked and Distributed Computing*, vol. 13, no. 1, pp. 1–16, 2025.

[24] F. R. Mughal, *et al.*, "An intelligent Hybrid-Q learning clustering approach and resource management within heterogeneous cluster networks based on reinforcement learning," *Transactions on Emerging Telecommunications Technologies*, vol. 35, no. 4, p. e4852, 2024.

[25] S. S. Sefati, *et al.*, "A Comprehensive Survey on Resource Management in 6G network based on Internet of Things," *IEEE Access*, 2024.

[26] R. Ramli and B. M. Lee, "An Overview of Deep Learning for Resource Management in mmWave-NOMA," *IEEE Access*, 2024.

[27] O. T. H. Alzubaidi, *et al.*, "Minimizing Power Consumption and Interference Mitigation of Downlink NOMA HetNets by IRS-Supported Aerial Base Stations," *IEEE Access*, 2025.

[28] U. Ghafoor, *et al.*, "Cluster based resource management using H-NOMA in heterogeneous networks beyond 5G," *Ad Hoc Networks*, vol. 149, p. 103252, 2023.

[29] K. R. Balmuri, *et al.*, "A long short-term memory network-based radio resource management for 5G network," *Future Internet*, vol. 14, no. 6, p. 184, 2022.

[30] T. Akhtar, C. Tselios, and I. Politis, "Radio resource management: approaches and implementations from 4G to 5G and beyond," *Wireless Networks*, vol. 27, pp. 693–734, 2021.

[31] S. Gowri and S. Vimalanand, "QoS-Aware Resource Allocation Scheme for Improved Transmission in 5G Networks with IoT," *SN Computer Science*, vol. 5, no. 2, p. 234, 2024.

[32] S. A. Latif, *et al.*, "AI-empowered, blockchain and SDN integrated security architecture for IoT network of cyber physical systems," *Computer Communications*, vol. 181, pp. 274–283, 2022.

[33] S. Bharany, *et al.*, "Energy-efficient clustering scheme for flying ad-hoc networks using an optimized LEACH protocol," *Energies*, vol. 14, no. 19, p. 6016, 2021.

[34] S. Mukherjee, S. Gupta, O. Rawlley, and S. Jain, "Leveraging big data analytics in AI-enabled IoT and industrial IoT for the development of sustainable smart cities," *Transactions on Emerging Telecommunications Technologies*, vol. 33, no. 12, p. e4618, 2022.