A Survey on User Grouping Schemes in Non-Orthogonal Multiple Access (NOMA)

Sajjad Ahmed[1,2], Norshidah Katiran[1,*], Ariffuddin Joret[1], Shaharil Mohd Shah[1],
Muhammad Inam Abbassi[3], and Faiz Asraf Saparudin[4]
[1] Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia (UTHM), Johor, Malaysia
[2] Faculty of Engineering, The University of Larkano, (TUL), Larkano, Sindh, Pakistan
[3] Faculty of Electrical and Electronic Engineering Technology, Universiti Teknikal Malaysia Melaka (UTeM), Malaysia
[4] Faculty of Engineering Technology, Universiti Tun Hussein Onn Malaysia, Malaysia
Email: sajjadbhatti_35@ hotmail.com (S.A.), norshida@uthm.edu.my (N.K.), ariff@uthm.edu.my (A.J.), shaharil@uthm.edu.my (S.M.S.), inamabbasi@utem.edu.my (M.I.A.), faizs@uthm.edu.my (F.A.S.)

***Abstract*—In wireless networks, managing an increasing number of users becomes increasingly challenging as user density rises. To address these challenges, various algorithms are employed to divide users into smaller, more controllable groups. This approach is crucial for optimizing the performance of Non-Orthogonal Multiple Access (NOMA) systems, which are a key component of next-generation wireless networks like 5G and 6G. User grouping schemes in NOMA systems are essential for optimizing resource allocation, mitigating interference, improving spectral efficiency, ensuring fairness, and reducing complexity. As wireless networks evolve, particularly with the integration of advanced technologies like Coordinated Multi-Point (CoMP), Internet of Things (IoT), Millimeter-Wave (mmWave), Terahertz (THz), Unmanned Aerial Vehicles (UAVs), Multi-Input Multi-Output (MIMO), and 5G-6G, effective user grouping will become increasingly critical. This research paper provides a systematic classification and analysis of various user grouping schemes, offering valuable insights for enhancing network performance in next-generation wireless networks.**

***Index Terms*—User grouping schemes, Non-Orthogonal Multiple Access (NOMA), Coordinated Multi-Point (CoMP), Unmanned Aerial Vehicles (UAV), Internet of Things (IoT)**

I. Introduction

In the future, wireless networks are poised to handle massive data rates due to the proliferation of bandwidth-intensive applications, streaming services, and emerging technologies. The sheer volume of users and connected devices is also expected to surge. To meet these unprecedented demands, network architects must develop efficient strategies. One such approach is network partitioning, where the network is divided into smaller user grouping and employs appropriate algorithms. This enables more effective resource management by allowing localized resource allocation, thereby mitigating congestion and interference. Non-orthogonal multiple access (NOMA) is a promising technology for next-generation wireless networks, enhancing spectral efficiency and bandwidth utilization [1]. It allows multiple users to share the same radio resources, allowing them to operate in the same frequency band and simultaneously [2]. NOMA distinguishes users based on their power levels, allowing them to coexist within the same resource block [3]. It was proposed as a candidate radio access technology for 5G cellular systems, as it serves multiple users using the same time and frequency resources, leading to improved system performance.

In NOMA networks, the adoption of user grouping strategies is crucial to tackling various critical challenges and enhancing network performance. A primary objective is to improve spectral efficiency. By grouping users based on similar channel characteristics or quality of service requirements, NOMA networks can more effectively allocate orthogonal resources, resulting in increased capacity utilization and better spectrum utilization using Power Domain (PD) NOMA [4]. PD-NOMA is a technique for enhancing performance in downlink cooperative networks by serving users around a 5G base station at the same frequency and time but with varying power levels, [5] using superposition coding and Successive Interference Cancellation (SIC).

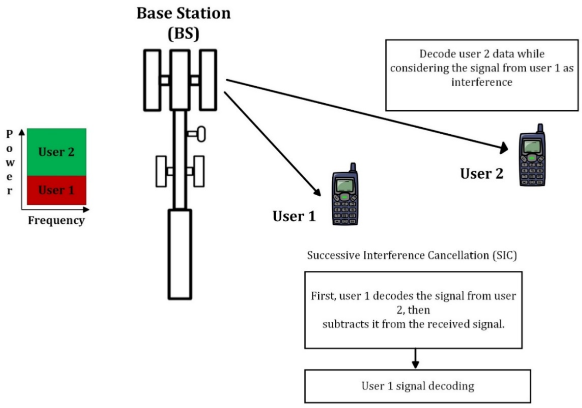

Fig. 1. Two users PD-NOMA scenario.

In a two-user PD-NOMA scenario, as shown in Fig. 1 one user near the base station is considered strong due to

Manuscript received May 26, 2024; revised August 30, 2024; accepted September 27, 2024.
*Corresponding author

its substantial channel gain, while the other is weak due to diminished channel gain. Both signals are combined at the transmitter end using distinct power coefficients. Path loss affects the weak user, causing a greater portion of power to be allocated to the weak user. This results in a higher Signal-to-Noise Ratio (SNR) for the weak user's Signal, Indicating (SIC). However, the strong user's transmission is perceived as noise at the weak user's receiver. Furthermore, user grouping schemes promote fairness and quality of service provisioning by enabling more equitable resource allocation tailored to individual user needs. Lastly, the adoption of clustering schemes simplifies resource allocation algorithms, reducing computational complexity and overhead.

This research paper introduces novel contributions to the understanding of NOMA and its user grouping schemes in next-generation wireless networks. It provides new frameworks, comparative analyses, and syntheses that offer fresh perspectives on optimizing network performance, especially in high-density user environments. These contributions offer new perspectives and tools that will shape the future of wireless communications in dense and complex environments, going beyond merely cataloging existing knowledge.

II. Integration of NOMA with Multiple Technologies

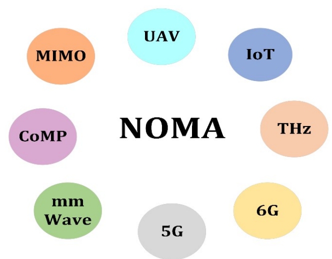

Fig. 2. NOMA integration with multiple technologies.

The integration of NOMA with various technologies, as illustrated in Fig. 2, including Coordinated Multi-Point (CoMP) transmission and reception, the Internet of Things (IoT), and more, offers the potential to unlock new capabilities and improve the performance of wireless communication systems across a wide range of applications NOMA user grouping schemes have been applied in various scenarios and real-world case studies, particularly in next-generation wireless networks like 5G and emerging 6G technologies. In a European Union research project, NOMA user grouping was integrated with CoMP to enhance coverage and throughput in suburban environments. In a smart factory deployment in Germany, it was used to manage communication between IoT devices, allowing for more effective resource allocation and reduced interference. NOMA user grouping was also used in disaster recovery exercises in Southeast Asia, where Unmanned Aerial Vehicles (UAVs) were used to provide temporary wireless coverage. In 5G trials in New York City, NOMA-based user grouping was applied to Millimeter-Wave (mmWave) communication systems to manage interference and optimize resource allocation. The trials demonstrated significant improvements in data throughput and coverage reliability in urban environments.

A. CoMP-NOMA

CoMP techniques involve the coordinated operation of multiple base stations to improve coverage, spectral efficiency, and user experience. CoMP techniques improve services for cell-edge users by enhancing data rates. They can be categorized into three types: Coordinated Scheduling and Coordinated Beamforming (CS/CB), Joint Transmission (JT), and Transmission Point Selection (TPS) [6]. CS/CB involves Base Stations (BSs) coordinating scheduling decisions and beamforming strategies to optimize user performance. JT involves simultaneous transmission from multiple BSs to a single user, enhancing signal quality and system capacity. TPS focuses on selecting the most suitable BS for serving a specific user based on channel conditions and other relevant factors. By integrating NOMA with CoMP, resources can be optimally allocated across coordinated base stations, enabling better interference management, enhanced user fairness, and higher system capacity [7–9]. NOMA's ability to exploit multi-user diversity and power domain multiplexing complements the coordinated beamforming and interference coordination aspects of CoMP, resulting in improved network performance [10].

B. IoT-NOMA

Conventional Orthogonal Multiple Access (OMA) methods, including Time-Division Multiple Access (TDMA) and Frequency-Division Multiple Access (FDMA), assign distinct time slots or frequency bands to various devices for transmission. However, these techniques may not be suitable for IoT networks due to the large number of devices and sporadic traffic patterns. NOMA, on the other hand, allows multiple devices to share the same time-frequency resources by utilizing power domain multiplexing. In NOMA, devices with better channel conditions are allocated more power, allowing them to transmit with higher reliability even if they share the same resources with devices experiencing poorer channel conditions. IoT-NOMA adapts the NOMA concept specifically for IoT applications, where the devices typically have low-power and low-complexity constraints [11]. By efficiently managing the allocation of resources among IoT devices, IoT-NOMA aims to improve the spectral efficiency, reliability, and scalability of IoT networks [12–14]. This can be particularly useful in scenarios where a large number of IoT devices need to transmit small amounts of data sporadically, such as in smart cities, industrial automation, and environmental monitoring applications.

As NOMA systems are increasingly integrated with IoT and other sensitive technologies, addressing security and privacy concerns is critical. These concerns, ranging from eavesdropping and interference-based attacks to privacy issues in user grouping and DoS attacks, highlight the need for robust security mechanisms tailored to the unique characteristics of NOMA. By employing advanced encryption, privacy-preserving algorithms, decentralized resource allocation, and strong authentication protocols, NOMA systems can be made more secure and resilient, ensuring the safe deployment of these technologies in next-generation wireless networks.

C. UAV—NOMA

UAVs are increasingly being deployed for various applications, including aerial surveillance, disaster management, and delivery services. Integrating NOMA with UAV communication systems can enhance their performance by enabling efficient spectrum utilization, improved connectivity, and enhanced coverage [15–17]. UAV-NOMA systems improve spectral efficiency by enabling multiple UAVs to share the same frequency resources, especially in limited spectrum availability or high-bandwidth communication scenarios [18]. NOMA's power allocation strategy ensures UAVs with better channel conditions receive higher power allocations, enhancing data rates and throughput. This is crucial for real-time data transmission and high-bandwidth communication links. NOMA also enhances the reliability of UAV communication links by dynamically adjusting power allocations based on channel conditions, ensuring robust communication even in challenging environments or interference. UAV-NOMA systems can facilitate the deployment of IoT devices and sensor networks in remote or inaccessible areas by providing reliable and high-throughput communication links [19]. This enables applications such as environmental monitoring, precision agriculture, disaster response, and infrastructure inspection.

D. mmWave—NOMA

mmWave communication refers to the use of electromagnetic waves with frequencies in the millimeter range, typically between 30 GHz and 300 GHz, for wireless communication [20]. These frequencies offer significantly wider bandwidths compared to lower frequency bands used in traditional wireless communication systems, enabling higher data rates and capacity. mmWave technology is a key enabler for next-generation wireless networks, including 5G and beyond, due to its potential to deliver multi-gigabit-per-second data rates and support for massive connectivity. mmWave communication combined with NOMA techniques offers several advantages, including increased spectral efficiency due to wide bandwidths, enhanced throughput for users with favorable channel conditions, improved reliability in varying channel conditions, and support for massive connectivity [21–23]. NOMA's power allocation scheme ensures reliable transmission, even in challenging environments, by allocating more power to users experiencing better channel conditions. Additionally, mmWave NOMA can support a large number of devices, including IoT devices, by efficiently managing resource allocation among them. Overall, mmWave-NOMA offers numerous benefits for network performance.

E. Terahertz (THz)—NOMA

Terahertz frequencies refer to the electromagnetic spectrum with frequencies typically ranging from 0.1 to 10 terahertz, or equivalently, wavelengths between 30 micrometers and 3 millimeters [24]. Terahertz waves offer vast bandwidths and the potential for extremely high data rates, making them a promise for ultra-fast wireless communication. THz communication combined with NOMA offers several benefits, including enhanced spectral efficiency, improved throughput, and reliable communication [25, 26]. The wide bandwidth in the terahertz spectrum, combined with NOMA's power domain multiplexing, allows for more efficient utilization of frequency resources, leading to higher data rates and capacity in THz communication systems [27]. NOMA's power allocation strategy ensures users with better channel conditions receive higher power allocations, resulting in faster data transmission rates. It also enhances the reliability of THz communication links by dynamically adjusting power allocations based on channel conditions, ensuring robust communication even in challenging environments or interference. THz-NOMA systems can support a massive number of devices or users [28], each with different channel conditions, scalability is crucial for applications like IoT.

F. MIMO-NOMA

MIMO is a wireless communication technology that enhances data throughput and link reliability by using multiple antennas at the transmitter and receiver [29]. It uses spatial diversity and multipath propagation to transmit multiple data streams simultaneously, enhancing spectral efficiency and system capacity. MIMO technology combined with NOMA techniques offers several benefits, including increased spectral efficiency, enhanced throughput, and support for massive connectivity [30, 31]. MIMO-NOMA systems utilize both spatial and power domain multiplexing, allowing multiple data streams to be transmitted simultaneously over the same frequency band, resulting in increased data throughput and capacity. This approach also allows for higher data rates compared to traditional systems, as users with better channel conditions can be assigned higher power levels and transmitted over multiple spatial streams. Additionally, MIMO-NOMA can support a large number of users or devices by efficiently managing spatial and power resource allocation, making it crucial for applications like IoT [32, 33] and future wireless networks.

G. 5G/6G—NOMA

The evolution from 5G to 6G communications will bring about new requirements, use cases, and technological challenges. NOMA is expected to play a significant role in shaping the future of wireless communication systems, bridging the gap between current and future generations of mobile networks. 5G networks aim for higher data rates, lower latency, and increased reliability [34, 35]. NOMA can help achieve these goals by enabling efficient sharing of time-frequency resources among multiple users, leading to increased spectral efficiency. This scalability is crucial for applications like smart cities, industrial automation, and healthcare, as 5G networks support a massive number of devices, including IoT devices and sensors [36, 37].

6G networks aim to support higher data rates and lower latency [38]. NOMA can help achieve this by efficiently using available spectrum resources and enabling simultaneous transmission of multiple data streams. Combining 6G with IoT supports a massive number of devices [39, 40]. 6G networks may also integrate satellite communication for ubiquitous connectivity across urban, rural, and remote areas, ensuring seamless connectivity and high-quality service delivery [41, 42].

The integration of NOMA with multiple technologies offers a pathway toward more efficient, scalable, and versatile wireless communication systems. By leveraging NOMA's unique capabilities in resource allocation, interference management, and multi-user diversity, these integrated solutions can address the evolving demands of modern communication networks across a wide range of applications and deployment scenarios.

III. User Grouping Schemes in NOMA

The NOMA system employs various user grouping schemes to optimize resource allocation, interference management, and system performance. These schemes use algorithms and strategies to categorize users based on different criteria, as illustrated in Fig. 3.

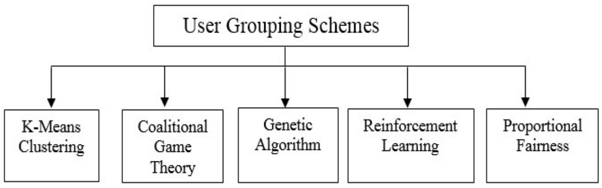

Fig. 3. User grouping schemes in NOMA

A. K-Means Clustering Based User Grouping

K-means clustering simplifies resource allocation in scenarios where a Base Station (BS) serves multiple users. It achieves this by grouping users based on their Channel State Information (CSI) and spatial correlation.

The K-means algorithm is employed to cluster users based on their CSI, and subsequently, the users are grouped into distinct clusters based on their proximity to the cluster centers [43]. This approach has demonstrated an effective trade-off between the aggregate data rate and user fairness.

K-means clustering is useful for grouping users with similar channel conditions together. This grouping can help in allocating the available resources optimally, such as power allocation and subcarrier allocation, in NOMA systems. K-means clustering can also be employed to group users based on their proximity or similarity in terms of their channel characteristics, traffic patterns, or quality of service requirements [44]. This grouping can aid in efficiently applying NOMA techniques to serve multiple users simultaneously. NOMA relies on the principle of Successive Interference Cancellation (SIC) to decode multiple signals simultaneously at the receiver. K-means clustering can be used to group users in a way that minimizes interference among them, thereby enhancing the performance of SIC. In NOMA systems employing beamforming techniques, K-means clustering can help in grouping users that can be served by the same beamforming vector [45]. This can lead to improved spectral efficiency and reduced interference. Table I shows a summary of K-means clustering-based user grouping in NOMA.

TABLE I: K-means Clustering Based on User Grouping in NOMA

Ref.	Classification	System model	Problem	Design objective	Optimization method	Main findings
[46]	mmWave - NOMA	Downlink+ single BS+ Multiple users+ Multiple clusters.	To optimize the performance of mm Wave NOMA systems in imperfect (SIC) involving efficient user grouping, beamforming optimization, and power allocation.	To develop algorithms that jointly address user grouping, beamforming, and power allocation to maximize the throughput.	Cross entropy (CE) & K-mean based clustering	The proposed algorithms for joint user grouping, beamforming, and power allocation in mmWave-NOMA systems with imperfect SIC.
[47]	UAV-NOMA	Downlink+ Single BS+ Single UAV+ Multiple users.	The optimization challenges in a downlink NOMA system integrated with UAVs.	To improve user pairing and power allocation in a downlink NOMA-UAV system, taking into account the imperfections in SIC.	K-mean clustering algorithm	The performance improvements achieved by the proposed machine learning-based approach for user pairing and power allocation in the downlink NOMA-UAV system with imperfect-SIC.
[48]	6 G -NOMA	Downlink + One BS + Multiple users	To address the challenges posed by short-packet communication in (6G) networks.	To achieve low-latency communication while ensuring extended coverage and spectral efficiency.	K-means algorithm	The study evaluates the performance of the short-packet C-NOMA communication system, revealing the influence of channel usage and the number of UEs on BLER and sum rate.
[49]	CoMP-NOMA	Downlink+ Multiple BS+ Multiple users	To address re-source allocation issues for CoMP-NOMA networks, addressing the	To optimize resource allocation to enhance system performance.	K-means algorithm & Adap-tive User Pairing algorithm (AUP)	The proposed scheme, demonstrated through simulation, is more effective in enhancing the system sum-rate and

			challenges of spectrum scarcity and inter-network interference.			reducing interference in ultra-high user and base station density compared to other techniques.
[50]	MMC Net-works- NOMA	Downlink One BS +Multiple users+ 2 cluster	Addressing the limitations of traditional K-means clustering	Enhance clustering by integrating NOMA principles into the K-means algorithm in MMC Networks	Enhanced K-means algo-rithm	The proposed scheme demonstrated superior net-work sum throughput compared to traditional K-means.
[51]	MISO-NOMA	Uplink + One BS multiple K users	Investigating the user grouping and power control in the uplink (MISO-NOMA) networks.	To develop an effective user grouping scheme for multiantenna uplink NOMA transmission.	K-means algorithm	The study proposes a terference-compression-based user grouping method for overall power control, followed by a per-cluster power adjustment and an improved K-means method for channel correlations and gain differences.
[52]	THz-MIMO-NOMA	Downlink+ One Micro BS +Multiple small BS + Multiple users	Addressing energy efficiency challenges in Terahertz MIMO-NOMA systems, particularly related to user grouping, hybrid precoding, and power optimization.	Develop an energy-ef-ficient user grouping algorithm for Terahertz MIMO-NOMA systems	Enhanced K-means algo-rithm	The study proposes a fast convergence scheme for user grouping in a NOMA-MIMO system using an enhanced K-means machine learning algorithm, utilizing a hybrid precoding scheme
[53]	mmWave-NOMA	Downlink + One BS +Multiple users	Addressing challenges in user grouping for mmWave-NOMA systems, with a focus on eraging unsupervised machine learning techniques.	To develop an unsuper-vised machine learning-based user grouping algorithm for mmWave-NOMA systems	K-means algorithm	Channel correlations efficiently measure K-means-based clustering, and a closed-form expression for optimal power allocation is developed for each cluster, assuming equal allocation of power.

B. Coalitional Game Theory-Based User Grouping

Coalitional game theory can indeed be applied in the context of NOMA systems. In NOMA, multiple users share the same time-frequency resources, but their signals are separated based on power domain multiplexing rather than traditional orthogonal allocation. Coalitional game theory can be used to model the interactions between users in forming coalitions to improve their individual or collective utilities. Users in a NOMA system can form coalitions based on their mutual interests, such as improving their overall throughput, minimizing interference, or maximizing their fairness in resource allocation. Coalitional game theory provides frameworks for users to form stable coalitions where they can cooperate to achieve common goals [54]. Within each coalition, users can negotiate and cooperate to allocate transmit power, subcarrier assignment, or other resources optimally to maximize their joint utility.

Coalitional game theory helps in modeling these negotiations and designing mechanisms for fair and efficient resource allocation [55]. Users belonging to different coalitions may have conflicting interests, especially in NOMA where power-domain multiplexing introduces inter-user interference. Coalitional game theory can be used to model the interactions between different coalitions, where they may cooperate or compete to optimize their individual or collective utilities. Coalitional game theory also addresses the stability and fairness of coalition formations [56]. Stable coalition structures ensure that no subset of users has an incentive to deviate from their coalition and form a new one. Moreover, coalitional game theory provides mechanisms for ensuring fairness in resource allocation among users within and across coalitions. Table II shows a summary of Coalitional game theory-based user grouping in NOMA.

TABLE II: COALITIONAL GAME THEORY-BASED USER GROUPING IN NOMA

Ref.	Classification	System model	Problem	Design objective	Optimization method	Main findings
[57]	UAV-NOMA	UAVs, + attacker, and ground nodes	To address the security challenges in unmanned aerial vehicle (UAV) communications.	To create a secure communication framework for UAVs	Efficient incentive scheme based on the coalitional game	The proposed scheme enhances the utilities of legal UAVs and network security compared to conventional schemes, according to simulation results.
[58]	UAV-IoT-NOMA	UAVs, + IoT devices+ satellites+	To address security issues in UAV communications	The goal is to minimize the computational overhead of terminal	A low-complexity algorithm based on a coalition game approach	The proposed algorithm effectively optimizes UAV emergency

		control center	during emergency situations, focusing on improving network services and ensuring efficient communication for UAVs in critical situations.	devices (such as marine Internet of Things (IoT) devices) while ensuring timely task completion and energy efficiency		communication in a NOMA-based marine IoT context, demonstrating its feasibility compared to existing schemes in the literature.
[59]	JT-CoMP -NOMA	Downlink + Multiple BS+ Multiple users	Addressing the challenge of providing improved service to cell-edge users in downlink NOMA	To develop a solution using coalition formation games for optimizing the downlink NOMA and MU-MIMO small cell systems	Coalition formation algo-rithm	The proposed scheme successfully formed coalitions of RRHs, facilitated intercell inter-interference cancellation for cell-edge users, and resulted in an immediate increase in throughput.
[60]	JT-CoMP-NOMA	Downlink+ Multiple BS+ Multiple users	Addressing the challenge of radio resource management in small cell networks and NOMA for improved efficiency.	To improve spectral efficiency, overall network performance, and resource allocation among users.	Cooperative Coalition game algorithm	The Cooperative Coalition game algorithm forms optimal Remote radio heads (RRH), groups, improving edge user throughput and overall cell network throughput, as shown in the results.
[61]	5G -NOMA	Uplink+ Single BS+ Multiple K users	Addressing the chal-lenge of user grouping in NOMA systems with a focus on generalized and overlapping scenarios.	To develop a solution for generalized user grouping in NOMA based on an overlapping coalition formation game.	Overlapping coalition formation (OCF) algorithm	The algorithm successfully converges to a stable coalition structure within finite iterations, enabling efficient optimization of GuG and power control solutions.
[62]	MEC network-NOMA	Uplink+ Single BS+ Multiple UE users' equipment's	Investigating Computation offloading in multi-carrier NOMA-enabled MEC systems.	To minimize the energy consumption and/or overall latency of UEs	Coalition formation game	A low-complexity algorithm that achieves Nash-stable solution and outperforms baseline schemes.
[63]	MIMO-NOMA	Downlink+ Single BS+ two mobile users (Mus).	Investigating MIMO-NOMA clustering with beamforming and power allocation	To minimize the power consumption of MUs	An improved coalition game approach	The study presents a linear optimization method for beamforming and power allocation, as well as a low-complexity algorithm for MU clustering.
[64]	mm-wave-NOMA	Downlink+ Single BS+ Multiple N users'	Investigating User grouping and power allocation in mmWave-NOMA systems.	To maximize the sum rate of the system.	A Stackelberg game approach	The study presents a low-complexity algorithm for user grouping and power allocation, comparing its performance with OMA-based schemes.

C. Genetic Algorithm-Based User Grouping

Using a genetic algorithm (GA) for user grouping in NOMA systems can be an innovative approach to optimize resource allocation and enhance system efficiency. NOMA allows multiple users to share the same time-frequency resources, exploiting the power domain for multiplexing, which is particularly beneficial for enhancing spectral efficiency and accommodating diverse quality-of-service requirements. GA is used to solve complex optimization problems [65], such as non-convex and challenging resource allocation problems. They adapt to changing environments, user requirements, and system constraints, finding robust solutions even when channel information is imperfect or noisy. GA aids in user grouping and pairing decisions, enhancing system efficiency [66]. It strikes a balance between exploring new solutions (diversification) and exploiting promising ones (intensification), ensuring efficient resource utilization while avoiding premature convergence to suboptimal solutions. By balancing fairness, throughput, and energy efficiency, GA helps optimize user clusters and ensure efficient resource utilization in NOMA systems.

Researchers have developed a Genetic Algorithm (GA) to optimize Energy Efficiency (EE) in downlink wireless systems by combining millimeter-wave technology with non-NOMA [67]. The algorithm targets the asymmetric data rate of user applications, specifically addressing the non-convex Energy Efficiency (EE) problem in an imperfect channel state information (CSI) downlink mm-Wave NOMA system. A recent study proposes an energy-efficient resource allocation scheme using a Genetic Algorithm (GA) for heterogeneous networks [68]. The study focuses on designing an energy-efficient scheme that enables shared spectrum access for small cells while maintaining the quality of service for macro cell users. Additionally, the scheme aims to reduce overall energy consumption by transitioning underutilized small cells to sleep mode. Table III shows the summary of genetic algorithm-based user grouping in NOMA.

TABLE III: GENETIC ALGORITHM-BASED USER GROUPING IN NOMA

Ref.	Classification	System model	Problem	Design objective	Optimization method	Main findings
[69]	IoT-NOMA	Downlink + Single BS+ Multiple users	The optimization challenges in (NOMA) networks integrated with (IoT) devices	To develop a novel optimization algorithm for multi-objective optimization in NOMA-IoT networks.	Genetic Algorithm-Based Reinforcement Learning (GA-RL)	The GA-RL algorithm for multi-objective optimization in NOMA-IoT networks is evaluated for improvements in system throughput, delay reduction, energy efficiency enhancement, and fairness compared to traditional techniques.
[70]	MIMO-NOMA	Downlink + Multiple BS+ Multiple users' equipment's	Optimization challenges in downlink MIMO heterogeneous networks, focusing on beamforming techniques to improve NOMA system performance in diverse environments	The study focuses on designing semi-blind beamforming techniques for downlink MIMO-NOMA heterogeneous networks to optimize system throughput, minimize interference, and enhance user fairness.	Genetic algorithm GA-based heuristic optimization scheme	The paper presents performance analysis and evaluation results of a proposed semi-blind beamforming algorithm for downlink MIMO-NOMA heterogeneous networks, highlighting improvements in system throughput, interference mitigation, and spectral efficiency.
[71]	UAV-NOMA	Downlink + multiple UAV + multiple cluster + multiple user each cluster	To address the issue of efficient resource allocation in multi-cluster NOMA networks involving UAVs, focusing on spectral efficiency, interference minimization, and resource utilization optimization.	To develop a novel resource allocation scheme for multi-cluster NOMA-UAV networks, enhancing performance metrics like throughput, latency, and energy efficiency.	Genetic algorithm	Optimization of UAV transmission power, hovering locations, and duration using optimal clusters and routing, adopting SCA for convex subproblems, and proposing an iterative algorithm for resource allocation.
[72]	V2X-NOMA	Downlink+ Single BS+ Multiple UE users' equipment's	Latency and user throughput problem in NOMA systems	Maximize the sum rate of the system	A genetic algorithm approach with continuous pool	The study presents a low-complexity algorithm for hyper-fraction channel and power allocation, comparing its performance with OMA-based schemes.
[73]	5G-NOMA	Downlink+ Single BS+ 2 (UE) users' equipment's	Addressing Multi-user radio resource allocation for NOMA downlink systems	Maximize the geometric mean of user throughputs	Genetic algorithm (GA)	A robust heuristic that swiftly converges to the desired solution, balancing the balance between system throughput and user fairness.
[74]	NOMA	Downlink+ Single BS+ multiple M users	User grouping in the NOMA scenario with no limit on the number of users in each cluster	Maximize the system's total throughput under minimum rate constraints	Genetic algorithm (GA)	The algorithm is designed to minimize computational complexity and outperform other heuristic and random user grouping methods using a greedy strategy.
[67]	MmWave-NOMA	Downlink+ Single BS+ 2 (UE) users' equipment's	The study addresses the non-convex energy efficiency problem in an imperfect CSI downlink mmWave NOMA system.	Maximize the energy efficiency of the system	Genetic algorithm (GA)	The GA-derived solution is nearly identical to the optimal value and outperforms conventional orthogonal multiple access, enhancing the EE by over 75%.
[75]	IoT-6G-NOMA	Downlink+ Single BS+ multiple IoT nodes	Addresses the challenge of power allocation in 6G-enabled Internet of Things (IoT) networks.	To enhance the spectral efficiency and energy efficiency of NOMA-based 6G-enabled IoT nodes.	Multi-objective genetic algorithm (MOGA)	A QoS-aware power assignment approach was developed to improve the spectral efficiency and energy of NOMA-based IoT nodes in the 6G era.

D. Reinforcement Learning-Based User Grouping

Reinforcement Learning (RL) based user grouping in NOMA systems presents an intriguing approach to optimizing resource allocation, user pairing, power allocation, and other aspects of NOMA networks. RL algorithms can learn optimal resource allocation policies based on changing channel conditions and user requirements [76]. NOMA networks operate in complex environments with varying user densities, mobility patterns, and interference levels. RL techniques enable NOMA systems to adapt autonomously and optimize performance without explicit models. RL technique can optimize system parameters like power allocation, user pairing, and decoding in order to maximize throughput and fairness [77]. RL can explore novel resource allocation strategies that may not be feasible or apparent through traditional optimization techniques, leading to innovative solutions that improve the efficiency and effectiveness of NOMA systems. User dynamics, such as traffic demands and Quality of Service (QoS) requirements, significantly impact system performance. RL-based approaches facilitate self-organizing capabilities in NOMA networks, enabling them to configure and optimize their operation without human intervention, especially in large-scale deployments where manual management becomes impractical.

In scenarios where cellular networks face congestion, Unmanned Aerial Vehicles (UAVs) can assist by offloading traffic. NOMA can be employed at each UAV to enhance spectral efficiency. Multi-agent RL techniques can optimize UAV placement, power allocation, and resource utilization. These algorithms learn from interactions with the environment and adapt to varying conditions, improving overall system efficiency [78]. In a recent study, researchers proposed a semi-supervised reinforcement learning-based solution to the problem of user grouping and power allocation in NOMA systems [79]. The solution uses the (OMA) and one of its variants to resolve the grouping in NOMA systems.

Table IV shows the summary of reinforcement learning -based user grouping in NOMA.

TABLE IV: REINFORCEMENT LEARNING-BASED USER GROUPING IN NOMA

Ref.	Classification	System model	Problem	Design objective	Optimization method	Main findings
[79]	NOMA	Downlink+ one BS+ Multiple K users	NOMA systems face problems in grouping users into prespecified time slots and determining power allocation for each user	Develop a semi-supervised reinforcement learning-based solution for user grouping in NOMA systems.	Reinforcement learning-based solution	The proposed semi-supervised reinforcement learning solution effectively optimizes user grouping in NOMA systems.
[80]	MIMO-NOMA	Downlink+ one BS+ Multiple K users	Addressing challenges in beam selection, hybrid beamforming, and user grouping in Massive MIMO-NOMA systems,	Optimize hybrid beamforming strategies to enhance spectral efficiency and user experience	Reinforcement learning-based beam-user selection and novel user grouping methods.	The RL-based DFT-NOMA algorithm, utilizing channel correlation and gain information, significantly enhances inferior energy efficiency and spectral efficiency by 42% compared to existing schemes
[81]	mm Wave-NOMA	Downlink+ Multiple BS+ Multiple K users	Addressing issues in mm-wave NOMA network, such as Successive Interference Cancellation (SIC), higher intra-beam interference, and inter-beam inter-cell interference.	To maximize the aggregate network capacity by jointly addressing user-cell association and selecting the optimal number of beams.	Reinforcement learning algorithm.	TQL and Q-learning show a 12% rate of improvement under mobility conditions, while Q-learning and BSDC outperform TQL in stationary scenarios but achieve a 29% convergence speedup.
[82]	UAV-NOMA	Uplink + Single UAV + Single cluster + multiple user	Optimizing resource allocation and network performance in NOMA-UAV networks, addressing challenges due to dynamic UAV movements, varying channel conditions, and efficient spectrum utilization.	The research aims to create an adaptive reinforcement learning framework for NOMA-UAV networks, focusing on dynamic resources and allocation to enhance network performance metrics like throughput, latency, and energy efficiency.	Reinforcement learning (RL)	Adaptive reinforcement learning framework for NOMA-UAV networks outperforms exhaustive, greedy, and random policies, outperforming SIC in interference marred environments, despite increased complexity.
[83]	5G-NOMA	Downlink+ one BS+ Multiple M users	Addressing challenges in user grouping and power allocation in NOMA systems,	Implement a reinforcement learning-based solution for power allocation to	Reinforcement learning algorithm	The proposed Q-learning algorithm with user grouping achieves the highest throughput, overcoming multiple

				enhance overall system performance.		NOMA constraints like transmission power budget and minimum user data rate requirements.
[84]	IoT-NOMA	Uplink+ one BS+ Multiple N users	This study addresses two key issues in fair resource allocation in NOMA techniques: dynamic user allocation and balancing resource blocks and network traffic.	To create an intelligent resource allocation scheme for uplink NOMA-IoT communications to optimize the average performance of sum rates.	Deep reinforcement learning (DRL) and SARSA-learning	The framework offers a long-term guaranteed average rate with reliability and stability and has proven to be efficient for complex scenarios.
[85]	NOMA	Downlink+ one BS+ Multiple N users	The issue lies in the optimal allocation of resources like power and channels to users to enhance system performance.	Optimize power allocation and channel assignment in NOMA systems using Deep reinforcement learning (DRL) techniques.	Deep reinforcement learning framework	The study introduces a deep reinforcement learning framework utilizing an attention-based neural network for channel assignment problems, demonstrating superior performance compared to two other approaches.
[86]	NOMA	Uplink+ one BS+ Multiple N users	Addressing the challenge of throughput improvement in the uplink of grant-free NOMA	To develop a solution using Deep Reinforcement Learning (DRL) for improving the throughput of the uplink in grant-free NOMA systems	Deep reinforcement learning Based Grant-Free NOMA Algorithm	The proposed algorithm, based on DRL, outperforms slotted ALOHA NOMA with a 156% gain on system throughput when the number of devices is five times the subchannels.

E. Proportional Fairness-Based User Grouping

Proportional fairness in NOMA refers to the concept of distributing resources among users in a way that ensures each user receives a fair share relative to their channel conditions and quality of service requirements. In NOMA, multiple users share the same time-frequency resources, and their signals are separated based on power domain, allowing them to access the channel simultaneously. Achieving proportional fairness in NOMA involves allocating transmit power levels to users in such a manner that the system maximizes a fairness metric while satisfying certain constraints, such as power constraints and quality of service requirements. This technique simplifies resource allocation in scenarios where a base station (BS) serves multiple users [85]. It calculates priorities for active users using Proportional Fairness (PF). The user with the highest priority is selected, and its corresponding Resource Block (RB) is determined. Other users assigned to the same RB are chosen based on a user-grouping strategy that considers Channel State Information (CSI) and spatial correlation [86]. This approach achieves a favorable trade-off between total data rate and user fairness [87].

One approach to achieving proportional fairness in NOMA is to use optimization techniques to allocate transmit power levels to users dynamically [88], considering factors such as channel conditions, data rates, and QoS requirements. This optimization process aims to maximize a fairness metric, such as the proportional fairness index, subject to constraints such as total transmit power and individual user QoS requirements. Table V shows a summary of PF-based user grouping in NOMA.

TABLE V: PROPORTIONAL FAIRNESS-BASED USER GROUPING IN NOMA

Ref.	Integration	System model	Problem	Design objective	Optimization method	Main findings
[86]	User-centric (UC) networks-NOMA	Downlink multiple BS+ multiple users	Resource allocation issues in UC networks by examining slot resource allocation and precoding design over consecutive time-slots.	To achieve proportional-fair resource allocation, ensuring each user receives a fair share of available resources while enhancing system performance.	Proportional-fair resource allocation scheme	The scheme addresses UE grouping and intra-group resource allocation issues using modularity-based user grouping and parallel distributed PFRA algorithms, utilizing local CSI for large-scale network applications.
[89]	UAV-NOMA	Downlink One UAV + multiple users	The challenge lies in efficient power allocation considering UAV mobility and dynamic network conditions.	It aims to improve the transmission rate for users with relatively worse channel state information while minimizing the overall sum rate loss.	Proportional-fair scheme	The solution addresses user pairing and subchannel allocation, determining the optimal power allocation factor for users on the same subchannel, and allocating appropriate power to improve performance.
[90]	IoT-NOMA	Uplink+ Primary and secondary BS + IoT devices	To investigate scheduling and power allocation problems in industrial cognitive IoT over NOMA	To maximum throughput in NOMA-IoT network	Proportional-fair scheme	The study suggests fairness-aware algorithms that balance throughput and fairness constraints, potentially enhancing the performance of cognitive

		networks using imperfect channel state information and spectrum sensing.			heterogeneous NOMA networks in industrial IoT scenarios.
[91]	NOMA	Downlink + One BS + multiple users	Investigating the resource allocation problem in a downlink multi-carrier (NOMA) system with K users and N sub-carriers	To maximize the expected sum capacity under a proportional user fairness constraint	Proportional-fair resource allocation scheme.	The proposed algorithm can offer higher anticipated system capacity with the same order of time complexity under the same proportional user fairness constraint compared to the conventional OFDMA.
[92]	NOMA	Downlink + One BS + multiple users	Investigating the optimization problem of associated with the selection of users, assignment of subcarriers, and allocation of power.	To increase the sum capacity under a general proportional user fairness constraint	Proportional-fair resource allocation scheme.	The proposed algorithm optimizes NOMA sum capacity by pairing users with the smallest starving indexes, assigning subcarriers and power to different pairs, and enhancing system capacity over conventional OFDMA systems.
[93]	5G	Downlink One BS + M users	Investigating the power allocation problem of NOMA system based on QoS	To develop a power allocation algorithm that ensures proportional fairness among users.	Proportional-fair based Karush-Kuhn-Tucker (KKT) constraints.	The data rate aligns with NOMA's fundamental principle, indicating that users with poor channel conditions allocate more power, while those with better conditions allocate less power.
[94]	5G	Downlink One BS + M users	Addresses the issue of resource allocation in downlink NOMA cellular systems.	To optimize energy efficiency while ensuring the minimum data rate within the base station's limited power budget.	Proportional-fair based a model solver and power optimization scheme	The proposed algorithm optimizes throughput for multiple users on the same channel using a channel assignment technique and DC programming for power allocation.

TABLE VI: THE COMPARISON OF LIMITATIONS OF USER GROUPING SCHEMES IN NOMA

No.	User grouping schemes	Limitations
1	K-Means clustering	Sensitivity to Initial Conditions: K-Means clustering is susceptible to preliminary cluster centroids placement, causing varying final cluster assignments. To mitigate this, multiple runs with different initializations are used [95]. Assumption of Spherical Clusters: K-Means assumes spherical clusters with equal variance, but real-world scenarios may have different shapes and variances, and NOMA user groups may have diverse channel conditions [96]. Handling Outliers: Outliers can significantly affect K-Means results, dragging centroids and affecting cluster boundaries. Preprocessing steps like outlier removal are crucial before applying K-Means [95]. Determining the Number of Clusters (K): K-Means requires pre-specified clusters (k), which can be challenging in NOMA systems to determine the optimal number of user groups, as incorrect choices can result in suboptimal outcomes [97]. Scaling with Dimensions: K-Means performance can degrade as dimensions increase, but distance-based similarity measures can converge in high-dimensional spaces, and techniques like Principal Component Analysis can help overcome this limitation [96]. Cluster Shapes and Density: K-Means struggle with varying cluster sizes and densities, potentially causing non-uniform clusters in NOMA user groups due to imbalanced channel conditions [98].
2	Coalitional Game Theory (CGT)	Complexity and Scalability: CGT-based approaches model user interactions as coalitions, increasing computational complexity with network size. Finding optimal coalitions becomes expensive and impractical for real-time scenarios as the network scales up [99]. Optimal Coalition Formation: CGT offers a framework for coalition formation, but finding the globally optimal structure can be challenging due to the NP-complete problem and the use of approximation algorithms [99]. Dynamic User Behavior: CGT-based approaches assume static coalitions, but dynamic environments require users to switch or form new ones, requiring continuous reformation, and introducing overhead [100]. Assumptions About User Cooperation: CGT assumes rational users act in their best interest, but in practice, users may not always cooperate optimally or exhibit selfish behavior, impacting coalition effectiveness [101].
3	Genetic Algorithm (GA)	Computational Complexity: Genetic algorithms, due to their high computational cost and complexity, can be challenging to implement in real-time, especially in large-scale systems [102]. Convergence Speed: Genetic algorithms may face slow convergence rates, especially in complex optimization problems, resulting in longer execution times and delayed optimal or near-optimal solutions [102]. Dynamic Environments: NOMA systems operate in dynamic environments with changing channel conditions, user mobility, and traffic patterns, which genetic algorithms may struggle to adapt to efficiently due to their static problem formulation [103]. Limited Communication Overhead Consideration: Genetic algorithms may overlook communication overhead in NOMA systems, affecting system performance due to factors like signaling overhead, feedback latency, and channel estimation complexity [104].
4	Reinforcement Learning (RL)	Complexity and Training Time: RL algorithms require significant computational resources and time for training, making them challenging in NOMA systems with rapidly changing channel conditions, potentially hindering real-time adaptation [105]. Sample Efficiency: RL requires extensive samples for effective policy learning, while NOMA can be challenging to collect due to limited communication resources [106]. Reward Design: The choice of reward function significantly influences RL performance in NOMA clustering, as poorly designed rewards can lead to suboptimal policies [106]. Model Complexity and Interpretability: The complexity of RL models can make understanding their decision-making process challenging, hence, in NOMA, interpretable policies are preferred for network operators [105].
5	Proportional Fairness (PF)	User Interference: PF-based user grouping aims for fairness by allocating resources proportionally, but interference between users with different channel gains can negatively impact communication quality and system performance [107]. Resource Wastage: NOMA user grouping approaches often divide users into disjoint sets, potentially wasting power resources. Efficient utilization of available resources is crucial for maximum capacity gain [108]. Complexity and Scalability: PF-based algorithms use iterative optimization, increasing computational complexity

	with network size, making optimal solutions costly and impractical in real-time scenarios [109]. Trade-off Between Fairness and Efficiency: PF aims for fairness, but balancing fairness with system performance can be challenging, potentially sacrificing throughput or spectral efficiency [110].

F. The Comparison of Limitations of User Grouping Schemes in NOMA

Table VI evaluates the comparison of limitations of user grouping schemes in the NOMA system, categorized into five groups, highlighting their challenges and limitations.

IV. Conclusion

The research emphasizes the importance of user grouping schemes in NOMA communication for improving network performance, particularly in densely populated networks. This strategy optimizes resource allocation and minimizes interference. It also applies to emerging technologies like IoT, UAVs, and advanced transmission techniques like CoMP, MIMO, mm Wave, and THz. It also applies to 5G and 6G networks. The paper discusses user grouping schemes in wireless networks, including Proportional Fairness, K-Means clustering, Coalitional Game Theory, Genetic Algorithm, and Reinforcement Learning. It highlights their importance in managing network resources and adapting to changing conditions. The paper emphasizes the critical role of these schemes in ensuring optimal network performance and service quality as wireless networks accommodate a larger number of users. The increasing number of users in a network makes finding optimal user grouping schemes increasingly complex. Researchers are developing low-complexity methods to address this challenge. This survey paper encourages researchers to explore user grouping techniques in NOMA networks to improve network efficiency and resource utilization. However, the paper discusses the limitations of user grouping techniques in in the NOMA network. Despite these challenges, the paper emphasizes the importance of ongoing investigation to address these limitations and enhance the effectiveness of NOMA communication systems.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

All authors contributed to writing the paper and approved the final version.

Acknowledgment

This research was supported by the Research Management Center of University of Universiti Tun Hussein Onn Malaysia (UTHM) through TIER1 Grant (vot Q367).

References

[1] A. Nauman, M. Maashi, and H. K. Alkahtani., "Efficient resource allocation and user association in NOMA-enabled vehicular-aided HetNets with high altitude platforms," *Comput. Commun.*, vol. 216, pp. 374–386, Jan. 2024.

[2] H. Fares, R. Bonnefoi, J. Wakim, and Y. El Lamti, "When asymmetry helps: Joint power and blocklength optimization for non-orthogonal multiple access in downlink communications," *IEEE Open J. Commun. Soc.*, vol. 5, pp. 1803–1813, Jan. 2024.

[3] H. Cui, K. Niu, M. Ren, and J. Huo, "Polar coded power domain non-orthogonal multiple access system: Construction and optimization," *IEEE Commun. Lett.*, vol. 28, no. 3, pp. 607–611, 2024.

[4] M. Ghous, A. K. Hassan, Z. H. Abbas, G. Abbas, A. Hussien, and T. Baker, "Cooperative power-domain NOMA systems: An overview," *Sensors*, vol. 22, no. 24, 2022, doi: 10.3390/s22249652.

[5] T. Sefako and T. Walingo, "Biological resource allocation algorithms for heterogeneous uplink PD-SCMA NOMA networks," *IEEE Access*, vol. 8, pp. 194950–194963, 2020.

[6] S. Chantaraskul, P. Tarbut, and K. Nuanyai, "Load-aware greedy dynamic CoMP clustering mechanism for DPS CoMP in 5G networks," *Int. J. Networked Distrib. Comput.*, vol. 11, no. 1, pp. 31–48, 2023.

[7] S. Rezvani, N. M. Yamchi, M. R. Javan, and E. A. Jorswieck, "Resource allocation in virtualized CoMP-NOMA HetNets: multi-connectivity for joint transmission," *IEEE Trans. Commun.*, vol. 69, no. 6, pp. 4172–4185, 2021.

[8] Y. Dai, J. Liu, M. Sheng, N. Cheng, and X. Shen, "Joint optimization of BS clustering and power control for NOMA-enabled CoMP transmission in dense cellular networks," *IEEE Trans. Veh. Technol.*, vol. 70, no. 2, pp. 1924–1937, 2021.

[9] H. Sun, L. Zhang, J. Hou, T. Q. S. Quek, X. Wang, and Y. Zhang, "CoMP transmission in downlink NOMA-based cellular-connected UAV networks," *IEEE Trans. Wirel. Commun.*, 2023, doi: 10.1109/TWC.2023.3341153.

[10] H. Wang, C. Liu, Z. Shi, Y. Fu, and R. Song, "Power minimization for uplink RIS-assisted CoMP-NOMA networks with GSIC," *IEEE Trans. Commun.*, vol. 70, no. 7, pp. 4559–4573, 2022.

[11] M. Fayaz, W. Yi, Y. Liu, and A. Nallanathan, "Transmit power pool design for grant-free NOMA-IoT networks via deep reinforcement learning," *IEEE Trans. Wirel. Commun.*, vol. 20, no. 11, pp. 7626–7641, 2021.

[12] W. Khalid and H. Yu, "Security improvement with QoS provisioning using service priority and power allocation for NOMA-IoT networks," *IEEE Access*, vol. 9, pp. 9937–9948, 2021, doi: 10.1109/ACCESS.2021.3049258.

[13] N. U. Zaman, A. K. Hassan, Z. H. Abbas, G. Abbas, M. Bilal, and S. Pack, "Performance analysis of NOMA enabled multi-user co-operative IoT network with SWIPT protocol," *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 35, no. 8, #101639, 2023.

[14] S. Thapliyal, R. Pandey, and C. Charan, "Analysis of NOMA based UAV assisted short-packet communication system and blocklength minimization for IoT applications," *Wirel. Networks*, vol. 28, no. 6, pp. 2695–2712, 2022.

[15] B. K. S. Lima, R. Dinis, D. B. Costa, R. Oliveira, and M. Beko, "User pairing and power allocation for UAV-NOMA systems based on multi-armed bandit framework," *IEEE Trans. Veh. Technol.*, vol. 71, no. 12, pp. 13017–13029, 2022.

[16] Y. Tong, M. Sheng, J. Liu, and N. Zhao, "Energy-efficient UAV-NOMA aided wireless coverage with massive connections," *Sci. China Inf. Sci.*, vol. 66, no. 12, pp. 1–15, 2023.

[17] T. Zhang, Z. Wang, Y. Liu, W. Xu, and A. Nallanathan, "Joint resource, deployment, and caching optimization for AR applications in dynamic UAV NOMA networks," *IEEE Trans. Wirel. Commun.*, vol. 21, no. 5, pp. 3409–3422, 2022.

[18] Z. Wang, T. Zhang, Y. Liu, and W. Xu, "Caching placement and resource allocation for AR application in UAV NOMA networks," in *Proc. IEEE Glob. Commun. Conf. GLOBECOM*, 2020. doi: 10.1109/GLOBECOM42002.2020.9322556

[19] Y. Pan, H. Hu and M. Zhang, "Joint resource scheduling and trajectory design for multi-UAV-assisted uplink NOMA networks," *AEU - Int. J. Electron. Commun.*, vol. 164, #154619,

Mar. 2023. doi: 10.1016/j.aeue.2023.154619
[20] N. V. Vinh and P. V. Tri, "Performance assessment of millimeter-wave NOMA system with intelligent reflecting surface," *IEEE Access*, vol. 10, pp. 66143–66152, 2022
[21] A. Khazali, M. G. Shayesteh, and H. Kalbkhani, "User grouping and power allocation for energy efficiency maximization in mmWave-NOMA heterogeneous networks," *Wirel. Networks*, vol. 28, no. 6, pp. 2403–2420, 2022.
[22] K. Tang, G. Xu, P. Yan, H. Zhu, and W. Feng, "Coverage performance of cooperative NOMA mmWave networks with wireless power transfer," *Comput. Commun.*, vol. 218, pp. 85–96, 2024. doi: 10.1016/j.comcom.2024.01.008
[23] B. C. Nguyen, T. M. Hoang, L. T. Dung, T. Kim, and N. Van Vinh, "On performance of full-duplex UAV system with multiple NOMA users and millimeter-wave communications," *Phys. Commun.*, vol. 55, 2022. doi: 10.1016/j.phycom.2022.101895
[24] S. R. Sabuj, M. Rubaiat and M. Iqbal, "Machine-type communications in NOMA-based terahertz wireless networks," *Int. J. Intell. Networks*, vol. 3, pp. 31–47, May 2022.
[25] Z. Ding and H. V. Poor, "Design of THz-NOMA in the presence of beam misalignment," *IEEE Commun. Lett.*, vol. 26, no. 7, pp. 1678–1682, 2022.
[26] Z. Ding and H. V. Poor, "Joint beam management and power allocation in THz-NOMA networks," *IEEE Trans. Commun.*, vol. 71, no. 4, pp. 2059–2073, 2023.
[27] S. R. Sabuj, A. M. M. S. Khan, and M. Hamamura, "Application of non-orthogonal multiple access for machine type communication in sub-terahertz band," *Comput. Networks*, vol. 182, #107508, Feb. 2020.
[28] Z. Hu, C. Han, Y. Deng, and X. Wang, "Multi-task deep reinforcement learning for terahertz NOMA resource allocation with hybrid discrete and continuous actions," *IEEE Trans. Veh. Technol.*, 2024. doi: 10.1109/TVT.2024.3381238
[29] S. Markkandan, K. Aggarwal, K. Ashok, K. Selvakumarasamy, R. K. Kaushal, and M. M. Jadhav, "Design of precoder for a MIMO–NOMA system using Gaussian mixture modelling," *Opt. Quantum Electron.*, vol. 56, no. 1, pp. 1–25, 2024.
[30] R. Shankar, B. P. Chaudhary and H. Mehraj, "Impact of node mobility on the DL based uplink and downlink MIMO-NOMA network," *Int. J. Inf. Technol.*, vol. 15, no. 6, pp. 3391–3404, 2023.
[31] N. Le Cuong, T. M. Hoang, and P. T. Hiep, "Secrecy outage performance of MIMO-NOMA relay systems with MRT/MRC schemes," *Comput. Commun.*, vol. 219, pp. 116–127, 2024. doi: 10.1016/j.comcom.2024.03.004
[32] S. C. Lam, T. N. Thi, and N. T. Phuong, "On performance of short-packet ultra-reliable and low-latency communications NOMA MIMO relay networks," *Phys. Commun.*, vol. 61, 2023. doi: 10.1016/j.phycom.2023.102196
[33] T. M. Hoang, L. T. T. Huyen, X. N. Tran, and P. T. Hiep, "Outage probability of aerial base station NOMA MIMO wireless communication with RF energy harvesting," *IEEE Internet Things J.*, vol. 9, no. 22, pp. 22874–22886, 2022.
[34] A. Akbar, S. Jangsher, and F. A. Bhatti, "NOMA and 5G emerging technologies: A survey on issues and solution techniques," *Comput. Networks*, vol. 190, #107950, 2021. doi: 10.1016/j.comnet.2021.107950
[35] U. Ghafoor, M. Ali, H. Z. Khan, A. M. Siddiqui, and M. Naeem, "NOMA and future 5G & B5G wireless networks: A paradigm," *J. Netw. Comput. Appl.*, vol. 204, #103413, 2022. doi: 10.1016/j.jnca.2022.103413
[36] W. U. Khan, F. H. Memon, K. Dev, M. A. Javed, D. T. Do, and N. M. F. Qureshi, "Ambient BackCom in beyond 5G NOMA networks: A multi-cell resource allocation framework," *Digit. Commun. Networks*, vol. 8, no. 6, pp. 1005–1013, 2022.
[37] O. Abuajwa and S. Mitani, "Dynamic resource allocation for energy-efficient downlink NOMA systems in 5G networks," *Heliyon*, vol. 10, no. 9, 2024. doi: 10.1016/j.heliyon.2024.e29956
[38] X. Peng, X. Yuan, and K. Zhang, "Clustered NOMA-based downlink adaptive relay coordinated transmission scheme for future 6G cell-free edge network," *Peer-to-Peer Netw. Appl.*, vol. 15, no. 1, pp. 612–625, 2022.
[39] I. N. A. Ramatryana, G. B. Satrya, and S. Y. Shin, "Adaptive traffic load in IRSA-NOMA prioritizing emergency devices for 6G enabled massive IoT," *IEEE Wirel. Commun. Lett.*, vol. 10, no. 12, pp. 2713–2717, 2021.
[40] I. N. A. Ramatryana and S. Y. Shin, "Priority Access in NOMA-based slotted ALOHA for overload 6G massive IoT," *IEEE Commun. Lett.*, vol. 26, no. 12, pp. 3064–3068, 2022.
[41] Y. Prathyusha and T. L. Sheu, "A data collection scheme for IoT using NOMA techniques in UAV-LEO 6G networks," in *Proc. Int. Conf. 6G Networking*, 2023. doi: 10.1109/6GNet58894.2023.10317736
[42] S. Chege and T. Walingo, "Energy efficient resource allocation for uplink hybrid power domain sparse code nonorthogonal multiple access heterogeneous networks with statistical channel estimation," *Trans. Emerg. Telecommun. Technol.*, vol. 32, no. 1, pp. 1–27, 2021. doi: 10.1002/ett.4185
[43] Y. Lin, K. Wang, and Z. Ding, "Unsupervised machine learning-based user clustering in THz-NOMA systems," *IEEE Wirel. Commun. Lett.*, vol. 12, no. 7, pp. 1130–1134, 2023.
[44] M. Katwe, K. Singh, P. K. Sharma, C. P. Li, and Z. Ding, "Dynamic user clustering and optimal power allocation in UAV-assisted full-duplex hybrid NOMA system," *IEEE Trans. Wirel. Commun.*, vol. 21, no. 4, pp. 2573–2590, 2022.
[45] A. Han, T. Lv, and X. Zhang, "UAV beamwidth design for ultra-reliable and low-latency communications with NOMA," in *Proc. 2019 IEEE Int. Conf. Commun. Work.*, 2019. doi: 10.1109/ICCW.2019.8756803
[46] B. Lim, W. J. Yun, J. Kim, and Y. C. Ko, "Joint user clustering, beamforming, and power allocation for mmWave-NOMA with imperfect SIC," *IEEE Trans. Wirel. Commun.*, vol. 23, no. 3, pp. 2025–2038, 2024.
[47] S. S. Rana, G. Verma, and O. P. Sahu, "Machine learning based improved user-pairing and power allocation with imperfect-successive interference cancellation for downlink NOMA-UAV system," *Int. J. Wirel. Inf. Networks*, vol. 31, no. 1, pp. 29–36, 2024.
[48] T. M. C. Chu, H. J. Zepernick, and T. Q. Duong, "Short-packet cooperative NOMA communications with K-means user clustering," in *Proc. 2023 IEEE Int. Conf. Commun. Work. Sustain. Commun. Renaissance*, 2023, pp. 1794–1799.
[49] S. Zhao, J. Xie, and C. Li, "Resource allocation for CoMP-NOMA transmission in ultra dense networks," in *Proc. 2023 IEEE 5th Int. Conf. Civ. Aviat. Saf. Inf. Technol.*, 2023, pp. 1485–1490.
[50] E. Cabrera and R. Vesilo, "An enhanced k-means clustering algorithm with non-orthogonal multiple access (NOMA) for MMC networks," in *Proc. 2018 28th Int. Telecommun. Networks Appl. Conf.*, 2018. doi: 10.1109/ATNAC.2018.8615298
[51] M. Liu, J. Zhang, K. Xiong, M. Zhang, P. Fan, and K. B. Letaief, "Effective user clustering and power control for multiantenna uplink NOMA transmission," *IEEE Trans. Wirel. Commun.*, vol. 21, no. 11, pp. 8995–9009, 2022.
[52] H. Zhang, H. Zhang, W. Liu, K. Long, J. Dong, and V. C. M. Leung, "Energy efficient user clustering, hybrid precoding and power optimization in terahertz MIMO-NOMA systems," *IEEE J. Sel. Areas Commun.*, vol. 38, no. 9, pp. 2074–2085, 2020.
[53] J. Cui, Z. Ding, P. Fan, and N. Al-Dhahir, "Unsupervised machine learning-based user clustering in millimeter-wave-NOMA systems," *IEEE Trans. Wirel. Commun.*, vol. 17, no. 11, pp. 7425–7440, 2018.
[54] C. Liu, J. Wang, L. Feng, H. Lu, H. Sun, and R. Q. Hu, "Coalitional game theory-based resource allocation strategy for robust IRS-VLC system," *Photonics*, vol. 11, no. 6, 2024. doi: 10.3390/photonics11060582
[55] C. Xu, G. Zheng, and L. Tang, "Energy-aware user association for NOMA-based mobile edge computing using matching-coalition game," *IEEE Access*, vol. 8, pp. 61943–61955, 2020.
[56] B. T. Tinh, L. D. Nguyen, H. H. Kha, and T. Q. Duong, "Practical optimization and game theory for 6G ultra-dense networks: Overview and research challenges," *IEEE Access*, vol. 10, pp. 13311–13328, 2022.
[57] L. Xie, Z. Su, Q. Xu, N. Chen, Y. Fan, and A. Benslimane, "A secure UAV cooperative communication framework: Prospect theory based approach," *IEEE Trans. Mob. Comput.*, 2024. doi: 10.1109/TMC.2024.3367124
[58] T. Lyu, H. Xu, F. Liu, M. Li, L. Li, and Z. Han, "Computing offloading and resource allocation of NOMA based UAV emergency communication in the marine internet of thing," *IEEE Internet Things J.*, 2023. doi: 10.1109/JIOT.2023.3348164
[59] P. Georgakopoulos, T. Akhtar, C. Mavrokefalidis, I. Politis, K.

Berberidis, and S. Koulouridis, "Coalition formation games for improved cell-edge user service in downlink NOMA and MU-MIMO small cell systems," *IEEE Access*, vol. 9, pp. 118484–118501, 2021.

[60] T. Akhtar, P. Georgakopoulos., and C. Mavrokefalidis, "Efficient radio resource management with coalition games using NOMA in small cell networks," in *Proc. IEEE Glob. Commun. Conf.*, 2020. doi: 10.1109/GLOBECOM42002.2020.9348260

[61] W. Chen, S. Zhao, R. Zhang, and L. Yang, "Generalized user grouping in NOMA based on overlapping coalition formation game," *IEEE J. Sel. Areas Commun.*, vol. 39, no. 4, pp. 969–981, 2021.

[62] Q. V. Pham, H. T. Nguyen, Z. Han, and W. J. Hwang, "Coalitional games for computation offloading in NOMA-enabled multi-access edge computing," *IEEE Trans. Veh. Technol.*, vol. 69, no. 2, pp. 1982–1993, 2020.

[63] J. Ding, J. Cai, and C. Yi, "An improved coalition game approach for MIMO-NOMA clustering integrating integrating beamforming and power allocation," *IEEE Trans. Veh. Technol.*, vol. 68, no. 2, pp. 1672–1687, 2019.

[64] K. Wang, J. Cui, Z. Ding and P. Fan, "Stackelberg game for user clustering and power allocation in millimeter wave-NOMA systems," *IEEE Trans. Wirel. Commun.*, vol. 18, no. 5, pp. 2842–2857, 2019.

[65] X. Yan, K. An, C. Wang, W. Zhu, Y. Li, and Z. Feng, "Genetic algorithm optimized support vector machine in noma-based satellite networks with imperfect CSI," in *Proc. 2020 IEEE Int. Conf. Acoust. Speech Signal Process*, 2020, pp. 8817–8821.

[66] Q. Huang, J. Cui and Z. Ding, "Throughput maximization for multi-cluster NOMA-UAV networks," in *Proc. 2022 IEEE Glob. Commun. Conf.*, 2022, pp. 3730–3735.

[67] R. Aldebes, K. Dimyati and E. Hanafi, "Genetic algorithm for optimizing energy efficiency in downlink mmwave NOMA system with imperfect CSI," *Symmetry*, vol. 14, no. 11, #2345, 2022.

[68] X. Qi, S. Khattak, and A. Zaib, "Energy efficient resource allocation for 5G heterogeneous networks using genetic algorithm," *IEEE Access*, vol. 9, pp. 160510–160520, 2021.

[69] S. Majhi and P. Mitra, "A genetic algorithm-based reinforcement learning algorithm for multi-objective optimization in NOMA-IoT networks," in *Proc. NERC 2022 Artificial Intelligence and Data Science Based R&D Interventions*, pp. 75–88. doi: 10.1007/978-981-99-2609-1_6

[70] S. U. Rehman, J. Ahmad, A. Manzar, and M. Moinuddin, "Performance analysis and design of semi-blind beamforming for downlink MIMO–NOMA heterogeneous network," *Telecommun. Syst.*, vol. 85, no. 4, pp. 551–562, 2024.

[71] Q. Huang, W. Wang, W. Lu, N. Zhao, A. Nallanathan, and X. Wang, "Resource allocation for multi-cluster NOMA-UAV networks," *IEEE Trans. Commun.*, vol. 70, no. 12, pp. 8448–8459, 2022.

[72] S. Lee, J. Kim, J. Park, and S. Cho, "Grant-free resource allocation for NOMA V2X uplink systems using a genetic algorithm approach," *Electron.*, vol. 9, no. 7, pp. 1–15, 2020.

[73] Ö. F. Gemici, F. Kara, I. Hokelek, G. K. Kurt, and H. A. Cırpan, "Resource allocation NOMA for downlink systems: Genetic algorithm approach," in *Proc. 2017 40th Int. Conf. Telecommun. Signal Process.*, 2017, pp. 114–118.

[74] H. You, Z. Pan, N. Liu, and X. You, "User clustering scheme for downlink hybrid NOMA systems based on genetic algorithm," *IEEE Access*, vol. 8, pp. 129461–129468, 2020.

[75] S. K. Saraswat, V. K. Deolia, and A. Shukla, "Allocation of power in NOMA based 6G-enabled internet of things using multi-objective based genetic algorithm," *J. Electr. Eng.*, vol. 74, no. 2, pp. 95–101, 2023.

[76] M. Hosam, M. Ehab, B. Mohammed, D. Saad, O. A. M. Aly, and O. Elnahas, "Reinforcement learning based sum rate maximization for UAV-assisted NOMA system," in *Proc. 2023 11th Int. Japan-Africa Conf. Electron. Commun. Comput.*, 2024, pp. 244–248.

[77] E. Vaezpour, L. Majzoobi, M. Akbari, S. Parsaeefard, and H. Yanikomeroglu, "A deep learning-based approach for cell outage compensation in NOMA networks," *IEEE Open J. Veh. Technol.*, vol. 3, pp. 149–166, Mar. 2022.

[78] R. Zhong, X. Liu, Y. Liu, and Y. Chen, "Multi-agent reinforcement learning in NOMA-aided UAV networks for cellular offloading," *IEEE Trans. Wirel. Commun.*, vol. 21, no. 3, pp. 1498–1512, 2022.

[79] R. O. Omslandseter, L. Jiao, Y. Liu, and B. John Oommen, "User grouping and power allocation in NOMA systems: A novel semi-supervised reinforcement learning-based solution," *Pattern Anal. Appl.*, vol. 26, no. 1, pp. 1–17, 2023.

[80] I. Ahmed, M. K. Shahid, and T. Faisal, "Deep reinforcement learning based beam selection for hybrid beamforming and user grouping in massive MIMO-NOMA system," *IEEE Access*, vol. 10, pp. 89519–89533, July 2022.

[81] M. Elsayed, M. Erol-Kantarci, and H. Yanikomeroglu, "Transfer reinforcement learning for 5G new radio mmwave networks," *IEEE Trans. Wirel. Commun.*, vol. 20, no. 5, pp. 2838–2849, 2021.

[82] S. K. Mahmud, Y. Liu, Y. Chen, and K. K. Chai, "Adaptive reinforcement learning framework for NOMA-UAV networks," *IEEE Commun. Lett.*, vol. 25, no. 9, pp. 2943–2947, 2021.

[83] S. Rezwan, S. Shin, and W. Choi, "Efficient user clustering and reinforcement learning based power allocation for NOMA systems," in *Proc. Int. Conf. ICT Converg.*, 2020, pp. 143–147.

[84] W. Ahsan, W. Yi, Z. Qin, Y. Liu, and A. Nallanathan, "Resource allocation in uplink NOMA-IoT networks: A reinforcement-learning approach," *IEEE Trans. Wirel. Commun.*, vol. 20, no. 8, pp. 5083–5098, 2021.

[85] X. Liu, Y. Chang, C. Liu, and Y. Zhang, "User-grouping based resource allocation in downlink MU-MIMO systems with proportional fairness," in *Proc. 2017 3rd IEEE Int. Conf. Comput. Commun.*, 2017, pp. 564–568.

[86] S. Wu, Y. Wei, S. Zhang, and W. Meng, "Proportional-fair resource allocation for user-centric networks," *IEEE Trans. Veh. Technol.*, vol. 71, no. 2, pp. 1549–1561, 2022.

[87] S. A. H. Mohsan and Y. Lie, "A survey of deep learning based NOMA: State of the art, key aspects, open challenges and future trends," *Sensors,* 2023. https://doi.org/10.3390/s23062946

[88] G. Taricco, "Optimum power allocation for HARQ-aided NOMA with proportional fairness on fading channels," *IEEE Access*, vol. 12, pp. 2327–2339, Jan. 2024.

[89] H. Zhang, B. J. Wang, C. Chen, X. Cheng, and H. Li, "Resource allocation in uav-noma communication systems based on proportional fairness," *J. Commun. Inf. Networks*, vol. 5, no. 2, pp. 111–120, 2020.

[90] L. Xu, W. Yin, X. Zhang, and Y. Yang, "Fairness-aware throughput maximization over cognitive heterogeneous NOMA networks for industrial cognitive IoT," *IEEE Trans. Commun.*, vol. 68, no. 8, pp. 4723–4733, 2020.

[91] C. L. Wang, M. H. Liu, and Y. C. Shen, "Proportional-fairness resource allocation based on statistical channel state information for a downlink multicarrier NOMA system," in *Proc. 2021 15th Int. Conf. Signal Process. Commun. Syst.*, 2021. doi: 10.1109/ICSPCS53099.2021.9660308

[92] C. L. Wang and C. W. Hung, "Proportional-fairness resource allocation for a downlink multicarrier NOMA system," in *Proc. 2020 14th Int. Conf. Signal Process. Commun. Syst.*, 2020. doi: 10.1109/ICSPCS50536.2020.9310054

[93] J. Li, D. Mei, D. Deng, I. Khan, and P. Uthansakul, "Proportional fairness-based power allocation algorithm for downlink NOMA 5G wireless networks," *Comput. Mater. Contin.*, vol. 65, no. 2, pp. 1571–1590, 2020.

[94] P. Gupta and D. Ghosh, "User fairness and QoS aware based effective resource allocation for downlink NOMA cellular systems," *Wirel. Pers. Commun.*, vol. 131, no. 2, pp. 991–1012, 2023.

[95] B. K. Mishra, S. N. Mohanty and R. R. Baidyanath., "An efficient framework for obtaining the initial cluster centers," *Sci. Rep.*, vol. 13, no. 1, pp. 1–20, 2023.

[96] V. Melnykov and X. Zhu, "An extension of the *K*-means algorithm to clustering skewed data," *Comput. Stat.,* vol. 34, pp. 373–394, 2019. doi: https://doi.org/10.1007/s00180-018-0821-z

[97] M. Ahmed, R. Seraj, and S. M. S. Islam, "The k-means algorithm: A comprehensive survey and performance evaluation," *Electron.*, vol. 9, no. 8, pp. 1–12, 2020.

[98] A. M. Ikotun, A. E. Ezugwu, L. Abualigah, B. Abuhaija, and J. Heming, "K-means clustering algorithms: A comprehensive review, variants analysis, and advances in the era of big data," *Information Sciences*, vol. 622, pp. 178–210, Apr. 2023.

[99] V. K. Papanikolaou, P. D. Diamantoulakis, and G. K.

Karagiannidis, "User grouping for hybrid VLC/RF networks with NOMA: A coalitional game approach," *IEEE Access*, vol. 7, pp. 103299–103309, 2019. doi:10.1109/ACCESS.2019.2930169

[100] M. Gautam and M. Benidris, "Coalitional game theory in power systems: applications, challenges, and future directions," in *Proc. 2023 IEEE Texas Power Energy Conf.*, 2023. doi: 10.1109/TPEC56611.2023.10078455

[101] A. Kumar and K. Kumar, "A game theory based hybrid NOMA for efficient resource optimization in cognitive radio networks," *IEEE Trans. on Network Science and Engineering*, vol. 8, no. 4, pp. 3501–3514, 2021.

[102] S. Katoch, S. S. Chauhan, and V. Kumar, "A review on genetic algorithm: past, present, and future," *Multimedia Tools and Applications*, vol. 80, pp. 8091–8126, Feb. 2021.

[103] B. Alhijawi and A. Awajan, "Genetic algorithms: theory, genetic operators, solutions, and applications," *Evol. Intell.*, 2023. doi: 10.1007/s12065-023-00822-6

[104] K. Abedpour, M. Hosseini Shirvani, and E. Abedpour, "A genetic-based clustering algorithm for efficient resource allocating of IoT applications in layered fog heterogeneous platforms," *Cluster Comput.*, vol. 27, no. 2, pp. 1313–1331, 2024.

[105] B. A. Wallace and J. Si, "Continuous-time reinforcement learning: new design algorithms with theoretical insights and performance guarantees," *IEEE Trans. on Neural Networks and Learning Systems*, 2024. doi: 10.1109/TNNLS.2024.3392237

[106] G. Dulac-Arnold, N. Levine and D. J. Mankowitz, "Challenges of real-world reinforcement learning: Definitions, benchmarks and analysis," Machine Learning, vol. 110, no. 9, pp. 2419–2468, 2021.

[107] M. R. Hojeij, "Resource allocation techniques for non-orthogonal multiple access systems. Networking and Internet Architecture," *Ecole nationale supérieure Mines-Télécom Atlantique*, 2018.

[108] Y. Huang, X. He, and Y. Du, "Research on user pairing techniques based on NOMA in cognitive radio networks," *J. Comput. Commun.*, vol. 11, no. 3, pp. 131–145, 2023.

[109] J. He, S. Shi, and Z. Xu, "User grouping and power allocation in NOMA-based internet of things," *Wirel. Networks*, vol. 6, 2023. doi: 10.1007/s11276-023-03251-6

[110] Y. Jin and M. Hayashi, "Trade-off between fairness and efficiency in dominant alpha-fairness family," in *Proc. IEEE Conf. Comput. Commun. Work.*, 2018, pp. 391–396.

Sajjad Ahmed received a bachelor of engineering in computer engineering and master of engineering in computer communication from Pakistan. He is currently pursuing his Ph.D. degree at Universiti Tun Hussein Onn Malaysia (UTHM), Johor, Malaysia, as part of the Internet of Things (IoT) research group. His research interests include mobile communication, the Internet of Things (IoT), and Artificial Intelligence (AI).

Norshidah Katiran graduated from Universiti Teknologi Malaysia (UTM) with the degree of bachelor of electrical engineering (telecommunications) in 2001 and obtained her Ph.D. degree in electrical engineering in 2015 from UTM Malaysia. Currently, she is serving as a senior lecturer (UTHM). Her research interests include resource allocation for wireless networks, and MIMO networks.

Ariffuddin Joret is a senior lecturer at the Faculty of Electrical and Electronic Engineering (FKEE), Universiti Tun Hussein Onn Malaysia (UTHM) In 2018, he graduated with his Ph.D. degree in the field of signal processing at UTHM. His current research interests include Ground Penetrating Radar, and Internet of Things (IoT) system development and application.

Shaharil Mohd Shah obtained his Ph.D. degree in communication engineering from the University of Birmingham, UK in 2016. He is currently a senior lecturer in the Department of Communication Engineering, (UTHM). His area of research includes, but not limited to, design of microwave devices.

Muhammad Inam Abbasi completed Ph.D. degree in electrical engineering in 2016. He worked as a post-doctoral research fellow at Wireless Communication Centre (WCC), Universiti Teknologi Malaysia (UTM) from 2017-2018. Currently, is working as a senior lecturer at the Faculty of Electrical and Electronic Engineering Technology, Universiti Teknikal Malaysia Melaka (UTeM).

Faiz Asraf Saparudin received his Ph.D. degree in electrical engineering (telecommunication) from Universiti Teknologi Malaysia in 2015. He is currently a faculty member at the Faculty of Engineering Technology, Universiti Tun Hussein Onn Malaysia. His research interests include radio resource management, distributed algorithms, multi-agent systems, and game-theoretic approaches for next-generation mobile networks.