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Outage reduction in 5G uplink cooperative NOMA using PSO-optimized relay selection and successive interference cancelation

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Abstract

5G radio access networks face significant challenges, particularly related to user outages. While non-orthogonal multiple access (NOMA) has emerged as a promising solution for efficient spectrum sharing in 5G, it struggles to address outage issues. Reducing outage probability and enhancing system performance in NOMA networks is crucial. Previous efforts have focused on selecting cooperative relay nodes to mitigate outages, but most approaches fail to ensure low outage probability under adverse channel conditions. To address this, we propose a novel uplink cooperative NOMA system that utilizes successive interference cancelation (SIC) at the receiver end. In this system, a user with superior channel conditions serves as a relay for another user, ensuring more robust communication. Additionally, we integrate particle swarm optimization (PSO) for dynamic relay selection, effectively reducing outages, optimizing energy consumption, and significantly improving data rates. The inclusion of PSO-based relay selection demonstrates a substantial improvement in network performance. We compared the performance of particle swarm optimization (PSO) with that of the genetic algorithm (GA) and deep reinforcement learning (DRL). Our findings show that PSO achieved a throughput improvement rate of 68.76%, while GA resulted in an average improvement rate of 50.15%, and DRL produced a 46.38% improvement. These results highlight the effectiveness of PSO in enhancing system performance during outages. Furthermore, while PSO-based relay selection excels in outage scenarios, direct transmission proves more efficient under non-outage conditions, as revealed by our comparative analysis. This dual insight into relay and non-relay conditions provides a comprehensive understanding of the advantages and limitations of relay-based communication in 5G NOMA networks. However, instances of premature convergence were observed, warranting further investigation.

Keywords: NOMA, Cooperative communication, D2D, Outage probability, Particle swarm optimization

1 Introduction

Cellular networks are rapidly becoming an integral part of modern life, shaping how we communicate, work, entertain ourselves, and navigate the world. Their importance continues to grow as technology evolves and connectivity becomes increasingly essential in various aspects of our lives. This trend has led to an exponential increase in the number of mobile users, resulting in a significant rise in system traffic. However, it also poses challenges such as performance degradation and reduced spectral efficiency. To address these issues, new techniques have been introduced in current 3 G, LTE/LTE-A/4 G (Long Term Evolution Advanced) networks. Despite advancements in spectral efficiency and speed, 4 G networks still struggle to meet consumer demands [1]. In the future, almost everything will be connected via the internet, with the Internet of Things (IoT) playing a key role in continuous and high-speed communication. 5G systems are well-positioned to support this use case, and their expansion is accelerating. According to the Ericsson Mobility Report, 5G subscriptions are predicted to reach 5.6 billion by the end of 2029 [2]. The same report states, "More than 100 service providers are offering fixed wireless service access over 5G." Beyond these considerations, an important question arises: how will 5G transform the world? Over the last two decades, successive generations of wireless networks have been deployed to provide better and faster communication [3]. However, the quest to achieve high data rates, low latency, and connectivity for a growing number of devices is still ongoing. The emergence of data-intensive applications, such as UHD video streaming, online gaming, and cloud services, has further accelerated the demand for higher data speeds. Radical improvements in core technologies are essential to achieving these goals. The communication industry recognizes the significance of IoT and is actively working to address its challenges and opportunities. IoT applications can be categorized into two groups: massive ma chine-type communication (M-MTC) and mission-critical applications. These applications involve a vast number of connected nodes, including smart homes, wireless sensor networks, and safe city projects. Such applications require extremely low response times, which current systems cannot provide [4]. Thus, reducing latency is a critical requirement for 5G. 5G will function as a heterogeneous network, connecting a massive number of devices through device-to-device (D2D) and machine-to-machine (M2M) communication. Since D2D is a promising candidate for 5G, its challenges and integration into 5G systems have been extensively studied in [5, 6]. These studies highlight the synergy between 5G and 6G advancements, which further enhance solutions through edge computing [7]. To maximize spectral efficiency while addressing previous challenges, an effective multiple access technique is required. 5G builds upon 1 G to 4 G technologies, enhancing data rates and reducing latency through improved techniques such as Orthogonal Frequency Division Multiplexing (OFDM), Sparse Code Multiple Access (SCMA), and Filter Bank Multi-Carrier (FBMC). It also employs non-orthogonal multiple access (NOMA) for power and spectral efficiency. However, 5G networks still face challenges, including spectrum availability, interoperability, security, privacy, energy consumption, device and network management, and outage probability. Outage probability is a critical concern in 5G networks, as it measures the likelihood of a wireless link failing to meet Quality of Service (QoS) requirements, leading to communication loss or failure to achieve expected data rates. We propose that selecting the best relay for communication can help mitigate outages and enhance system performance.

2 Contributions

The primary objective of this study is to ensure a reduced outage probability, which is essential for meeting the reliability and Quality of Service (QoS) requirements promised by 5G. The key contributions of the proposed model for outage reduction are as follows:

1. This study investigates the effectiveness of an uplink cooperative 5G NOMA system designed for cell edge users (CEU). It strategically selects a user with favorable channel conditions to act as a relay for mitigating poor channel conditions at an outage node, thereby significantly reducing outage probability.
2. The proposed communication model evaluates NOMA performance in two scenarios: one without relay assistance and the other with relay support. The proposed model excels at achieving high data rates, particularly in outage scenarios, demonstrating the effectiveness of relay-based communication.
3. The proposed solution optimizes relay selection using PSO and leverages D2D communication, resulting in a 68.75% improvement in the throughput (data rate) of an outage node, surpassing GA and DRL, which achieved 50.15% and 46.38%, respectively.

3 Background

5G, an advanced evolution of 4 G technology, aims to support high-speed data traffic, connect diverse devices, achieve high spectral efficiency with optimized energy utilization, ensure ultra-low latency, and facilitate high-reliability applications. Researchers are exploring advanced modulation schemes, such as NOMA, beamforming, novel antenna designs, edge computing, resource scheduling, and machine learning, to optimize network management and efficiency [8]. Multiple technologies are expected to interact synergistically to address these challenges and unlock the full potential of next-generation networks [9].

3.1 Non-orthogonal multiple access (NOMA)

NOMA, or Power Domain NOMA, is a promising candidate for 5G systems. It differentiates network users based on their power coefficients while allowing them to share the same resources (time, frequency, and code) [10]. To optimize Power Domain NOMA in a 5G system, it is combined with successive interference cancelation at the receiver [11]. Figure 1 demonstrates the power level allocation and decoding process for two different users. The key concept is that based on the channel condition, NOMA users are assigned different power levels. These users are paired according

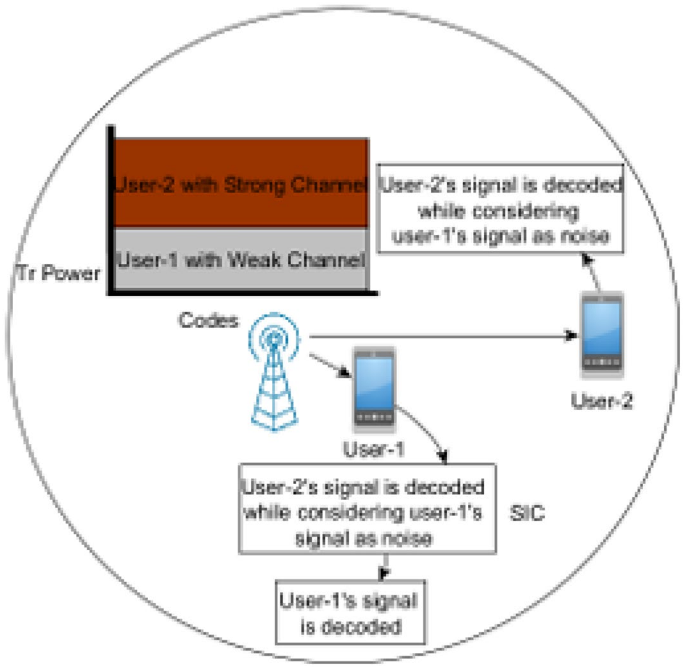

Fig. 1 Power Domain NOMA; SIC detects the stronger signal (User-2) first and then cancels it to detect the weaker signal (User-1). and User-2 and how the signal are decoded at these ends

Table 1 Comparison of uplink and downlink NOMA [12]

Aspect	Downlink NOMA	Uplink NOMA
Implementation complexity	High complexity due to multi-user detection and interference cancelation at each user's receiver.	Lower complexity as multi-user detection and interference cancelation is centralized at the BS.
Intracell/cluster interference	Strong channel users face high interference due to strong channels and high transmit powers of weak users.	Weak channel users face high interference from strong channel users' transmissions.
SIC at receiver(s)	Performed at strong channel users to decode and cancel weak users' signals before decoding their own.	Performed at the BS to decode and cancel strong users' signals before decoding weak users' signals.
Inter-cell interference	Similar to OMA [13], interference originates from neighboring co-channel BSs, but impact varies among users.	Not explicitly detailed, but centralized SIC at the BS can mitigate inter-cell interference effectively.

to their distinct power coefficients. Ideally, users with better channel conditions are paired with those having weaker channel gains.

Consider a downlink transmission from a base station (BS) to two user equipment (UEs) user-1 and user-2. Let x_k, h_k, and α_k denote the signal constellation, channel coefficient, and power allocation coefficient for UE_k, respectively. The received signal at UE_k, denoted by y_k, can be represented as shown in Eq. 1.

$$y_k = h_k\left(\sqrt{\alpha_1 P}x_1 + \sqrt{\alpha_2 P}x_2\right) + w_k, \tag{1}$$

where P is the transmission power of the BS and w_k is the additive white Gaussian noise. Assume $\alpha_1 < \alpha_2$. The process of SIC involves initially detecting the stronger signal x_2 while treating the rest of the signals as noise. Subsequently, the weaker signal x_1 is detected after canceling x_2 from the received signal.

3.2 Uplink vs downlink NOMA

The key distinctions between uplink and downlink NOMA are summarized in Table 1, highlighting their unique challenges and advantages. This study proposes the use of uplink NOMA, primarily due to its lower implementation complexity compared to downlink NOMA. However, it is essential to acknowledge that each implementation has its own advantages and challenges, and neither approach entirely supersedes the other [12].

3.3 Imperfect SIC and channel state information

SIC is a powerful technique for improving spectral efficiency in 5G networks, but it can suffer from error propagation if the decoding order or channel estimations are not accurate. This error propagation occurs when an error in decoding one user's signal cascades, negatively impacting the decoding of subsequent signals. This issue is particularly problematic in scenarios with tightly coupled interference. Imperfect channel state information and imperfect SIC are the major contributors to this problem [14, 15]. Inaccurate channel estimations can lead to errors during the initial decoding stages. Furthermore, the efficiency of SIC heavily relies on the correct ordering of users based on their channel conditions or power levels. Thus, an incorrect decoding order can amplify errors, further deteriorating system performance. Fortunately, these issues are addressable. To mitigate them, robust channel estimation techniques are available and can be employed to improve CSI accuracy. Dynamically optimizing the decoding order based on real-time channel conditions is another effective strategy to minimize error propagation. From this perspective, Zhen Chen and Bin Liu [16] introduced a flexible SIC decoding approach, called a switching SIC scheme, which dynamically decides the decoding order based on the ratio of each user's instantaneous received power to their target data rate. Dynamic ordered decoding is also proposed by Gao et al. [17] and adaptive decoding by Gavas et al. [18]. Deep and machine learning-based approaches have also been proposed to address these issues [19–21]. Furthermore, the use of advanced error correction codes can help detect and rectify errors early in the decoding process, ensuring more reliable performance [22, 23].

3.3.1 PSO, genetic algorithm, deep reinforcement learning

In this study, we prefer PSO over other candidates, such as genetic algorithms and deep reinforcement learning, due to its simplicity, low computational cost, and easy implementation in hardware [24–26]. PSO is ideal for hardware-constrained environments because of its low computational cost, energy efficiency, and ease of implementation on microcontrollers and FPGAs. In contrast, DRL excels in dynamic relay selection with real-time learning but requires high computational resources, making hardware deployment more challenging. However, we also believe that PSO is useful for performing initial optimization and identifying potential relay candidates, while reinforcement learning can further refine the selection process dynamically by adapting to changes in network conditions. RL enables its agent to make decisions by performing actions to maximize cumulative rewards over time. For relay selection, the agent can observe network states, such as signal strength and energy constraints, and select a relay based on these observations. The agent may be rewarded for improved performance (e.g., throughput, energy efficiency), which helps continuously optimize relay selection. Combining PSO for initial exploration and RL for dynamic refinement may provide a robust and efficient solution for relay selection in modern wireless networks [27].

3.4 Device-to-device communication (D2D)

Cooperative communication enables resource sharing among users through three-terminal networks, comprising source, relay, and destination terminals. It is particularly useful in D2D communication, which improves energy efficiency, throughput, and latency rates [28]. There are four types of D2D communication: operator-controlled relaying, operator-controlled direct communication between UEs, link establishment controlled by UEs, and UE-controlled direct communication. D2D communication uses spectrum allocation strategies like in-band and out-band, allowing for licensed and unlicensed bands, such as Bluetooth, ZigBee, and WiFi. It can be autonomous or operator-controlled, offering flexibility in network management.

4 Related work

Several studies have investigated downlink NOMA, exploring its various applications. NOMA with superposition coding is employed in a two-point Coordinated Multi-Point (CoMP) scenario to enhance the performance of NOMA edge users, as demonstrated by Nissel et al. [29]. The outage performance of one user in uplink NOMA is examined by Zhang et al. [30], revealing its dependence on a second user with a higher decoding order. The concept of Coordinated and Direct Relay Transmission (CDRT) for NOMA was derived by Kim et al. [31], while Sun et al. [32] explored the outage probability of a relay system using NOMA technology. This research aims to analyze and understand the reliability and performance of NOMA in relay communication scenarios.

Inter-cell interference (ICI) and intracell interference significantly impact the performance of cell edge users (CEUs). Elhattab et al. [33] exploited the cooperation between base stations to mitigate ICI's effects on CEUs. Cooperation between a dedicated relay and a cell center user is utilized by Pei et al. [34] to improve the Quality of Service (QoS) at the cell edge. Under a slow-fading channel model, Tang et al. [35] examined the attainable rate region of NOMA while considering the limitations of outage probability. This provides insights into the trade-offs and potential improvements in data transmission rates compared to orthogonal multiple access (OMA).

In a hybrid network, cross-interference between various communication systems can severely impact system performance and coverage. The use of D2D and CDRT is shown to improve system performance for both cell center users (CCUs) and CEUs, as demonstrated by Xu et al. [36]. Assuming no direct link between the eNB and CEUs, Liang et al. [37] investigated and found that cooperative NOMA is superior to cooperative OMA. In their research, Zou et al. [38] exploited the use of D2D communication. They demonstrated through the analysis of their simulation results that D2D-aided NOMA achieves higher ergodic sum rates than conventional OMA. Kader et al. [39] studied NOMA-based cellular transmission and D2D communication between similar users simultaneously. Not only 5G but also 6G [40] envisions D2D communication applications in 6G systems. The proposed scheme by Yu et al. [41] found that optimal relay selection in NOMA improves the throughput of edge users and the overall system.

Liang et al. [42] proposed a cooperative NOMA downlink scheme in which a strong user is selected through an algorithm to act as a Decode-and-Forward (DF) relay for a weaker user. The use of the Maximum Ratio Combining (MRC) technique shows a significant performance increase in NOMA compared to conventional NOMA, as reported by Lei et al. [43]. The outage performance of multiple CEUs has been studied under a CDRT full-duplex scenario by Pei et al. [44]. Their proposed scheme showed that the performance of a CEU can be improved by using a relay. Bepari et al. [45] proposed a downlink NOMA partial cooperative scheme where a combination of Amplify-and-Forward (A&F), DF, and MRC is employed to increase the reliability of the network for CEUs. The use of a relay also helps decrease the block error rate. The study conducted by Lai et al. [46] evaluates the average block error rate (BLER) of a cell center user in a NOMA system. The theoretical results show that using a cell center user as a relay lowers the BLER for cell edge users. Since SIC is performed by the user with a strong channel, Kara et al. [47] proposed a threshold-based cooperative NOMA scheme, where the center user only forwards the signal to the CEU if the signal-to-noise ratio (SNR) is above a predefined threshold. The study by Kurup et al. [48] focused on the outage probabilities of two users facing strong and weak signals under cooperative NOMA in log-normal fading channels. Their results showed that cooperation can reduce the system's outage issues.

Recent advancements in 5G have focused on enhancing network performance, reliability, and security through various innovative approaches to relay selection, such as machine learning-based relay selection, complexity-aware relay selection, reconfigurable intelligent surfaces (RIS), artificial neural networks (ANN) for relay selection, and cooperative diversity with deep learning. Shamganth et al. [49] introduced an intelligent relay selection mechanism for D2D communication using ANN with Radial Basis Function Neural Network (RBFNN). In 5G networks, D2D communication is essential for offloading traffic and enhancing the user experience, though efficient relay selection remains challenging in dynamic environments. Their proposed method adjusts relay criteria based on real-time network conditions by integrating threshold-based selection and ANN's predictive capabilities. Deep learning-based relay selection has gained significant attention from the research community, and some of the proposed solutions include Hernandez-Carlon et al. [50] and Ahmed et al. [51]. A simple cooperative diversity method based on DL-aided relay selection is proposed by Wei Jiang and Hans D. Schotten [52]. Since relay selection is crucial for 5G mmWave networks to mitigate path loss and enhance reliability, Aldossari et al. [53] applied ANN with multilayer perceptron to classify path loss, which enabled efficient relay selection and handover. Complexity-aware relay selection is proposed by Zhang et al. [54], Zhao et al. [55], and Ezzeldin et al. [56]. Cheng et al. [57] studied the performance of CEUs in NOMA, which was assisted by IRS. RIS and IRS enhance wireless communication by dynamically controlling signal propagation. IRS, a subset of RIS, focuses on passive reflection for energy-efficient signal manipulation.

4.1 Conclusion of the related work

Literature review shows that Power Domain NOMA with SIC is one of the key modulation technologies that increases power and spectral efficiency; it, along with optimized cooperative relay selection, can reduce the outage probability and increase system performance. Furthermore, the indispensable contribution of power allocation cannot be overstated, playing a vital role in enabling effective SIC and ensuring sustained high system performance.

5 Proposed method

We consider the scenario of uplink cooperative NOMA in which multiple users are sharing the same system resources. Figure 2 represents our proposed system model in which the User Equipment UE near the Evolved Node B (eNB) serves as a relay for the cell edge user. It is anticipated that NOMA will exhibit an OFDM-like waveform. The main distinction is that in OFDM, multiple users share the same sub-carriers in orthogonal time slots, while in NOMA, users share the same resources across time, frequency, or code domains simultaneously. Let $S = S_1 + S_2$ denote the total number of sub-carriers for cellular communication. Multiple users share S_1 sub-carriers simultaneously. These users are multiplexed in the power domain at the eNB. The relay is allocated S_2 sub-carriers. The eNB employs maximal ratio combining (MRC) for both the direct and relay paths of the cell

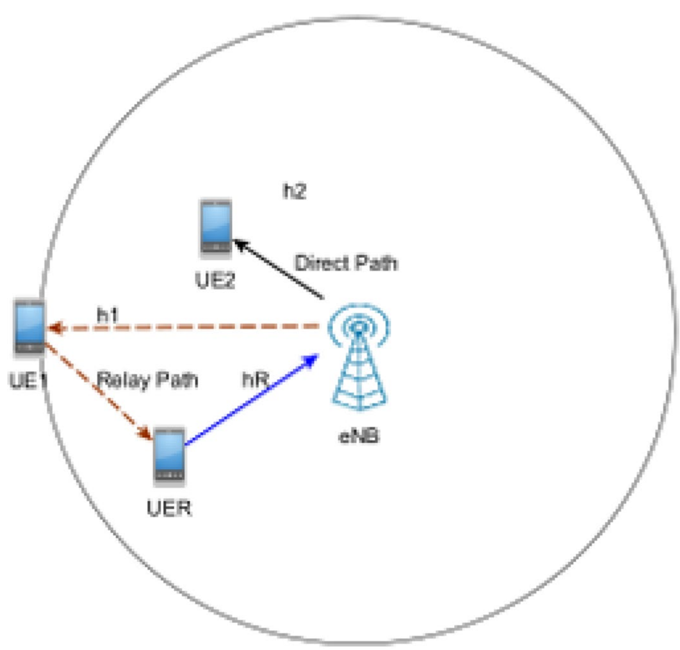

Fig. 2 Proposed system model; make use of relay node for mitigating outage

edge user (CEU). This resembles a hybrid D2D model, where D2D does not entirely replace cellular communication. In addition to the relaying path, a direct connection exists between the source and destination.

The channel between Evolved Node B (eNB) and User Equipment (UE) is denoted as h_i, where $h_i = \frac{g_i}{l_i}$. Here, g_i and l_i represent the Rayleigh fading gain and path loss, respectively, with $l_i = \sqrt{1 + d^{\mu}}$. This expression shows that the UE and eNB are separated by a distance d, and μ is the path loss exponent ranging from 2 to 4. The channels are arranged in ascending order as $|h_1|^2 \leq ... \leq |h_M|^2$ for $1 \leq i \leq M$. The probability density function (pdf) of $|g_i|^2$ is computed using Eq. 2.

$$f_{|g_i|^2}(x) = \frac{1}{2\eta^2} e^{\frac{-x}{2\eta^2}} \tag{2}$$

where η is the variance of the distribution. Assuming there are M UEs sharing the same uplink resources, then the received message at the eNB can be written in the form of Eq. 3.

$$Y = \sum_{i=1}^{M} \sqrt{\alpha_i P} h_i x_i + N_o \tag{3}$$

Here, P represents the transmit power. The power allocation coefficient of the *i-th* UE is represented by α_i, where $\alpha_1 \geq ... \geq \alpha_M$. h_i denotes the channel gain between UE_i and the eNB, while x_i represents the transmit message. N_o is additive white noise with $\mathcal{N}(0, \sigma^2)$. To distinguish signals from the superimposed signal, SIC is applied at the eNB. The order of decoding is based on signal strength, meaning the stronger signal is optimally decoded first, followed by the weaker one. Before decoding the M-th user, the eNB decodes the prior (M-1) users and subtracts them from the overlapped signal. Thus, the achievable SNR at the *i*-th user is given by Eq. 4.

$$SNR_i = \frac{\alpha_i P |h_i|^2}{\sum_{k=i+1}^{M} \alpha_k P |h_k|^2 + \sigma^2} \tag{4}$$

The proposed system model is shown in Fig. 2.

6 Experimentation

6.1 Direct transmission phase

For simplicity, we assume that only two users are sharing S_1. In this phase, UE_1 sends messages to the eNB as well as to the relay, as shown in Fig. 2. The connection between the D2D pair is considered an overlay, ensuring no interference between D2D and cellular links. A dedicated portion of the available spectrum is used for D2D communication. According to Eq. 3, the signal received at eNB can be written using Eq. 5 and at the relay by Eq. 6.

$$Y = \sqrt{\alpha_1 P} h_1 x_1 + \sqrt{\alpha_2 P} h_2 x_2 + \sigma^2 \tag{5}$$

$$Y_{1,R} = \sqrt{\alpha_1 P} h_{1,R} x_1 + \sigma_{1,R}^2 \tag{6}$$

Here in Eqs. 5 and 6, α_1 and α_2 represent the power allocation coefficients of UE_1 and UE_2, respectively, with $\sum_{i=1}^{M} \alpha_i = 1$. h_1 and h_2 are the channel gains between the eNB and UEs, i.e., UE_1 and UE_2. In addition, $h_{1,R}$ is the channel gain between the D2D pair. The variances of additive white noise at the eNB and UE_R are denoted by σ^2 and $\sigma^2_{1,R}$, respectively, with $\mathcal{N}(0,1)$. Assuming the decoding order discussed in [58] after applying SIC at the eNB, the SNR required to detect the message from UE_1 is computed using Eq. 7.

$$SNR_1 = \frac{\alpha_1 P |h_1|^2}{\alpha_2 P |h_2|^2 + \sigma_1^2} \tag{7}$$

Under ideal conditions, assuming that UE_1 is completely decoded and subtracted from Y_1, SNR required to detect UE_2 is computed using Eq. 8.

$$SNR_2 = \frac{\alpha_2 P |h_2|^2}{\sigma_2^2} \tag{8}$$

6.2 Relay transmission phase

6.2.1 Particle swarm optimization for relay node selection

Particle swarm optimization (PSO) is a bio-inspired optimization algorithm that refines candidate solutions, represented as particles p_i, by mimicking the collaborative behavior of flocks of birds. In this study, PSO is applied to minimize outages, reduce energy consumption, and enhance data reliability. The global best (gbest) PSO updates the position of each particle p_i based on the swarm's best-performing solution p^*. Each particle has a current position in the search space, a velocity v_i, and a personal best position p_i', where it achieved its best performance according to the objective function $f(p_i)$, also referred to as the fitness function. The proposed approach employs a star-shaped social network topology, enabling particles to share information and collaboratively explore the search space. By optimizing energy consumption or maximizing reliability, this method identifies the most energy-efficient and reliable relay node configuration, reducing outages and improving communication performance.

The fitness function used in the relay selection process evaluates the suitability of a relay node based on multiple factors, including energy availability, transmission range, path loss, and signal-to-noise ratio (SNR), as given in Eq. 9. The function first retrieves the energy level $E_{r,i}$, position p, and transmission range $R_{r,i}$ of the relay node i. The Euclidean distances from the relay node to both the outage node d_{on} and the base station d_{bs} are computed as $d_{\text{on}} = \sqrt{(p_{x,i} - p_{x,\text{on}})^2 + (p_{y,i} - p_{y,\text{on}})^2}$ and $d_{\text{bs}} = \sqrt{(p_{x,i} - p_{x,\text{bs}})^2 + (p_{y,i} - p_{y,\text{bs}})^2}$. Here, $(p_{x,\text{on}}, p_{y,\text{on}})$, $(p_{x,\text{bs}}, p_{y,\text{bs}})$, and $(p_{x,i}, p_{y,i})$ are the coordinates of the outage node, base station, and relay node, respectively. The path loss penalty Π_{pl} accounts for the increased signal attenuation over distance and is given by $\Pi_{\text{pl}} \approx \max(1, d_{\text{bs}} + d_{\text{on}})$. To ensure that the relay can establish communication with both the outage node and the base station, a transmission range sufficiency condition is enforced. If the relay node's range is insufficient, a heavy penalty Π_{tr} is applied as follows:

$$\Pi_{\text{tr}} = \begin{cases} \infty, & \text{if } d_{\text{bs}} > R_{r,i} \text{ or } d_{\text{on}} > R_{r,i} \\ 1, & \text{otherwise} \end{cases}$$

The SNR factor, which determines the quality of transmission, is simplified and applied as $\mathrm{SNR} \approx \frac{E_{r,i}}{d_{\mathrm{bs}}+d_{\mathrm{on}}+1}$. Finally, the overall fitness function is computed as given in Eq. 9:

$$F_i = \frac{\Pi_{\mathrm{tr}} \times \Pi_{\mathrm{pl}}}{E_{r,i} \times \mathrm{SNR}} \tag{9}$$

Here, $F_i = f(p_i)$ and p_i represent the configuration of the relay node, consisting of $E_{r,i}, (p_{x,i}, p_{y,i}), R_{r,i}, d_{\mathrm{bs}}, d_{\mathrm{on}}$. These parameters are required to compute the fitness of a swarm particle's position p_i. This function ensures that the selection process favors relay nodes with sufficient energy, minimal path loss, adequate transmission range, and a strong SNR, leading to improved network performance and efficient data transmission.

Among all personal best positions p_i', the one with the lowest value is referred to as the global best position, p^*, representing the most optimal relay node configuration discovered by the swarm. Nodes update their personal best position p_i' and the global best position p^* using Eqs. 10 and 11, respectively. Similarly, the velocity v_i of particle i is updated using Eq. 12.

$$p_i'(t+1) = \begin{cases} p_i(t+1) & \text{if } f(p_i(t+1)) < f(p_i'(t)) \\ p_i'(t) & \text{otherwise} \end{cases} \tag{10}$$

$$p^*(t+1) = \arg\min_i f(p_i'(t+1)) \tag{11}$$

$$v_i(t+1) = \omega_{\mathrm{i}} \cdot v_i(t) + \omega_{\mathrm{c}} \cdot r_1 \cdot (p_i'(t) - p_i(t)) + \omega_{\mathrm{s}} \cdot r_2 \cdot (p^*(t) - p_i(t)) \tag{12}$$

The velocity and position vectors of particle (node) i at time t are denoted as $v_i(t)$ and $p_i(t)$, respectively. The personal best position of particle i is $p_i'(t)$, and the global best position is $p^*(t)$, determined up to time t. The acceleration constants $\omega_{\mathrm{i}}, \omega_{\mathrm{c}}, \omega_{\mathrm{s}}$ control the inertia, cognitive, and social components of the PSO framework, with values $\omega_{\mathrm{i}} = 0.7$, $\omega_{\mathrm{c}} = 1.5$, and $\omega_{\mathrm{s}} = 1.5$. These constants balance exploration and exploitation during the optimization process. The system uses 30 relay nodes, each with an energy level of Uniform$(0.5, 1.0)$, and 10 particles initialized randomly at positions $p = (x, y)$, where $x, y \sim$ Uniform$(0, 100)$. The base station energy is set to 30 J, and the data size is 100 units. The random coefficients r_1 and r_2 for the cognitive and social components are drawn from Uniform$(0, 1)$ at each time t. Figure 3 illustrates the key steps in the optimized relay node selection process.

From the experimentation and testing, the results discussed in Sect. 8 reveal that, in the event of an outage, the data rate improves with PSO-based relay selection. However, in the absence of an outage, direct transmission outperforms relay-based transmission, making the use of a relay node unnecessary.

During the relay transmission phase, UE_R employs amplify-and-forward ($A[NONSPACE]\&F$) to amplify the signal received from UE_1 to the eNB with an amplification gain [59]. The message received at the eNB is given by Eq. 14, which is the product of Eq. 13 and Eq. 6.

$$Y_R = G h_R Y_{1,R} + \sigma_R^2 \tag{13}$$

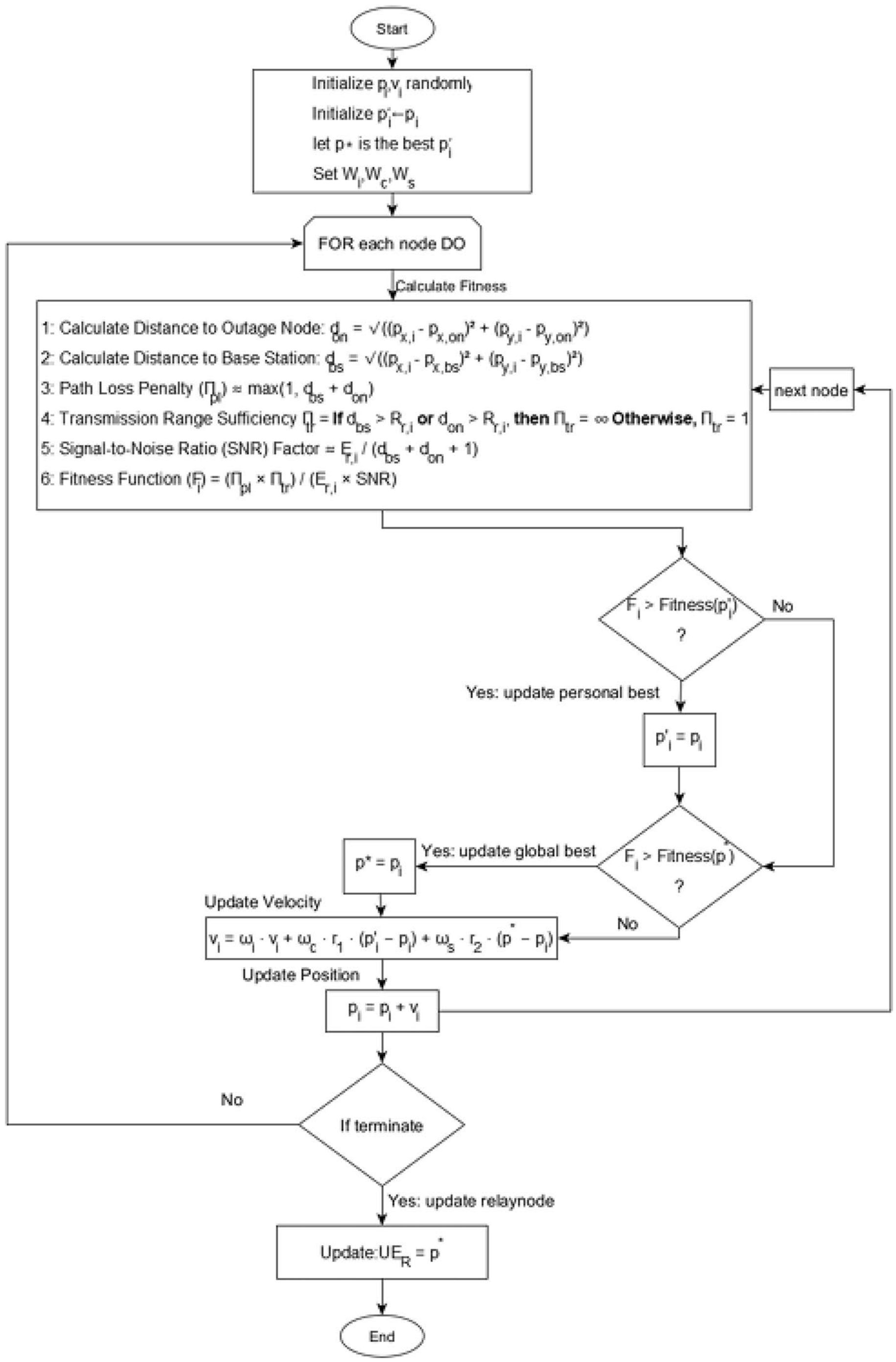

Fig. 3 PSO flowchart for relay node selection. This figure shows key steps of PSO algorithm with significant detail for the selection of relay node

$$Y_R = Gh_R h_{1,R} \sqrt{\alpha_1 P} x_1 + Gh_R \sigma_{1,R}^2 + \sigma_R^2 \tag{14}$$

Here $G = \sqrt{P_R/(E[Y_{1,R}] + \sigma_{1,R}^2)}$. h_R is the channel gain between the relay node and the eNB. The SNR required to detect UE_R is computed using Eq. 15.

$$SNR_R = \frac{G^2|h_R|^2|h_{1,R}|^2\alpha_1 P}{G^2|h_R|^2\sigma_{1,R}^2 + \sigma_R^2} \tag{15}$$

Assuming 1 Hz bandwidth and applying MRC at eNB the SNR achieved is expressed using Eq. 16.

$$SNR = B\frac{\alpha_1 P|h_1|^2}{\alpha_2 P|h_2|^2 + \sigma_1^2} + (1-B)\frac{G^2|h_R|^2|h_{1,R}|^2\alpha_1 P}{G^2|h_R|^2 + \sigma_R^2} \tag{16}$$

Comparing Eq. 16 with Eq. 6, one can realize that the cooperation of the relay significantly enhances reliability.

6.2.2 Some key considerations

The use of PSO for relay selection can introduce computational complexity, potentially making real-time implementation challenging, especially for large networks. Therefore, it is crucial to consider how the proposed method scales for networks with a high number of relays or users, as this could lead to inefficiencies in practical deployment scenarios. We suggest that, in such cases, instead of searching the entire space, the algorithm should reduce the search space. While this may compromise optimal relay selection, it can enhance scalability, which outweighs the inefficiencies caused by attempting to achieve super-optimal relay selection.

Usually, time and space complexity is analyzed using worst-case, best-case, and average-case scenarios, represented as $O()$, $\omega()$, and $\theta()$, respectively. Worst-case complexity, often considered the most useful, is expressed using Big-O notation, ignoring lower-order terms. For example, if an algorithm has a time complexity of $f(n) = 5n^3 + 2n^2 + 7n + 4$, it is asymptotically $O(n^3)$ since lower-order terms ($2n^2$, $7n$, and 4) become negligible as n grows large. It represents the maximum number of operations an algorithm performs for input size n, while best-case complexity defines the lower bound, and average case considers typical steps needed. Time and space complexity analysis in optimization algorithms like PSO helps evaluate their efficiency, scalability, and feasibility for large-scale problems, ensuring optimal performance with minimal computational cost. In wireless relay selection using PSO, time complexity analysis ensures efficient convergence and real-time decision making, while space complexity

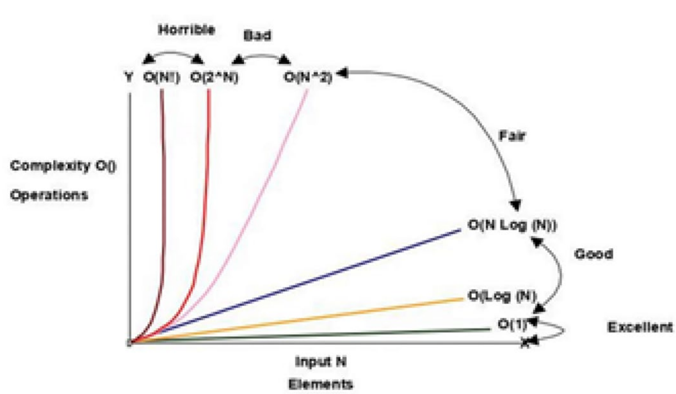

Fig. 4 Computational complexity benchmark. This figure illustrates how the computational complexity of an algorithm can be mapped using the same standards

helps manage resource constraints, optimizing relay selection for enhanced network performance. Understanding algorithm complexities is crucial in such cases. The computational costs of standard PSO include the initialization $O(D \cdot N)$, fitness evaluation $O(D \cdot N)$, and velocity and position update $O(2 \cdot D \cdot N)$; N and D are the swarm size and dimension, respectively. Thus, if T is the number of iterations, the time complexity of PSO is $O(\text{initialization} + \text{fitness evaluation} + \text{velocity and position update})$, or $O((D \cdot N) + (D \cdot N) + 2(D \cdot N))$, which simplifies to $O(T \cdot D \cdot N)$ [60]. A complex fitness function requires more computation, so a low-complexity function is recommended for efficiency. The performance of the algorithm can be illustrated in Fig. 4. Present PSO lies in the domain of good algorithms, but a more adaptive PSO approach, tailored to network requirements such as low complexity and large-scale networks, can be employed to further address the challenges of large networks [61–64].

6.3 Power control in uplink NOMA

It is anticipated that the waveform of NOMA will resemble OFDM. However, in NOMA, multiple users share the resource block (sub-carriers) simultaneously, employing different power levels in the same time, frequency, and code domain. The open-loop component in LTE is defined in [65] as Eq. 17.

$$P_i = P_o + vPL_i + 10\log_{10}(RB_i) \tag{17}$$

Here, P_o represents the target arrived power at the eNB; v is the path loss attenuation factor of fractional transmission power control (TPC), indicating how much path loss needs to be considered. RB_i denotes the number of resource blocks that are allocated to the i^{th} user. In our scenario, this can be expressed for UE_1 and UE_2 using Eq. 18, Eq. 19, and their difference using Eq. 20.

$$P_1 = P_o + vPL_1 + 10\log_{10}(RB) \tag{18}$$

$$P_2 = P_o + vPL_2 + 10\log_{10}(RB) \tag{19}$$

The ratio of their powers can be derived as follows, ultimately leading to Eq. 21.

$$1 - P_2 = vPL_1 - vPL_2 \tag{20}$$

$$\begin{aligned} &og_{10}\left(\frac{P_1 * PL_2}{P_2 * PL_1}\right) = 0 \\ &\frac{P_1}{P_2} = \frac{PL_1}{PL_2} \end{aligned} \tag{21}$$

$$\frac{\alpha_1 P}{\alpha_2 P} = \frac{l_1^2}{l_2^2} \tag{22}$$

7 Outage analysis of both phases

7.1 Outage probability of direct phase

The outage probability is a crucial metric for evaluating system performance. An outage is said to be occurred when the eNB is unable to detect the message from UE, meaning that the SNR of the UE falls below a predefined threshold. Subsequently, from Eq. 6, the outage probability of UE_1 in the first phase can be expressed by Eq. 23.

$$\begin{aligned} P_{out}^{D} =& P\left\{\frac{\alpha_1 P|h_1|^2}{\alpha_2 P|h_2|^2+\sigma_1^2} < \gamma_{th}\right\} \\ =& P\left\{\frac{\alpha_1 P\frac{|g_1|^2}{l_1^2}}{\alpha_2 P\frac{|g_2|^2}{l_2^2}+\sigma_1^2} < \gamma_{th}\right\} \\ =& P\left\{\frac{|g_1|^2}{|g_2|^2+\beta_1} < \gamma_1\right\} \end{aligned} \tag{23}$$

where $\gamma_{th} = 2^{\tilde{R_1}} - 1$, $\tilde{R_1}$ is target data rate, $\gamma_1 = \frac{\gamma_{th}\alpha_2 P l_1^2}{\alpha_1 P l_2^2}$ and $\beta_1 = \frac{\sigma_1^2 l_2^2}{\alpha_2 P}$. Assume $X_1 = |g_1|^2$, $X_2 = |g_2|^2$ and $Y = X_2 + \beta_1$, where $|g_1|^2$ and $|g_2|^2$ are exponentially distributed independent random variables. Then Eq. 23 can be re-written as Eq. 24.

$$\begin{aligned} P_{out}^{D} =& P\left\{\frac{X_1}{Y} < \gamma_1\right\} = \int_{\beta_1}^{\infty}\int_{y-\beta_1}^{\gamma_1 y} f(x_1, y)dx_1 dy \\ =& \int_{\beta_1}^{\infty}\int_{y-\beta_1}^{\gamma_1 y} 2f(x_1)f(y)dx_1 dy \end{aligned} \tag{24}$$

The last step of Eq. 24 is obtained by considering order statistics under the assumption $|g_2|^2 \leq |g_1|^2$ [66] [67]; the appendix can be referred to for details. After the above considerations, we have the outage probability of phase 1 (direct transmission) given by Eq. 25.

$$\begin{aligned} P_{out}^{D} =& 1 - \frac{2}{1+\gamma_1} e^{\frac{-\gamma_1\beta_1}{2\eta^2}} \\ P_{out}^{D} =& 1 - \frac{2}{1+\gamma_{th}} e^{\frac{-\gamma_{th} l_1^2 \sigma_1^2}{2\eta^2\alpha_1 P}} \end{aligned} \tag{25}$$

7.2 Outage probability of relay phase

To find outage probability of relay path, means eNB is unable to detect message from relay; then by considering relay transmission Eq. 14, the outage probability of relay phase can be computed using Eq. 26.

$$
\begin{aligned}
P_{out}^{R} =& P\left\{ \frac{G^2|h_R|^2|h_{1,R}|^2\alpha_1 P}{G^2|h_R|^2+\sigma_R^2} < \gamma_{th} \right\} \\
=& P\left\{ \frac{|h_{1,R}|^2\alpha_1 P}{1+\dfrac{\sigma_R^2}{G^2|h_R|^2}} < \gamma_{th} \right\} \\
=& P\left\{ |g_{1,R}|^2 < \gamma_2(1+\frac{C}{|g_R|^2}) \right\} \\
=& \int_0^{\infty}\int_0^{\gamma_2(1+\dfrac{C}{x_R})} f(x_{1,R},x_R)dx_{1,R}dx_R \\
=& 1-\frac{1}{\eta^2}\sqrt{\gamma_2 C}e^{\frac{-\gamma_2}{2\eta^2}}K_1\left(\sqrt{\frac{\gamma_2 C}{\eta^4}}\right)
\end{aligned}
\tag{26}
$$

In Eq. 26, $K_1(.)$ is the first-order modified Bessel function of second kind, $\gamma_2 = \frac{\gamma_{th} l_{1,R}^2}{\alpha_1 P}$ and $C = \frac{\sigma_R^2 l_R^2}{G^2}$. The overall system outage of the cell edge user is defined by Eq. 27 as both paths cannot achieve reliable detection.

$$
P_{out} = P_{out}^{D} P_{out}^{R} \tag{27}
$$

8 Results analysis and discussion

In this section outage probability is evaluated. The distance between eNB and the cell edge user is 200 ms. The horizontal axis is defined as $\frac{P_1}{\sigma^2}$, where P_1 is the target arrived power of UE_1 and $P_R \geq P_1$. Since the variance of the noise power is 1, the transmitted SNR is equal to the transmitted power. The power allocation coefficients are $\alpha_1 = \frac{4}{5}$ and $\alpha_2 = \frac{1}{5}$ if only two users are sharing the channel. For $M > 2$ $, \alpha_i = \frac{M-i+1}{n}$ and n to select such that $\sum_{i=1}^{M} \alpha_i = 1$.

In Fig. 5, the outage performance is illustrated for $\tilde{R} = 1$ (target data rate), considering the full path loss. The graph reveals that in the higher SNR region's tail, the cell edge user demonstrates slightly superior performance compared to relying solely on the relay path. Conversely, in the lower SNR region, the incorporation of a relay exhibits enhanced outage performance. This observation underscores the dynamic nature of the system, where the performance advantages between direct cell edge communication and relay-assisted communication fluctuate based on the SNR levels.

Figure 6 illustrates the outage performance for different values of ν (where $\nu = \{0.4, 0.5, 0.7\}$), specifically in the context of 5G NOMA with relay nodes. Notably, the outcomes highlight that cooperative NOMA consistently outperforms conventional NOMA, especially in the low SNR region. This observation underscores the consistent advantage of cooperative NOMA, particularly with relay nodes, over traditional NOMA across the different ν values. It reinforces the efficacy of the proposed approach

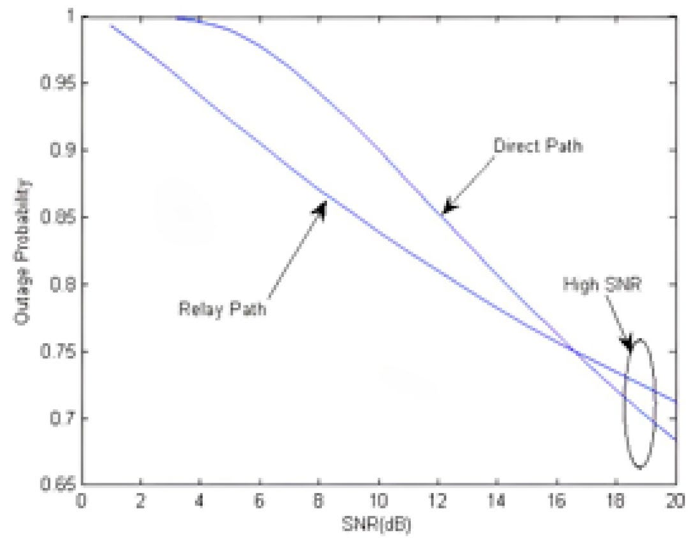

Fig. 5 outage performance of cell edge for $v = 1$; the figure compares outage performance at $\tilde{R} = 1$, with relay-assisted communication outperforming at low SNR and direct communication at high SNR

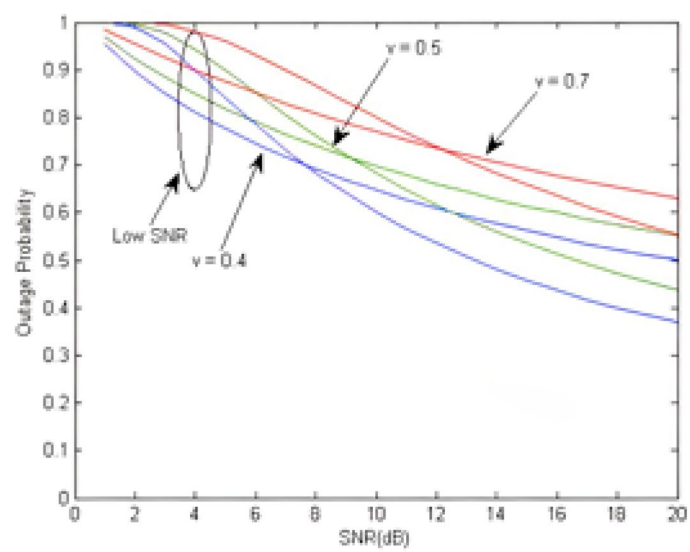

Fig. 6 Outage performance of cell edge for different values of $v = \{0.4, 0.5, 0.7\}$; cooperative NOMA with relays consistently outperforms conventional NOMA, especially in low SNR regions

in mitigating outages and improving system performance, especially in scenarios with challenging SNR conditions.

Figure 7 shows the outage performance for different target data rate. It is observed that with the larger target data rate, the use of a relay still performs better across all SNR regions, which suggests that, even with an increased target data rate, the incorporation of a relay node continues to exhibit superior performance across all SNR regions. This observation aligns with the concept that relay-assisted communication, particularly within the framework of 5G NOMA, consistently enhances system

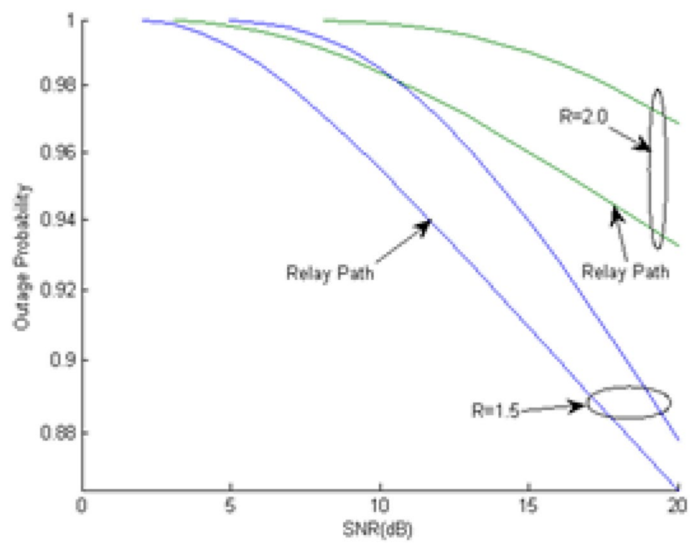

Fig. 7 Outage performance of cell edge for $\tilde{R} = 1.5$ and $\tilde{R} = 2.0$; the figure compares outage performance; relay-assisted systems outperform non-relay systems across all SNR regions and data rates

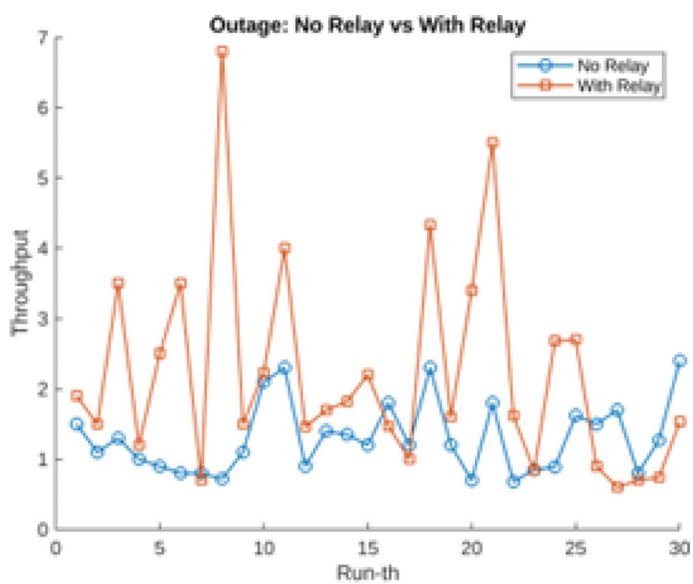

Fig. 8 Throughput in the case of outage; PSO-selected relays improve throughput; improvement rate is ≈ 68.76%

performance. The use of a relay appears to be a robust strategy, maintaining its efficacy even when aiming for higher data rates. This finding underscores the reliability and potential advantages of integrating relay nodes in 5G NOMA scenarios for outage reduction and improved performance.

Utilizing PSO for optimal relay selection significantly enhances network performance, as shown in Fig. 8. Without a relay, the throughput (data rate) typically ranges from 0.5 to 2.7, with an average of approximately 1.3. However, when a relay is strategically selected using PSO, the throughput increases, ranging from 0.6 to 7, with an average of approximately 2.204. This highlights the effectiveness of PSO in

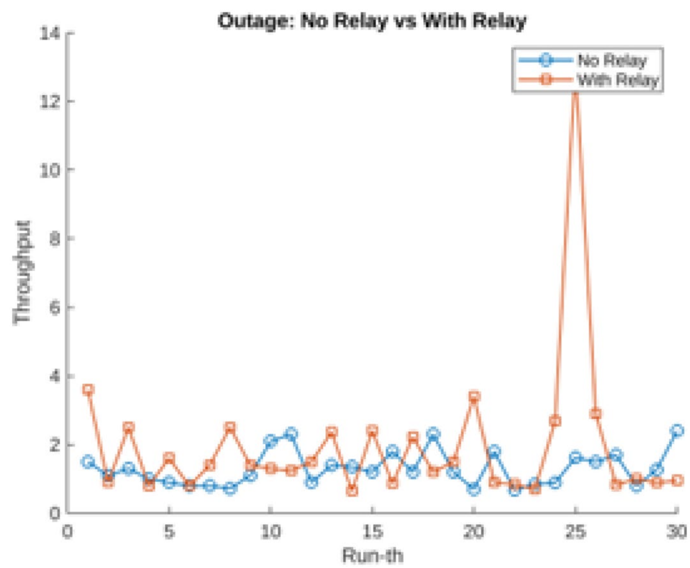

Fig. 9 Throughput in the case of outage; GA-selected relays improve throughput; improvement rate is ≈ 50.15%

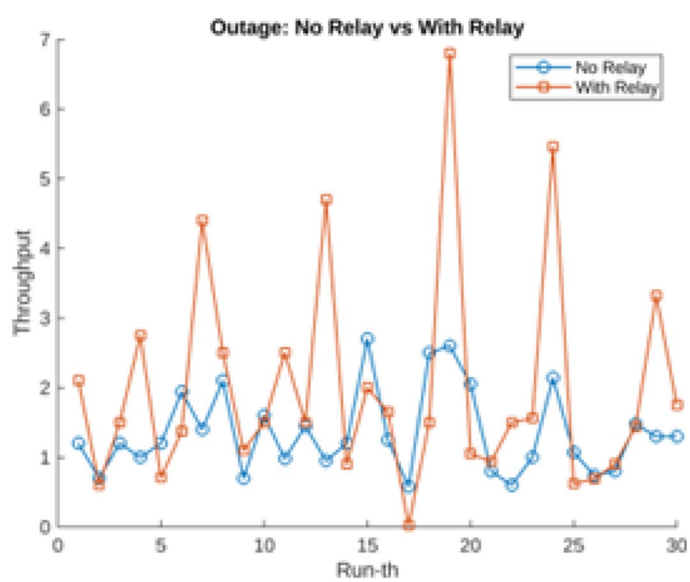

Fig. 10 Throughput in the case of outage; DRL-selected relays improve throughput; improvement rate is ≈ 46.38%

mitigating outages and improving system performance. Furthermore, Fig. 8 illustrates that during an outage, PSO-based relay selection significantly boosts data rates, ensuring more robust communication. To assess the effectiveness of PSO, we compared it with GA and DRL. PSO demonstrated an improvement of approximately 68.76%, outperforming GA, which showed an average improvement of 50.15%, and DRL, which achieved 46.38%, as shown in Figs. 8, 9, and 10, respectively. Here, improvement rate $= \frac{\text{new throughput} - \text{old throughput}}{\text{old throughput}} \times 100$. While PSO demonstrated more stability, GA exhibited fluctuating performance. GA was configured with a mutation rate of 0.01 and a tournament size of 3. DRL, a machine learning technique where an agent learns to make decisions by interacting with an environment and optimizing its actions to maximize cumulative rewards, was also evaluated [68]. In our test, the DRL model used a state representation based on five factors: the relay node's energy, distance to the base station, distance to the outage area, transmission range, and signal quality factor. The action space consisted of 30 nodes, with a learning rate of 0.0001, a discount factor of 0.95, an exploration rate decay of 0.995, a batch size of 32, and a memory size of 2000. The model was trained using the Adam optimizer with gradient clipping at 1.0 to ensure stable learning. It employed a deep Q-network (DQN) with two hidden layers of 64 ReLU-activated neurons each. Additionally, the model incorporated an ϵ-greedy exploration strategy, a target network update mechanism, and reward clipping for stability. Alternative loss functions, such as Huber loss, might be used in place of mean squared error (MSE) to enhance robustness.

These findings emphasize the effectiveness of PSO-based relay selection in enhancing network performance, particularly in outage scenarios. While PSO optimally selects relays to maximize throughput, direct transmission remains preferable in non-outage conditions, as highlighted by our comparative analysis. This dual perspective on relay-based and direct transmission strategies provides a comprehensive understanding of their advantages and limitations in 5G NOMA networks.

A comparison is made with closely related studies, and the findings are listed in Table 2. The table describes the context, focused area, use or non-use of a relay, metrics, major contributions, applications, simulation insights, and limitations. It demonstrates that our study extensively investigates the proposed solutions not only using a single PSO methodology but also incorporating GA and DRL. After careful analysis, it was concluded that PSO is more suitable than genetic algorithm- and DRL-based relay selection methods, whereas other studies rely solely on the results of a single or no optimization algorithm.

9 Limitations and challenges

1. While PSO optimizes relay selection, the additional energy required for relay communication may offset the savings, as both the relay and source users consume more energy in the process.
2. The system assumes a suitable relay is always available, but in mobile or sparse networks, finding an optimal relay may not be feasible, which could affect system performance.
3. PSO's iterative nature can be slow to converge in dynamic environments, limiting real-time applications where rapid decision making is essential.
4. Relay nodes (other users) may be reluctant to act as relays due to energy costs, potentially hindering the practical implementation of the system without proper incentives.
5. The proposed solution relies on the assumption of perfect channel state conditions rather than imperfect ones. Error propagation due to imperfect channel state infor-

Table 2 Comparison of related works on cooperative NOMA and relay selection approaches

Aspect	Belmekki et al. [69]	Do et al. [70]	Agarwal et al. [71]	Bhatti et al. (Proposed Approach)
Context	Cooperative NOMA in vehicular communications (intersections vs. highways).	Relay-aided CR-NOMA in cognitive radio networks.	Generalized fading for uplink (UL) and downlink (DL) NOMA.	Uplink cooperative NOMA with PSO for relay selection.
Focus Area	Outage probability analysis with road-based interference modeling.	Impact of FD/HD relay selection and interference in CR-NOMA.	Analysis of fading effects and diversity orders for NOMA.	Novel relay selection method (PSO) to reduce outage probability and boost throughput.
Relay Use	Decode-and-Forward (DF) relay at intersections.	Full-duplex (FD) and half-duplex (HD) relay selection.	No relay; focuses on fading and ordering schemes.	PSO-optimized relay selection in uplink cooperative NOMA.
Key Metrics	- Outage probability. - Impact of vehicle density and path loss.	- Outage probability. - Ergodic capacity.	- Outage probability. - Outage floor. - Diversity orders.	- Outage probability. - Threefold throughput improvement compared to direct transmission.
Interference Handling	Road interference modeled using Poisson Point Process.	Interference from primary users considered.	Statistical and instantaneous CSI for interference analysis.	Relays mitigate interference for cell edge users; incorporates inter-cell interference.
Major Contributions	- NOMA outperforms OMA in all scenarios. - Intersection scenarios show worse performance than highways.	- PRS improves far-user performance in CR-NOMA. - HD outperforms FD under severe interference.	- Closed-form outage expressions for various fading distributions.	- Introduced PSO for optimal relay selection, outperforming traditional methods (e.g., random or static relay selection). - Achieved significant outage reduction and throughput gains.
Comparison with Other Methods	- Focuses on cooperative OMA vs. NOMA; no explicit relay selection comparison.	- Compares PRS with other relay schemes (e.g., max-min relay selection).	- Focuses on power allocation and channel effects; no relay-based techniques.	- PSO-optimized relay selection compared against direct transmission and static relay methods. - Demonstrated clear superiority in outage reduction and throughput improvement.
Simulation Insights	- Cooperative NOMA is robust at intersections but degrades with high interference.	- Relays improve performance, especially for distant users.	- High SNR regime provides clear insights into diversity effects.	- PSO-based relay selection triples throughput compared to direct transmission. - Significant performance improvement over non-optimized relay schemes.
Applications	Vehicular communications in high-interference zones (e.g., intersections).	Spectrum sharing for CR networks in beyond-5G systems.	NOMA system design for varying channel conditions in 5G.	Enhanced communication for cell edge users in 5G uplink networks.
Limitations	Limited to intersection scenarios and fixed relay positions.	Focuses on CR-NOMA; less exploration of non-cognitive setups.	Assumes static channel characteristics in some scenarios.	High dependence on relays; incurs PSO overhead for real-time operation.

mation is effectively handled in wireless networks through refined channel state estimation algorithms and error detection and correction mechanisms.

10 Conclusion

The proposed uplink cooperative NOMA system, utilizing SIC and PSO, makes a significant contribution to addressing outages and improving system performance in 5G networks. NOMA's ability to enhance spectral efficiency through effective power allocation and user connectivity during outages is further strengthened by the integration of relay nodes. These nodes provide a robust strategy to ensure communication reliability, even under challenging channel conditions, and help maintain required data rates. Despite some traces of premature convergence, leveraging PSO for dynamic relay selection enables the system to achieve substantial improvements in throughput, potentially tripling the data rate while simultaneously optimizing energy efficiency and resource utilization. This approach has promising real-world applications beyond simulations. For instance, in smart city infrastructure, it can support seamless connectivity for critical services like transportation and healthcare, ensuring robust communication in dynamic and dense environments. In industrial IoT scenarios, the method can efficiently manage massive device connectivity and ensure reliable data transfer, which is critical for Industry 4.0 operations. Furthermore, it is well-suited for disaster recovery or emergency scenarios, where dynamic relay selection and low latency are primary goals. Future efforts could focus on deploying this framework in real-world testbeds, addressing practical challenges such as hardware constraints, real-time mobility, and environmental variations to validate its performance and scalability in diverse applications. Instances of premature convergence were also observed, warranting further investigation. Fine-tuning the parameters of PSO, GA, and DRL is required to dynamically and intelligently adapt to the environment.

11 Future work

The proposed PSO-based relay selection mechanism demonstrates significant potential for enhancing network performance in 5G NOMA systems, particularly in reducing outages and optimizing energy consumption. However, as networks evolve toward 6G, new challenges and opportunities arise. By 2030, the expected launch year of 6G [72], the number of machine-type devices is projected to reach 97 billion, driving global mobile data traffic to 5.016 ZB per month. This surge, fueled by urbanization, smart city ecosystems, and emerging technologies like AI and IoE, necessitates robust and agile ICT infrastructure, with cellular networks playing a critical role in supporting extreme data rates, high bandwidth, and QoS [73]. Future research could focus on incorporating low-cost public key cryptographic protocols such as ECDH (Elliptic Curve Diffie-Hellman) into 6G to extend connectivity to resource-constrained devices in the Internet of Everything (IoE). Security solutions proposed in [74, 75] can also be considered for securing D2D communication. This approach ensures secure and energy-efficient communication, enhancing data security and relay selection while addressing the unique challenges faced by low-resource devices in the evolving IoE ecosystem. In addition, future work can further enhance the system's applicability and effectiveness, provided the assumption of perfect channel state conditions is lifted:

1. Extending PSO-based relay selection to 6G with the integration of AI capabilities can address the challenges posed by the highly dynamic and complex nature of 6G environments. AI's ability to learn from historical data and predict channel behavior, combined with PSO-based optimization, can enable adaptive and intelligent decision making for relay selection in real-time 6G networks. This approach ensures optimal performance in scenarios with rapidly changing channel conditions, diverse user requirements, and heterogeneous network configurations, ultimately enhancing energy efficiency, minimizing latency, and improving overall system reliability [76].
2. As 6G is expected to support billions of interconnected small devices across diverse applications such as IoT, smart cities, and Industry 4.0, efficient resource allocation becomes a critical challenge. PSO-based resource allocation, integrated with deep learning approaches, may provide scalable and adaptive solutions by dynamically optimizing spectrum and energy usage. This ensures minimal interference and latency while maximizing throughput and network reliability [77]. This approach is particularly suited for managing the complex and dynamic requirements of massive device connectivity in 6G networks.
3. Energy-efficient relay selection is essential for addressing the scalability and energy challenges of IoT devices in smart cities, agriculture, and healthcare. Extending PSO-based approaches to IoT can integrate energy-harvesting techniques to enhance network lifespan, adapt to diverse device requirements, and scale effectively for large IoT ecosystems. This ensures optimized performance and resource management [78].

Abbreviations

5G	Fifth generation
M2M	Machine-to-machine
CCU	Cell center users
DF	Decode-and-forward
NOMA	Non-orthogonal multiple access
QoS	Quality of service
SIC	Successive interference cancelation
ICI	Inter-cell interference
GA	Genetic algorithm
RIS	Reconfigurable intelligent surfaces
DRL	Deep reinforcement learning
D2D	Device-to-device
CEU	Cell edge users
A &F	Amplify-and-forward
MRC	Maximum ratio combining
PSO	Particle swarm optimization
SNR	Signal-to-noise ratio
BLER	Block error rate
gbest	Global best (method in PSO)
IoE	Internet of everything
IRS	Intelligent reflecting surfaces
DQN	Deep Q-network

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Author contributions
All authors contributed equally.

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Availability of data and materials
Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

Declarations

Competing interests
There is no conflict of interest.

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