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CSI-Aware Adaptive PSO-Based Power Allocation for Enhancing SIC Reliability in Imperfect-CSI NOMA Systems

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ABSTRACT

Future wireless networks must accommodate massive connectivity under stringent spectral- and energy-efficiency requirements, thereby intensifying the demand for robust power-domain nonorthogonal multiple access (NOMA). The performance of NOMA critically depends on reliable successive interference cancellation (SIC), whose effectiveness deteriorates under imperfect channel state information (CSI) due to estimation errors, mobility, and hardware nonlinearities. To mitigate these challenges, this paper proposes an adaptive particle swarm optimization (PSO)-based power allocation framework that enhances SIC robustness by dynamically learning optimal power coefficients in the presence of CSI uncertainty. The problem is reformulated as a constrained multiobjective optimization task that incorporates decoding-order stability, interference propagation effects, user fairness, and rate performance. The proposed adaptive PSO integrates CSI uncertainty directly into its update dynamics through error-aware adjustment of inertia and acceleration parameters. Extensive numerical evaluations conducted under realistic imperfect-CSI assumptions show that the proposed method significantly improves fairness, sum-rate stability, and SIC error resilience, achieving up to 98% successful SIC operations in medium-to-high signal-to-noise ratio (SNR) regimes. These findings demonstrate the practicality of lightweight, AI-driven optimization techniques for improving the reliability of NOMA-enabled 5G-and-beyond wireless systems.

1 | Introduction

The evolution toward beyond-5G and 6G wireless communication systems is driving the deployment of highly heterogeneous and densely connected networks that must simultaneously support massive connectivity, high spectral efficiency, ultralow latency, and reliable service delivery. Among the candidate multiple-access technologies, nonorthogonal multiple access (NOMA) has emerged as a promising solution due to its ability to accommodate multiple users on the same time–frequency resource block through power-domain multiplexing [1, 2]. By enabling concurrent transmissions and exploiting differences in user channel conditions, NOMA can significantly improve spectrum utilization and support diverse quality-of-service (QoS) requirements. A fundamental component of NOMA operation is successive interference cancellation (SIC), whereby users with stronger channel gains sequentially decode and remove signals intended for weaker users before recovering their own information [3].

Despite its advantages, the performance of NOMA systems is highly dependent on the accuracy of channel state information

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(CSI) and the effectiveness of power-allocation strategies. In practical wireless environments, perfect CSI is rarely available due to estimation errors, feedback delays, user mobility, hardware impairments, and channel aging effects [4]. Consequently, imperfect CSI introduces residual interference, decoding-order instability, and SIC error propagation, which can substantially degrade system throughput, fairness, and reliability [5, 6]. Recent studies have further shown that imperfect SIC and hardware impairments can significantly reduce outage performance and spectral efficiency in practical NOMA deployments, emphasizing the need for robust interference-management and resource-allocation mechanisms [7–10] [11]. Therefore, designing power-allocation frameworks capable of maintaining stable SIC performance under CSI uncertainty remains a critical challenge for future wireless networks [12].

Extensive research has been conducted on robust resource-allocation techniques for imperfect-CSI NOMA systems. Conventional approaches primarily rely on convex optimization, iterative approximation methods, and stochastic programming techniques to maximize throughput, improve energy efficiency, or satisfy fairness constraints [3, 5, 12]. Although these methods can achieve near-optimal performance, their computational complexity often increases significantly with problem dimensionality and CSI uncertainty. More recently, machine-learning- and deep reinforcement learning (DRL)-based resource-allocation frameworks have been proposed to adaptively learn transmission policies in dynamic wireless environments. However, DRL-based approaches generally require extensive training datasets, long convergence periods, and considerable computational resources, which may limit their applicability in latency-sensitive communication scenarios.

Beyond conventional optimization techniques, recent intelligent-surface-assisted and cooperative hybrid NOMA architectures have demonstrated promising improvements in reliability and spectral efficiency under imperfect SIC conditions. Kennedy and Kumaravelu reported significant outage-probability reduction and sum-capacity enhancement through intelligent omni-surface (IOS)-aided hybrid NOMA systems operating under imperfect SIC [7]. Similarly, IOS-assisted cooperative hybrid NOMA frameworks have been shown to improve spectral efficiency despite hardware distortions and imperfect SIC [9]. Dipinkrishnan and Kumaravelu further demonstrated that optimized power-allocation and user-pairing strategies can substantially enhance spectral efficiency in multiuser NOMA systems under hardware and SIC imperfections [8]. Recent studies have also investigated outage analysis and power optimization under Rician-fading environments as well as reliability enhancement through intelligent-surface-assisted cooperative NOMA architectures [8, 11]. These findings highlight the growing importance of robust power-allocation mechanisms capable of mitigating CSI uncertainty and SIC degradation in next-generation wireless networks.

Metaheuristic optimization methods, particularly particle swarm optimization (PSO), have attracted considerable attention because of their low implementation complexity, rapid convergence behavior, and suitability for solving highly nonconvex optimization problems [8–10]. Several PSO-based NOMA resource-allocation schemes have been proposed to improve throughput, energy efficiency, and resource utilization [11–15]. However, most existing PSO-based approaches either assume ideal CSI conditions or focus primarily on throughput and energy-efficiency optimization without explicitly addressing SIC reliability, decoding-order stability, and CSI-induced uncertainty. Furthermore, existing studies rarely incorporate CSI uncertainty directly into the PSO update dynamics, leaving the optimization process vulnerable to channel-estimation errors and SIC-performance degradation. This limitation becomes increasingly significant as intelligent-surface-enhanced NOMA architectures continue to improve spectral efficiency and reliability through advanced interference management, thereby creating a need for lightweight optimization frameworks that explicitly account for CSI uncertainty during resource allocation [8, 10].

The recent work in [16] proposed a PSO-based energy-efficient power-allocation framework for downlink NOMA systems under imperfect CSI. While that study demonstrated improvements in throughput and energy efficiency, it did not explicitly model SIC reliability, decoding-order preservation, or uncertainty-aware adaptation of PSO parameters. In contrast, the present work introduces a CSI-aware adaptive PSO framework that dynamically adjusts swarm parameters according to channel uncertainty levels, incorporates Monte Carlo–based robustness evaluation, and explicitly optimizes SIC success probability alongside throughput and fairness objectives [17–22]. Unlike recent IOS-assisted and hybrid NOMA studies that primarily focus on outage, capacity, and spectral-efficiency enhancement through advanced network architectures [7–11], the present work specifically targets SIC reliability preservation under imperfect CSI through uncertainty-aware adaptive optimization.

Motivated by these limitations, this paper proposes an adaptive PSO-based power-allocation framework specifically designed to enhance SIC reliability in imperfect-CSI NOMA systems. The proposed framework directly incorporates CSI uncertainty into the optimization process through adaptive parameter tuning and stochastic fitness evaluation. In addition, SIC reliability, achievable sum rate, and user fairness are jointly optimized within a unified multiobjective optimization formulation. By evaluating candidate power-allocation vectors over multiple CSI-error realizations, the proposed approach learns robust transmission strategies capable of maintaining reliable SIC performance under realistic channel uncertainties.

The main contributions of this work are summarized as follows:

a. We identify and model the primary causes of SIC unreliability under imperfect CSI, including decoding-order instability, residual interference, and error propagation effects.

b. We formulate a normalized multiobjective optimization problem that jointly maximizes achievable sum rate, SIC reliability, and user fairness under practical NOMA constraints.

c. We develop a CSI-aware adaptive PSO algorithm in which the inertia weight and acceleration coefficients are dynamically adjusted according to CSI estimation-error variance to improve convergence robustness.

d. We integrate Monte Carlo–based uncertainty evaluation into the optimization process, enabling the swarm to learn

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power-allocation solutions that remain reliable across multiple CSI-error realizations.

e. We conduct extensive simulations involving different CSI uncertainty levels, swarm configurations, convergence conditions, and NOMA cluster sizes (3-user, 4-user, and 5-user scenarios) to evaluate scalability and robustness.

f. We compare the proposed framework with fixed power allocation, classical PSO, robust convex optimization (RCO), and DRL-assisted resource-allocation approaches, demonstrating competitive performance with significantly lower computational complexity.

Simulation results demonstrate that the proposed adaptive PSO framework achieves approximately 98% SIC success probability while simultaneously improving throughput consistency and fairness under moderate CSI uncertainty. These findings highlight the potential of lightweight uncertainty-aware metaheuristic optimization techniques for enhancing the reliability and practicality of NOMA-enabled access networks in future 5G-and-beyond wireless communication systems, as summarized in Table 1.

TABLE 1 | Summary of NOMA under imperfect CSI.

Challenge/approach	Key insights and solutions	References
SIC reliability under imperfect CSI	Residual interference, decoding-order instability, SIC error propagation, fairness degradation	[1, 2, 4–6, 22]
Robust power allocation	Convex optimization, iterative approximation, stochastic programming, metaheuristic optimization, Monte Carlo uncertainty modeling	[3, 5, 12, 13, 16, 16–19]
IOS-/surface-assisted NOMA and hybrid NOMA	Reliability enhancement, outage reduction, sum-capacity improvement, intelligent-surface-assisted interference management under imperfect SIC	[7, 8, 10]
Spectral-efficiency enhancement under imperfections	Power allocation, user pairing, outage optimization, spectral-efficiency improvement under imperfect SIC, hardware impairments, and fading channels	[9, 11]
Learning-based resource allocation	DRL-assisted adaptation and intelligent decision-making under dynamic wireless environments	[14, 15]
Multiobjective optimization	Joint optimization of sum rate, fairness, energy efficiency, reliability, and SIC robustness	References [1, 3, 5, 7–12, 18, 19],
Proposed adaptive PSO framework	CSI-aware parameter adaptation, Monte Carlo robustness evaluation, SIC-aware optimization, decoding-order preservation, adaptive uncertainty handling	This work

2 | System Model and Problem Definition

2.1 | System Framework

We consider a downlink power-domain NOMA system in which a single base station (BS) simultaneously serves a cluster of $U \in \mathbb{N}$ single-antenna users over a shared time–frequency resource block. Each user experiences distinct propagation conditions due to path loss, shadowing, multipath fading, and hardware impairments, resulting in heterogeneous channel gains.

For SIC operation, users are indexed according to their channel strengths such that [23]:

$$|h_1|^2 \le |h_2|^2 \le \cdots \le |h_U|^2, \tag{1}$$

where h_U denotes the complex wireless channel coefficient of the Uth user, $|h_U|^2$ represents the channel power gain of user U, and U denotes the total number of users in the NOMA cluster. User 1 corresponds to the weakest-channel user, and User U corresponds to the strongest-channel user.

The ordering condition implies that users are arranged in ascending order according to their channel strengths. Consequently, users with weaker channel gains are allocated larger transmission power coefficients to guarantee reliable signal reception, while users with stronger channel gains are assigned lower transmission power and employ SIC to sequentially decode and remove signals intended for weaker users before detecting their own information signal.

To reflect practical deployment conditions, the BS operates under imperfect CSI. The estimated channel coefficient of user U is modeled as follows [24]:

$$\widehat{h}_u = h_u + e_u, \tag{2}$$

where h_u denotes the true channel coefficient, $\widehat{h}_u$ denotes the estimated channel coefficient, and $e_u \sim CN(0, \sigma_e^2)$ represents the CSI estimation error with variance σ_e^2.

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The power-allocation vector is defined as follows:

$$P = \left[p_1, p_{2,\cdots,}, p_U\right]^T, \tag{3}$$

where p_u denotes the transmission power allocated to user U.

The power-allocation coefficients must satisfy both the total transmit-power constraint and the NOMA power-ordering condition [25].

$$\sum_{u=1}^{U} p_u = p_T, \quad p_1 \geq p_2 \geq \cdots \geq p_U \geq 0, \tag{4}$$

where p_T denotes the maximum available transmit power at the BS.

Figure 1 illustrates the considered downlink NOMA transmission model. The BS broadcasts a superimposed signal to all users, with weaker users receiving larger power coefficients, while stronger users employ SIC to remove previously decoded signals prior to detecting their own messages.

During reception, user u sequentially decodes the signals intended for all weaker users ($k < u$) before decoding its own information signal. Under imperfect CSI conditions, estimation errors may alter the perceived received-power ordering, leading to decoding-order mismatches, residual interference, and SIC error propagation [7–10] [11].

2.2 | Problem Statement

For a strong user u attempting to decode the signal intended for user $k(k < u)$, the received signal-to-interference-plus-noise ratio (SINR) under imperfect CSI conditions is expressed as follows [2]:

$$\gamma_{u\longrightarrow k} = \frac{p_k\left|\widehat{h}_u\right|^2}{\sum_{i=k+1}^{U} p_i\left|\widehat{h}_u\right|^2 + \sigma_n^2}, \tag{5}$$

where σ_n^2 denotes the additive white Gaussian noise (AWGN) power.

Successful decoding requires

$$\gamma_{u\longrightarrow k} \geq \gamma_{th}, \tag{6}$$

where γ_{th} represents the minimum SINR threshold corresponding to the target transmission rate

$$\underset{2}{\mathrm{Log}}\left(1 + \gamma_{th}\right). \tag{7}$$

2.2.1 | SIC Reliability Metric

To quantify decoding robustness, the SIC reliability is defined as

$$\Pr\left\{\gamma_{u\longrightarrow k} \geq \gamma_{th}, \forall k < u\right\}, \tag{8}$$

which is estimated using multiple Monte Carlo realizations of CSI estimation errors.

A SIC operation is considered successful only when all preceding decoding stages satisfy the required SINR threshold. Consequently, failure at any stage of the SIC chain is regarded as SIC failure for the corresponding user due to SIC error propagation effects [16].

2.2.2 | Sum-Rate Performance

The achievable system sum rate is expressed as

$$\sum_{u=1}^{U} \underset{2}{\mathrm{Log}}\left(1 + \gamma_u\right), \tag{9}$$

where γ_u denotes the effective post-SIC SINR experienced by user u.

2.2.3 | Fairness Metric

User fairness is evaluated using Jain's Fairness Index as follows:

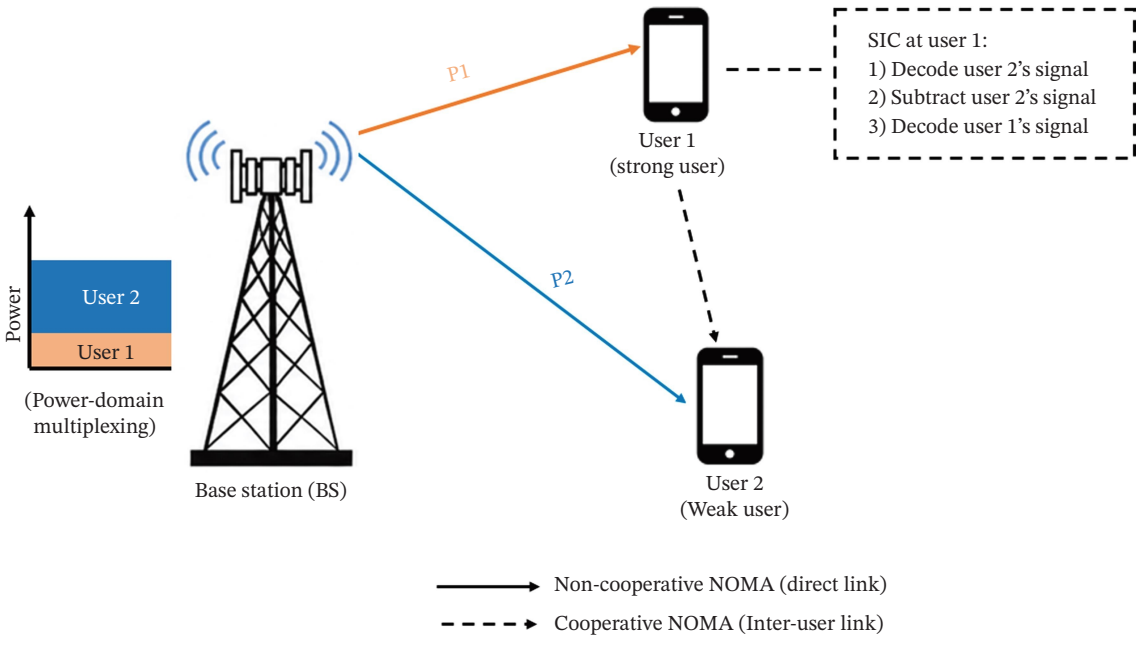


FIGURE 1 | Downlink NOMA transmission structure.

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$$\frac{\left(\sum_{u=1}^{U} R_u\right)^2}{U\sum_{u=1}^{U} R_u^2}, \tag{10}$$

where R_u denotes the achievable data rate of user u.

2.2.4 | Multiobjective Optimization Formulation

Since the considered performance objectives possess different numerical scales, normalization is first performed prior to aggregation. The overall optimization problem is formulated as follows [12]:

$$\max_P \left[\alpha_1 \overline{R}_{sum}(P) + \alpha_2 \overline{\eta}_{SIC}(P) + \alpha_3 \overline{J}(P)\right], \tag{11}$$

subject to

$$\sum_{u=1}^{U} p_u \le P_T, \text{ and } p_1 \ge p_2 \ge \cdots \ge p_U \ge 0, \tag{12}$$

where $\overline{R}_{\text{sum}}$ denotes the normalized sum-rate metric, $\overline{\eta}_{SIC}$ denotes the normalized SIC reliability metric, and $\overline{J}$ denotes the normalized Jain's Fairness Index.

The weighting coefficients satisfy the normalization condition ($\alpha_1 + \alpha_2 + \alpha_3 = 1$), where α_1, α_2, and α_3, respectively, determine the relative importance of throughput, SIC reliability, and fairness in the optimization process. Since the considered objectives have different numerical scales, all metrics are first normalized to the interval $[0, 1]$ prior to aggregation. This normalization prevents any individual objective from dominating the fitness evaluation and ensures a balanced contribution from all performance metrics. The weighting coefficients are selected empirically to achieve a practical trade-off among throughput enhancement, fairness preservation, and SIC reliability improvement under imperfect CSI conditions.

The resulting optimization problem is highly nonconvex due to the following:

- Stochastic CSI uncertainty,
- Coupled multiuser interference,
- SIC error propagation,
- Conflicting optimization objectives, and
- NOMA power-ordering constraints.

Consequently, obtaining a closed-form optimal solution using conventional optimization techniques becomes computationally intractable, thereby motivating the use of the proposed adaptive PSO-based optimization framework.

3 | Adaptive PSO-Driven Power Allocation Under Imperfect CSI

3.1 | Power Allocation as a Robust Multiobjective Search Problem

The imperfect-CSI NOMA power-allocation problem is formulated as a robust multiobjective optimization problem solved using an adaptive PSO framework.

Since the power-allocation vector P has already been defined in Section 2, equation (3), the optimization is performed over the feasible solution set as follows:

$$\mathcal{P} = \left\{P: \sum_{u=1}^{U} p_u \le P_T,\ p_1 \ge p_2,\ \ldots,\ \ge pu \ge 0\right\}. \tag{13}$$

For every candidate solution P, the optimization framework evaluates the performance vector as follows:

$$\left[R_{sum}(P),\ \eta_{SIC}(P),\ \mathrm{J}(P)\right], \tag{14}$$

which contains the following:

- Achievable sum rate $R_{sum}(P)$,
- SIC reliability $\eta_{SIC}(P)$,
- Jain's Fairness Index $\mathrm{J}(P)$.

To avoid scale imbalance among the optimization objectives, all performance metrics are normalized prior to aggregation. The overall fitness function is, therefore, defined as

$$F(P) = \alpha_1 \overline{R}_{sum} + \alpha_2 \overline{\eta}_{SIC} + \alpha_3 \overline{J} \tag{15}$$

subject to

$$\alpha_1 + \alpha_2 + \alpha_3 = 1, \tag{16}$$

where $\overline{R}_{sum}$ denotes the normalized sum rate, $\overline{\eta}_{SIC}$ denotes the normalized SIC reliability, and $\overline{J}$ denotes the normalized fairness index.

The weighting coefficients ($\alpha_1 + \alpha_2 + \alpha_3 = 1$) are selected empirically to maintain a balanced trade-off among throughput, reliability, and fairness objectives. Due to stochastic CSI uncertainty, coupled multiuser interference, SIC error propagation, and NOMA power-ordering constraints, the resulting optimization problem becomes highly nonconvex and difficult to solve using classical optimization techniques. In the simulations, equal weighting ($\alpha_1 = \alpha_2 = \alpha_3 = 1/3$) is adopted to avoid bias toward any single objective and to ensure balanced optimization of throughput, SIC reliability, and fairness.

3.2 | Proposed Adaptive PSO Model

In the proposed framework, each particle represents a feasible power-allocation vector belonging to the admissible search space $\mathcal{P}$.

The velocity-update equation of the lth particle is expressed as

$$\begin{aligned} \mathrm{v}^{(l)}(t+1) = {} & \omega(t)\mathrm{v}^{(l)}(t) + c_1(t) r_1 \left(P^{*,l} - P^{(l)}(t)\right) \\ & + c_2(t) r_2 \left(P^{g} - P^{(l)}(t)\right), \end{aligned} \tag{17}$$

while the position-update equation is given by

$$P^{(l)}(t+1) = P^{(l)}(t) + \mathrm{v}^{(l)}(t+1), \tag{18}$$

where $P^{*,l}$ denotes the personal-best solution obtained by the $l-th$ particle, P^g represents the global-best solution among all particles, $r_1, r_2 \sim u(0, 1)$ are uniformly distributed random variables, $\omega(t)$ denotes the inertia weight, and $c_1(t)$ and $c_2(t)$ represent the cognitive and social acceleration coefficients, respectively.

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3.2.1 | Feasibility Preservation

After every position update, a projection-normalization procedure is applied to ensure that all candidate solutions remain feasible.

First, negative power coefficients are clipped to zero. The power coefficients are then reordered to satisfy the NOMA ordering constraint as follows:

$$p_1 \geq p_2 \geq \cdots \geq p_U. \tag{19}$$

Finally, the power-allocation vector is normalized such that

$$\sum_{u=1}^{U} p_u = p_T. \tag{20}$$

This feasibility-preservation procedure guarantees that every particle remains inside the admissible NOMA search space throughout the optimization process.

3.2.2 | CSI-Aware Adaptation Mechanism

To improve robustness under imperfect CSI conditions, the PSO control parameters are dynamically adjusted according to the CSI estimation-error variance σ_e^2. The adaptive inertia-weight update is defined as follows [26]:

$$\omega\left(\sigma_e^2\right) = \omega_{\max} - \alpha\sigma_e^2. \tag{21}$$

The adaptive cognitive-coefficient update is expressed as

$$c_1\left(\sigma_e^2\right) = c_{1,\max}\left(1 - \beta\sigma_e^2\right). \tag{22}$$

The adaptive social-coefficient update is given by

$$c_2\left(\sigma_e^2\right) = c_{2,\min} + \gamma\sigma_e^2, \tag{23}$$

where $\omega_{\max}$ denotes the maximum inertia weight, $c_{1,\max}$ represents the maximum cognitive acceleration coefficient, $c_{2,\min}$ denotes the minimum social acceleration coefficient, α, β, and γ are adaptive scaling constants controlling the sensitivity of the PSO parameters to CSI uncertainty, and σ_e^2 represents the CSI estimation-error variance.

As the CSI error variance increases, the inertia weight gradually decreases to suppress excessive particle oscillations and improve convergence stability under uncertain channel conditions. Simultaneously, the cognitive coefficient decreases while the social coefficient increases, enabling the swarm to transition progressively from exploration-oriented behavior toward exploitation-oriented convergence as CSI uncertainty becomes more severe.

This CSI-aware adaptive mechanism improves the robustness and stability of the optimization process by preserving decoding-order consistency and mitigating SIC error propagation caused by channel fluctuations. Consequently, the proposed adaptive PSO framework achieves enhanced power-allocation reliability and improved SIC performance in multiuser downlink NOMA systems operating under imperfect CSI environments [27, 28].

3.3 | Adaptive PSO Algorithm

Algorithm 1 summarizes the proposed CSI-aware adaptive PSO procedure for robust NOMA power allocation.

3.4 | Fitness Evaluation Under Imperfect CSI

For each candidate power-allocation vector, the following procedure is performed. First, Monte Carlo CSI-error samples are generated according to

$$e_u^{(m)} \sim CN\left(0, \sigma_e^2\right). \tag{24}$$

The imperfect CSI realizations are then constructed as

$$\widehat{h}_u^{(m)} = h_u + e_u^{(m)}. \tag{25}$$

Subsequently, SIC decoding is simulated and the reliability metric is estimated as

$$\eta_{SIC}(P) \approx \frac{1}{M}\sum_{m=1}^{M} 1\left\{\text{all SIC stages succeed}\right\}. \tag{26}$$

Finally, the fitness value is evaluated using equation (11).

This Monte Carlo–enhanced evaluation enables the adaptive PSO framework to learn power-allocation patterns that remain robust under realistic CSI uncertainty conditions.

3.5 | Computational Complexity and Monte Carlo Overhead Analysis

To clarify the computational overhead associated with Monte Carlo–based fitness evaluation, the proposed adaptive PSO framework employs a moderate number of CSI-error realizations to achieve a practical trade-off between robustness and computational efficiency. Instead of exhaustively evaluating all possible CSI perturbations, the optimization process utilizes limited stochastic sampling during each PSO iteration to estimate SIC reliability with acceptable accuracy and manageable computational cost.

Furthermore, the proposed framework considers a low-dimensional user-cluster model together with a constrained feasible search space, thereby significantly reducing the overall optimization burden. The CSI-aware adaptive updates of the inertia weight and acceleration coefficients involve only lightweight arithmetic operations, introducing minimal additional complexity compared with classical PSO.

The computational complexity of the proposed adaptive PSO framework can be expressed using Big-O notation as

$$\mathcal{O}(\mathrm{I} \times \mathrm{P} \times \mathrm{U} \times \mathrm{M}), \tag{27}$$

where I denotes the number of PSO iterations, P represents the swarm size, U is the number of users in the NOMA cluster, M denotes the number of Monte Carlo CSI realizations used during fitness evaluation.

For comparison, the computational complexity of classical PSO without Monte Carlo-based robustness evaluation is given by

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ALGORITHM 1 | CSI-Aware Adaptive PSO for Robust NOMA Power Allocation.

Input:

$U \longleftarrow$ Number of NOMA users

$p_T \longleftarrow$ Total transmit power

$\sigma_e^2 \longleftarrow$ CSI estimation-error variance

$I_{\max} \longleftarrow$ Maximum PSO iterations

$S \longleftarrow$ Swarm size

$M \longleftarrow$ Number of Monte Carlo CSI realizations

$\alpha_1, \alpha_2, \alpha_3 \longleftarrow$ Fitness-function weights

Output:

Optimal power-allocation vector

$P^* = [p_1, p_{2,} \cdots, p_U]^T$

Initialization

-Randomly initialize swarm particles $P^{(l)}, l = 1, \ldots, S$.

-Enforce NOMA constraints:

$\sum_{u=1}^{U} p_u \le p_{T,} \quad p_1 \ge p_2 \ge \cdots \ge p_U \ge 0$

-Initialize particle velocities $v^{(l)}$,.

-Initialize personal-best solutions $P^{(*,l)}$.

-Initialize global-best solution P^g.

-Set adaptive PSO parameters: $\omega_{\max}$, $c_{1,\max}$, $c_{2,\min}$

Main Optimization Procedure

For $t = 1$ **to** $I_{\max}$

For each particle l

Generate M imperfect-CSI realizations according to equation (2)

For each realization:

-Compute SIC decoding SINR using equation (5).

-Check SIC success condition using equation (6).

-Estimate SIC reliability using equation (8).

-Compute achievable sum rate using equation (9).

-Compute Jain's fairness index using equation (10).

Average the performance metrics across all Monte Carlo realizations.

Normalize

$R_{sum}, \quad \eta_{SIC}, \quad \mathrm{J}$

Compute fitness using equation (15):

$F(P) = \alpha_1 \overline{R}_{sum} + \alpha_2 \overline{\eta}_{SIC} + \alpha_3 \overline{J}$

If current fitness improves personal best: $P^{(*,l)} \longleftarrow P^{(l)}$

End For

Update global-best solution P^g.

Update adaptive PSO parameters using equations (21)–(23):

$\omega(\sigma_e^2), \quad c_1(\sigma_e^2), \quad c_2(\sigma_e^2)$

(Continues)

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ALGORITHM 1 | (Continued)

Update particle velocity using equation (17):

$$v^{(l)}(t+1) = \omega(t)v^{(l)}(t) + c_1(t)r_1(P^{*,l} - P^{(l)}(t)) + c_2(t)r_2(P^g - P^{(l)}(t))$$

Update particle position:

$$P^{(l)}(t+1) = P^{(l)}(t) + v^{(l)}(t+1)$$

Apply feasibility-preservation procedure:

-Clip negative powers.

-Reorder powers to satisfy

$$p_1 \geq p_2 \geq \cdots \geq p_U$$

-Normalize powers so that

$$\sum_{u=1}^{U} p_u \leq p_T$$

-Ensure the particle remains inside the feasible set defined in equation (13).

End For

Return

Optimal power-allocation vector corresponding to the global-best particle:

$$P^* = P^g$$

$$\mathcal{O}(I \times P \times U), \tag{28}$$

since only a single fitness evaluation is performed for each particle during every iteration. The proposed adaptive PSO introduces an additional factor M to account for the Monte Carlo CSI realizations used to estimate SIC reliability. Nevertheless, because the user-cluster size remains relatively small and only a moderate number of CSI realizations are employed, the resulting computational complexity remains significantly lower than that of many robust convex-optimization and deep-learning-based resource-allocation techniques.

Moreover, the adaptive updates of the inertia weight and acceleration coefficients require only simple arithmetic operations and therefore introduce negligible computational overhead relative to the fitness-evaluation process, as summarized in Table 2.

4 | Numerical Results and Discussion

4.1 | Simulation Setup

A downlink power-domain NOMA system operating under imperfect CSI conditions is considered. The estimated channel coefficient of user (u) follows the imperfect-CSI model defined in equation (2), where the CSI estimation error is modeled as a complex Gaussian random variable with variance (σ_e^2). To evaluate robustness under different uncertainty conditions, the CSI error variance is varied from 0.01 to 0.10.

To investigate scalability, simulations are performed for 3-user, 4-user, and 5-user NOMA clusters. Increasing the number of users introduces additional interference interactions and increases the probability of SIC error propagation, thereby providing a rigorous evaluation of the proposed framework under dense NOMA deployment scenarios.

The proposed adaptive PSO framework is compared against the following benchmark schemes:

- Fixed power allocation (FPA);
- Random feasible allocation (RFA);
- Classical PSO;
- RCO-based power allocation;
- DRL-based power allocation.

The inclusion of RCO and DRL benchmarks provides broader validation against representative robust optimization approaches commonly employed in imperfect-CSI NOMA systems. While convex optimization techniques often achieve high solution accuracy, they incur considerable iterative computational complexity in non-convex environments. Similarly, DRL-based approaches require extensive training datasets and longer convergence times. In contrast, the proposed adaptive PSO framework seeks to maintain competitive performance while preserving computational efficiency suitable for practical deployment.

Additional simulation scenarios are conducted to evaluate the effects of CSI estimation-error variance, swarm size, and iteration count on optimization performance. Swarm sizes ranging from 10 to 40 particles and iteration counts ranging from 20 to 50 are considered. Furthermore, convergence behavior and computational complexity are analyzed to validate the practicality of the proposed framework.

The performance evaluation focuses on five key metrics:

- SIC reliability η_{SIC};
- Achievable sum rate R_{sum};
- Jain's fairness index J;

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TABLE 2 | Simulation parameters.

Parameter	Value	Parameter	Value
Number of users (U)	**3, 4, and 5**	**Pathloss model**	**Distance based**
SNR range	0–30 dB	Total bandwidth	1 MHz
Total transmit power (P_T)	1 W	CSI error variance (σ_e^2)	0.01–0.10
NOMA configuration	Downlink power-domain NOMA	SIC decoding order	Strong-to-weak
PSO swarm size (p)	10, 20, 30, 40	PSO iterations (I)	20, 30, 40, 50
Maximum inertia weight ($\omega_{\max}$)	0.9	Minimum inertia weight ($\omega_{\min}$)	0.4
Maximum cognitive coefficient ($C_{1,\max}$)	2.0	Minimum social coefficient ($C_{2,\min}$)	1.0
Adaptation constants (α, β, γ)	1.0, 0.5, 0.5	Channel model	Rayleigh fading
Noise power density	−174 dBm/Hz	Decoding threshold (γ_{th})	10^{-3}
User distances	Near: 80 m, Mid: 150 m, Far: 250 m	Power constraint	$\sum_{u=1}^{U} p_u = p_T$,
Monte Carlo realizations (M)	1000	Complexity metric	$\mathcal{O}(\mathrm{I} \times \mathrm{P} \times \mathrm{U} \times \mathrm{M})$
Benchmark schemes	FPA, RFA, Classical PSO, RCO, DRL	Performance metrics	SIC reliability, sum rate, fairness, convergence, scalability
Fixed power allocation	(0.6, 0.3, 0.1) (3-user baseline)	CSI sensitivity analysis	($\sigma_e^2 = 0.01$–0.10)

- Convergence stability;
- Scalability with increasing user-cluster size.

The performance metrics presented in this section are directly associated with the normalized multiobjective fitness function defined in equation (15).

$$F(\boldsymbol{P}) = \alpha_1 \overline{R}_{sum} + \alpha_2 \overline{\eta}_{SIC} + \alpha_3 \overline{J} \tag{29}$$

where $\overline{R}_{sum}$, $\overline{\eta}_{SIC}$, and $\overline{J}$ denote the normalized sum-rate, SIC-reliability, and fairness metrics, respectively. The weighting coefficients α_1, α_2, and α_3 regulate the relative importance of throughput, reliability, and fairness during optimization.

To provide direct validation of each fitness-function component, Figure 2 evaluates the SIC-reliability objective $\overline{\eta}_{SIC}$, Figure 3 evaluates the sum-rate objective $\overline{R}_{sum}$, and Figure 4 evaluates the fairness objective $\overline{J}$. Consequently, Figures 2–4 directly reflect the three objectives jointly optimized by the proposed adaptive PSO framework. In addition, Figure 5 presents the convergence behavior of the algorithm, Figure 6 examines scalability across different NOMA cluster sizes, and Figure 7 investigates robustness under varying CSI estimation-error variances.

4.2 | Results and Discussion

The obtained results demonstrate that the proposed adaptive PSO framework is highly effective in preserving the required NOMA decoding hierarchy under imperfect CSI conditions. By incorporating CSI-aware parameter adaptation, the proposed method significantly reduces decoding-order inversions compared with classical PSO, thereby maintaining a stable SIC structure and mitigating error propagation throughout the decoding chain. This enhanced stability is consistently reflected across the performance trends illustrated in Figure 2 through Figure 7.

4.2.1 | SIC Reliability Analysis

Figure 2 presents the SIC reliability performance under varying SNR conditions and CSI uncertainty levels. The proposed adaptive PSO framework consistently achieves the highest SIC success probability across the entire SNR range.

For the baseline 3-user scenario, the proposed method attains approximately 98% SIC reliability at moderate-to-high SNR values while maintaining reliability above 90% even under severe CSI uncertainty conditions ($\sigma_e^2 = 0.10$). In contrast, FPA and RFA exhibit substantially lower and less stable reliability performance because of their inability to adapt to CSI fluctuations and interference variations. Classical PSO achieves moderate improvement but remains more susceptible to decoding-order instability under imperfect CSI conditions.

Compared with RCO and DRL-based approaches, the proposed adaptive PSO achieves comparable SIC reliability while avoiding the substantial computational overhead associated with iterative convex optimization and the extensive offline training complexity required by DRL frameworks.

The superior reliability performance is primarily attributed to the CSI-aware adaptation mechanism, which dynamically adjusts the inertia weight and acceleration coefficients according to CSI uncertainty levels. This adaptive behavior suppresses oscillatory

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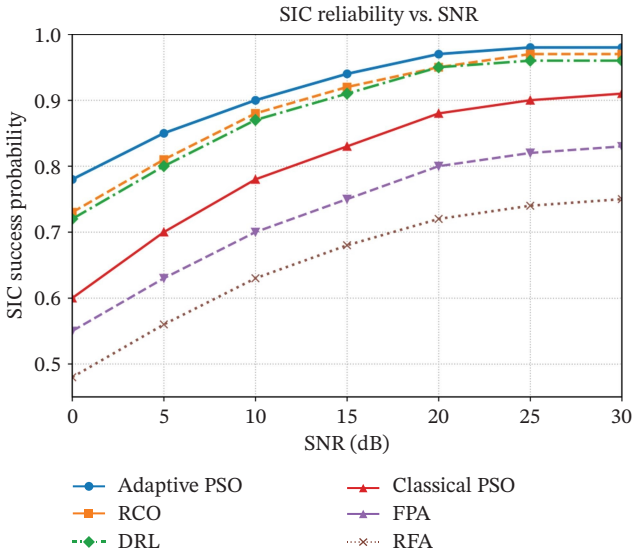


FIGURE 2 | SIC reliability vs. SNR.

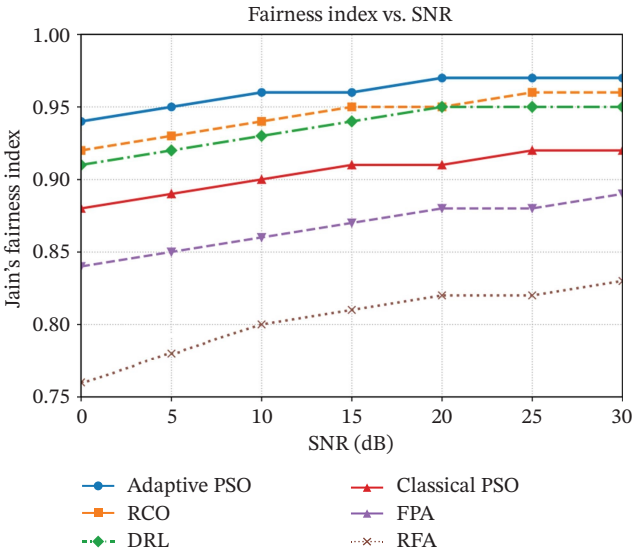


FIGURE 4 | Fairness index vs. SNR.

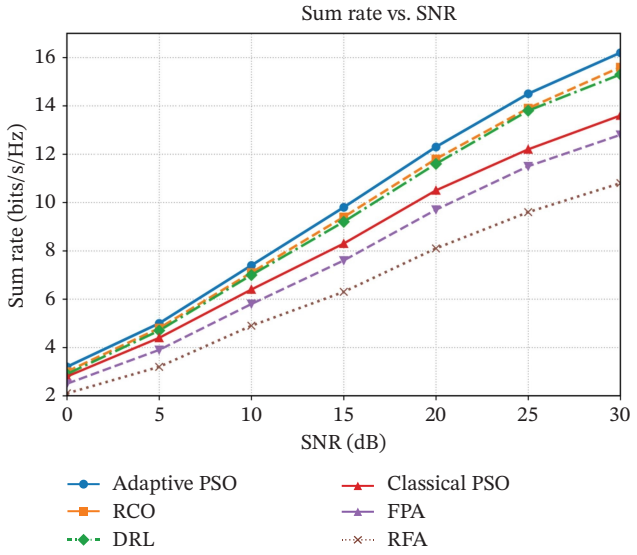


FIGURE 3 | Sum rate vs. SNR.

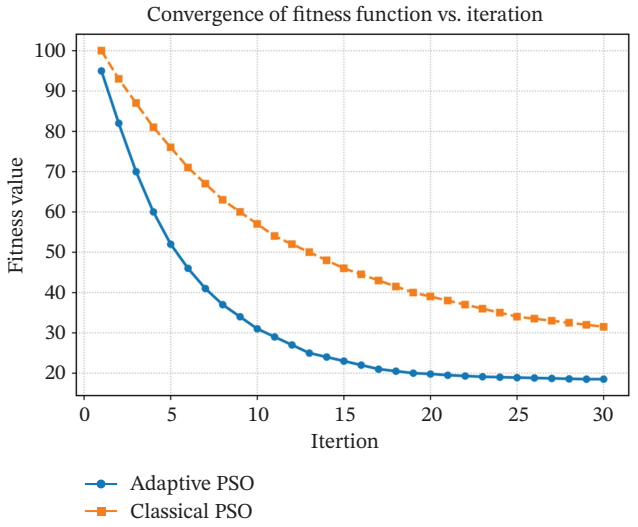


FIGURE 5 | Convergence of fitness function vs. iteration.

particle movement, preserves the SIC decoding order, and minimizes residual interference caused by imperfect channel estimation.

4.2.2 | Sum-Rate Performance Analysis

Figure 3 illustrates the achievable sum-rate performance of the evaluated schemes.

The proposed adaptive PSO consistently achieves the highest throughput across the entire SNR range. Relative to FPA, throughput gains of approximately 18%–27% are observed, while improvements of approximately 12%–19% are achieved compared with classical PSO.

RFA demonstrates the weakest throughput performance because of its lack of structural optimization and high sensitivity to CSI distortions. Although RCO provides competitive throughput performance, its iterative optimization complexity increases significantly under highly nonconvex imperfect-CSI environments. Similarly, DRL-based approaches demonstrate adaptive learning capability but require substantial training data, extensive parameter tuning, and longer convergence periods.

These results confirm that integrating CSI uncertainty directly into the optimization process enables the proposed adaptive PSO framework to identify more efficient and robust power-allocation patterns even when channel knowledge is imperfect.

4.2.3 | Fairness Performance Analysis

Figure 4 presents Jain's Fairness Index for the evaluated schemes.

The proposed adaptive PSO maintains consistently high fairness values across all SNR conditions and user-cluster configurations. The fairness index remains close to unity, indicating balanced rate allocation among users despite heterogeneous channel conditions and CSI uncertainty. FPA and RFA exhibit noticeable

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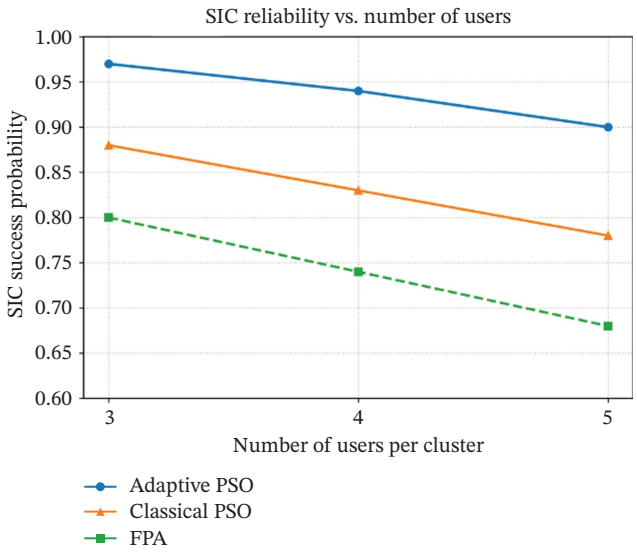


FIGURE 6 | SIC reliability vs. number of users.

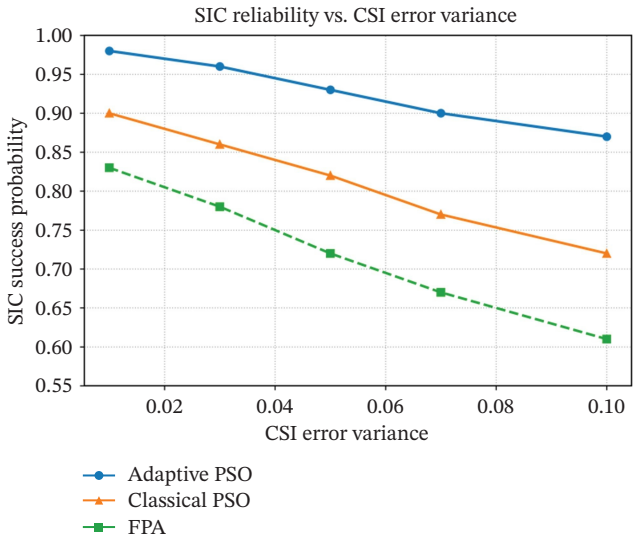


FIGURE 7 | SIC reliability vs. CSI error variance.

fairness degradation, particularly under high CSI-error variance conditions. Classical PSO achieves moderate fairness improvement relative to conventional allocation strategies but remains less stable under severe uncertainty conditions.

The consistently high fairness achieved by the proposed framework confirms that the normalized multiobjective fitness formulation effectively balances throughput maximization, fairness preservation, and SIC reliability simultaneously.

4.2.4 | Convergence Analysis

Figure 5 illustrates the convergence behavior of the proposed adaptive PSO framework by tracking the evolution of the fitness function across optimization iterations. The results indicate that the adaptive PSO converges faster and more smoothly than classical PSO under imperfect CSI conditions. The CSI-aware adaptation of the inertia weight and acceleration coefficients suppresses oscillatory swarm behavior and improves convergence stability during optimization. In most simulation scenarios, convergence is achieved within approximately 40–50 iterations, demonstrating that the proposed framework does not require excessive optimization cycles and is therefore suitable for practical real-time resource-allocation applications.

4.2.5 | Scalability Analysis

Figure 6 evaluates the scalability performance of the proposed framework by analyzing SIC reliability as the number of NOMA users increases from 3 to 5.

As expected, increasing the number of users intensifies multiuser interference and increases SIC error propagation. Nevertheless, the proposed adaptive PSO consistently preserves the required decoding order and maintains high SIC reliability across all cluster sizes.

Only moderate degradation in reliability is observed for the 4-user and 5-user configurations, whereas benchmark schemes experience significantly larger performance deterioration. Furthermore, fairness remains relatively stable across increasing cluster sizes, confirming the robustness of the proposed framework for dense-user deployment scenarios.

These findings demonstrate that the proposed adaptive PSO framework scales effectively with increasing NOMA cluster size and remains suitable for future massive-connectivity wireless communication systems.

4.2.6 | CSI Sensitivity Analysis

Figure 7 investigates the sensitivity of the proposed framework to CSI estimation-error variance.

As the CSI error variance increases from 0.01 to 0.10, the performance of all evaluated methods gradually degrades because of increased channel uncertainty and residual interference effects. However, the proposed adaptive PSO exhibits the smallest performance degradation among all benchmark schemes.

This robustness is achieved through the adaptive adjustment of PSO control parameters according to CSI uncertainty levels, enabling the swarm to maintain stable convergence and preserve feasible decoding-order structures even under highly uncertain channel conditions.

In summary, the results presented in Figure 2–7 demonstrate that the proposed adaptive PSO framework simultaneously improves SIC reliability, throughput performance, fairness preservation, convergence stability, and scalability while maintaining lower computational complexity than RCO- and DRL-based alternatives. These characteristics make the proposed framework a strong candidate for practical deployment in future NOMA-enabled 5G-and-beyond wireless communication systems.

5 | Conclusion

This study presented a CSI-aware adaptive PSO-based power-allocation framework for enhancing SIC reliability in downlink NOMA systems operating under imperfect CSI. Unlike conventional power-allocation approaches, the proposed framework directly incorporates CSI uncertainty into the optimization process through adaptive adjustment of the PSO inertia weight

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and acceleration coefficients, enabling the swarm to respond dynamically to varying levels of channel-estimation error. Furthermore, Monte Carlo–based fitness evaluation was integrated into the optimization framework to improve robustness against stochastic CSI fluctuations and decoding-order instability.

The power-allocation problem was formulated as a constrained multiobjective optimization task that jointly maximizes the achievable sum rate, SIC reliability, and user fairness while satisfying NOMA power-ordering constraints. Numerical investigations conducted under different CSI uncertainty levels demonstrated that the proposed adaptive PSO framework consistently outperforms fixed power allocation, random feasible allocation, and classical PSO approaches. The results showed SIC success probabilities approaching 98%, together with significant improvements in throughput and fairness under imperfect CSI conditions.

Additional scalability studies involving 3-user, 4-user, and 5-user NOMA clusters confirmed that the proposed framework effectively mitigates SIC error propagation and preserves decoding-order stability even as user density increases. Comparative analysis with robust convex-optimization and DRL-based resource-allocation methods further demonstrated that the proposed adaptive PSO achieves competitive performance while maintaining substantially lower computational complexity and implementation overhead. Complexity and convergence analyses also verified that the adaptive parameter-update mechanism introduces negligible additional computational cost while improving optimization stability and convergence speed.

Overall, the results confirm that lightweight uncertainty-aware metaheuristic optimization can serve as an effective and practical solution for enhancing SIC robustness, spectral efficiency, and fairness in future NOMA-enabled 5G-and-beyond wireless communication networks. Future work may extend the proposed framework to cooperative NOMA, massive-user scenarios, intelligent reflecting surface (IRS)-assisted networks, and machine-learning-enhanced adaptive resource-allocation architectures for next-generation 6G communication systems.

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All authors have read and approved the final manuscript.

Ethics Statement

The authors have nothing to report.

Consent

The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

No publicly available datasets were used in this study. The results were generated through numerical simulations of the proposed adaptive PSO-based power-allocation framework. All relevant simulation parameters and methodological details are provided within the manuscript.

References

1. A. S. De Sena, F. R. M. Lima, D. B. Da Costa, et al., "Massive MIMO-NOMA Networks With Imperfect SIC: Design and Fairness Enhancement," *IEEE Transactions on Wireless Communications* 19, no. 9 (2020): 6100–6115, https://doi.org/10.1109/twc.2020.3000192.

2. Y. Iraqi and A. Al-Dweik, "Power Allocation for Reliable SIC Detection of Rectangular QAM-Based NOMA Systems," *IEEE Transactions on Vehicular Technology* 70, no. 8 (2021): 8355–8360, https://doi.org/10.1109/tvt.2021.3096648.

3. Z. Wei, D. W. K. Ng, J. Yuan, and H.-M. Wang, "Optimal Resource Allocation for Power-Efficient MC-NOMA With Imperfect Channel State Information," *IEEE Transactions on Communications* 65, no. 9 (2017): 3944–3961, https://doi.org/10.1109/tcomm.2017.2709301.

4. V. Aswathi and A. V Babu, "Full/Half Duplex Cooperative NOMA Under Imperfect Successive Interference Cancellation and Channel State Estimation Errors," *Institute of Electrical and Electronics Engineers Access* 7 (2019): 179961–179984, https://doi.org/10.1109/access.2019.2959001.

5. F. Fang, H. Zhang, J. Cheng, S. Roy, and V. C. M. Leung, "Joint User Scheduling and Power Allocation Optimization for Energy-Efficient NOMA Systems With Imperfect CSI," *IEEE Journal on Selected Areas in Communications* 35, no. 12 (2017): 2874–2885, https://doi.org/10.1109/jsac.2017.2777672.

6. Y. Zhang, X. Zhao, S. Geng, et al., "Power Allocation Algorithms for Stable Successive Interference Cancellation in Millimeter Wave NOMA Systems," *IEEE Transactions on Vehicular Technology* 70, no. 6 (2021): 5833–5847, https://doi.org/10.1109/tvt.2021.3077270.

7. H. S. J. Kennedy, V. B. Kumaravelu, P. Selvaprabhu, A. Murugadass, and S. Viruthagiri, "Enhancing Reliability and Spectral Efficiency in Future Wireless Networks via Intelligent Omni-Surface Enhanced MU-MIMO Cooperative Hybrid NOMA," *Scientific Reports* (2026).

8. H. S. John Kennedy and V. B. Kumaravelu, "Enhancing Outage Performance and Sum Capacity in Multi-User Environments Through IOS-Aided Hybrid NOMA Under Imperfect SIC," *EURASIP Journal on Wireless Communications and Networking* 2025, no. 1 (2025): 39, https://doi.org/10.1186/s13638-025-02458-9.

9. R. Dipinkrishnan and V. B. Kumaravelu, "Spectral Efficiency Enhancement in Multiuser NOMA over Nakagami-M Fading Channels Through Power Allocation and Pairing Strategies Under Hardware and SIC Imperfections," *Scientific Reports* 15, no. 1 (2025): 38211, https://doi.org/10.1038/s41598-025-22024-z.

10. H. S. John Kennedy and V. B. Kumaravelu, "Intelligent Omni-Surface-Assisted Cooperative Hybrid Non-Orthogonal Multiple Access: Enhancing Spectral Efficiency Under Imperfect Successive Interference

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Cancellation and Hardware Distortions," *Sensors* 25, no. 7 (2025): 2283, https://doi.org/10.3390/s25072283.

11. R. Dipinkrishnan and V. B. Kumaravelu, "Outage Analysis and Power Optimization in Uplink and Downlink NOMA Systems With Rician Fading," *Results in Engineering* 25 (2025): 104021.

12. M. Katwe, K. Singh, C.-P. Li, and Z. Ding, "Spectral-Efficient Downlink Systems Under Imperfect SIC and CSI: MC-NOMA or Partial NOMA?" *IEEE Wireless Communications Letters* 13, no. 1 (2023): 133–137, https://doi.org/10.1109/lwc.2023.3322991.

13. J. Xu and Z. Liang, "Energy Efficiency Optimization of NOMA IoT Communication for 5G," *Mobile Networks and Applications* 27, no. 3 (2022): 862–873, https://doi.org/10.1007/s11036-021-01815-4.

14. C. E. Garcia, M. R. Camana, and I. Koo, "Particle Swarm Optimization-Based Secure Computation Efficiency Maximization in a Power Beacon-Assisted Wireless-Powered Mobile Edge Computing NOMA System," *Energies* 13, no. 21 (2020): 5540, https://doi.org/10.3390/en13215540.

15. S. Lu, G. Xu, L. Zhu, Z. Song, and W. Zhang, "An Adaptive Power Allocation for NOMA-Based Multi-Layer Satellite System," *IEEE Transactions on Wireless Communications* 24 (2025).

16. O. F. Chukwudi, M. D. Buhari, B. O. Sadiq, and E. Edozie, "Adaptive Energy-Efficient Power Allocation in Downlink NOMA Systems With Imperfect CSI: A PSO-Based Approach for Improving SIC Accuracy and System Performance," *Institute of Electrical and Electronics Engineers Access* 13 (2025).

17. A. Masaracchia, D. B. Da Costa, T. Q. Duong, M.-N. Nguyen, and M. T. Nguyen, "A PSO-Based Approach for User-Pairing Schemes in NOMA Systems: Theory and Applications," *Institute of Electrical and Electronics Engineers Access* 7 (2019): 90550–90564, https://doi.org/10.1109/access.2019.2926641.

18. S. Abdel-Razeq, H. Shakhatreh, A. Alenezi, A. Sawalmeh, M. Anan, and M. Almutiry, "PSO-Based UAV Deployment and Dynamic Power Allocation for Uav-Enabled Uplink NOMA Network," *Wireless Communications and Mobile Computing* 2021, no. 1 (2021): 2722887, https://doi.org/10.1155/2021/2722887.

19. C. E. García, M. R. Camana, and I. Koo, "Low-Complexity PSO-Based Resource Allocation Scheme for Cooperative Non-Linear SWIPT-Enabled NOMA," *Institute of Electrical and Electronics Engineers Access* 10 (2022): 34207–34220, https://doi.org/10.1109/access.2022.3162838.

20. M. Chakraborty, E. Sharma, H. A. Suraweera, and H. Q. Ngo, "Analysis and Optimization of RIS-Assisted Cell-Free Massive MIMO NOMA Systems," *IEEE Transactions on Communications* (2024).

21. X. Wang, R. Chen, Y. Xu, and Q. Meng, "Low-Complexity Power Allocation in NOMA Systems With Imperfect SIC for Maximizing Weighted Sum-Rate," *Institute of Electrical and Electronics Engineers Access* 7 (2019): 94238–94253, https://doi.org/10.1109/access.2019.2926757.

22. W. U. Khan, X. Li, A. Ihsan, M. A. Khan, V. G. Menon, and M. Ahmed, "NOMA-Enabled Optimization Framework for Next-Generation Small-Cell IoV Networks Under Imperfect SIC Decoding," *IEEE Transactions on Intelligent Transportation Systems* 23, no. 11 (2021): 22442–22451, https://doi.org/10.1109/tits.2021.3091402.

23. V. Ozduran and N. Nomikos, "Performance Analysis of Inverse Successive Interference Cancellation in NOMA-Based Communications," *Wireless Networks* 30, no. 3 (2024): 1893–1907, https://doi.org/10.1007/s11276-023-03618-9.

24. B. Li, Q. Zheng, X. Tian, et al., "A Survey of Artificial Intelligence Enabled Channel Estimation Methods: Recent Advance, Performance, and Outlook," *Artificial Intelligence Review* 58, no. 6 (2025): 1–35, https://doi.org/10.1007/s10462-025-11202-0.

25. R. Zhou, "UAV-Based Opportunistic Non-Orthogonal Multiple Access Network," *IEEE Transactions on Vehicular Technology* 15 (2026).

26. O. Levy and N. Shlezinger, "Rapid and Power-Aware Learned Optimization for Modular Receive Beamforming," *IEEE Transactions on Communications* 73 (2025).

27. I. Chivers and J. Sleightholme, "An Introduction to Algorithms and the Big O Notation," in *Introduction to Programming With Fortran: With Coverage of Fortran 90, 95* (Springer, 2003), 359–364.

28. W. Zou, H. Xu, C. Chen, and C. Wu, "An Enhanced MOPSO Algorithm for Multi-Objective UAV Path Planning in Mountainous Environments," *Symmetry* 17, no. 11 (2025): 1890, https://doi.org/10.3390/sym17111890.

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