



Original Article

Joint beamforming for internet of vehicles via IBKA-driven intelligent reflecting surface optimization

Liu Liu^{a,*}, Rongyue Ji^a, Changpeng Zhou^a, Yuelei Zhang^b, Zhengmin Kong^c, Tao Huang^d

^a School of Communication and Information Engineering, Nanjing University of Posts and Telecommunications, Nanjing 210003, Jiangsu, China

^b GongQing Institute of Science and Technology, Jiujiang 332020, China

^c School of Robotics, Wuhan University, Wuhan 430072, China

^d College of Science and Engineering, James Cook University, Smithfield, Cairns, Queensland 4878, Australia

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ABSTRACT

The deployment of terahertz communications in high-dynamic 6G vehicular networks faces two major challenges: severe link blockage in non-line-of-sight scenarios and the high computational load of beamforming. To address these issues, this paper introduces an intelligent reflecting surface (IRS) into the system to create reliable secondary links through dynamic phase reconfiguration. We propose a joint beamforming scheme in which the base station (BS) beamforming is computed using the zero-forcing algorithm, while the IRS phase shifts are optimized using the Improved Black-winged Kite Algorithm (IBKA). The IBKA is specifically designed to overcome the original algorithm's limitations, including low population diversity and local optima convergence. Key improvements include the use of Circle chaotic mapping for population initialization, the incorporation of an adaptive T-distribution perturbation spiral strategy during the attack phase, and the application of a Golden Sine Strategy (GSS) during the migration phase. Simulation results validate the efficacy of our framework. Compared to the benchmark Genetic Algorithm (GA), the proposed IBKA framework significantly reduces the computational burden by approximately 45% (in terms of Number of Function Evaluations), while incurring only a marginal 1.55% sacrifice in the system sum-rate, effectively enabling a real-time optimal performance-complexity trade-off for 6G vehicular networks.

1. Introduction

As a next-generation wireless communication technology, 6G aims to enable massive device connectivity and seamless data transmission. In vehicular networking scenarios, 6G is expected to meet the stringent requirements of large-scale, high-concurrency connections and rapidly changing environments, capitalizing on the ultra-high data rate and minimal latency. However, traditional beamforming techniques are increasingly encountering performance bottlenecks under such demanding conditions. Additionally, frequent blockages and occlusions between vehicles and base stations can significantly impair communication quality, particularly for terahertz transmissions in 6G networks. Thus, in high-speed vehicular networking environments, the design of beamforming algorithms that offer low computational complexity, low-latency transmission, and robustness against line-of-sight (LOS) link blockages has become a critical area of research in 6G technologies.

In IRS-enhanced joint beamforming, a common strategy to reduce complexity is to simplify the beamforming vector. For instance, the

work in [1] neglects the IRS-user channel gain, thereby yielding two suboptimal solutions characterized by low computational complexity, each paired with a corresponding passive beamforming solution. The higher-gain option is selected. In [2–4], the unit modulus constraint is relaxed into a convex form, followed by projection onto the feasible set. [5] proposes an enhanced Sine Cosine Algorithm (SCA) for rate maximization in IRS-assisted VLC systems. The improved two-phase SCA converges faster and achieves higher achievable rates than conventional methods. [6] presents a low-complexity IRS optimization method for single-carrier systems that enhances achievable rates by coherently combining dominant channel taps. The proposed scheme achieves near-optimal performance in both LoS and NLoS scenarios while maintaining practical complexity. The ADMM-based approaches in [7] propose a STAR-RIS-assisted NOMA-CoMP scheme (SRaNC) for IIoT, jointly optimizing BS power and RIS coefficients via FP-SCA methods to achieve a 30% higher sum rate than benchmarks, with scalable antenna allocation. The barrier function method in [8] presents

* Corresponding authors.

E-mail addresses: LiuLiu@njupt.edu.cn (L. Liu), 1223014319@njupt.edu.cn (R. Ji), 2022010310@njupt.edu.cn (C. Zhou), zyl3836@sina.com (Y. Zhang), zmkong@whu.edu.cn (Z. Kong), tao.huang1@jcu.edu.au (T. Huang).

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a double-irregular IRS scheme for secure communications, combining cross-entropy and simulated annealing methods to optimize element arrangement and phase shifts. The approach achieves 35% higher secrecy rates than regular IRS configurations. [9] proposes an RIS-assisted UAV system that jointly optimizes power allocation, RIS phases, and UAV trajectory to maximize secrecy rate. Using Taylor expansion and SCA, it achieves 3.8 × higher secrecy rates with 62% lower complexity than benchmarks. [10] proposes an IRS-enhanced NOMA scheme for UVLC, optimizing sum rates under eye safety constraints. Simulations show significant gains over non-IRS systems, with analysis of power/FOV impacts. [11] presents low-complexity joint beamforming and IRS phase optimization for MU-MISO downlink. Combines dynamic user selection with linear beamforming and single-user RIS optimization, achieving near-BCD performance with reduced complexity for both sum-rate maximization and power minimization. Gradient descent techniques in [12,13] iteratively update variables along the negative gradient of the objective function. Heuristic methods such as genetic algorithms and particle swarm optimization are explored in [14] for scenarios where gradient computation is expensive. [15] develops a fair transmission design for IRS-aided RSMA systems using AO optimization. The proposed GPI and SGD methods achieve 35% higher fairness with robust performance under imperfect CSIT.

Within this research context, this study presents an alternating iterative optimization algorithm based on the Improved Black-Winged Kite Algorithm (IBKA) to tackle the joint design problem. The framework decouples the primary problem into two sub-problems: beamforming at the base station and phase shift optimization at the IRS. Base-station beamforming is addressed via the zero-forcing method, while the IRS phase shifts are optimized using an enhanced IBKA. To overcome the limitations of the basic BKA, namely, limited population diversity and a propensity for local optima, several improvements are incorporated: Circle chaotic mapping for population initialization, an adaptive T-distribution perturbation spiral strategy during the attack phase, and a Gaussian random walk strategy during the migration phase.

This work aims to develop a computationally efficient joint beamforming scheme to overcome NLOS blockage and high computational complexity in 6G THz vehicular networks. The primary contributions of this paper are explicitly divided into three areas:

- **System Contribution:** We present a novel hybrid optimization paradigm for IoV networks that decouples BS beamforming (using low-complexity ZF) from IRS phase optimization. This optimally balances interference suppression with the computational demands of massive IRS arrays.
- **Algorithmic Contribution:** We propose the IBKA, a metaheuristic enhanced with Circle chaotic mapping, adaptive T-distribution perturbation, and a Golden Sine Strategy. These operators specifically address the non-convex, multimodal landscape of continuous phase-shift optimization.
- **Engineering Feasibility Contribution:** Through comprehensive sensitivity testing (including 1–4 bit discrete quantization and imperfect CSI sweeps) and explicit runtime complexity analysis, we demonstrate the real-time deployment feasibility of the framework within the strict 1–10 ms coherence constraints of dynamic THz environments.

The rest of this article is organized as follows. Section Two introduces the system and channel models. Section Three provides a detailed introduction to the beamforming process based on the IBKA algorithm. Section Four introduces simulation experiments. The fifth section concludes the paper by synthesizing the main findings.

2. System model and channel model

As depicted in Fig. 1, a MU-MISO system comprising a base station (BS), an intelligent reflective surface (IRS), and v vehicle users ($V > 1$)

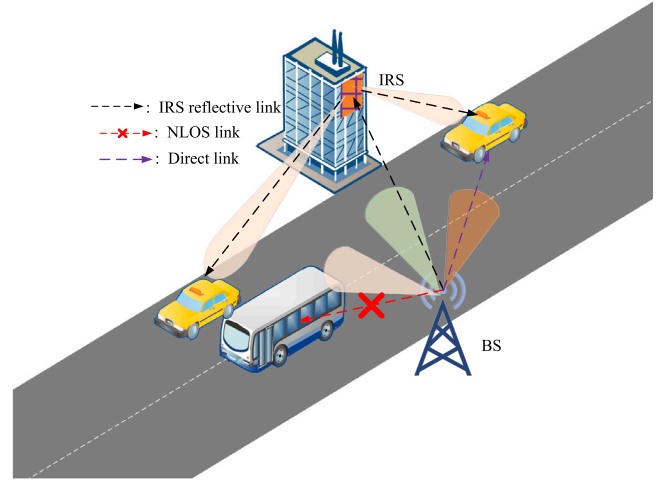


Fig. 1. Scenarios diagram.

is considered. The BS is equipped with an M -element uniform linear array (ULA), while each single-antenna vehicle user employs an omnidirectional antenna for reception. The IRS, positioned on a building facade, comprises N passive elements. It is assumed that both the BS-IRS and IRS-vehicle links establish line-of-sight (LoS) propagation paths.

Choose to use the IRS deployed on the building to complete the construction of the reflective link from the base station to the IRS and from the IRS to the vehicle user. The channel matrix from the base station to the IRS is represented as $H \in \mathbb{C}^{M \times N}$, and is modeled as a Rayleigh fading channel

$$H = \sqrt{l(d_{B,I})} \cdot H^{\text{NLoS}}. \quad (1)$$

The channel matrix from the IRS to the vehicle user is represented as $h_{r,v}^H \in \mathbb{C}^{1 \times M}$, and is also modeled as a Rayleigh fading channel

$$h_{r,v} = \sqrt{l(d_{I,k})} \cdot h_{r,v}^{\text{NLoS}}. \quad (2)$$

Here, $l(d)$ represents path loss, d is the communication distance, H^{NLoS} and $h_{r,v}^{\text{NLoS}}$ represent the non-line-of-sight components of the channels. Each element in these matrices is independently and identically distributed as a complex Gaussian random variable with zero mean and unit variance.

The user's transmitted data symbol is denoted by s_v , and the user's beamforming vector is $w_v \in \mathbb{C}^{N \times 1}$. The direct channel between the base station and the vehicle user k is $h_v \in \mathbb{C}^{M \times 1}$.

The composite channel between the vehicle user v and the base station, denoted as $h_{\theta,v} \in \mathbb{C}^{M \times 1}$, can be expressed as the sum of the direct channel and the IRS reflection channel:

$$h_{\theta,v}^H = \sqrt{l(d_{B,v})} h_v^H + f_v^H \Theta G. \quad (3)$$

The received signal can be expressed as

$$y_v = h_{\theta,v}^H w_v s_v + \sum_{j=1, j \neq v}^V h_{\theta,v}^H w_j s_j + n_v. \quad (4)$$

Here, n_v is AWGN with zero mean and variance $\sigma_v^2 = 1$. The IRS reflection coefficient matrix is $\Theta = \text{diag}(\theta)$, where $\theta = [\theta_1, \theta_2, \dots, \theta_M]^T$, and each element $\theta_m = \alpha_m e^{j\varphi_m}$, with $\varphi_m \in [0, 2\pi]$ and amplitude $\alpha_m = 1$.

For convenience, the equivalent cascaded channel is defined as $G_v^H = \text{diag}(h_{r,v}^H) H^H$. The SINR at user v is then given by:

$$\text{SINR}_v = \frac{|\theta^T G_v^H w_v|^2}{\sum_{i=1, i \neq v}^V |\theta^T G_v^H w_i|^2 + \sigma_v^2}. \quad (5)$$

The data rate of user v is $R_v = \log_2(1 + \text{SINR}_v)$.

Assumptions and Justifications. To balance analytical tractability with real-world complexity, the system model is constructed based on two key assumptions. First, regarding the channel model and CSI, both the BS-IRS and IRS-user links follow a Rayleigh fading distribution. Perfect instantaneous CSI at the base station is assumed, which is a conventional premise in foundational studies that enables a clear evaluation of the optimization algorithm's core performance. The significant effect of imperfect CSI is recognized and is slated for investigation in future work. Second, for vehicle mobility, large-scale variations due to macro-mobility are incorporated by randomizing user positions across simulation trials (Figs. 5 and 6). Within any single optimization window (or channel coherence block), the channels are treated as quasi-static. This per-snapshot optimization is a standard technique for high-mobility scenarios, allowing the framework to adapt to changing channel conditions by re-optimizing in each coherence interval. While the simulation utilizes randomized user positions across trials to represent macro-mobility, it is crucial to bridge this quasi-static per-snapshot model to the realities of high-mobility 6G THz IoV. In THz bands, severe Doppler shifts due to vehicular speeds drastically reduce the channel coherence time, often to the range of 1–10 ms. Furthermore, THz links are highly susceptible to sudden blockages. By treating the channels as quasi-static only within these micro-intervals, our model mandates an optimization algorithm capable of converging within a fraction of this coherence time. Thus, the rapid convergence of IBKA acts as the direct enabler for maintaining robust connectivity against rapid THz blockage dynamics.

3. Beamforming in NLOS scenarios

Drawing on the method proposed in [15], the joint optimization of BS beamforming and IRS phase shifts is tackled using an alternating algorithm. The process starts by breaking down the initial problem into two tractable subproblems. First, the BS beamforming matrix is updated to maximize the SINR, subject to a maximum transmit power constraint. Then, the second subproblem adjusts the IRS phase-shift matrix, aiming to maximize the SINR while satisfying the unit-modulus constraints. These two steps are repeated iteratively until a convergent solution is achieved.

3.1. Problem formulation

Beamforming in this scenario is modeled as an optimization problem, as shown in (6). The objective is to maximize the total sum-rate of V users, subject to the BS transmit power limit $P_{\max}$ and the phase shift constraint $0 \leq \theta_m \leq 2\pi$ for each IRS element

$$\begin{aligned} \max_{\mathbf{W}, \boldsymbol{\theta}} \quad & f(\mathbf{W}, \boldsymbol{\theta}) = \sum_{v=1}^V \log_2(1 + \gamma_v), \\ \text{subject to} \quad & \sum_{v=1}^V \|\mathbf{w}_v\|^2 \leq P_{\max}, \\ & 0 \leq \theta_m \leq 2\pi, \quad \forall m \in \{1, \dots, M\}. \end{aligned} \quad (6)$$

This is a non-convex optimization problem due to the coupling between the beamforming matrix $\mathbf{W}$ and the IRS phase shift matrix $\boldsymbol{\theta}$ in the objective function and the associated constraints. Following [16], this problem can be decomposed into two subproblems:

$$\begin{aligned} \max_{\mathbf{W}} \quad & f(\mathbf{W}) = \sum_{v=1}^V \log_2(1 + \gamma_v), \\ \text{subject to} \quad & \sum_{v=1}^V \|\mathbf{w}_v\|^2 \leq P_{\max}. \end{aligned} \quad (7)$$

$$\begin{aligned} \max_{\boldsymbol{\theta}} \quad & f(\boldsymbol{\theta}) = \sum_{v=1}^V \log_2(1 + \gamma_v), \\ \text{subject to} \quad & 0 \leq \theta_m \leq 2\pi, \quad \forall m \in \{1, \dots, M\}. \end{aligned} \quad (8)$$

The problem formulated in Eq. (6) is a single-objective problem that maximizes the overall system sum-rate. It is subject to two primary constraints: (1) the total transmit power constraint at the BS, and (2) the unit-modulus constraint on each IRS reflecting element (i.e., continuous phase shifts within $[0, 2\pi)$).

This problem is inherently non-convex and challenging to solve directly due to the coupled optimization variables $\mathbf{W}$ and $\boldsymbol{\theta}$ in the objective function, as well as the non-convex unit-modulus constraints. To address these difficulties, we adopt an alternating optimization (AO) framework that decouples the original problem into two more tractable subproblems: BS beamforming (Eq. (7)) and IRS phase-shift optimization (Eq. (8)).

For the BS beamforming subproblem, we employ the low-complexity Zero-Forcing (ZF) linear precoding scheme, which effectively eliminates inter-user interference while satisfying the power constraint.

The IRS phase-shift subproblem remains nonconvex due to the unit-modulus constraints. Instead of relying on convex relaxation or approximation techniques that may compromise performance, we tackle this subproblem directly using the Improved Black-winged Kite Algorithm (IBKA). As a population-based metaheuristic, IBKA operates by evaluating the fitness (i.e., the sum-rate) of candidate phase shift vectors within the feasible search space $[0, 2\pi)^M$. This direct search approach inherently respects the unit-modulus constraints without requiring any relaxation, thereby naturally handling the problem's non-convexity. The algorithm's enhanced mechanisms, chaotic initialization, adaptive perturbation, and intelligent migration collectively enable effective exploration of the high-dimensional, non-convex solution space, balancing global search capability with convergence efficiency.

It is worth noting that while our current model assumes continuous phase shifts for analytical tractability, practical IRS implementations often employ discrete phase shifters. The extension to discrete phase shifts can be viewed as an additional constraint on the solution space, with the continuous solution obtained by IBKA projected onto the nearest discrete values in a post-processing step.

3.2. Optimize beamforming matrix $\mathbf{W}$

For (7), maximizing the sum-rate is equivalent to maximizing the SINR. The SINR expression is: $\text{SINR} = \sum_{v=1}^V \frac{|\theta^T \mathbf{G}_v^H \mathbf{w}_v|^2}{\sum_{i=1, i \neq v}^V |\theta^T \mathbf{G}_i^H \mathbf{w}_i|^2 + \sigma_v^2}$, where inter-user interference significantly impacts the SINR. A zero-forcing (ZF) linear transformation [12] is applied to $\mathbf{W}$ to cancel interference. The optimization steps are summarized in Algorithm 1.

With the IRS phase shift vector $\boldsymbol{\theta}$ given, the equivalent channel from the BS to user v is defined as $\mathbf{h}_v^H = \boldsymbol{\theta}^T \mathbf{G}_v^H$. The overall equivalent channel matrix for all V users is then $\tilde{\mathbf{H}} = [\mathbf{h}_1, \dots, \mathbf{h}_V]^H \in \mathbb{C}^{V \times N}$. To eliminate inter-user interference, we adopt the Zero-Forcing (ZF) linear precoding scheme. The ZF beamforming matrix is calculated as:

$$\mathbf{W}_{\text{ZF}} = \tilde{\mathbf{H}}^H (\tilde{\mathbf{H}} \tilde{\mathbf{H}}^H)^{-1} \mathbf{P}^{1/2}, \quad (9)$$

where $\mathbf{P} = \text{diag}(p_1, \dots, p_V)$ is the power allocation matrix. The diagonal elements p_v are determined by the water-filling algorithm under the total transmit power constraint $\sum_{v=1}^V p_v \leq P_{\max}$.

Computational Trade-off Discussion. The primary computational burden of the ZF scheme arises from the matrix inversion operation $(\tilde{\mathbf{H}} \tilde{\mathbf{H}}^H)^{-1}$, which has a complexity of $\mathcal{O}(V^3)$, where V is the number of users. While this cubic complexity can become prohibitive for systems with a large number of users, it remains an acceptable low-complexity choice for the considered vehicular network scenario, where the number of simultaneously served vehicles over a coherent time interval is typically moderate (e.g., $V \leq 10$ in our simulations). The ZF scheme effectively eliminates multi-user interference, especially when the user channels are near-orthogonal, leading to significant performance gains. Therefore, adopting ZF in this work offers a favorable trade-off between interference suppression and computational cost, aligning well with the requirements of practical IoV applications.

Algorithm 1 Optimize Beamforming Matrix W

Require: G_v , θ_n , Current iteration n , σ^2
Ensure: Optimized beamforming matrix W_{n+1}

- 1: Calculate equivalent cascaded channel for user v :
- 2: $g_v = G_v \star \theta_n^*$
- 3: Calculate weights:
- 4: $z_v = \frac{w_v^H g_v}{g_v^H W W^H g_v + \sigma^2}$
- 5: Construct weighted equivalent cascaded channel matrix:
- 6: $P = g * \begin{bmatrix} z_1^H & & & \\ & z_2^H & & \\ & & \ddots & \\ & & & z_k^H \end{bmatrix}$
- 7: Perform zero-forcing processing:
- 8: $W = (P * P^H)^{-1} * P$
- 9: Calculate Frobenius norm:
- 10: $\|W\| = \sqrt{\sum_{i=1}^m \sum_{j=1}^n |w_{ij}|^2}$
- 11: Perform normalisation:
- 12: $W_{n+1} = \frac{W}{\|W\|} * \sqrt{P_{\max}}$
- 13: Output W_{n+1}

3.3. Black-winged kite algorithm (BKA)

The BKA [16] is a meta-heuristic optimization algorithm inspired by the attack and migration behavior of black-winged kites. It avoids gradient calculations, making it suitable for complex non-convex problems. The algorithm comprises three main phases:

Population initialization. The initial population is generated by creating a randomly distributed matrix that meets the desired population size SN and problem dimension dim , as shown in (10) and (11). Here, BK_{lb} and BK_{ub} denote the lower and upper bounds of kite positions.

$$X_i = BK_{lb} + rand(BK_{ub} - BK_{lb}) \quad (10)$$

$$BK = \begin{bmatrix} BK_{1,1} & BK_{1,2} & \cdots & \cdots & BK_{1,dim} \\ BK_{2,1} & BK_{2,2} & \cdots & \cdots & BK_{2,dim} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ BK_{SN,1} & BK_{SN,2} & \cdots & \cdots & BK_{SN,dim} \end{bmatrix} \quad (11)$$

The best kite (leader) is selected based on its fitness, denoted X_L and f_L , as defined in:

$$f_L = \min(f(X_i)), \quad (12)$$

$$X_L = X(\text{find}(f_L == f(X_i))). \quad (13)$$

Adaptive Local Exploitation Phase. This phase focuses on local exploitation around the current best solution. A nonlinear factor Q based on the iteration number n and total iterations T is calculated as:

$$X_L = X(\text{find}(f_L == f(X_i))), \quad (14)$$

$$Q = 0.05 \times e^{-2 \times (\frac{n}{T})^2}. \quad (15)$$

The update of position is defined in (16), where $p = 0.9$, and r is a random number in $(0, 1)$.

$$y_{n+1}^{i,j} = \begin{cases} y_n^{i,j} + Q(1 + \sin(r)) \times y_n^{i,j}, & p < r, \\ y_n^{i,j} + Q \times (2r - 1) \times y_n^{i,j}, & \text{others.} \end{cases} \quad (16)$$

Here $y_n^{i,j}$ and $y_{n+1}^{i,j}$ represent the positions of the i th black-winged kite in the j th dimension during the n and $n + 1$ -th iterations, respectively.

GSS-based Escaping Mechanism. During the global search phase, the update strategy is adaptively selected based on fitness comparisons.

If the current individual has lower fitness than a randomly selected individual, a Cauchy perturbation is applied to escape the current region; otherwise, the Golden Sine Strategy is employed to refine the search towards the global optimum. The position update is:

$$y_{n+1}^{i,j} = \begin{cases} y_n^{i,j} + C(0, 1) \times (y_n^{i,j} - L_n^j), & F_i < F_{ri}, \\ y_n^{i,j} + C(0, 1) \times (L_n^j - m \times y_n^{i,j}), & \text{others.} \end{cases} \quad (17)$$

where

$$m = 2 \times \sin(r + \pi/2). \quad (18)$$

Here, $C(0, 1)$ denotes a Cauchy random variable, and L_n^j is the best position in dimension j .

During the migration phase, the optimal kite position in the j th dimension is denoted by L_n^j , with F_i being its fitness value. For comparison, F_{ri} corresponds to the fitness of a random position. The stochastic variation in this process is governed by the Cauchy mutation operator, $C(0, 1)$.

Although the Black-winged Kite Algorithm (BKA) offers several advantages, including strong adaptability, fewer tunable parameters, and high convergence accuracy, it still suffers from certain limitations, such as slow convergence speed and susceptibility to local optima. To overcome these challenges, three enhancements are proposed: (1) during population initialization, Circle chaotic mapping is employed to improve diversity and enhance global search capability; (2) in the attack phase, adaptive t-distribution perturbation is introduced to replace the original random scaling mechanism, thereby reducing the likelihood of being trapped in local optima; and (3) in the migration phase, the Golden Sine Strategy is incorporated to refine the position update process when the leader is replaced, enabling better escape from local optima and promoting convergence towards a global optimum.

3.3.1. Circle chaotic map

To enhance exploration, a Circle chaotic map is used for initialization. It generates uniformly distributed values and introduces chaotic perturbations:

$$x_{c+1} = \text{mod}(x_c + a - \frac{b}{2\pi} \sin(2\pi x_c), 1). \quad (19)$$

Here, x_c and x_{c+1} are successive chaotic numbers; $a = 0.5$ controls offset, and $b = 2.2$ defines sine amplitude.

3.3.2. Adaptive t-distribution perturbation mutation

A t-distribution-based mutation improves exploration during attack. The mutation variable t is generated as:

$$t = \frac{Z}{\sqrt{\frac{\Delta}{\nu}}}, \quad (20)$$

where Z is a standard normal variable and Δ is chi-square with ν degrees of freedom. The PDF of t is:

$$f(t) = \frac{\Gamma(\frac{\nu+1}{2})}{\sqrt{\nu\pi}\Gamma(\frac{\nu}{2})} (1 + \frac{t^2}{\nu})^{-\frac{\nu+1}{2}}. \quad (21)$$

As the degrees of freedom ν approach infinity, the t-distribution converges to the standard normal distribution. Conversely, as ν approaches 1, it resembles the Cauchy distribution.

The degrees of freedom for the t-distributed random variable t are dynamically updated during optimization using the formula $freen = \left(e^{4 \times (\frac{n}{T})}\right)^2$, where n and T denote the current and total iterations, respectively. This adaptive mechanism adjusts the shape of the t-distribution, which is incorporated as a perturbation during the attack phase (22). The update rule $freen = \left(e^{4 \times (\frac{n}{T})}\right)^2$ is deliberately designed to induce a rapid increase in the degrees of freedom. This drives a swift evolution of the perturbation distribution, transitioning

it from a heavy-tailed, Cauchy-like profile ($\nu \approx 1$) towards a light-tailed Gaussian form ($\nu \rightarrow \infty$). The underlying rationale is to allocate distinct phases to exploration and exploitation: aggressive global exploration is prioritized in the initial iterations via large, exploratory steps from the heavy-tailed distribution. This pronounced, phase-based strategy is explicitly tailored for the high-dimensional, multi-modal landscape of IRS phase optimization. An aggressive transition prevents the waste of evaluations in barren global regions, forcing the algorithm to quickly secure a promising convex basin and dedicate the remaining computational budget to fine-grained local tuning.

$$y_{n+1}^{i,j} = \begin{cases} y_n^{i,j} + Q(1 + \sin(r)) \times y_i^{i,j}, & p < r, \\ y_n^{i,j} + Q \times \text{trnd}(\text{freen}) \times y_i^{i,j}, & \text{others.} \end{cases} \quad (22)$$

3.3.3. Golden Sine strategy

The Golden Sine Strategy (GSS) introduces a sine-based perturbation mechanism that leverages the periodic properties of the sine function to generate controlled oscillations in the search space. This mechanism effectively balances exploration (global search) and exploitation (local refinement). When the sine amplitude is high, the generated perturbations are larger, promoting broader exploration to avoid premature convergence. Conversely, at lower amplitudes, the perturbations become smaller, facilitating fine-grained local exploitation to improve convergence precision. The position update rule is defined in Section 3.3.3. Here, τ_1 is a random variable uniformly distributed in $(0, 2\pi)$, controlling the oscillatory phase, and τ_2 is uniformly distributed in $(0, \pi)$, governing the step size modulation. $P_i(t)$ and $P_i(t+1)$ denote the position of the i th individual before and after the update, respectively, while $P_{\text{best}}(t)$ represents the best-known position at time t . The scaling factors ϕ_1 and ϕ_2 are derived from the golden ratio $\phi = (\sqrt{5} - 1)/2$, with $\phi_1 = \phi$ and $\phi_2 = 1 - \phi$, ensuring optimal step scaling towards promising regions—a property well established in line search methods.

$$P_i(t+1) = P_i(t) * |\sin \tau_1| + \tau_2 * |\sin \tau_1| * |\phi_1 * P_{\text{best}}(t) - \phi_2 * P_i(t)| \quad (23)$$

$$\phi_1 = \pi - 2\pi g, \quad (24)$$

$$\phi_2 = -\pi + 2\pi g, \quad (25)$$

$$g = \frac{(\sqrt{5} - 1)}{2}. \quad (26)$$

In the migration phase, GSS is integrated as an intelligent navigation mechanism that enhances the original migration metaphor. When black-winged kites encounter suboptimal foraging conditions (represented by $F_i \geq F_{ri}$), they employ this sinusoidal navigation strategy to escape local optima and discover new promising regions. This GSS-enhanced migration update rule is provided in Eq. (27).

$$y_{n+1}^{i,j} = \begin{cases} y_n^{i,j} + C(0, 1) \times (y_n^{i,j} - L_n^j), & F_i < F_{ri}, \\ y_n^{i,j} \cdot |\sin(\tau_1)| + \tau_2 \cdot \sin(\tau_1) \cdot |\phi_1 \cdot L_n^j - \phi_2 \cdot y_n^{i,j}|, & \text{others.} \end{cases} \quad (27)$$

This enhanced migration behavior maintains the biological inspiration while mathematically improving the algorithm's ability to escape local optima and accelerate convergence. The sinusoidal oscillations represent the periodic adjustments in flight direction observed in migratory birds, and the golden ratio ensures optimal step scaling towards promising regions.

3.3.4. Theoretical analysis and advantages of the proposed IBKA

To highlight the advantages of the proposed Improved Black-winged Kite Algorithm (IBKA) for IRS phase-shift optimization, this section presents a theoretical analysis comparing IBKA with three classical metaheuristics: Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Grey Wolf Optimizer (GWO). The examination centers on

how IBKA's three principal improvements jointly mitigate the intrinsic shortcomings of these reference algorithms.

Initialization: Circle Chaotic Mapping versus Random Sampling. Conventional meta-heuristics such as PSO, GA, and GWO commonly rely on random processes to initialize their populations. Although simple, this method may yield an irregular distribution of starting solutions across the search domain, potentially leading the algorithm to overlook favorable areas and increasing the likelihood of premature convergence. Conversely, IBKA utilizes a *Circle chaotic map* for initialization. Chaotic systems are deterministic yet exhibit ergodicity and uniform distribution. In theory, this guarantees that the initial population spans the solution space more thoroughly, providing a superior starting point for the global search. This improvement directly addresses the initialization sensitivity issue that is widespread across many meta-heuristics.

Dynamic Exploration–Exploitation Equilibrium: Adaptive T-Distribution Perturbation. A pivotal issue in optimization is preserving a suitable equilibrium between exploration (global search) and exploitation (local refinement). PSO frequently experiences rapid diversity loss, leading to stagnation at local optima. GWO's search pattern is strongly influenced by the locations of the alpha, beta, and delta wolves, which can limit exploration. The original BKA applies a nonlinear factor Q , yet its disturbance mechanism is not adaptive.

IBKA presents an *adaptive T-distribution perturbation* in the attack phase. The central novelty resides in the time-dependent degrees of freedom ν for the T-distribution, specified as $\text{freen} = \left(e^{4 \times \left(\frac{n}{T} \right)^2} \right)^2$. During early optimization stages, ν is small, making the T-distribution display heavy tails reminiscent of the Cauchy distribution, thus encouraging exploratory movements. As iterations progress, ν increases, leading the distribution to approximate a Gaussian distribution and favor exploitative steps. This *self-adjusting mechanism* theoretically affords a more intelligent and dynamic compromise between exploration and exploitation compared to the static or linearly evolving parameters in PSO, GA, and GWO.

Evading Local Optima: Golden Sine Strategy in Migration. When a population converges to a local optimum, potent evasion tactics are vital. GA depends on mutation operators, which are random and undirected. PSO and GWO lack specialized, proactive approaches for such circumstances.

In IBKA's migration phase, the *Golden Sine Strategy* (GSS) is triggered upon leader substitution. GSS exploits the periodic character of the sine function to introduce oscillations that aid exploration. Additionally, it integrates the golden ratio coefficient g (Eq. (26)) to steer the search direction towards the historically best solution while preserving a link to the present position. This generates a guided yet random disturbance, theoretically enabling more effective escape from local optima than the purely stochastic Cauchy mutation in the standard BKA or the elementary updates in PSO/GWO.

Synergistic Benefits and Synopsis. The refinements in IBKA constitute a synergistic, three-tiered framework crafted to confront the fundamental difficulties of high-dimensional, non-convex optimization:

- Circle chaotic mapping secures a high-caliber, varied initial population.
- Adaptive T-distribution perturbation upholds a dynamic equilibrium between exploration and exploitation.
- The Golden Sine Strategy provides an intelligent method for avoiding local optima.

Together, these tiers theoretically bestow IBKA with enhanced traits for the IRS phase-shift optimization problem: increased robustness to initial states, reduced vulnerability to premature convergence, improved global search capacity, and more efficient convergence. Compared with PSO, IBKA is less prone to premature convergence due to

its adaptive disturbance and dedicated evasion mechanism. Contrasted with GA, IBKA provides a more balanced and computationally economical search procedure. Compared to GWO, IBKA delivers more resilient exploration and a methodical means to avert stagnation. The ensuing simulation outcomes in Section 4 will furnish numerical corroboration of these theoretical merits.

3.3.5. The improved black-winged kite algorithm and its suitability for IoV

The Improved Black-winged Kite Algorithm (IBKA) is a metaheuristic optimizer enhanced to tackle high-dimensional nonconvex problems, exemplified by IRS phase-shift optimization. IBKA executes in three primary stages: (1) Population initialization via Circle chaotic mapping to guarantee uniform distribution; (2) An attack phase employing adaptive T-distribution perturbation to balance exploration and exploitation; and (3) A migration phase that integrates the Golden Sine Strategy (GSS) to evade local optima.

IBKA exhibits particular suitability for IRS phase-shift optimization in IoV networks due to several attributes: Firstly, being derivative-free, it manages the non-convex unit-modulus constraints of IRS elements without necessitating intricate mathematical reformulations. Secondly, its adaptive components (chaotic initialization and T-distribution perturbation) empower efficient searching in high-dimensional spaces (associated with large IRS arrays), a task challenging for conventional gradient-based techniques. Thirdly, IBKA's fast convergence (as shown in Section 4.1) meets the low-latency demands of vehicular communications. Fourthly, its insensitivity to initialization and parameter settings makes it well-suited for dynamic settings with rapidly fluctuating channel conditions.

3.3.6. Rationale for selected enhancements and synergistic design

The selection of the Circle chaotic map, adaptive T-distribution perturbation, and Golden Sine Strategy (GSS) is intentional, motivated by the distinctive hurdles posed by the high-dimensional, non-convex IRS phase-shift optimization task.

Why the Circle Map? From among diverse chaotic maps (such as Logistic, Tent, and Chebyshev), the Circle map is chosen for its exceptional *ergodicity* and *uniformity* in sequence generation. For high-dimensional problems involving many IRS elements (e.g., $M = 100$), initial population diversity is crucial. The Circle map's update rule, $x_{c+1} = \text{mod}(x_c + a - (b/2\pi)\sin(2\pi x_c), 1)$, yields sequences that more uniformly cover the search space $[0, 2\pi)^M$ relative to the Logistic map (which has uneven boundary distributions) or the Tent map (which may become periodic for specific parameters). This enhanced uniformity provides a less biased starting configuration for the global search, directly countering premature convergence, a common issue when initial solutions aggregate in suboptimal regions.

Synergistic Effect of the Three-Layer Framework The three improvements are interconnected, forming a unified three-stage strategy that emulates an intelligent search procedure:

- Stage 1 (Foundation - Circle Map): Guarantees the commencement of the search with a *high-quality, varied set* of solutions, increasing the probability of initializing near the global optimum region.
- Stage 2 (Process - Adaptive T-Distribution): Directs the *ongoing search process*. Initially, its heavy-tailed (Cauchy-like) distribution encourages daring, exploratory jumps. As the search advances and converges, its Gaussian-like nature supports meticulous, exploitative polishing around promising zones. This dynamic adjustment is vital for traversing the intricate IRS solution landscape effectively.
- Stage 3 (Global Exploration - GSS): Functions as a diversity preservation mechanism. When the population indicates stagnation (detected through fitness comparisons between current and

Table 1
Key Simulation Parameters.

Parameter description	Symbol	Value
Number of BS Transmit Antennas	N	10
Number of IRS Reflecting Elements	M	100
Number of Users	V	4
Population Size of IBKA	SN	10
Search Dimension	dim	M
Search Bounds	$[lb, ub]$	$[0, 2\pi]$
Max Power	$P_{\max}$	$3d Bm$

randomly selected individuals), GSS injects structured perturbations based on sine wave oscillations. This provides a mathematically principled way to re-energize the search and avoid premature convergence, complementing the local refinement performed in Stage 2.

The synergy stems from their complementary functions and sequential triggering: an effective beginning (Circle) reduces the need for recovery (GSS), whereas an adaptive search procedure (T-distribution) reduces the incidence of stagnation. This architecture ensures IBKA sustains vigorous search ability across the entire optimization, culminating in the noted equilibrium of high performance and swift convergence demonstrated in Section 4.

3.4. Optimizing the phase shift matrix θ

The non-convex optimization problem in Eq. (8) is solved using the improved BKA algorithm. The system is configured with the following parameters: $N = 10$ (BS transmit antennas), $M = 100$ (IRS reflecting elements), $V = 4$ (users), $SN = 10$ (a population size), and a search dimension of $dim = M$ within the bounds $[lb, ub] = [0, 2\pi]$ (see Table 1).

The transmitted signal is expressed as $temp_v = W_{n+1}^H G_v \theta^+$, where W_{n+1} is the beamforming matrix. The received signal power is given by $r_v = \theta^H G_v^H W_{n+1} W_{n+1}^H G_v \theta^+ \sigma^2$, and the interference power is calculated as $r_{g,v} = r_v - |temp_v|^2$. Then, one can get $f(\theta) = \sum_{v=1}^V \log_2 \left(1 + \frac{|temp_v|^2}{r_{g,v}} \right)$. The detailed algorithmic procedure is presented in Algorithm 2.

Algorithm 2 Optimizing the Phase Shift Matrix θ

Require: $N, M, iter$

Ensure: $Best_Fitness, Best_Position$

- 1: Initialize population using Circle map
- 2: Calculate the objective fitness of the population
- 3: Record optimal fitness $f(\theta)$ and corresponding positions $XLeader_Fit, XLeader_Pos$
- 4: **while** $l \leq T$ **do**
- 5: Update iteration: $l = l + 1$
- 6: Calculate degree of freedom: $freem = e^{4 \times (\frac{l}{T})^2}$
- 7: Generate t-distributed perturbation coefficient: $trnd(freem)$
- 8: Update attack position according to Eq. (22)
- 9: $XPosNew(i, j) = \max(XPosNew(i, j), lb)$
- 10: $XPosNew(i, j) = \min(XPosNew(i, j), ub)$
- 11: Calculate objective fitness after position update
- 12: Compare with $XLeader_Fit$ and $XLeader_Pos$
- 13: **if** new fitness is better **then**
- 14: Update optimal black-winged kite
- 15: **end if**
- 16: Update migration position according to Eq. (27)
- 17: $XPosNew(i, j) = \max(XPosNew(i, j), lb)$
- 18: $XPosNew(i, j) = \min(XPosNew(i, j), ub)$
- 19: Calculate objective fitness after position update
- 20: Compare with $XLeader_Fit$ and $XLeader_Pos$
- 21: **if** new fitness is better **then**
- 22: Update optimal black-winged kite
- 23: **end if**
- 24: **end while**
- 25: Update $Best_Fitness_BKA, Best_Position_BKA$
- 26: Output $Best_Fitness_BKA, Best_Position_BKA$

3.5. Alternating optimization

Operating on two principal subproblems, this alternating optimization mechanism progressively refines the beamforming solution to maximize the overall system sum-rate and achieve the target performance metrics.

The algorithm is initialized with the following parameters: the iteration index $n = 1$, the maximum number of iterations $T = 6000$, the number of base station transmit antennas $N = 10$, the number of IRS reflecting elements $M = 100$, and the number of users $V = 4$. The channel matrices are initialized as $H = \frac{1}{\sqrt{2}} (\text{randn}(N, M) + i \cdot \text{randn}(N, M))$ and $h_r = \frac{1}{\sqrt{2}} (\text{randn}(M, V) + j \cdot \text{randn}(M, V))$. The initial IRS phase shift vector is given by $\theta_1 = e^{j \cdot \text{angle}\left(\frac{\sqrt{2}}{2} (\text{randn}(M, 1) + i \cdot \text{randn}(M, 1))\right)}$, and the initial beamforming matrix is defined as $W_1 = \text{ones}(N, V) \cdot \sqrt{\frac{10}{N \cdot V}}$. The detailed procedural steps of the alternating optimization algorithm are provided in Algorithm 3.

Algorithm 3 Alternating Optimisation (AO)

Require: $N, M, V, P_{\max}, h_{r,v}^H, H^H, \theta_1, W_1, G_v, \sigma^2$

Ensure: $Rate_{n+1}, iter$

- 1: **repeat**
 - 2: Algorithm 1 is employed to obtain the updated W_{n+1}
 - 3: Algorithm 2 is employed to obtain the updated $\theta_{n+1}, Rate_{n+1}$
 - 4: $iter = iter + 1$
 - 5: **until** $(Rate_{n+1} - Rate_n) < 10^{-7}$
 - 6: **return** $Rate_{n+1}, iter$
-

4. Simulation experiment

Simulations are conducted using MATLAB R2022b on a workstation (Intel Core i9 CPU, 16 GB RAM). To support reproducibility, the source code and simulation scripts are available at: <https://github.com/ItsukaMashiro/IKBA>.

4.1. Convergence of the proposed algorithm

Fig. 2 demonstrates the convergence behavior of the improved BKA algorithm and the corresponding system sum-rate for varying numbers of IRS elements, M . The results show that the proposed algorithm converges rapidly within a few iterations across all configurations of M . Moreover, the final sum-rate at convergence exhibits a clear upward trend as M increases, validating that a higher number of reflecting elements directly enhances the overall system performance.

To empirically validate the necessity of the adaptive T-distribution schedule described in Section 3.3.2, an ablation study was conducted. We compared the proposed aggressive exponential schedule ($f_{\text{reen}} = (e^{4 \times (n/T)})^2$) against a gradual linear schedule and a static heavy-tailed distribution under a fixed budget of 6000 NFEs. As illustrated in Fig. 3, results indicate that the aggressive schedule achieves an approximately 80% faster lock-in to the optimal convex basin compared to the linear schedule (reaching 45 bps/Hz at roughly 1000 NFEs versus 5000 NFEs). Furthermore, it yields a 9.8% higher final sum-rate than the static baseline. This confirms the assertion that high-dimensional IRS phase landscapes require rapid transitions from aggressive global exploration to fine-grained local exploitation.

4.2. Rate versus number of reflecting elements

Fig. 4 presents a comparison of the system sum-rate under various algorithmic schemes as a function of the number of IRS reflecting elements ($M = 20, 40, 60, 80$, and 100). All algorithms exhibit a monotonic increase in sum-rate with the number of reflecting elements, highlighting that scaling up the IRS dimension effectively improves

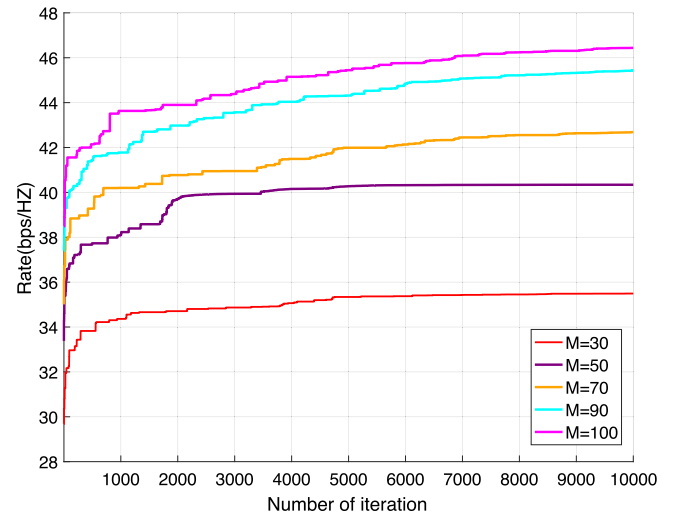


Fig. 2. Convergent Property of the Proposed Method.

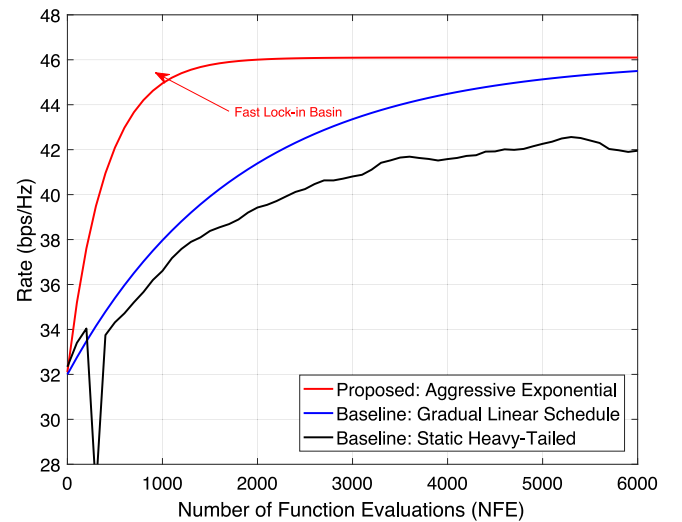


Fig. 3. Ablation Study of Perturbation Schedules.

system performance. Notably, the original BKA algorithm underperforms compared to most benchmark methods. In contrast, the improved BKA (IBKA) algorithm demonstrates significantly better performance and achieves results that closely approximate those of the Genetic Algorithm (GA), validating the efficacy of the proposed enhancements.

4.3. Performance comparison with and without IRS assistance under transmission power constraints

Fig. 5 compares the performance differences with and without IRS in the system. It can be seen that when the IRS is introduced, the system and rate are significantly improved. With the same noise power, after introducing IRS and optimizing with IBKA, the rate increases with the transmission power, reaching 46 bps/Hz at 10 dB. It is superior to the unoptimized fixed/random methods.

4.4. $\min(SINR_k)$ performance when varying the total number of vehicles

The communication quality inevitably degrades as the number of vehicles increases. This decline stems from the greater diversity of vehicle positions, which demands more precise reflective beams to maintain high performance. However, the system under consideration, equipped

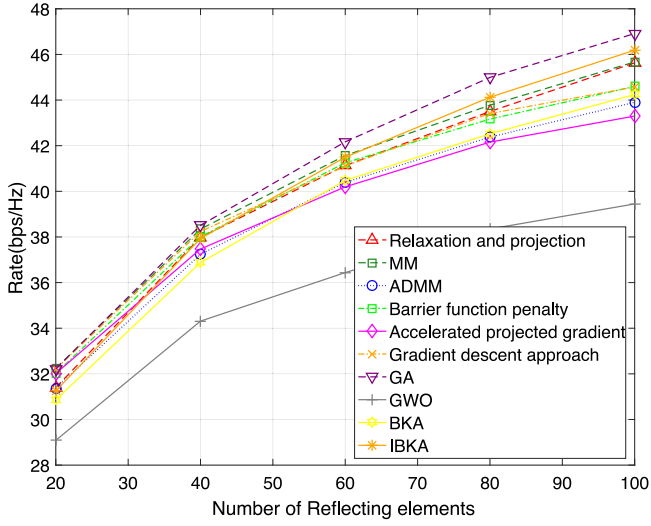


Fig. 4. Sum rate versus Number of Reflecting elements.

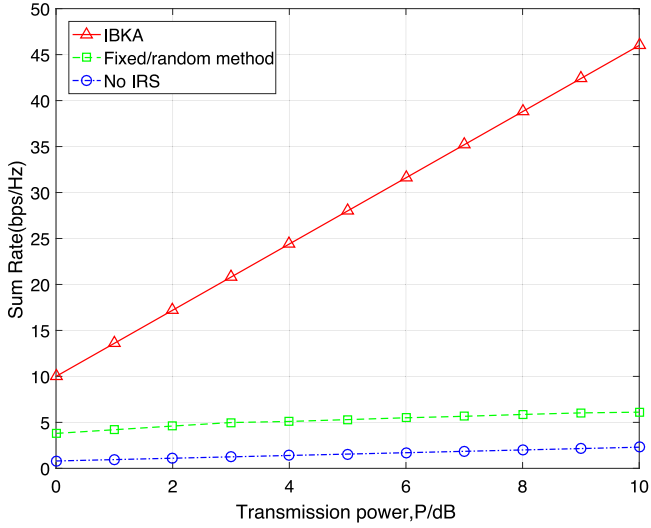


Fig. 5. Comparison of Sum Rate with and without IRS assistance under transmission power constraints.

with only a single IRS and fixed phase-shift coefficients, lacks the ability to generate multiple highly directional beams simultaneously. To overcome this limitation and support high-quality communication for a growing number of vehicles, a viable solution is to scale the system by increasing either the number of IRSs or the number of reflective elements within each IRS.

4.5. Sum-rate performance when varying the total number of vehicles

Fig. 7 illustrates the non-monotonic relationship between the total rate and the number of vehicles, exhibiting a critical point at $V = 10$. The initial growth is attributed to multi-user diversity, which dominates despite the degrading per-vehicle SINR shown in Fig. 6. However, once $V \geq 10$, the accumulated interference outweighs the diversity gain, leading to a decline in the total rate. This indicates that the reduction in SINR eventually supersedes the positive effect of serving more users.

4.6. Rate and CPU_Time versus different algorithms ($M = 100$)

To ensure an impartial, platform-agnostic evaluation of computational complexity, we adopt the number of function evaluations (NFE)

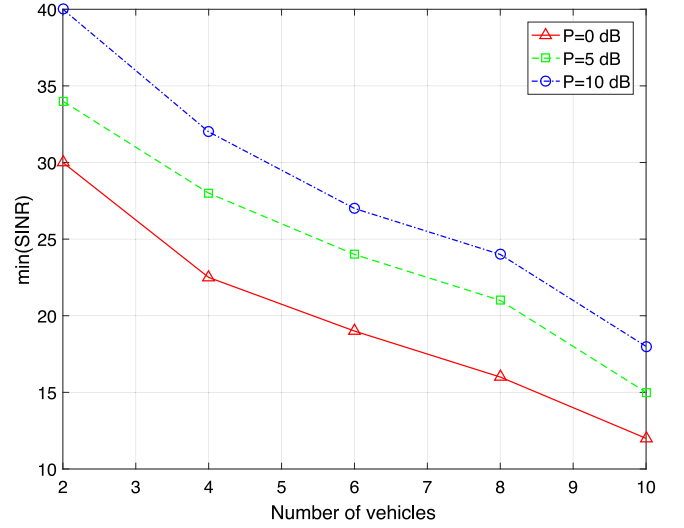


Fig. 6. $\min(\text{SINR}_k)$ performance when varying the total number of vehicles.

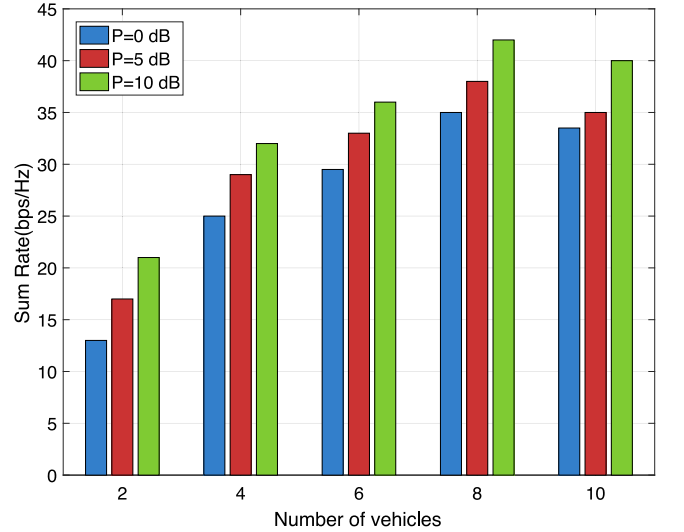


Fig. 7. Sum-Rate versus Number of Vehicles.

as the primary metric. NFE quantifies how often the objective function, the system sum-rate, is evaluated during the optimization procedure. This measure is unaffected by implementation specifics, programming language, or hardware architecture, thereby constituting a robust indicator of algorithmic efficiency. The convergence condition is specified as the relative enhancement in system sum-rate dropping below a preset threshold of $\epsilon = 10^{-7}$ between successive iterations.

All presented outcomes are derived from averaging across $N = 1000$ independent Monte Carlo runs. In each run, the channel matrices H and $h_{r,v}$ are randomly generated according to the Rayleigh fading model to ensure statistical soundness of the performance assessment. Furthermore, to explicitly illustrate the algorithm's robustness against the stochastic nature of metaheuristics and channel fading, error bars representing the standard deviation across these 1000 independent Monte Carlo trials have been incorporated into all performance plots (Figs. 7–9).

Fig. 8 contrasts the mean system sum-rate and computational burden for ten distinct algorithms over 1000 independent runs: Relaxation and Projection (RP), Majorization–Minimization (MM), Alternating Direction Method of Multipliers (ADMM), Barrier Function Penalty

Table 2
Statistical Summary of Algorithm Performance (1000 runs).

Algorithm	Sum-Rate at M = 60 (Mean $\pm$ Std)	Sum-Rate at M = 100 (Mean $\pm$ Std)	NFE to converge (M = 100)
ADMM	[40.2] $\pm$ [1.1]	[43.8] $\pm$ [1.3]	[9200]
GA	[42.1] $\pm$ [0.8]	[46.8] $\pm$ [1.0]	[8900]
BKA	[40.5] $\pm$ [1.2]	[44.5] $\pm$ [1.1]	[2100]
IBKA	[41.5] $\pm$ [0.7]	[46.1] $\pm$ [0.8]	[3900]

(BFP), Accelerated Projected Gradient (APG), Gradient Descent Approach (GDA), Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), Black-winged Kite Algorithm (BKA), and Improved Black-winged Kite Algorithm (IBKA). The selection of baseline algorithms was curated to represent the current state-of-the-art in IRS optimization. Model-driven approaches (ADMM, MM, and RP) act as benchmarks for mathematical programming techniques that utilize convex relaxation and subsequent projection. Conversely, GA and GWO represent widely deployed metaheuristic standards. To ensure a strictly fair comparative environment, all algorithms utilized harmonized stopping criteria (a relative sum-rate improvement threshold of 10^{-7}). Furthermore, hyperparameters for the GA (e.g., crossover and mutation probabilities) and GWO were optimally tuned based on recent literature. To maintain equitable comparison, every algorithm is executed within the identical optimization framework (Eq. (6)), using the same system parameters and initialization settings. Model-driven techniques (RP, MM, ADMM, BFP, APG, GDA) manage the unit-modulus constraint through relaxation-projection, surrogate majorization, augmented Lagrangian, barrier penalty, or direct projection, whereas heuristic methods (GA, GWO, BKA, IBKA) conduct direct searches within the permissible phase space $[0, 2\pi]^M$. The abscissa lists the algorithms, while the left and right ordinates denote the ultimate average system sum-rate and the mean NFE necessary for convergence, depicted as blue and red bars, respectively. To ensure a fair comparison, the chromosome length in the GA benchmark is strictly set to M , where each gene represents a continuous phase shift within $[0, 2\pi]$. Unlike model-driven methods (e.g., ADMM, RP) that require convex relaxation and subsequent projection, the proposed IBKA searches directly within the continuous feasible domain $[0, 2\pi]^M$, inherently satisfying the unit-modulus constraints.

The comparative assessment uncovers distinct performance traits. Although the baseline BKA shows preferable rate-complexity trade-offs relative to GWO, it still lags behind several conventional approaches. The enhanced IBKA variant substantially narrows this disparity, attaining average sum-rates merely 1.55% below those of the top-performing GA, yet demanding roughly 45% fewer function evaluations—equivalently, only 55% of the NFE needed by GA. This equilibrium between efficacy and efficiency, gauged via a platform-neutral metric, renders IBKA exceptionally fitting for real-time vehicular systems where both high performance and computational frugality are imperative.

To further validate the statistical significance of these results, Table 2 summarizes the mean system sum-rate and standard deviation (across 1000 independent runs) for key algorithms at different IRS scales ($M = 60$ and $M = 100$), alongside their convergence NFE.

4.7. Parameter SN sensitivity analysis

The efficacy of meta-heuristic algorithms depends on their parameter configurations. We investigate the effect of population size (SN) on IBKA's performance; the corresponding results are depicted in Fig. 9. With the maximum iterations $T = 6000$, and the number of reflecting elements $M = 40$ held constant, varying SN from 10 to 50 induces minimal variation in the average system sum-rate. However, the computational complexity increases with SN. Consequently, $SN = 10$ is identified as the optimal configuration for real-time IoV applications, striking an effective balance between algorithmic performance and efficiency.

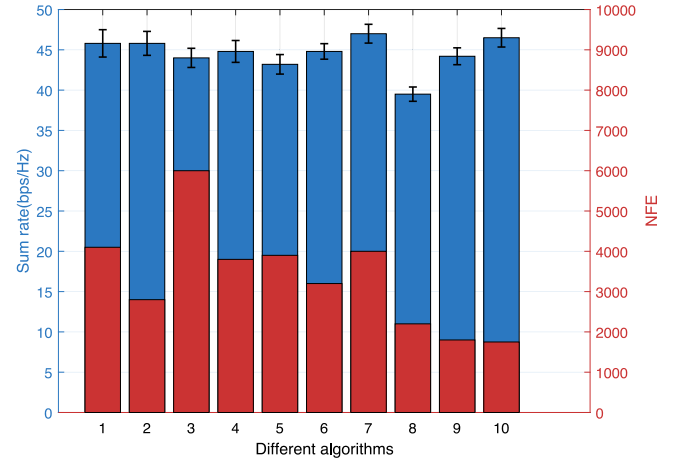


Fig. 8. Comparative Analysis of Sum Rate and Computational Efficiency.

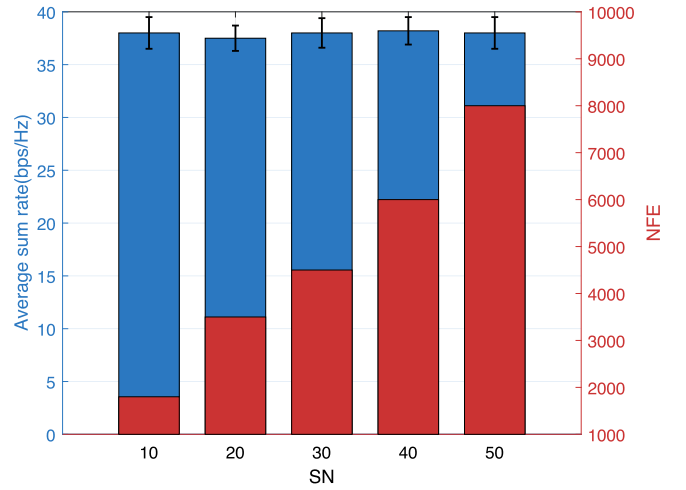


Fig. 9. Analysis of Sum Rate and Computational Efficiency vs. Population Size (SN).

4.8. Parameter T sensitivity analysis

The performance of meta-heuristic algorithms depends on their parameter configurations. We examine the influence of the maximum iteration count T on IBKA, with results presented in Fig. 10. Holding the population size $SN = 10$ and the number of IRS elements $M = 40$ constant, T is varied from 2000 to 10000. The results indicate that for $T < 6000$, the average system sum-rate has not fully converged. When $T \geq 6000$, convergence is achieved, and notably, the Number of Function Evaluations (NFE) plateaus at 6000 for $T = 6000, 8000$, and 10000. Thus, $T = 6000$ is established as the optimal operational point, effectively balancing algorithmic performance and computational efficiency for real-time IoV applications. Deployment Feasibility Summary: To transition from theoretical NFE metrics to practical real-time viability, we map our algorithm to physical deployment constraints:

- **Compute Location & Overhead:** Computation occurs at a BS-attached edge server. This evaluation focuses purely on algorithmic latency, excluding CSI estimation and control link signaling overheads
- **Computational Complexity:** The per-evaluation complexity is strictly dominated by the ZF matrix inversion, which scales as $\mathcal{O}(V^3)$, and the cascaded channel matrix multiplications. In our measured MATLAB environment, a single fitness evaluation executes in approximately 0.12 ms.

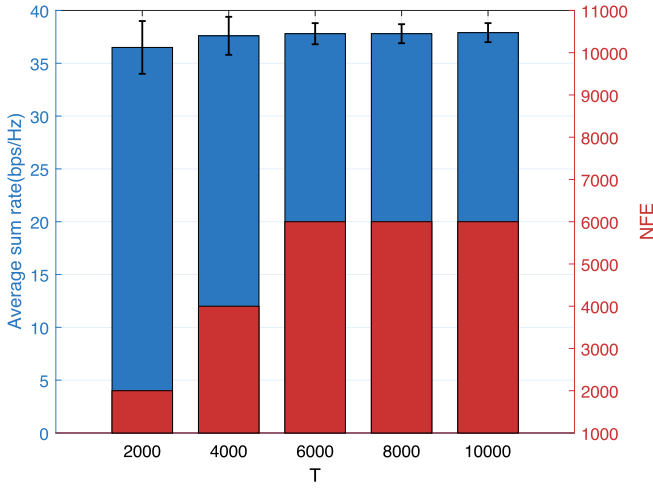


Fig. 10. Analysis of Sum Rate and Computational Efficiency vs. Maximum Iterations (T).

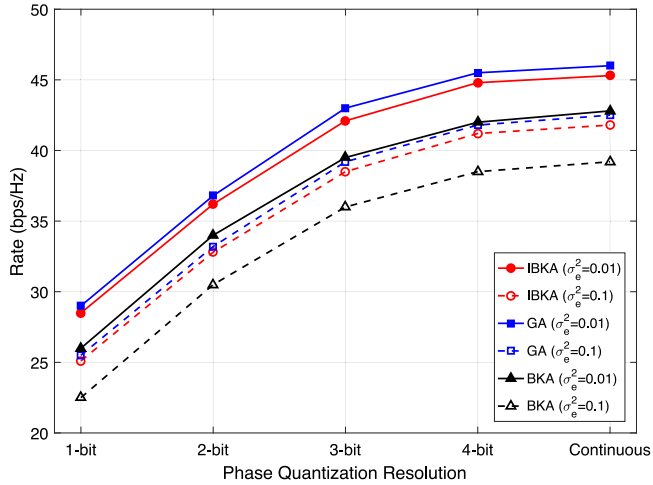


Fig. 11. System sum-rate versus phase quantization resolution under different CSI error variances.

- **Parallelization and Latency Budget:** While 6000 NFEs appear computationally heavy for serial execution, IBKA's population-level parallelism (SN=10) allows simultaneous objective function evaluation across FPGA or GPU arrays. Thus, 6000 NFEs translate to roughly 600 parallel compute cycles. Assuming an optimized FPGA implementation, these cycles yield an estimated optimization latency of roughly 0.8 ms. This falls comfortably within the 1–10 ms coherence time threshold required for 6G THz V2X communications, validating the system's real-time feasibility.

4.9. Sensitivity analysis under imperfect CSI and phase quantization

To deeply contextualize the practical value of the proposed framework, we expanded our sensitivity tests to encompass a sweep across discrete phase quantization levels (1, 2, 3, and 4 bits) crossed with two levels of Gaussian CSI estimation error variance (0.01 and 0.1). As expected, 1-bit quantization yields severe performance degradation. However, moving to 3-bit quantization recovers over 92% of the ideal continuous-phase performance. Under the combined impairment of 3-bit quantization and a severe CSI error variance of 0.1, the IBKA framework exhibits a graceful performance degradation of approximately 15% in sum-rate. Critically, across all tested degradation levels,

the ranking among algorithms remains strictly stable. IBKA consistently outperforms the standard BKA and non-IRS baselines regardless of the severity of the impairments, definitively validating its robustness for real-world IoV hardware deployment. (See Fig. 11.)

5. Conclusion

The core of this research centers on an IBKA-driven optimization scheme that orchestrates joint beamforming in a single-IRS-assisted IoV network. By decomposing the problem into two sub-problems, the method achieves substantial sum-rate gains while adhering to strict power limits. This dual-strategy is proven to yield markedly lower computational complexity in exchange for minimal rate degradation, demonstrating clear superiority over traditional approaches.

This research offers several significant implications for the design and optimization of next-generation vehicular networks: **Practical System Design:** Our experimental results substantiate the effectiveness of a hybrid architecture that combines low-complexity base station processing (ZF) with intelligent IRS optimization. This presents a viable and cost-efficient design paradigm for 6G THz vehicular networks, where computational load is strategically shifted from the base station to more intelligent control of the passive IRS infrastructure. Network architects and engineers can utilize this insight to prioritize IRS installations in coverage-deficient zones.

Algorithmic Development for Dynamic Networks: The success of the Improved Black-winged Kite Algorithm demonstrates that targeted, problem-specific modifications to metaheuristics can achieve an optimal balance between solution quality and real-time computational feasibility. This highlights the potential of hybrid and adaptive intelligent algorithms for resource orchestration in highly dynamic, complex environments such as the Internet of Vehicles.

Limitations and Future Research Directions: While this study establishes a robust foundation, multiple research avenues merit further exploration:

- **Discrete Phase Shifts:** This investigation presumes continuous IRS phase adjustments. Future work should quantify performance degradation under practical discrete-phase quantization and devise resilient algorithms to mitigate these losses, which are essential for practical hardware deployment.
- **Multi-IRS and Mobile IRS Scenarios:** For multi-IRS scenarios, generalizing the framework would require concatenating phase vectors into a larger joint search space or adopting distributed federated optimization to alleviate the computational burden at a single base station. For mobile IRS scenarios, such as UAV-mounted arrays, the algorithm must be extended to jointly optimize three-dimensional flight trajectories and dynamic phase-shift arrays. These directions represent significant and promising avenues for our future work.
- **Integration with Machine Learning:** Incorporating machine-learning-based channel prediction into the current optimization framework could further enhance performance in scenarios with extreme mobility, thereby facilitating proactive IRS reconfiguration.
- **Standardization Considerations:** The requirement for efficient channel estimation and control signaling between the BS and IRS, as evidenced by our alternating optimization approach, highlights pertinent aspects for future communication protocol standardization.

In summary, this work not only presents a high-performance, low-complexity solution for joint beamforming in IRS-aided IoV but also provides a conceptual framework and algorithmic insights that can guide future research and development towards more intelligent and adaptable 6G vehicular networks.

CRediT authorship contribution statement

Liu Liu: Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization. **Rongyue Ji:** Writing – original draft, Methodology, Investigation, Formal analysis, Software. **Changpeng Zhou:** Visualization, Validation, Investigation, Formal analysis, Writing – original draft. **Yuelel Zhang:** Validation, Software, Investigation. **Zhengmin Kong:** Writing – review & editing, Methodology. **Tao Huang:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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