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Enhancing reflective elements of intelligent reflective surfaces in 6G communications using artificial intelligence

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ABSTRACT

The dynamic landscape of 6G communication networks necessitates innovative strategies to address energy inefficiency and signal degradation in densely populated regions with limited line-of-sight (LOS) coverage. A novel technology known as an intelligent reflecting surface (IRS) has emerged; it can dynamically modify the characteristics of electromagnetic waves to enhance signal propagation. Unfortunately, current IRS models frequently neglect the balance between energy efficiency (EE) and the quantity of reflective elements (N) in Rayleigh fading scenarios. This study introduces an algorithm called dynamic-static particle swarm optimization (DS-PSO) aimed at improving EE and decreasing the quantity of reflective components in the performance optimization of IRS. The research assesses the proposed model in comparison to single-input single-output (SISO) systems, conventional IRS models, and IRS models from prior studies within a realistic urban framework. The optimized IRS, which only uses seven reflective elements, has a peak EE of 366 Mbit/Joule. This is a big improvement over IRS models from earlier research, as shown by the numbers. The findings indicate that artificial intelligence (AI)-driven optimization can enhance IRS technology for sustainable and efficient 6G networks.

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1. INTRODUCTION

6G wireless networks are being driven by applications that require more reliable and powerful connectivity. Non-line-of-sight (NLOS) signal degradation results in unstable connections and diminished energy efficiency (EE) in urban settings where buildings and other obstacles impede direct line of sight (LOS). The newly developed technology, known as intelligent reflecting surface (IRS), offers a viable answer to this problem. Programmable meta-atom surfaces may boost signal transmission and expand coverage by effectively and passively changing electromagnetic waves, eliminating the need for active amplification [1]–[5].

Current empirical investigations demonstrate that intelligent reflecting surfaces (IRSs) have achieved significant technological progress, but theoretical research implies that, under ideal circumstances, IRSs might outperform classical relays [6]. Unmanned aerial vehicles (UAVs) with integrated sensing and communication (ISAC) have recently been the subject of study for improving spectrum efficiency [7] and IRS-assisted UAVs for providing dynamic coverage in highly populated regions [8]–[10]. The fact that many current IRS designs need an excessive number of reflecting elements (N) is a big issue. The system becomes more costly, less user-friendly, and power-hungry as a result of this. The primary advantage of passive IRS technology is rendered useless by this approach. Having novel design solutions that provide superior EE with the fewest hardware difficulties is crucial in densely populated urban areas where long-distance visibility is limited, particularly in the presence of actual channel characteristics like as Rayleigh fading.

There are now many various methods to employ algorithms since they have become bigger. Deep reinforcement learning (DRL) is a more sophisticated approach to educate robots. It has been used for dynamic beamforming and resource allocation [7], [11]–[13]. It employs conventional optimization techniques such as block coordinate descent (BCD) [8] and alternating optimization (AO) [10], [14]. Basic performance analyses for complicated architectures, such as multi-antenna multi-IRS systems operating in generalized fading channels, have been conducted to enhance these applied studies [15]. Recent studies have also started to include non-ideal hardware features, like nonlinear energy harvesting circuits and workable phase-shift models, in recognition of a route to real-world implementation [16].

Despite these significant developments, a significant and ongoing problem that has been identified in numerous studies [8], [10], [11], [14], [16] is the frequent mishandling of the basic trade-off between EE and the N. High EE is frequently attained at the expense of hardware complexity; many models rely on a lot of elements [9], [17]–[19], or only work well in certain deployment scenarios [20], [21]. On the other hand, other methods have low EE, frequently as a result of their optimization algorithms' high computational overhead [11], [14]. Most of these studies assume mixed NLOS and LOS propagation conditions, which is perhaps the most important factor for urban 6G deployments. Pure Rayleigh fading, the predominant channel model in crowded urban areas with rich scattering and no direct LOS path, is ignored by this assumption. This oversight compromises the suitability of current solutions in the very settings where IRS technology is most promising. As a result, there is a glaring need for a low-complexity optimization framework that, in realistic Rayleigh fading conditions, maximizes EE with few reflective elements.

A dynamic-static particle swarm optimization (DS-PSO) framework for IRS-enabled 6G networks is presented in this paper to close this gap. Phase shifts and user scheduling are dynamically modified by the framework to optimize EE and minimize total N. We have three things to contribute: empirical validation showing superior EE (366 Mbit/Joule) with a minimal N (7) compared to benchmarks; an artificial intelligence (AI)-driven optimization algorithm DS-PSO, which decouples exploration and exploitation to optimize IRS performance with low complexity; and a comprehensive system model under realistic Rayleigh fading. This study provides an energy-efficient, scalable solution for urban communication infrastructure by addressing these problems and extending the use of IRS technology in next-generation networks.

The rest of the outline for the paper is below. Section 2 provides a description of the proposed DS-PSO algorithm, including its formulation, key characteristics, and computational complexity. The research methodology is presented in section 3, which includes the simulation setup, the problem formulation for EE optimization, and the system and channel model. A comparison with previous works, an ablation study on algorithmic convergence, an analysis of energy efficiency, a discussion of practical limitations, and an explanation of some significant issues for possible future research are all included in section 4, which is devoted to the results and discussion. In section 5, we finally provide the findings of our investigation.

2. PROPOSED ALGORITHM

The AI-powered DS-PSO algorithm, which maximizes the use of IRS, is covered in this section. In order to better balance exploration and exploitation in intricate, non-convex search spaces, DS-PSO improves on the traditional PSO by utilizing a hybrid topological paradigm with dual static (S) and dynamic (D) influence fields. Table 1 summarizes the main parameters controlling the algorithm's operation.

Table 1. Basic parameters for running the AI-based DS-PSO algorithm

Parameter	Value
Maximum Iteration (i)	1000
Particles (par) or (swarm size)	50
Probability of neighborhood restructuring periods	0.5
Coefficient of Intercept (spaced points of frequency)	1
The minimum values (V_{min}) and maximum values (V_{max}) of the search space's	(1, 70)

2.1. Algorithmic formulation

The DS-PSO algorithm, which is parameterized according to Table 1, functions in five main stages:

- Phase 1: the initialization stage. $PS = 50$ is used to initialize a swarm of PS particles. Every particle i is given a velocity $V_{par(i)}$ that is uniformly sampled from the range $[V_{min}, V_{max}] = [1, 70]$ and a randomized position $X_{par(i)}$ (within the search space). Each particle's initial position $X_{par(i)}$ is used to set its personal best (Pos_{par}), dynamic best ($D_{\text{par\_best}}$), and static best (S_{par_best}).

– Phase 2: dual-topology velocity modulation (velocity update). Particle velocities are updated each iteration using a tripartite attraction model that incorporates guidance from the particle's own memory and its topological neighbourhoods:

$$V_{par}(i) = C_c[V_{par}(i-1) + C_1R_1\left(Pos_{par}(i-1) - X_{par}(i-1)\right) + C_2R_2\left(D_{parbest}(i-1) - X_{par}(i-1)\right) + C_3R_3\left(S_{parbest}(i-1) - X_{par}(i-1)\right)] \quad (1)$$

where ($C_c \approx 0.7298$) is the constriction coefficient preventing divergence, ($C_1, C_2, C_3 = 4.1/3 \approx 1.3667$) are acceleration coefficients, and R_1, R_2, R_3 are random numbers uniformly distributed in [0, 1].

– Phase 3: position update and fitness evaluation. Particles relocate based on their updated velocity:

$$X_{par}(i) = X_{par}(i-1) + V_{par}(i) \quad (2)$$

An evaluation is conducted on the objective function $f(X_{par})$. The individual best (Pos_{par}), updating in the event that a better solution is discovered. Also updated appropriately are the static best S_{par_best} (best in the static neighborhood) and the dynamic best D_{par_best} (best in the dynamic neighborhood).

– Phase 4: restructuring the neighborhood dynamically. The dynamic neighbourhoods undergo stochastic reconfiguration with probability $probD = 0.5$ (as specified in Table 1). This helps break free from local optima by introducing exploratory noise.

– Phase 5: finalization and output. The algorithm returns the optimal particle position X_{par} and the associated fitness value $f(X_{par})$ when $i_{max} = 1000$ iterations have been completed.

The pseudocode for the DS-PSO algorithm is available in [22] for a detailed description of the algorithmic steps. Several recent optimization challenges, such as those mentioned in [23]–[25], have demonstrated the algorithm's resilience and effectiveness.

2.2. Key innovations

There are three main ways that DS-PSO is different from standard PSO: i) topological duality: by separating exploration (led by D_{par_best}) and exploitation (led by S_{par_best}) into different influence fields, it can use a well-rounded and successful search strategy; ii) stochastic reconfiguration: by using probabilistic restructuring of dynamic neighborhoods, population-based optimizers can avoid the common mistake of converging too quickly; and iii) triadic acceleration: the three-coefficient system (C_1, C_2, C_3) makes particle guidance better than the usual social/cognitive binary model. This makes convergence properties more reliable.

2.3. Complexity analysis

The difficulty of computing DS-PSO is one of the primary reasons it cannot be applied to real-time systems. Each iteration's complexity is $O(P)$, where P is the number of particles (50, according to Table 1). Since we need to adjust each particle's position and speed as well as check the fitness function, this linear scaling is required. While maintaining the $O(P)$ complexity, DS-PSO only adds a constant number of particles, but it takes more effort to remember the two best values for each particle (D_{par_best} and S_{par_best}).

Because of this, the optimization's overall cost is $O(IP)$, where I is the number of iterations (1000, according to Table 1). The main benefit of DS-PSO is how quickly it converges. Compared to classical PSO, DS-PSO usually yields a high-quality solution in a much smaller number of iterations (a smaller I) by skillfully balancing exploration and exploitation. It is perfect for real-time IRS Optimization problems because, in practice, this reduction in the number of iterations required can reduce the overall computational cost to $O(IP)$ while keeping the same performance threshold.

3. METHOD

This section describes the research methodology, which includes the formulation of the optimization problem, the system and channel models, and the comprehensive simulation setup.

3.1. System and channel model

The system model considers a source (S) communicating with a destination (D), aided by either a standard or an optimized IRS. The overall transmission architecture is depicted in Figure 1. The communication scenario illustrating the specific channel gains in both standard and optimized IRS-assisted links is shown in Figure 2. The performance of both IRS models is evaluated and compared against a baseline single-input single-output (SISO) system.

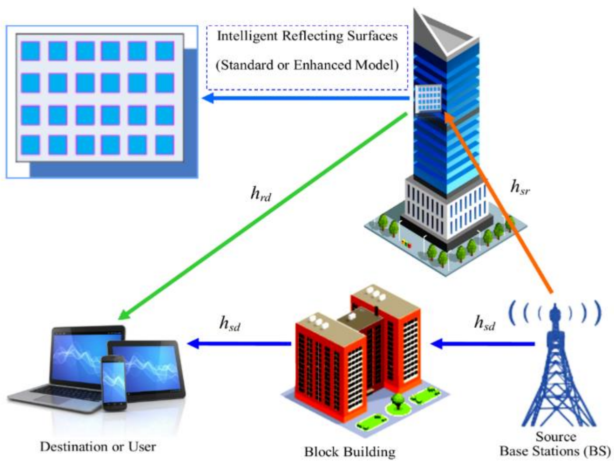

Figure 1. Data transmission supported by the (IRS *s*tandard/IRS *e*nhanced) models

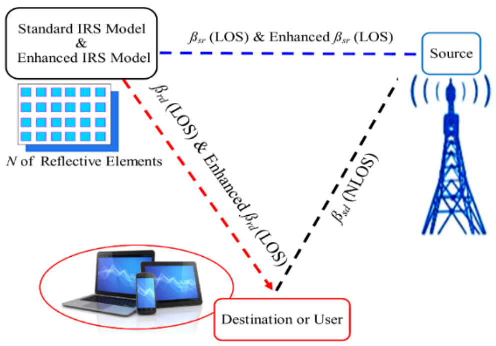

Figure 2. Destination variables for the communications system simulation setup with standard/enhanced IRS

For the baseline SISO channel, the received signal and its corresponding achievable rate are given by:

$$y = h_{\mathrm{sd}}\sqrt{ps} + n \tag{3}$$

$$R_{SISO} = \log_2\left(1 + \frac{p|h_{sd}|^2}{\sigma^2}\right) \tag{4}$$

where h_{sr} is the channel coefficient, s represents the information signal of unit-power, p represents the power of transmission, and $n \sim \mathcal{N}c(0, \sigma^2)$, represents the noise at the receiver (additive white Gaussian noise (AWGN)).

The standard IRS model comprises (N) passive reflecting elements. $h_{sr} \in \mathbb{C}^N$ represents the source-to-IRS channel, and $h_{rd} \in \mathbb{C}^N$ represents the IRS-to-destination channel. The IRS reflection matrix is $\Theta = \alpha diag.\left(e^{j\theta 1}, \ldots, e^{j\theta N}\right)$, where α is the reflection coefficient and (θ_n) are the phase shifts. The received signal with IRS assistance is:

$$y_{IRS} = (h_{sd} + h_{sr}^T \Theta h_{rd})\sqrt{ps} + n \tag{5}$$

The optimal phase shifts that align the reflected signals coherently at the destination determine the possible rate, which is given by (6).

$$R_{\mathrm{IRS}}(N) = \log_2\left(1 + \frac{p\left(|h_{sd}|+\alpha\sum_{n=1}^{N}|[h_{sr}]_n[h_{rd}]_n|\right)^2}{\sigma^2}\right) \tag{6}$$

The optimized IRS model (IRS^o) proposed in this work enhances performance by reducing the total N to N^o, while improving phase-shift optimization. Its reflection matrix is $\Theta^o = \alpha diag\left(e^{j\theta 1}, \dots, e^{j\theta N^o}\right)$. The received signal and achievable rate for this model are:

$$y_{IRS}^o = (h_{sd} + h_{sr}^T\Theta^o h_{rd})\sqrt{p^o s^o} + n^o \tag{7}$$

$$R_{IRS^o}^o(N^o) = \log_2\left(1 + \frac{p^o\left(|h_{sd}|+\alpha\sum_{n^o=1}^{N^o}|[h_{sr}]_{n^o}[h_{rd}]_{n^o}|\right)^2}{\sigma^2}\right) \tag{8}$$

where s^o is the information signal of unit-power, (p^o) is the power of transmission, and $n^o \sim \mathcal{N}c(0,\sigma^2)$, is the noise for the optimized system.

3.2. Optimization problem

The core objective is to optimize IRS-assisted communication with two key goals: maximizing EE and minimizing the number of IRS elements. This is formalized as a multi-objective optimization problem:

$$\min_{\Theta,N}[-EE(\Theta,N),N]^T \tag{9}$$

Subject to: rate constraint: $R(\Theta,N) \geq R_{min}$; Power constraint: $\|\ \Theta\ \|_F^2 \leq P_{max}$; Element limit: $N \leq N_{max}$.

In (10) can be used to determine EE by comparing the rate to the total energy consumption.

$$EE = R/P_{total} \tag{10}$$

where the total power consumption (P_{total}) includes: Transmit power p, static power consumption P_s (source) and P_d (destination), IRS element power dissipation NP_e Thus, the optimization problem becomes:

$$\max_{N,\Theta}\frac{R(N,\Theta)}{P_{total}(N)} \tag{11}$$

Subject to: minimum rate requirement: $R(N,\Theta) \geq R_{min}$; maximum IRS elements: $N \leq N_{max}$.

3.3. Simulation setup

The proposed model performance is evaluated through simulations using the 3rd generation partnership project (3GPP) urban micro (UMi) channel model at a carrier frequency of 3 GHz, incorporating both NLOS and LOS conditions for distances $d \geq 10$ m. The antenna gains for the transmitter (G_t) and receiver (G_r) are set to 5 dBi, and the destination device uses an omnidirectional antenna (0 dBi). Shadow fading is neglected.

The channel gain values for UMi-LOS and UMi-NLOS are computed using:

$$\beta(d)[dB] = G_t + G_r + \begin{cases} -37.5 - 22\log_{10}\left(\frac{d}{1\text{ m}}\right) & \mathit{if}\,\text{LOS} \\ -35.1 - 36.7\log_{10}\left(\frac{d}{1\text{ m}}\right) & \mathit{if}\,\text{NLOS} \end{cases} \tag{12}$$

Optimized UMi-LOS channel gain, resulting from the proposed algorithm application, is derived as:

$$\beta^o(d)[dB] = \text{Optimized }[G_t + G_r + \{-37.5 - 22\log_{10}(d/1\text{ m})\}]\ \mathit{if}\text{ optimized LOS} \tag{13}$$

The simulation presupposes that the IRS and the source are 70 meters apart. There is a 10 m range between the source and the destination/user. The total power consumption (P_{total}) is calculated for the standard IRS model, the optimized IRS model, and the SISO case using (14)-(16), respectively.

$$P_{IRS}^{Total}(N) = \frac{p_{IRS}(N)}{v} + P_s + P_d + NP_e \tag{14}$$

$$P^{o}{}_{IRS^o}^{Total}(N^o) = \frac{p^{o}{}_{IRS^o}(N^o)}{v} + P_s + P_d + N^o P_e \tag{15}$$

$$P_{SISO}^{Total} = \frac{p_{SISO}}{v} + P_s + P_d \tag{16}$$

The optimal number of elements for the standard and optimized IRS models is determined in (17), (18), respectively.

$$N^{opt(IRS)} = \sqrt[3]{\frac{(2^{R_d}-1)\sigma^2}{\alpha^2 \beta_{IRS} P_e}} - \frac{1}{\alpha}\sqrt{\frac{\beta_{sd}}{\beta_{IRS}}} \tag{17}$$

$$N^{o\,opt(IRS^o)} = \sqrt[3]{\frac{(2^{R_d}-1)\sigma^2}{\alpha^2 \beta_{IRS^o}^{o} P_e}} - \frac{1}{\alpha}\sqrt{\frac{\beta_{sd}^{o}}{\beta_{IRS^o}^{o}}} \tag{18}$$

The basic parameters are: noise power spectral density of -174 dBm/Hz, noise power of -94 dBm, a noise figure of 10 dB, a bandwidth of 10 MHz, a fixed source-destination distance of 10 m, and power dissipation per IRS element. $P_e = 5\,mW$, source and destination hardware power consumption $P_s = P_d = 100\,mW$ a maximum data rate $R_d \leq 10\,bit/s/Hz$, reflection coefficient $\alpha = 1$, and power amplifier efficiency $v = 0.5$.

The EE for each case-SISO, standard IRS, and optimized IRS via (19)-(21), respectively is evaluated as a function of N, with the SISO case ($N = 0$) serving as the baseline.

$$EE_{SISO} = R_d / P_{SISO}^{Total} \tag{19}$$

$$EE_{IRS} = R_d / P_{IRS}^{Total} \tag{20}$$

$$EE_{IRS^o}^{o} = R_d / P^{o}{}_{IRS^o}^{Total} \tag{21}$$

4. RESULTS AND DISCUSSION

The simulation analysis and its results are described in this section. However, the proposed DS-PSO was used to evaluate the improved IRS model by comparing it with previous studies and benchmark systems. These results are interpreted, their importance is emphasized, and the study’s limitations are acknowledged in the discussion.

4.1. Analysis of EE and reflective elements

The successful optimization of the crucial trade-off between EE and N is the main discovery of this work. The suggested DS-PSO-optimized IRS model essentially separates hardware complexity from high performance, as shown in Figure 3. We find that with just seven elements; this model maintains a consistent peak EE of 366 Mbit/Joule. On the other hand, traditional models are still constrained by the inefficient trade-off whereby EE decreases as N increases.

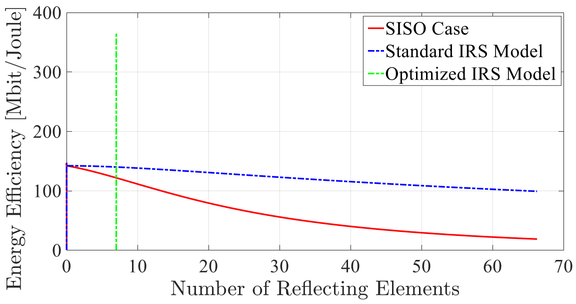

Figure 3. EE compared to the number of reflecting elements

In Figure 3, the SISO, standard IRS, and optimized IRS models' EE is plotted against the number of reflecting N. The graph clearly demonstrates a trade-off: for both the SISO and the conventional IRS benchmarks, EE decreases as N increases. However, this tendency is at odds with the DS-PSO-optimized IRS model, which relies on only seven pieces to maintain a peak EE of 366 Mbit/Joule. This illustrates the algorithm's capacity to differentiate between hardware complexity and high performance, which is an important step for 6G networks in the long run.

The SISO and conventional IRS benchmark models, on the other hand, demonstrate a substantial negative link between EE and N. When N grows from 7 to 66 in the SISO scenario, EE reduces a significantly, from 122.4 Mbit/Joule to 18.81 Mbit/Joule. Over the same range, the standard IRS model also gradually decreases from 140.2 Mbit/Joule to 99.19 Mbit/Joule. In order to effectively maximize resource utilization, intelligent, AI-driven optimization, like DS-PSO, is required. This proves that EE cannot benefit from merely increasing hardware complexity. The EE values that correlate to the trends in Figure 3 are described in detail in Table 2 for an exact quantitative analysis.

Table 2 shows the highest EE that each model can reach and the number of reflective N needed to get there. This shows the trade-off between performance and hardware complexity. The most important piece of information is that the optimized IRS model has a constant, higher EE, which shows that it is the most efficient.

Table 2. Peak performance comparison of the SISO, standard IRS, and optimized IRS models

Model	Optimal number of elements (N)	Peak EE (Mbit/Joule)
SISO	0 (Baseline)	122.4
Standard IRS	7	140.2
Optimized IRS (DS-PSO)	7	366.0

4.2. Comparative analysis with prior works

To put this performance in context, a strict comparison with earlier IRS/reconfigurable intelligent surface (RIS) studies (e.g., [6]–[11], [13], [14], [18]–[21], [26], [27]) was done. The results, which are shown in Table 3, focus on EE (in Mbit/Joule), number of reflective N, and operational distance (in meters) range. The results show a common trade-off in the literature: high EE is usually only possible in certain situations or requires a significant N. With an EE of 366 Mbit/Joule and a low N=7 over a useful 70m range, the suggested DS-PSO-optimized IRS (see Table 3, samples 20–22) stands out in this regard. This creates a new standard for balancing performance and hardware complexity.

These results demonstrate that there are numerous strategic trade-offs in the literature. Scaling up is challenging despite the high EE of some studies due to their high hardware usage. For example, although using 300 to 1500 elements, the Laplace transform (LT)-based IRS model developed by Wang and Zhang [11] only achieves a very low EE of 0.008 to 0.012 Mbit/Joule. This implies that the elements are used inefficiently. The fundamental concepts of design have evolved, as evidenced by the IRS literature of today. Purchasing high-end hardware is a popular strategy for increasing performance. One such is a hybrid RIS-UAV model [9]. EE may be as low as 1 Mbit/Joule or as high as 155 Mbit/Joule, even with 2,350 pieces. As the system becomes bigger, it becomes less dependable and helpful. Björnson *et al.* [6] say that the basic idea can get an EE of up to 146 Mbit/Joule, but it is neither practical or cost-effective since it has too many parts (76 to 164).

An interesting area of research is the application of algorithmic augmentation in highly constrained contexts. Even though some solutions work well, they aren't always appropriate. This is restricted to 5–30 components and a 2.2-meter range using the BCD method [8], which only yields 19–20 Mbit/Joule. Certain algorithms, like channel knowledge map (CKM) [20] and AO [14], can achieve moderate EE by focusing only on certain tasks. Effective UAV deployment [26] and user association algorithms [18] are examples of localized optimization strategies that work well when there are few elements in a small area.

Research from 2024 and 2025 shows that the industry is still trying to find the right balance between performance and complexity. Research such as Fotock *et al.* [27] global energy efficiency (GEE) algorithm examine active and passive RIS, DRL [7], and meta-learning soft actor-critic (Meta-SAC) [13] to better allocate resources in specific operational areas that are frequently constrained. All of these efforts ultimately lead to the same conclusion: using hardware designs that aren't very scalable in practice or that limit operational range too much is usually what causes algorithms to be inefficient or use too much energy. This continuing discussion demonstrates that a solution that optimizes efficiency while reducing hardware requirements and maintaining a realistic deployment scope is still required. This case study shows how well the suggested DS-PSO optimized IRS works. Our model shows that it is possible to avoid this common trade-off by getting an EE of 366 Mbit/Joule with only seven parts over a useful 70-meter distance. It has the best mix of complexity, efficiency, and operational range for use in crowded urban areas.

Table 3. The comparison of the results of this study with the results of previous studies

No. sample	Ref.	Year	Type	Energy efficiency (EE)	Number of elements (N)	Range of distance (d)	Method proposed
1	[6]	2020	IRS	[0, 146]	[76, 164]	80 m	Standard IRS model
2	[8]	2022	IRS	[19, 20]	[5, 30]	2.2 m	The BCD based iterative algorithm
3	[11]	2022	IRS	[0.01, 0.013]	[50, 100]	700 m	Derivative of LT
4	[11]	2022	IRS	[0.008, 0.012]	[300, 1500]	700 m	Derivative of LT
5	[9]	2023	RIS	140	[1, 256]	65 m	Active RIS-UAV
6	[9]	2023	RIS	[1, 155]	[1, 2350]	65 m	Hybrid RIS-UAV
7	[21]	2023	RIS	10	64	500 Km to 2000 Km	Non-orthogonal multiple access (NOMA) low earth orbit (LEO) satellite communication
8	[20]	2023	RIS	[0.01, 0.11] [0.01, 0.09] [0.01, 0.07]	10×10	50×50 m square area	CKM approach
9	[14]	2023	IRS	[8.35, 13.15]	80	100×100 m square area	AO algorithm
10	[14]	2023	IRS	[8.35, 12.5]	50	100×100 m square area	AO algorithm
11	[18]	2023	IRS	[0.66, 1.8]	25	100×100 m square area	User association (UA), active beamforming, and passive beamforming (PB) called (IUA/PB) algorithm
12	[26]	2023	RIS	[8.12, 12.7]	8	100 m	Energy-efficient unmanned aerial vehicle deployment (EEUD) algorithm
13	[27]	2024	Active RIS	[1.6, 11]	[4, 300]	100 m	GEE algorithm
14	[27]	2024	Passive RIS	[3.4, 14.3]	[2, 300]	100 m	GEE algorithm
15	[19]	2024	IRS	[115, 129]	[10, 50]	200 m	AO algorithm
16	[10]	2025	IRS	[1.2, 21×10^4]	[60, 120]	350 m	AO
17	[7]	2025	IRS	[1, 22]	[4, 36]	20×20 m square area	Proximal policy optimization (PPO) algorithm within DRL
18	[13]	2025	RIS	[18, 25]	[5, 35]	0.05 m	Meta-reinforcement learning (Meta-SAC algorithm)
19	This study	2025	IRS	[99.19, 140.2]	[1, 66]	70 m	Standard IRS model
20	This study	2025	Optimized IRS	< 366 or 7.32	7	70 m	Proposed DS-PSO algorithm
21	This study	2025	Optimized IRS	366	7	70 m	Proposed DS-PSO algorithm
22	This study	2025	Optimized IRS	> 366	7	70 m	Proposed DS-PSO algorithm

The active RIS-UAV model [9] reaches 140 Mbit/Joule, and the AO-based IRS by Chen *et al.* [19] achieves an impressive 115-129 Mbit/Joule with 10-50 elements over 200 m. Using 60-120 elements over a 350-meter range, Li *et al.* [10] provide an AO framework for IRS-UAV communications that shows a wide EE range of 1.2-21×10^4 Mbit/Joule. On the other hand, models that concentrate on the extreme range, such as the IRS satellite of NOMA-LEO satellite [21], obtain an EE of 10 Mbit/Joule with 64 elements over 500-2000 km. This is a completely different trade-off, where efficiency is less significant than coverage.

With 1-66 elements, the standard IRS model from this study (see Table 3, sample 19) achieves an EE of 99.19-140.2 Mbit/Joule, which is comparable to other high-performing works like [6], [19]. However, by combining an unprecedented EE (366 Mbit/Joule) with minimal hardware (7 elements), the DS-PSO-optimized IRS (see Table 3, samples 20-21) sets a new standard for terrestrial networks. Over a 70-meter range, this performance level can be sustained. Although the models in [10] and [21] concentrate on specific domains (long-range UAVs and satellites), our model better balances efficiency and complexity for internet of things (IoT) and dense urban applications where reducing hardware costs and power consumption is crucial.

4.3. Ablation study on algorithmic convergence

Table 4 demonstrates that an ablation study was conducted to test the strength and speed of convergence of the DS-PSO algorithm by varying the maximum number of iterations (i) (250, 500, and 1000 iterations) while maintaining the same swarm size of $p = 50$ particles.

Table 4. Ablation study on DS-PSO convergence (EE vs. max iterations)

Maximum iterations (I)	Achieved EE (Mbit/Joule)	Notes
250	342	~93.4% of peak performance
500	358	~97.8% of peak performance
1000 (baseline)	366	Peak performance

The results, which are compiled in Table 4, show that DS-PSO continues to perform admirably even when its iteration budget is limited. The performance was great at 250 iterations, even better at 500 iterations, and the best it had ever been at 1000 iterations. This model is still much better than the IRS standard model. This shows that DS-PSO can find a solution that is almost perfect in a short amount of time. This is a key feature for real-time apps that don't have a lot of processing power. The algorithm can effectively balance exploration and exploitation thanks to its dual-topology design, which facilitates rapid and stable convergence.

4.4. Discussion

Disentangling hardware complexity from EE is the primary objective, as shown in section 4.1. The number of components in conventional models decreases as their utility increases. However, the optimized IRS is most effective when used with few components. For 6G networks to function well in the long run, AI-driven optimization is crucial. Many feel this is not the proper way for the IRS to operate.

With this fresh perspective, it outshines even the most well-thought-out strategies. According to the comparison in section 4.2, the majority of prior research has concentrated on either operational efficiency, which often requires a large number of components [13], [26], or increased EE, which typically requires a smaller number of elements [6], [19]. Contrarily, our research demonstrates a more refined equilibrium. The finest and most efficient IRS is the one that has been enhanced with DS-PSO. In highly crowded metropolitan regions, this combination tackles scalability and cost head-on.

Section 4.3 proof of algorithmic robustness demonstrates the method's generalizability. Thanks to its fast and near-optimal solution finding capabilities, the DS-PSO method is fantastic. Applications that operate in real-time and adapt to dynamic wireless settings rely on this. Also, it is a measure of performance. In conclusion, this study illustrates that an advanced, low-complexity AI algorithm like DS-PSO is crucial to surpass minor improvements and enable the development of a new class of high-efficiency, low-complexity IRS implementations for future networks.

4.5. Practical limitations and future work

In this study, our results show significant superiority. This study must acknowledge its practical limitations, though. Real-world dynamic wireless environments make it challenging to obtain the optimal channel state information (CSI) that the proposed model assumes. The performance of the proposed optimization algorithm is deteriorated by estimation errors, feedback delays, and out-of-date channel information. The accuracy of the channel parameters h_{sr} and h_{sd} is the only factor that affects the algorithm's phase shift optimization.

Additionally, the best IRS devices are assumed to have lossless continuous phase shifters in the proposed model. Nonlinearities in practice are caused by device defects such as amplitude changes, cross-coupling between reflective elements, and quantized phase shifts. These have the potential to impact EE gains in ways that signal coherence cannot.

It is essential for future work to deal with the CSI with limited accuracy. We plan to improve the DS-PSO framework by adding effective optimization techniques that particularly address channel uncertainty. To ensure that the optimized phase shifts continue to work even in the event of an imperfect channel, the problem is set up using either statistical channel models or specific CSI errors. Adding more realistic device models to the simulation setup is also crucial. The low-resolution phase shifters used in later studies may enable IRS modeling. In order to provide a more accurate performance evaluation and potentially bridge the gap between theoretical analysis and practical viability, specific insertion losses are incorporated into real-world applications.

Determining the algorithm's strength is an important research topic, making testing the algorithm in dynamic propagation scenarios a significant challenge. A fixed urban cell with a range of about 70 meters served as the basis for the study's model. However, a larger simulation range can show the real-time performance of the DS-PSO algorithm, including its speed of convergence and scalability. This range may include highly mobile scenarios such as satellite communication, vehicle-to-vehicle communication, and different types of terrain. To improve the algorithm's scalability and generalization, it could be tested in non-NLOS environments and with vanishing distributions other than the Rayleigh distribution. It may therefore be better than the Rayleigh vanishing model.

Eventually, the study's focus might go beyond point-to-point communications. A good next step is to consider larger, more complex network architectures that make use of better IRSs. This could mean looking into how better IRS affects MIMO systems to make them more diverse overall, or it could mean that the surface could serve two purposes in ISAC frameworks. Looking into how the DS-PSO algorithm works with multiple users will also test how well it can be used in dense urban networks. This will be a logical and valuable advancement of this work, particularly in terms of interference management through intelligent beamforming.

5. CONCLUSION

The critical, and potentially unfeasible, balance between EE and device complexity is the primary challenge our study addresses, using IRSs for next-generation networks. We radically decoupled high performance from the large number of reflective elements by introducing a DS-PSO algorithm. The development of an optimized IRS model is our main achievement in this study. This model achieves an optimal EE of 366 Mb/J, using a stable, efficient reflective element set of only 7, enabled by AI-driven smart phase-shift optimization. Using a realistic Rayleigh vanishing channel model, the performance of our proposed model was maintained. The model is widely used in dense urban areas due to the extreme utility of the IRS technique. The results show a big difference in performance between the standard IRS model and the SISO baseline. As the number of elements went up, the EE went down a lot. As the number of elements went from 7 to 66, EE dropped sharply from 140.2 to 99.19 Mbit/J and from 122.4 to 18.81 Mbit/J, respectively. Advanced optimization is necessary because making hardware more complicated is not a good way to go. A comparative analysis with prior studies unequivocally illustrates the superiority of our methodology. However, some earlier research on large-scale devices has produced high EE, like a model that needs a smart reflective surface with 76 to 164 elements and has an EE of 146 Mbit/J. Previous research on devices in highly restricted environments has yielded only marginal efficiency. Our optimized IRS with DS-PSO, on the other hand, sets a new standard by combining the least amount of hardware with the most EE. We made the DS-PSO algorithm even more useful in real life by doing an ablation study on algorithmic convergence. It was verified that the proposed algorithm can achieve 93.4% of its maximum performance with just 250 iterations. For real-time applications, this is crucial. In the end, this study demonstrates that in order to surpass these minor enhancements and discover a solution that is scalable, economical, and energy-efficient, a low-complexity smart algorithm such as DS-PSO must be added. Sustainable development that prioritizes the infrastructure of next-generation urban communications networks can directly benefit from this nearly ideal solution.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
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CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

REFERENCES

[1] I. Hameed, A. Afridi, M. S. Baek, and H. K. Song, “Enhancing Physical Layer Security in WPCNs With IRS and Controlled Jamming for 6G IoT Applications,” *IEEE Access*, vol. 13, pp. 4670–4682, 2025, doi: 10.1109/ACCESS.2024.3525036.

[2] C. O. Nnamani, C. L. Anioke, S. Al-Rubaye, and A. Tsourdos, “Signal-to-Interference-Noise-Ratio Density Distribution for UAV-Carried IRS-to-6G Ground Communication,” *IEEE Access*, vol. 13, pp. 49824–49835, 2025, doi:

10.1109/ACCESS.2025.3549426.
[3] Y. Ma, R. Wu, Y. Zhang, Y. Shang, and L. Zhu, "Throughout Maximization for IRS-Assisted WPCN With Hybrid TDMA-NOMA Scheme," *IEEE Access*, vol. 13, pp. 23384–23398, 2025, doi: 10.1109/ACCESS.2025.3537988.
[4] M. Z. Iskandarani, "Effect of Intelligent Reflecting Surface on WSN Communication With Access Points Configuration," *IEEE Access*, vol. 13, pp. 13380–13394, 2025, doi: 10.1109/ACCESS.2025.3531637.
[5] N. Khan, A. Ahmad, A. Alwarafy, M. A. Shah, A. Lakas, and M. M. Azeem, "Efficient Resource Allocation and UAV Deployment in STAR-RIS and UAV-Relay Assisted Public Safety Networks for Video Transmission," *IEEE Open Journal of the Communications Society*, vol. 6, pp. 1804–1820, 2025, doi: 10.1109/OJCOMS.2025.3544440.
[6] E. Bjornson, O. Ozdogan, and E. G. Larsson, "Intelligent Reflecting Surface Versus Decode-and-Forward: How Large Surfaces are Needed to Beat Relaying?," *IEEE Wireless Communications Letters*, vol. 9, no. 2, pp. 244–248, 2020, doi: 10.1109/LWC.2019.2950624.
[7] Z. Ma *et al.*, "Deep Reinforcement Learning for Energy Efficiency Maximization in RSMA-IRS-Assisted ISAC System," *IEEE Transactions on Vehicular Technology*, vol. 74, no. 11, pp. 18273–18278, 2025, doi: 10.1109/TVT.2025.3580859.
[8] Y. Wu, F. Zhou, W. Wu, Q. Wu, R. Q. Hu, and K. K. Wong, "Multi-Objective Optimization for Spectrum and Energy Efficiency Tradeoff in IRS-Assisted CRNs With NOMA," *IEEE Transactions on Wireless Communications*, vol. 21, no. 8, pp. 6627–6642, 2022, doi: 10.1109/TWC.2022.3151624.
[9] C. Y. Goh, C. Y. Leow, and R. Nordin, "Energy Efficiency of Unmanned Aerial Vehicle with Reconfigurable Intelligent Surfaces: A Comparative Study," *Drones*, vol. 7, no. 2, p. 98, 2023, doi: 10.3390/drones7020098.
[10] J. Li, J. Liu, and J. Wang, "Optimizing spectrum and energy efficiency in IRS-enabled UAV-ground communications," *Computer Networks*, vol. 256, p. 110911, 2025, doi: 10.1016/j.comnet.2024.110911.
[11] W. Wang and W. Zhang, "Intelligent Reflecting Surface Configurations for Smart Radio Using Deep Reinforcement Learning," *IEEE Journal on Selected Areas in Communications*, vol. 40, no. 8, pp. 2335–2346, 2022, doi: 10.1109/JSAC.2022.3180787.
[12] W. Liu, X. He, H. Xu, Z. Wang, and A. Zhou, "Online deep learning based energy efficient optimization for IRS-assisted eMBB and URLLC services," *Physical Communication*, vol. 61, p. 102193, 2023, doi: 10.1016/j.phycom.2023.102193.
[13] A. Farhadi, R. Hatami, M. Robat Mili, C. Masouros, and M. Bennis, "A Meta-Learning Approach for Energy-Efficient Resource Allocation and Antenna Selection in STAR-BD-RIS Aided Wireless Networks," *IEEE Wireless Communications Letters*, vol. 14, no. 5, pp. 1421–1425, 2025, doi: 10.1109/LWC.2025.3543780.
[14] J. Jalali, A. Khalili, A. Rezaei, R. Berkvens, M. Weyn, and J. Famaey, "IRS-Based Energy Efficiency and Admission Control Maximization for IoT Users with Short Packet Lengths," *IEEE Transactions on Vehicular Technology*, vol. 72, no. 9, pp. 12379–12384, 2023, doi: 10.1109/TVT.2023.3266424.
[15] S. Penchala, S. K. Bandari, V. V. Mani, and A. Drosopoulos, "Controlled Wireless Channel using Multi-Antenna Multi-IRS Assisted Communication System: A Comprehensive Performance Analysis," *IEEE Latin America Transactions* , vol. 23, no. 2, pp. 114–124, 2025, doi: 10.1109/TLA.2025.10851399.
[16] B. Katiyar, D. Mishra, S. Modem, and R. Saini, "Energy efficiency maximization in IRS-aided cooperative WPCN with non-linear EH users," *Electronics Letters*, vol. 61, no. 1, 2025, doi: 10.1049/ell2.13291.
[17] C. Huang, A. Zappone, G. C. Alexandropoulos, M. Debbah, and C. Yuen, "Reconfigurable intelligent surfaces for energy efficiency in wireless communication," *IEEE Transactions on Wireless Communications*, vol. 18, no. 8, pp. 4157–4170, 2019, doi: 10.1109/TWC.2019.2922609.
[18] E. M. Taghavi, R. Hashemi, A. Alizadeh, N. Rajatheva, M. Vu, and M. Latva-Aho, "Joint Active-Passive Beamforming and User Association in IRS-Assisted mmWave Cellular Networks," *IEEE Transactions on Vehicular Technology*, vol. 72, no. 8, pp. 10448–10461, 2023, doi: 10.1109/TVT.2023.3260922.
[19] Q. Chen, Y. Zhou, W. Xu, and Y. Wu, "Energy-Efficient Resource Allocation for IRS-Assisted SWIPT-Enabled D2D Communications With Imperfect CSI," *IEEE Communications Letters*, vol. 28, no. 4, pp. 857–861, 2024, doi: 10.1109/LCOMM.2024.3364829.
[20] E. M.Taghavi, R. Hashemi, N. Rajatheva, and M. Latva-Aho, "Environment-Aware Joint Active/Passive Beamforming for RIS-Aided Communications Leveraging Channel Knowledge Map," *IEEE Communications Letters*, vol. 27, no. 7, pp. 1824–1828, 2023, doi: 10.1109/LCOMM.2023.3270491.
[21] W. U. Khan, E. Lagunas, A. Mahmood, S. Chatzinotas, and B. Ottersten, "Energy-Efficient RIS-Enabled NOMA Communication for 6G LEO Satellite Networks," *IEEE Vehicular Technology Conference*, vol. 2023–June. IEEE, 2023, doi: 10.1109/VTC2023-Spring57618.2023.10200793.
[22] D. Sanchez, "DS-PSO: Particle Swarm Optimization with Dynamic and Static Topologies," 2017.
[23] A. T. Alsahlanee, "Convergence Rate for Low-Pass Infinite Impulse Response Digital Filter," *Journal of Physics: Conference Series*, vol. 1963, no. 1, p. 12103, 2021, doi: 10.1088/1742-6596/1963/1/012103.
[24] V. Chau-Huy, M. T. P. Le, V. Nguyen-Duy-Nhat, N. Tran-Thi-Kim, and T. Pham-Viet, "PSO-Based Nonlinear Energy Harvesting Sum Maximization in IRS-Assisted WET System," *2025 10th International Conference on Applying New Technology in Green Buildings (ATiGB). IEEE*, pp. 315–319, July 25, 2025, doi: 10.1109/atigb66719.2025.11142146.
[25] A. T. R. Alsahlanee and J. K. S. Al-Safi, "Improving Channel Gain of 6G Communications Systems Supported by Intelligent Reflective Surface," *Indonesian Journal of Electrical Engineering and Informatics*, vol. 13, no. 1, pp. 57–68, 2025, doi: 10.52549/ijeei.v13i1.6169.
[26] Y. Yao, K. Lv, S. Huang, X. Li, and W. Xiang, "UAV Trajectory and Energy Efficiency Optimization in RIS-Assisted Multi-User Air-to-Ground Communications Networks," *Drones*, vol. 7, no. 4, p. 272, 2023, doi: 10.3390/drones7040272.
[27] R. K. Fotock, A. Zappone, and M. Di Renzo, "Energy Efficiency Optimization in RIS-Aided Wireless Networks: Active Versus Nearly-Passive RIS with Global Reflection Constraints," *IEEE Transactions on Communications*, vol. 72, no. 1, pp. 257–272, 2024, doi: 10.1109/TCOMM.2023.3320700.

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