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AN OPTIMIZATION-DRIVEN STRATEGY FOR INTELLIGENT PLACEMENT OF AIGC ADVERTISING

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As e-commerce continues to expand, AIGC-based advertising has gained momentum, making efficient and cost-effective ad placement a key priority for businesses. Because placement decisions are shaped by many interacting factors, this study proposes a research framework that formulates AIGC advertising placement as a multi-objective optimization problem and solves it using a locust optimization algorithm. The model defines objective functions, constraints, and fitness measures aligned with practical operating conditions, and then computes an optimal placement strategy through iterative optimization. To assess the approach, numerical simulations are carried out in MATLAB within an experimental environment. Results under standard test functions indicate strong algorithm stability and convergence, supporting the credibility of the optimization outcomes. Performance simulations further show that the resulting strategy achieves an optimal balance between dissemination efficiency and advertising expenditure, yielding a dissemination efficiency of 3,984 and an advertising cost of 9,783 yuan, thereby improving overall returns. These findings demonstrate the practical usefulness of the multi-objective locust optimization algorithm for guiding intelligent AIGC advertising placement.

Index Terms — locust optimization algorithm, AIGC advertising, objective function, constraint conditions

INTRODUCTION

With the rapid advancement of internet technologies, digital marketing has become a core pillar of modern corporate marketing. Especially with the rise of mobile networks, social platforms, and artificial intelligence, digital advertising has experienced major shifts in both format and content, transforming how ads are designed and delivered [1, 2]. As the digital and physical spheres integrate more tightly, AI-generated content (AIGC) is steadily driving a deep transformation by reshaping—and in some cases overturning—how digital content is produced and consumed. This shift is expected to greatly expand everyday digital experiences and serve as a foundational force supporting the move toward a new stage of digital civilization [3, 4, 5, 6]. At present, AIGC is responsible for about 38

In today's crowded communication ecosystem, advertising messages are increasingly disrupted by competing information streams. Under these conditions, ensuring that the right advertising content reaches the right audience within an overwhelming volume of information has become a central challenge in digital marketing. Conventional placement approaches often depend on experience-driven judgment and simple statistical methods; these practices are typically inefficient and fail to capture audiences at a deeper level, provide limited media selection, rely on subjective placement decisions, and make it difficult to quantify, manage, and optimize campaign outcomes. Moreover, such broad targeting frequently causes substantial waste of resources [13, 14, 15, 16]. The rise of multi-objective optimization algorithms offers a promising path for addressing these limitations.

Multi-objective optimization focuses on identifying a collection of Pareto-optimal (non-dominated) solutions when several objectives must be optimized simultaneously. A solution is considered non-dominated if no other alternative performs better across all objectives at once [17]. Widely used methods include genetic algorithms, particle swarm optimization, and simulated annealing, which can support balanced decision-making across key AIGC advertising indicators—such as click-through performance, conversion cost, brand risk management, creative quality, and coordination across multiple channels [18].

The comparative study reported in [19] showed that an AI-driven ad targeting method enhanced targeting precision and improved return on investment, strengthening the effectiveness of accurate ad delivery. In [20], the term frequency–inverse document frequency approach was applied to content analysis to interpret consumer behavior and anticipate market movements; when combined with AI-based hotspot tracking, it produced an ad placement strategy with stronger relevance and better timing. Work in [21] adopted big data techniques to assess the scale of high-precision, data-driven placements on advertising platforms and applied these techniques to content transmission pathways, improving placement accuracy, interactivity, and data utilization. Literature [22] combines big data, machine learning, and deep learning to construct an intelligent advertising decision system that builds user profiles, designs advertising strategies, forecasts and evaluates effectiveness, raises click-through and conversion rates, and enables more accurate and context-relevant placement. According to [23], strategies based on Thompson sampling, exponential greedy methods, and upper confidence bound techniques can all increase click-through rates, with Thompson sampling delivering better performance than the other two and enabling more efficient allocation of advertising resources. In [24], reinforcement learning is used to predict and adaptively learn user preferences, while genetic algorithms are integrated to search and refine advertising strategies, resulting in more precise digital ad placement, improved relevance, higher click-through rates, and reduced computational overhead. Study [25] applies particle swarm optimization to mine high-profit item sets efficiently from databases, extracting valuable transaction patterns that can guide online advertising placement. Finally, [26] proposes a heuristic approach for computing approximate optimal placement solutions supported by particle swarm optimization; the resulting strategy improves dissemination effectiveness while lowering costs and reducing repetition.

A synthesis of the existing literature indicates that AIGC advertising strategy design naturally fits a multi-objective optimization framework. Motivated by this, the present work proposes an AIGC placement strategy built on a multi-objective locust optimization algorithm. First, in line with real-world AIGC placement requirements, the objective function, constraints, and fitness formulation are specified. Next, the algorithm's update rules and solution efficiency settings—such as solution speed and position updates—are defined. With these components established, the multi-objective locust optimization algorithm is applied to solve the objective function and obtain an optimal AIGC advertising placement strategy. To assess whether the proposed approach meets the study's aims, validation is carried out from two perspectives: benchmark test functions and performance in practical application scenarios. The goal is to demonstrate that the multi-objective locust optimization algorithm can serve as a useful reference for enterprise decision-making in AIGC advertising placement.

RESEARCH ON ADVERTISING PLACEMENT BASED ON MULTI-OBJECTIVE OPTIMIZATION ALGORITHMS

Multi-objective optimization problems

Mathematical Model

There are multiple conflicting objectives in the practical application of nature and science, and such problems are commonly referred to as multi-objective problems (MOPs). Without loss of generality, taking minimization MOPs as an example, its mathematical description can be generalized as:

$$\begin{aligned} \min\ & \mathbf{F}(\mathbf{x}) = \left(f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_K(\mathbf{x})\right)^T, \\ \text{s.t.}\quad & \beta_j(\mathbf{x}) \geq 0, \quad j = 1, \ldots, J, \\ & \gamma_h(\mathbf{x}) = 0, \quad h = 1, \ldots, H, \\ & \mathbf{x} \in \mathbb{R}^K. \end{aligned} \tag{1}$$

where $\mathbf{x} = (x_1, x_2, \ldots, x_K)^T$ is the decision vector, $\mathbf{F}(\mathbf{x})$ is the objective vector, and $\beta_j(\cdot)$ and $\gamma_h(\cdot)$ denote inequality and equality constraints.

Due to the conflicting nature of the objectives in MOPs, multi-objective evolutionary algorithms cannot find a unique optimal solution that simultaneously minimizes all objective functions in decision space [27]. Therefore, the concept of Pareto optimality must be introduced.

Let $\mathbf{x}_1, \mathbf{x}_2$ be two decision vectors. $\mathbf{x}_1$ dominates $\mathbf{x}_2$ (denoted $\mathbf{x}_1 \prec \mathbf{x}_2$) if and only if:

$$\begin{cases} \forall i \in \{1, 2, \ldots, M\} : f_i(\mathbf{x}_1) \leq f_i(\mathbf{x}_2), \\ \exists j \in \{1, 2, \ldots, M\} : f_j(\mathbf{x}_1) < f_j(\mathbf{x}_2). \end{cases} \tag{2}$$

When no other feasible solution dominates $\mathbf{x}^*$, $\mathbf{x}^*$ is Pareto optimal. The set of all Pareto optimal solutions is:

$$PS = \left\{\mathbf{x} \in \mathbb{R}^K : \nexists \mathbf{y} \in \mathbb{R}^K \text{ such that } \mathbf{F}(\mathbf{y}) \prec \mathbf{F}(\mathbf{x})\right\}. \tag{3}$$

Conflicting Goals

An important condition for MOPs is that objectives are mutually conflicting. Suppose X is a subset of the decision space. Two objectives can be related as:

- Conflict: if for $\mathbf{x}_1, \mathbf{x}_2 \in X$, $f_i(\mathbf{x}_1) \le f_i(\mathbf{x}_2)$ implies $f_j(\mathbf{x}_1) \ge f_j(\mathbf{x}_2)$.
- Support: if $f_i(\mathbf{x}_1) \le f_i(\mathbf{x}_2)$ implies $f_j(\mathbf{x}_1) \le f_j(\mathbf{x}_2)$.
- Independence: otherwise.

An example is given by $f_1(x) = 1.5 + \sin(x)$ and $f_2(x) = 1.5 + \cos(x)$: the objectives conflict on $[\pi/2, \pi]$ but not on $[\pi, 3\pi/2]$.

Locust Optimization Algorithm

With the development of artificial intelligence, numerous intelligent optimization algorithms have been proposed. Typical algorithms include genetic algorithms, tabu search, simulated annealing, and particle swarm optimization. The multi-objective locust optimization algorithm has a simple structure, strong search capabilities, and stable performance. Therefore, this paper selects the locust optimization algorithm for model construction.

Single-objective locust optimization algorithm

The Locust Optimization Algorithm (GOA) can be used to address minimization or maximization problems. The life cycle of locusts is divided into larval and adult stages. Based on this, GOA is divided into development (local search) and exploration (global search).

The locust position update can be written as:

$$\mathbf{F}_i = \mathbf{E}_i + \mathbf{G}_i + \mathbf{A}_i, \tag{4}$$

where $\mathbf{F}_i$ is the position of the i-th locust, $\mathbf{E}_i$ denotes interactions, $\mathbf{G}_i$ gravitational influence, and $\mathbf{A}_i$ wind influence.

The interaction term is:

$$\mathbf{E}_i = \sum_{\substack{j=1 \\ j\neq i}}^{N} f(d_{ij}) \frac{\Delta \mathbf{d}_{ij}}{d_{ij}}, \tag{5}$$

where $d_{ij} = \|\Delta \mathbf{d}_{ij}\|$ is distance, $\frac{\Delta \mathbf{d}_{ij}}{d_{ij}}$ is the unit vector, and $f(\cdot)$ is typically:

$$f(d) = \delta\, e^{-d/t} - e^{-d}, \tag{5a}$$

with δ the attraction strength and t the attraction length scale (distance often controlled within $[1,4]$).

Gravitational and wind terms:

$$\mathbf{G}_i = -\theta\, \mathbf{e}_\theta, \qquad \mathbf{A}_i = \nu\, \mathbf{e}_\nu, \tag{6}$$

where θ is gravitational constant with direction $\mathbf{e}_\theta$, and ν is wind coefficient with direction $\mathbf{e}_\nu$.

A common GOA update form:

$$\mathbf{F}_i = \sum_{\substack{j=1 \\ j\neq i}}^{N} f(d_{ij}) \frac{\Delta \mathbf{d}_{ij}}{d_{ij}} - \theta\, \mathbf{e}_\theta + \nu\, \mathbf{e}_\nu. \tag{7}$$

After scaling to the search bounds, an improved form is:

$$\mathbf{F}_i = \psi \sum_{\substack{j=1 \\ j\neq i}}^{N} f(d_{ij}) \frac{\Delta \mathbf{d}_{ij}}{d_{ij}} + \left(\frac{\mathbf{U}_d - \mathbf{L}_d}{2} \right) + \mathbf{T}, \tag{8}$$

where $\mathbf{U}_d, \mathbf{L}_d$ are upper/lower bounds in dimension d, $\mathbf{T}$ is a target (best) position, and ψ is a contraction factor:

$$\psi = \psi_{\max} - (\psi_{\max} - \psi_{\min}) \frac{t}{T}. \tag{9}$$

Here t is the current iteration, and T is the maximum number of iterations.

GOA steps (summary): (1) Initialize parameters. (2) Compute fitness and keep best position $\mathbf{F}$. (3) Update ψ using (9). (4) Update locust positions using (8), recompute fitness, update best $\mathbf{F}$. (5) Repeat until reaching max iterations and output $\mathbf{F}$.

Multi-objective locust optimization algorithm

As real-world problems become complex, single-objective optimization is insufficient; multi-objective optimization has become a focal topic. A multi-objective problem can be written in minimization form:

$$\begin{aligned} \min \quad & \mathbf{F}(\mathbf{J}) = (f_1(\mathbf{J}), f_2(\mathbf{J}), \ldots, f_t(\mathbf{J})), \\ \text{s.t.} \quad & g_i(\mathbf{J}) \geq 0, \quad i = 1, \ldots, m, \\ & h_i(\mathbf{J}) = 0, \quad i = 1, \ldots, p, \\ & L_i \leq J_i \leq U_i, \quad i = 1, \ldots, n. \end{aligned} \tag{10}$$

Pareto dominance (multi-objective): $\mathbf{J}$ dominates $\mathbf{y}$ if it is no worse in all objectives and better in at least one.

Pareto optimal solution set:

$$\Xi_{\text{set}} = \{\mathbf{J} : \nexists \mathbf{y} \in X \text{ such that } \mathbf{F}(\mathbf{y}) \prec \mathbf{F}(\mathbf{J})\}. \tag{11}$$

Pareto front:

$$\Xi_{\text{front}} = \{\mathbf{F}(\mathbf{J}) : \mathbf{J} \in \Xi_{\text{set}}\}. \tag{12}$$

The primary difference between MOGOA and GOA lies in objective updating. MOGOA maintains an archive of non-dominated solutions (Pareto set), and updates it each iteration. If archive capacity is exceeded, solutions are removed probabilistically to maintain diversity, using probability proportional to neighborhood density (as described in the PDF).

Building an AIGC advertising placement decision-making model

Objective Function

Assume a company invests in AIGC advertising for a new product. Let the advertising budget be C_0. The company chooses media/websites from m types (e.g., variety shows, dramas, games, social media, short videos, etc.), selecting n_i candidates per type.

The model aims to maximize effectiveness while minimizing cost:

(1) Maximize dissemination effectiveness

$$\max S = \sum_{i=1}^{m} \sum_{j=1}^{n_i} (u_{ij}a + d_{ij}(1-a))\, x_{ij}, \tag{13}$$

where S is total effectiveness, $x_{ij} \in \{0,1\}$ indicates whether medium j in type i is selected, u_{ij} is traffic metric, d_{ij} is transaction metric, and $a \in [0,1]$ is a weight.

(2) Minimize advertising cost

$$\min C = \sum_{i=1}^{m} \sum_{j=1}^{n_i} c_{ij} x_{ij}, \tag{14}$$

where c_{ij} is the cost metric of that medium.

(3) Budget constraint

$$\sum_{i=1}^{m} \sum_{j=1}^{n_i} c_{ij} x_{ij} \le C_0. \tag{15}$$

(4) Select exactly one medium per type

$$\sum_{j=1}^{n_i} x_{ij} = 1, \qquad i = 1, 2, \ldots, m. \tag{16}$$

(5) Binary selection

$$x_{ij} \in \{0,1\}, \qquad i = 1, \ldots, m,\ j = 1, \ldots, n_i. \tag{17}$$

The cycle is set to 15 days for updating parameters dynamically from real-time media data (as described in the PDF).

Constraints

A constrained minimization problem can be written as:

$$\begin{aligned} &\min f(\mathbf{x}), \\ &\text{s.t. } g_i(\mathbf{x}) \le 0, \quad i = 1, 2, \ldots, q, \\ &\quad\;\; h_i(\mathbf{x}) = 0, \quad i = q+1, \ldots, m. \end{aligned} \tag{18}$$

Constraint violation for individual $\mathbf{x}$:

$$G_i(\mathbf{x}) = \begin{cases} \max\{g_i(\mathbf{x}), 0\}, & 1 \le i \le q, \\ \max\{|h_i(\mathbf{x})| - \delta, 0\}, & q+1 \le i \le m, \end{cases} \tag{19}$$

where δ is tolerance (e.g., 0.001 or 0.0001). Total constraint violation:

$$v(\mathbf{x}) = \sum_{i=1}^{m} G_i(\mathbf{x}). \tag{20}$$

Fitness calculation and screening of non-inferior solution sets

Each candidate has two fitness values: (i) advertising cost and (ii) dissemination efficiency, computed primarily from (13)–(15). Non-inferior (non-dominated) solutions satisfying the budget constraint and not dominated by other solutions are stored in a non-inferior set. The set is updated each iteration by merging old and new sets and removing dominated points.

Locust Speed and Position Updates

The locust velocity and position update used in the paper:

$$V^{k+1} = \omega V^k + c_1 r_1 (P_{id}^k - X^k) + c_2 r_2 (P_{gd}^k - X^k), \tag{21}$$

$$X^{k+1} = X^k + V^{k+1}. \tag{22}$$

Here ω is inertia weight, $r_1, r_2 \in [0,1]$ random, k iteration, P_{id} personal best, P_{gd} global best, c_1, c_2 constants.

Dynamic inertia update:

$$\omega = \omega_{\max} - (\omega_{\max} - \omega_{\min}) \left(\frac{\text{iter}}{\text{MaxIT}}\right)^2, \quad \omega_{\max} = 1.2,\ \omega_{\min} = 0.1. \tag{23}$$

Optimal solution for locusts

Individual best X_{best} is updated by dominance comparison between current solution and historical best; if incomparable, one is selected randomly. The group best g_{best} is selected randomly from the non-dominated archive.

EXPLORATION AND ANALYSIS OF AIGC ADVERTISING PLACEMENT STRATEGIES

Algorithm verification analysis based on test functions

Experimental setup

Experimental environment: Windows 8, CPU Intel Core i7-10210U (2.60GHz), memory 32GB, MatlabR2016(a). The proposed MOGOA is compared with related algorithms including GOA, chaotic GOA variants (CGOA1/CGOA2), GA, and GWO. Parameters: population size $N = 60$, iterations 200, dimension 60, $c_{\min} = 0.0001$, $c_{\max} = 1$. Each algorithm is run independently 100 times; performance is evaluated using mean and variance.

Ten standard benchmark test functions are used. The theoretical optimal solutions are 0, so smaller final results indicate better performance. Functions F1–F6 are single-modal; F7–F10 are multi-modal (used to test global search and escape from local optima).

Experimental Results

Table 1 shows experimental comparison results. Figure 1 provides convergence curves for the 10 functions.

Table 1: Test results of functions F1–F10 (mean, variance, time).

Function	Index	GOA	MOGOA	CAGOA1	GA	CGOA2	CAGOA
F1	Average	5.21E+01	5.09E-07	2.38E+01	1.24E-08	4.11E+01	2.11E+02
	Variance	35.0838	2.16E-08	19.17833	9.18E-09	17.1451	92.8539
	Time	50.216	70.232	51.418	35.082	53.172	52.069
F2	Average	5.08E+00	7.13E-05	6.32E-01	2.27E-02	1.46E-01	414.1939
	Variance	4.1062226	6.16E-06	1.115057	0.041483	0.315368	320.3716
	Time	51.072	75.272	63.176	47.161	65.361	64.226
F3	Average	3.15E+03	7.09E-07	6.22E+03	7.15E+03	2.21E+03	5.26E+06
	Variance	1521.391	3.66E-08	2244.01	6422.216	1247.376	2129.163
	Time	52.084	74.355	65.274	60.011	67.116	64.222
F4	Average	1.69E+01	2.49E-04	2.66E+01	1.88E+01	9.78E+00	2.07E+01
	Variance	6.4549	6.95E-06	25.2322	14.2937	10.2914	1.24905
	Time	51.216	87.172	62.311	54.269	64.212	61.322
F5	Average	1.12E+04	2.44E+01	1.55E+04	5.14E+04	2.14E+03	3.17E+03
	Variance	8.3981	0.01507	2.2517	8.4089	1.1877	2.2216
	Time	63.104	88.266	63.391	48.241	64.475	63.096
F6	Average	1.48E+01	1.38E-02	2.08E+01	1.28E+03	5.79E+01	3.16E+01
	Variance	4.27084	0.00273	14.0541	14.341	55.3477	22.009
	Time	62.368	75.816	62.226	48.096	63.192	61.146
F7	Average	9.18E+01	4.07E+01	1.45E+02	1.26E+02	1.18E+02	2.12E+02
	Variance	21.2332	71.2984	37.1513	20.0836	14.2719	22.3516
	Time	63.328	85.161	66.366	46.191	68.232	65.241
F8	Average	6.08E+00	4.49E-04	1.46E+01	1.12E+01	6.26E+00	6.19E+00
	Variance	0.74068	0.00028	0.15248	6.03674	1.36888	1.00251
	Time	132.417	183.216	136.116	94.461	137.145	135.061
F9	Average	1.16E+00	8.39E-07	1.06E+00	1.34E+01	1.06E+00	1.19E+00
	Variance	0.04247	1.15E-07	0.03052	11.1296	0.0382	0.03634
	Time	162.333	178.164	180.316	95.266	183.211	178.495
F10	Average	1.15E+00	8.41E-07	1.13E+00	8.46E+00	1.11E+00	1.18E+00
	Variance	0.13061	7.11E-04	0.21282	6.44042	0.12241	0.1153
	Time	163.232	210.207	175.466	105.176	180.448	162.261

Exploring Advertising Placement Strategies from a Multi-Objective Perspective

Generation of sample data

It is difficult to obtain statistical data about websites. This paper takes a small and medium-sized e-commerce enterprise as a reference object. Based on the collection of a large amount of website data, representative data is constructed according to the characteristics of different types of websites and their comparisons. The sample data is shown in Table 2. In specific implementation, solutions should be sought based on real-time data.

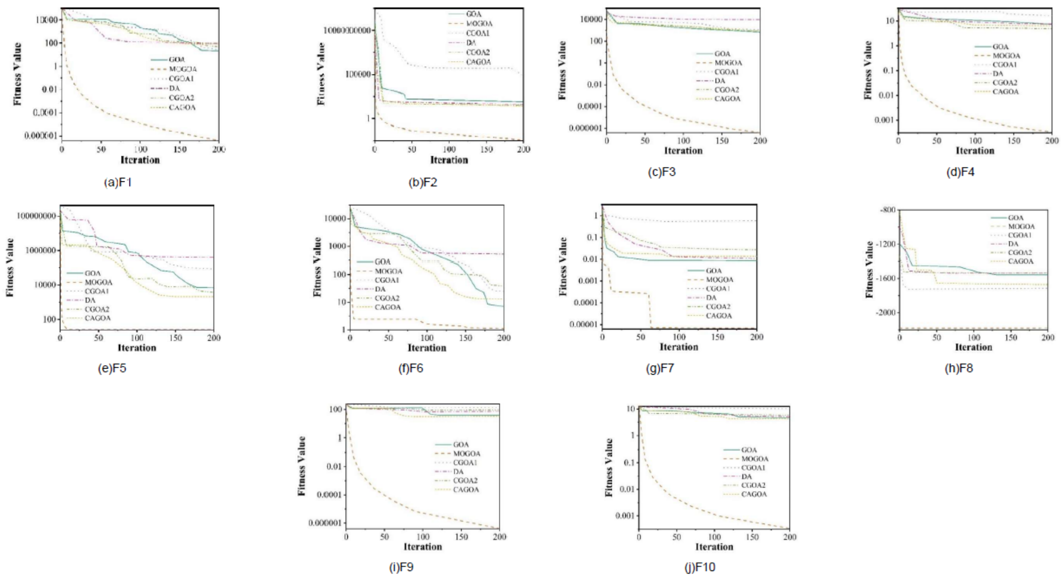

Figure 1: Iterative curves of fitness values for 10 test functions.

Table 2: Sample data.

Website type	Introduced traffic (units)	Transaction volume (units)	Communication effectiveness	Advertising expenses (yuan)
Portal website	12960	170	1430	3257
Portal website	8904	124	1022	2650
Portal website	10111	177	1137	2836
Portal website	9005	82	979	3282
Professional Website	2648	12	320	994
Professional Website	3515	60	445	1272
Professional Website	4397	43	483	1469
Professional Website	2753	7	329	1509
Search engine	3425	76	427	1362
Search engine	5201	103	542	1584
Search engine	6022	90	678	1805
Search engine	4544	38	469	1407
Video website	7985	103	930	2385
Video website	7259	78	806	2292
Video website	9067	78	1025	2505
Video website	8981	78	968	2792
Joint store	1798	42	263	446
Joint store	2100	57	254	555
Joint store	2603	92	307	681
Joint store	1737	32	186	687

Simulation results

Simulation experiments provide the final non-inferior solution set and the corresponding positions of the locusts. The positions correspond to the selected websites, and the non-inferior set represents objective results under the decision. The dual-objective model yields the non-inferior solution set shown in Table 3. The distribution in objective space forms a Pareto front (Figure 2).

For AIGC advertising, dissemination efficiency can be weighted higher. For example, if maximizing dissemination efficiency is the primary objective, one preferred solution from the non-dominated set has total dissemination efficiency 3,984 and total advertising cost 9,783 yuan.

Table 3: Non-inferior solution set based on dual-objective decision-making.

Comm. eff.	Cost	Comm. eff.	Cost	Comm. eff.	Cost
3003	8142	3938	9641	3638	9030
3081	8201	2900	7985	3732	9161
3304	8466	2844	7968	3421	8695
3310	8547	3827	9317	3624	8947
2891	7977	3107	8187	3434	8673
3054	8160	3457	8734	2939	8073
3278	8523	3677	9130	2679	7820
3091	8244	3142	8295	3399	8594
3141	8268	3782	9231	3733	9181
3003	8083	3609	8925	3200	8297
3173	8322	3732	9215	3530	8816
3984	9783	3704	9099	3889	9547
3252	8429	3398	8643	3591	8856
3536	8831	3615	9011	3377	8600
2810	7870	3877	9495	3673	9068
2976	8104	3225	8414	3480	8740

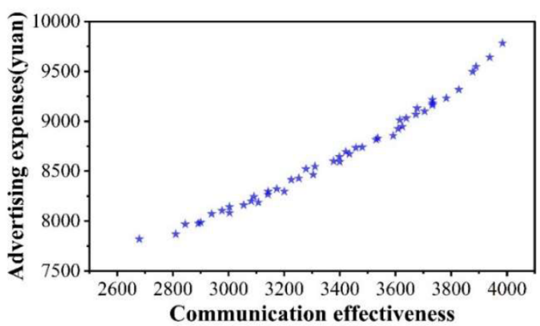

Figure 2: The distribution of Pareto Optimal Set in the target space.

CONCLUSION

To formulate a development strategy that satisfies advertising placement demands, this study integrates multi-objective optimization theory and proposes an AIGC advertising placement approach built on a multi-objective locust optimization algorithm. First, a simulated experimental setting is established and key algorithm parameters are configured. MATLAB is then used to conduct numerical simulations and evaluate the real-world feasibility of the proposed AIGC placement scheme. Results across 10 benchmark test functions show that MOGOA achieves superior performance on most functions compared with alternative algorithms, confirming the algorithm's convergence behavior and operational stability and laying a theoretical basis for evaluating its practical effectiveness. In the application-oriented simulation, AIGC advertising achieves a total dissemination effectiveness of 3,984 with an associated cost of 9,783 yuan, indicating that the resulting placement strategy better matches current market trends. These findings further suggest that the multi-objective locust optimization algorithm can serve as a practical reference for enterprise decision-making in AIGC advertising placement.

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