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Proposing an AIGC advertising intelligent placement strategy based on optimization algorithms

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Abstract With the emergence and development of e-commerce, AIGC advertising has emerged, and optimizing AIGC advertising placement has become one of the primary concerns for businesses. Given the numerous factors influencing AIGC advertising placement strategies, this study proposes a research framework for AIGC advertising placement strategies based on a multi-objective locust optimization algorithm. First, based on actual conditions, the objective function, constraints, and fitness are set. Then, through computational solutions, the optimal solution for AIGC advertising placement strategies is obtained. To validate the reliability of this scheme, numerical simulation analysis is conducted using MATLAB software in an experimental simulation environment. Under the influence of the test function, it is concluded that the algorithm exhibits excellent stability and convergence, ensuring the rigor of subsequent research results. Through algorithm performance simulation analysis, the optimal dissemination efficiency and advertising costs of the AIGC advertising strategy were obtained, with values of 3,984 and 9,783 yuan, respectively, maximizing the benefits of the AIGC advertising strategy. This also validated the practical application effectiveness of the multi-objective locust optimization algorithm in AIGC advertising strategy.

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

I. Introduction

With the rapid development of internet technology, digital marketing has become an indispensable part of corporate marketing strategies. In particular, driven by the development of mobile internet, social media, and artificial intelligence technology, the forms and content of digital advertising have undergone revolutionary changes [1], [2].

Against the backdrop of the accelerated integration of the digital and physical worlds, AI-generated content (AIGC) is quietly leading a profound change, reshaping or even subverting the production and consumption patterns of digital content, which will greatly enrich people's digital lives and be an indispensable supporting force for the future to move towards a new era of digital civilization [3]-[6]. AIGC covers 38% of the world's digital advertising content generation, and the click-through rate is as much as 2 times higher than that of traditional ad generation content, allowing creative ads to be generated in real time according to current dynamic needs [7], [8]. However, this has also led to an explosion of generated content, which has had an impact on ad delivery. The media resources of advertising are greatly abundant, the increase of media contact devices distracts consumers' attention, consumers' media contact behaviors are more diversified, consumers' choice and initiative are also greatly enhanced, their consumption psychology and behavior characteristics are more difficult to grasp, and it is difficult to achieve personalized advertising persuasion with unified advertising information [9]-[12].

In today's complex communication environment, advertising campaigns face increasing interference from other information. Against this backdrop, accurately delivering advertising content to target audiences amid a sea of information has become a major challenge in the field of digital marketing. Traditional advertising campaigns rely on experience-based intuition and basic statistical techniques, which are not only inefficient but also lack a deep understanding of the audience, offer limited media options, have arbitrary placement choices, and make it difficult to accurately measure and control advertising effectiveness. Additionally, these methods are overly broad, leading to significant resource wastage [13]-[16]. The emergence of multi-objective optimization algorithms has provided a new approach to addressing this issue.

Multi-objective optimization algorithms refer to finding a set of non-dominated solutions when multiple optimization objectives exist. These solutions are not dominated by other solutions across all objectives, meaning there are no other solutions that outperform them across all objectives [17]. Common multi-objective optimization algorithms include genetic algorithms, particle swarm optimization algorithms, and simulated annealing algorithms, which provide optimal solutions for balancing AIGC advertising metrics such as click-through rates, conversion costs, brand risk control, advertising creativity, and multi-channel coordination [18].

In the comparative experiments described in Reference [19], an AI-based ad targeting algorithm improved ad targeting effectiveness and achieved a higher return on investment, thereby promoting precise ad placement. Reference [20] applied the term frequency-inverse document frequency technique to content analysis to analyze consumer behavior and predict market trends. Combined with AI hotspot tracking technology, this approach yielded an ad placement strategy featuring highly relevant and appropriate content and timing. In [21], big data algorithms were used to evaluate the volume of high-precision data-driven ad placements on ad platforms, and these algorithms were applied to ad content transmission paths to enhance ad placement accuracy, interactivity, and data utilization. Literature [22] integrates big data, machine learning, and deep learning to develop an intelligent advertising placement decision-making system to create user profiles, formulate advertising strategies, predict and evaluate advertising effectiveness, improve advertising click-through rates and conversion rates, and achieve more accurate and relevant advertising placement. Literature [23] indicates that advertising placement strategies implemented using Thompson sampling algorithms, exponential greedy algorithms, and upper confidence bound algorithms can improve click-through rates, with Thompson sampling algorithms outperforming the other two algorithms and providing more efficient allocation strategies for advertising resources. Literature [24] uses reinforcement learning to predict and dynamically learn user preferences, combined with genetic algorithms to explore and optimize advertising strategies, achieving precise digital advertising placement, improving accuracy and relevance, thereby increasing click-through rates and reducing computational costs. Literature [25] employs particle swarm optimization algorithms to efficiently mine high-profit item sets from databases, identifying high-profit item sets in transaction data to provide pathways for online advertising placement. Literature [26] provides a heuristic algorithm for solving approximate optimal solutions for ad placement, supported by the particle swarm optimization algorithm. The ad placement strategies implemented by this algorithm achieve better dissemination effectiveness while reducing costs and repetition rates.

By reviewing relevant materials, it can be determined that AIGC advertising strategies fall under the category of multi-objective optimization problems. In response to this scenario, an AIGC advertising strategy supported by a multi-objective ant colony optimization algorithm has been developed. First, based on the actual situation of AIGC advertising placement, the corresponding objective function, constraints, and fitness were determined. Subsequently, the algorithm's solution speed and position update were set. After completing a series of preparatory tasks, the multi-objective locust optimization algorithm was used to solve the objective function, ultimately yielding the optimal solution for the AIGC advertising placement strategy. To verify whether this research approach aligns with the research objectives, we conducted validation analyses from two aspects: test functions and practical application performance. The aim is to validate that the multi-objective locust optimization algorithm can provide reference for enterprises' AIGC advertising placement decisions.

II. Research on advertising placement based on multi-objective optimization algorithms

II. A. Multi-objective optimization problems

II. A. 1) Mathematical Model

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

$$\begin{aligned} \min_{x\subseteq R^K} imize\ \ & F(x)=\left(f_1(x),f_2(x),\dots,f_M(x)\right)^T \\ subject\ to\ \ & \beta_j(x)\geq 0,\quad j=1,\dots,J \\ & \gamma_h(x)=0,\quad h=1,\dots,H \end{aligned} \tag{1}$$

where $x=(x_1,x_2,\cdots,x_K)^T\in X\subseteq R^K$ is the decision vector of MOPs, and R^K is the K-dimensional decision space, $F(x)=(f_1(x),f_2(x),\dots,f_M(x))^T\in Y\subseteq \mathbb{R}^M$ is the objective vector of the MOP, where $\mathbb{R}^M$ is the M-dimensional objective space, the objective function $F(x)$ defines the mapping function from the M-dimensional decision space to the objective space, $\beta_j(x)$ and $\gamma_h(x)$ represent the j th inequality constraint and the h th equality constraint of the MOP, respectively, while J and H represent the number of inequality constraints and equality constraints, respectively. As shown in Figure 1, an example of an MOP with two decision variables and a two-dimensional objective space is provided. This example approximately describes how the vector-valued function F maps solutions from the feasible set R^K to the feasible set R^M in the objective function space. The objective function space has attracted significant attention in evolutionary multi-objective optimization because it is where the performance of each candidate solution is evaluated.

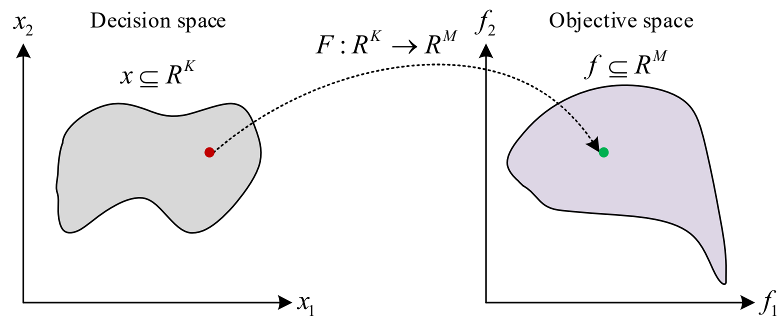


Figure 1: The search space of MOPs

Due to the conflicting nature of the objectives in MOPs, MOEAs cannot find a unique optimal solution that simultaneously minimizes all objective functions in decision space R^K [27]. Therefore, the concept of Pareto optimality must be introduced to weaken the relationships between solutions. In multi-objective optimization, the Pareto dominance criterion assumes that x_1, x_2 are the two decision variables of the MOP. Solution x_1 dominates solution $x_2 \left(x_1 \prec x_2\right)$ if and only if the two decision variables satisfy the condition in formula (2). The formula is:

$$\begin{aligned} &\forall i \in \{1,2,\ldots,M\}: f_i(x_1) \le f_i(x_2) \\ &\wedge \exists j \in \{1,2,\ldots,M\}: f_j(x_1) < f_j(x_2) \end{aligned} \tag{2}$$

Figure 2 provides an example of dominance relations in a 2D objective space. As shown in the figure, solution x_4 has values that are smaller than those of solution x_2 for both objectives, so $x_4 \prec x_2$. Additionally, solution x_4 dominates solution x_1 because the values of both solutions are equal for objective f_1, but the value of x_4 is smaller than that of x_1 for objective f_2. Furthermore, Pareto dominance is a partial order because there are some solutions in the objective space that are incomparable, such as x_1 and x_3.

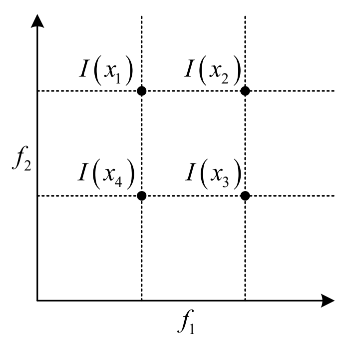


Figure 2: Diagram the Pareto dominance relationship

Therefore, in order to obtain the optimal solution set, the algorithm needs to find a set of solutions x in the decision space such that the objective vector values of these solutions are not dominated by any other feasible solutions [28]. Since no solution dominates x_4, x_4 is considered non-dominated. For solutions x_1 and x_3, since $x_1 \equiv x_3$ and $x_3 \equiv x_1$, they are not dominated by each other. When no other solution dominates the solution $x^* \in R^K$ in the decision space R^K, i.e., $\neg\exists x \in R^K : x \prec x^*$, the solution x^* is Pareto optimal. The set of all solutions that satisfy Pareto optimality is called the Pareto optimal solution set. Its definition is as follows:

$$PS_{opt} = \left\{ x \in R^K \,\middle|\, \nexists y \in R^K : F(y) \prec F(x) \right\} \tag{3}$$

Figure 3 illustrates the concept of the Pareto optimal solution set and their mapping in the objective space as the Pareto frontier. In the figure, blue points represent Pareto optimal solutions. In the decision space, these solutions are referred to as Pareto optimal decision vectors, while in the objective space, they are called Pareto optimal objective vectors. The Pareto frontier is composed of these Pareto optimal solutions. It is important to note that the number of Pareto optimal solutions for a multi-objective problem may be infinite, making it impractical to obtain the entire Pareto frontier in real-world scenarios. In practice, decision-makers aim to obtain an approximate solution that includes as much information about the Pareto frontier as possible. This allows them to select an element from these approximate solutions as the final solution or use the obtained information to specify preferences to aid in the search and identification of a satisfactory solution.

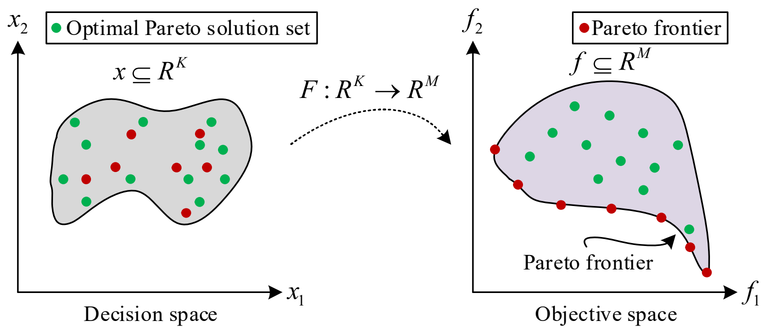


Figure 3: Illustration of the optimal Pareto solution set and the Pareto front

II. A. 2) Conflicting Goals

An important condition for MOPs is that the objectives are mutually conflicting. If there is no conflict between the objectives, each objective of the problem can be optimized separately. Of course, in real-world problems, there are also cases where some sub-objectives are mutually conflicting. Suppose X is a subset of R^K. Two objectives can be associated in the following ways:

(1) When two solutions x_1, x_2 are in the solution set X, if $f_i(x_1) \le f_i(x_2)$, it means that there exists $f_j(x_1) \ge f_j(x_2)$, then f_i and f_j are considered to be in conflict.

(2) When two solutions x_1, x_2 in the solution set X satisfy $f_i(x_1) \le f_i(x_2)$ implies that $f_j(x_1) \le f_j(x_2)$, then f_i and f_j are considered mutually supportive.

(3) When two solutions x_1, x_2 in the solution set X satisfy other conditions, then f_i and f_j are considered to be mutually independent.

All possible relationships between objectives are provided. As defined, when two objectives satisfy conditions 2 and 3, then there is no conflict between them. When $X = R^K$, it is considered that objective f_i and objective f_j are globally conflicting (or supporting). However, in many MOPs, the relationships between objectives are not global, and when comparing different subsets of R^K, the relationships between objectives may also change. Figure 4 provides an example where two objective functions $f_1 = 1.5 + \sin(x)$ and $f_2 = 1.5 + \cos(x)$ exist. The two objectives are conflicting in the interval $[\pi/2, \pi]$ but not in the interval $[\pi, 3\pi/2]$.

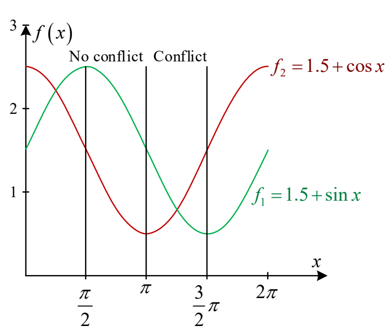


Figure 4: Diagram the relationship between the objective functions

Additionally, non-conflicting objectives are also referred to as non-essential or redundant objectives. When non-conflicting objectives are removed from the original set of objectives, the final Pareto frontier remains unchanged. Therefore, based on the concept of non-essential objectives, it is verified that the Pareto dominance relationship remains unchanged when certain objectives are removed. Let F_i and F_j be two subsets of objectives in $F = f_1, f_2, \cdots, f_M$. If the two sets satisfy the relationship $(\prec_{F_i} \subseteq \prec_{F_j}) \wedge (\prec_{F_j} \subseteq \prec_{F_i})$, then these two objectives are non-conflicting. In other words, F_i and F_j are called mutually non-conflicting only when the corresponding relationships $\prec_{F_i}$ and $\prec_{F_j}$ are the same, but F_i and F_j are not necessarily equal. The definition of non-conflict is useful because if two target subsets are non-conflicting, F_i can be replaced with F_j to obtain the same Pareto optimal frontier. The objectives in F_j are called basic objectives, while those in $F \setminus F_j$ are called non-basic or redundant objectives.

II. B. Locust Optimization Algorithm

With the development of artificial intelligence, researchers both domestically and internationally have proposed numerous intelligent optimization algorithms. Typical intelligent optimization algorithms include genetic algorithms, tabu search algorithms, simulated annealing algorithms, and particle swarm algorithms. These algorithms have been widely applied to address various real-world problems, such as image processing, signal processing, and advertising placement strategies. The multi-objective locust optimization algorithm has a relatively simple structure, strong search capabilities, and stable performance, making it highly adaptable. Therefore, this paper selects the locust optimization algorithm for model construction, and the optimization algorithm will be detailed below.

II. B. 1) 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 primarily divided into larval and adult stages. During the larval stage, locusts can only move slowly within a small range, while in the adult stage, they are adept at jumping and can move quickly over long distances. Based on this characteristic of locusts, the GOA algorithm can be divided into two components: development and exploration. The development component corresponds to the larval stage and is used for local search, while the exploration component corresponds to the adult stage and is used for global search. The process of locusts searching for food sources can be viewed as the process of finding the optimal solution, and this behavior can be defined by the following mathematical formula:

$$F^i = E^i + G^i + A^i \tag{4}$$

where F^i represents the position of the i th locust, E^i represents the interaction between locusts, G^i represents the gravitational influence, and A^i represents the wind direction. The most important influencing factor is the interaction between locusts E^i, which can be expressed as:

$$\begin{cases} E^i = \sum_{j=1 \wedge j \neq i}^{N} f(\Delta d_{ij}) \Delta \vec{d}_{ij} \\ \Delta d_{ij} = \left| \bar{l}_j - \bar{l}_i \right| \\ \Delta \vec{d}_{ij} = (\bar{l}_j - \bar{l}_i) / \Delta d_{ij} \\ f(\Delta d_{ij}) = \delta \cdot \exp(-\Delta d_{ij} / t) - \exp(-\Delta d_{ij}) \end{cases} \tag{5}$$

where Δd_{ij} denotes the distance between locusts, and $\Delta \vec{d}_{ij}$ denotes the unit vector between locusts. $f(\cdot)$ is a function of the interaction between locusts affected by the parameters δ and t, where δ is the strength of attraction and t is the length ratio of attraction. To ensure that individual locusts perform well in their search capabilities, the distance between locusts is controlled within the range of $[1, 4]$.

The gravitational and wind direction factors affecting locusts can be specifically expressed as:

$$\begin{cases} G^i = -\theta \cdot \vec{e}_\theta \\ A^i = \nu \cdot \vec{e}_\nu \end{cases} \tag{6}$$

where θ and $\vec{e}_\theta$ are the gravitational constant and the unit vector pointing toward the center of the Earth, respectively, and ν and $\vec{e}_\nu$ are the wind coefficient and the unit vector affected by wind, respectively. According to the above formula, the position F^i of the locust can be updated as follows:

$$F^i = \sum_{j=1 \wedge j \neq i}^{N} f\left(\left|\bar{l}_j - \bar{l}_i\right|\right) \cdot (\bar{l}_j - \bar{l}_i) / \Delta d_{ij} - \theta \cdot \vec{e}_\theta + \nu \cdot \vec{e}_\nu \tag{7}$$

In order to enhance the performance of the algorithm for better solving optimization problems, the final locust position formula can be obtained after improvement:

$$F^i = \psi \left(\sum_{j=1 \wedge j \neq i}^{N} \psi \frac{\vec{U}_d - \underrightarrow{L}_d}{2} \cdot y(\Delta d_{ij}) \Delta \vec{d}_{ij} + T \right) \tag{8}$$

where $\vec{U}_d$ and $\underrightarrow{L}_d$ represent the upper and lower bounds of the d th dimension, respectively, and T is the corresponding target value. The parameter ψ is the contraction factor. As the number of iterations increases, the local search capability gradually strengthens, while the global search capability weakens. This process can be expressed as:

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

t and T represent the current iteration count and the maximum iteration count, respectively, while $\psi_{\max}$ and $\psi_{\min}$ represent the maximum and minimum values, respectively.

The specific implementation steps of the GOA algorithm are summarized as follows:

Step 1: Initialize all parameters.

Step 2: Calculate the individual fitness values of each locust in the population and retain the position F of the locust with the best fitness value.

Step 3: Update the parameter ψ using formula (9).

Step 4: Update the locust positions using formula (10), recalculate the locust fitness values, and update the position of the optimal locust F.

Step 5: Determine whether the maximum iteration count has been reached. If the condition is not met, jump to Step 3 and repeat the following steps. If the condition is met, exit and return F.

II. B. 2) Multi-objective locust optimization algorithm

As the problems encountered in real life become increasingly complex, single-objective optimization can no longer meet people's needs, and multi-objective optimization has gradually become a focal point of academic research. Multi-objective optimization problems typically involve multiple objective functions and decision variables, with conflicting relationships among the objective functions. This means that optimizing one objective function may require sacrificing the performance of other objective functions. Therefore, multi-objective optimization problems generally involve coordinating multiple objective functions to achieve the most optimal overall state. The solution to a multi-objective optimization problem is typically a set of equilibrium solutions, i.e., a collection of multiple solutions known as the Pareto optimal solution set. This paper first introduces relevant theoretical issues in multi-objective optimization, such as Pareto solutions, the Pareto frontier, and minimization problems.

(1) Minimization problems

Multi-objective optimization problems can often be transformed into minimization problems for solution, as shown in the following formula:

$$\begin{aligned} &Minimize: F(\mathrm{J}) = \{f_1(\mathrm{J}), f_2(\mathrm{J}), \cdots, f_t(\mathrm{J})\} \\ &Subject\ to: \begin{cases} g_i(\vec{\mathrm{J}}) \geq 0, & i = 1, \cdots, m \\ h_i(\vec{\mathrm{J}}) = 0, & i = 1, \cdots, p \\ \underline{L}_i \leq \vec{\mathrm{J}}_i \leq \vec{U}_i, & i = 1, \cdots, n \end{cases} \end{aligned} \tag{10}$$

where F is the objective variable, $\vec{\mathrm{J}}$ is the decision variable, $\underline{L}_i$ and $\vec{U}_i$ are the upper and lower bounds of variable x_i, respectively, t is the number of objective functions, n is the number of decision variables, g_i and

h_i are the i th inequality constraint and equality constraint, respectively, m is the number of inequality constraints, and n is the number of equality constraints.

(2) Pareto dominance

If there are decision variables $\vec{J} = (\vec{J}_1, \cdots, \vec{J}_k)$ and $\vec{y} = (\vec{y}_1, \cdots, \vec{y}_k)$, when $\vec{T} \succ \vec{y}$, we denote that $\vec{J}$ Pareto dominates $\vec{y}$, if and only if $\forall k \in [1,k], [f(\vec{J}_k) \geq f(\vec{y}_k)] \wedge [\exists t \in [1,k] : f(\vec{J}_k)]$.

(3) Pareto optimality and optimal solution set

If the decision variable $\vec{J} = (\vec{J}_1, \cdots, \vec{J}_k)$ satisfies the condition $/\exists \vec{y} \in X \; s.t. \; F(\vec{y}) \succ F(\vec{J})$ is satisfied, then $\vec{J} = (\vec{J}_1, \cdots, \vec{J}_k)$ is called a Pareto optimal solution, and the set of Pareto optimal solutions is called the Pareto optimal solution set:

$$\Xi^{set} = \left\{ \vec{J}, \vec{y} \in X \,\middle|\, \exists F(\vec{y}) \succ F(\vec{J}) \right\} \tag{11}$$

(4) Pareto frontier

The set of objective function values corresponding to the Pareto optimal solution forms the Pareto frontier, that is:

$$\Xi^{front} = \left\{ F(\vec{J}) \,\middle|\, \vec{J} \in \Xi^{set} \right\} \tag{12}$$

The primary difference between the MOGOA algorithm and the GOA algorithm lies in the process of updating the objective. In single-objective optimization problems, the objective can be selected by choosing the current optimal solution during the search. In contrast, multi-objective optimization problems utilize random selection methods to progressively identify optimal solutions, which are then ranked and archived. Specifically, the archive is used to store the currently searched non-dominated Pareto optimal solutions. The capacity of the archive is predefined and cannot be changed before the algorithm begins. During each iteration update, if the solutions in the archive cannot dominate the newly searched non-dominated solutions, the new non-dominated solutions are added to the archive, thereby achieving the goal of updating the solutions in the archive. However, when the archive's capacity is limited and insufficient to accommodate new solutions, the algorithm removes some solutions from the archive with a certain probability $P_i = 1/N_i$ to increase capacity, where N_i is the number of Pareto optimal solutions near the i th solution in the archive.

II. C.Building an AIGC advertising placement decision-making model

II. C. 1) Objective Function

In the process of constructing a comprehensive evaluation of AIGC advertising effectiveness based on a multi-objective locust optimization algorithm, assume that a company, in order to promote its newly launched product, chooses to invest in AIGC advertising based on its current advantage over other advertising formats. The company's AIGC advertising budget is C_0, and it now decides to select a combination of websites for AIGC advertising. The types of websites/media include online variety shows, original dramas, online games, social media, short videos, etc., with a total of m types. The company needs to select from among the m types of websites/media, initially selecting n_i ($i = 1, 2, \ldots, m$, same below) from each type. Based on this, the company further analyzes and selects the communication effectiveness of online variety shows, original series, online games, social media, short videos, and other media, as well as the advertising cost parameters of each, to determine the optimal AIGC advertising placement locations, AIGC advertising formats, and AIGC advertising pricing standards. Thus, the company established an optimized decision-making model for AIGC advertising placement based on the core objective of minimizing AIGC advertising costs while maximizing AIGC advertising effectiveness. This model includes the following objective functions:

(1) AIGC advertising effectiveness—objective function for maximizing dissemination effectiveness:

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

In Equation (13), S represents the AIGC advertising effectiveness evaluation index, i.e., the total communication effectiveness of AIGC advertising. x_{ij} is the decision variable for AIGC ads, specifically taking the value 1 if the company selects the j th medium in the i th category of media, and 0 otherwise. u_{ij} represents the AIGC ad traffic evaluation metric, specifically reflecting the traffic generated by the j th medium in the i th category of media. d_{ij}

represents the transaction volume evaluation metric for AIGC ads, specifically reflecting the transaction volume generated by the j th media in the i th media category through AIGC ads.

(2) Objective function for minimizing AIGC ad placement costs:

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

In equation (14), C represents the total advertising cost evaluation index for AIGC advertisements. c_{ij} represents the advertising cost evaluation index for AIGC advertisements, specifically reflecting the cost index for the j th AIGC advertising medium in the i th category of media.

(3) The sum of the advertising costs for all AIGC advertising media cannot exceed the target function of the company's advertising budget:

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

In equation (15), c_{ij} represents the advertising cost evaluation index for AIGC advertisements, specifically reflecting the cost index of the j th AIGC advertising medium in the i th category of media. x_{ij} is the decision variable for AIGC advertisements, with a specific value of 1 if the enterprise selects the j th medium in the i th category, and 0 otherwise.

(4) Objective function for selecting only one AIGC advertising medium across all types of online advertising media:

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

In equation (16), x_{ij} is the decision variable for AIGC advertising, with a specific value of 1 if the company chooses the j th medium in the i th category, and 0 otherwise.

(5) Objective function for whether to choose the n_i th AIGC advertising medium in the m th category:

$$x_{ij} \in \{0,1\} \; i = 1, 2, \ldots, m \; j = 1, 2, \ldots, n_i \tag{17}$$

In model (17), whether to select the n_i th AIGC advertising medium in the m th category is represented by 1 if selected and 0 otherwise. Based on the time series of the current AIGC advertising media, the cycle is primarily set to 15 days, and new data is generated to dynamically adjust the relevant parameters in the model. The constant within the interval [0,1] is specifically set based on the emphasis placed on traffic and sales requirements by the advertising objectives.

II. C. 2) Constraints

Constrained optimization problems can be classified into constrained single-objective optimization problems and constrained multi-objective optimization problems according to the number of objectives. Without loss of generality, in the case of minimization, constrained single-objective optimization problems can be described as follows:

$$\begin{aligned} & \min f(\vec{x}) \\ & s.t.: g_i(\vec{x}) \le 0, i = 1, 2, \cdots, q \\ & h_i(\vec{x}) = 0, i = q+1, \cdots, m \end{aligned} \tag{18}$$

In the equation, $\vec{x} = (x_1, x_2, \cdots, x_n) \in X \subset \Re^n$, that is, in the n-dimensional decision space, $\vec{x} = (x_1, x_2, \cdots, x_n)$ is the decision vector, and $f(\vec{x})$ is the objective function. $g_i(\vec{x}) \le 0 (i = 1, 2, \cdots, q)$ are inequality constraint functions, with a total of q functions. $h_i(\vec{x}) = 0 (i = q+1, \cdots, m)$ are equality constraint functions, with a total of $m-q$ functions.

Ω is the feasible region, and the decision vector $\vec{x} \in \Omega \subseteq X$. X is an n-dimensional rectangular solid in $\Re^n$, $x_k^l \le x_k \le x_k^n$, x_k^l and x_k^n are the upper and lower bounds of the k th dimension, respectively, and $k = 1, \cdots, n$. In the decision space, a solution that satisfies all m constraints simultaneously is called a feasible solution, and the feasible region is the space composed of all feasible solutions.

In constraint optimization, constraints are typically either equalities or inequalities. Equality constraints are usually converted into inequality constraints for processing. The degree of constraint violation of an individual x in the population at the i th constraint is represented as:

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

Among them, there are a total of m constraints. When converting equality constraints to inequality constraints, the tolerance parameter δ of the equality constraints is generally set according to the required precision, usually 0.001 or 0.0001. Therefore, the total constraint violation degree of individual x, also known as the constraint default degree, is expressed as:

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

For constrained multi-objective optimization problems, due to the constraints imposed by the constraints, the set of optimal solutions must be based on the feasibility of the decision vector. The final optimization results must not only ensure the feasibility of the decision vector, but also take into account requirements such as the approximation and distribution of the set of optimal solutions.

II. C. 3) Fitness calculation and screening of non-inferior solution sets

Based on the aforementioned computational process, the initial swarm of locusts from the AIGC advertising effectiveness comprehensive evaluation is used to calculate the fitness values of each locust in the AIGC advertising effectiveness comprehensive evaluation. Ultimately, the optimal individual position of the locusts in the AIGC advertising effectiveness comprehensive evaluation and the global optimal position of the AIGC advertising effectiveness comprehensive evaluation are determined. Since the AIGC advertising effectiveness comprehensive evaluation solves a multi-objective optimization problem for the Pareto optimal solution, each individual has two fitness values: one is the advertising cost of the AIGC advertising effectiveness comprehensive evaluation, and the other is the dissemination efficiency of the AIGC advertising effectiveness comprehensive evaluation. The calculation of the locust fitness values for the AIGC advertising effectiveness comprehensive evaluation primarily references formulas (13), (14), and (15).

In the non-inferior solution set for the comprehensive evaluation of AIGC ad effectiveness, there are two parts. The first part is the initial non-inferior solution set for the comprehensive evaluation of AIGC ad effectiveness. The second part is the updated non-inferior solution set for the comprehensive evaluation of AIGC ad effectiveness. Among these, the initial non-inferior solution set for the comprehensive evaluation of AIGC ad effectiveness is the case where there are no other locusts in S_x, C_x are all superior to that locust. That is, when a locust must satisfy the C_0 constraint while not being dominated by other locusts, the AIGC advertising effectiveness comprehensive evaluation locust is placed in the non-inferior solution set. Additionally, before the locust is updated, a locust is randomly selected from the non-inferior solution set as the optimal locust in the population. The computational steps for updating and screening the non-inferior solution set for AIGC advertising effectiveness comprehensive evaluation include two steps: The first step is to merge the old non-inferior solution set and the new non-inferior solution set for AIGC advertising effectiveness comprehensive evaluation, thereby obtaining a new non-inferior solution set for AIGC advertising effectiveness comprehensive evaluation. The second step involves screening out the new non-inferior solution set for the AIGC advertising effectiveness comprehensive evaluation based on the dominance relationships within the non-inferior solution set formed in the previous step.

II. C. 4) Locust Speed and Position Updates

In the comprehensive evaluation of AIGC advertising effectiveness, according to the above calculation process, the speed and position of locusts in the comprehensive evaluation of AIGC advertising effectiveness are updated based on the following formula:

$$V^{k+1}=\omega V^k+c_1r_1(P_{id}^k-X^k)+c_2r_2(P_{gd}^k-X^k) \tag{21}$$

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

Among them, ω is the inertial weight. r_1 and r_2 are random numbers between 0 and 1. k is the current iteration number. P_{id}^k is the optimal locust position of the individual. P_{gd}^k is the global optimal locust position. c_1

and c_2 are constants. V is the current speed of the individual locust. X is the current position of the individual locust.

ω is dynamically updated according to equation (21), where iter is the current iteration count, MaxIT is the maximum iteration count, $\omega_{\max} = 1.2$, and $\omega_{\min} = 0.1$. Equation (16) describes how ω decreases from $\omega_{\max}$ to $\omega_{\min}$ during the iteration process.

$$\omega = \omega_{\max} - (\omega_{\max} - \omega_{\min}) * (iter / MaxIT)^2 \tag{23}$$

II. C. 5) Optimal solution for locusts

The comprehensive evaluation of AIGC advertising effectiveness includes the individual optimal locust $Xbest$ and the population optimal locust $gbest$, where the dominant locust is selected from the current new locusts and the individual optimal locust to update the individual optimal locust. This is done by comparing the fitness value of the current locust with the fitness value of the best position $Xbest$ it has experienced. If the former is better, $Xbest$ is updated. When neither locust is a dominant locust, a locust is randomly selected from them as the new individual optimal locust $Xbest$. A locust randomly selected from the non-dominated solution set is used as the AIGC advertising effectiveness comprehensive evaluation group optimal locust $gbest$.

III. Exploration and Analysis of AIGC Advertising Placement Strategies

III. A. Algorithm verification analysis based on test functions

III. A. 1) Experimental setup

Based on the experimental requirements, the experimental environment for this study was determined as follows: operating system Windows 8, CPU Intel Core i7-10210U, clock speed 2.60GHz, memory 32GB, and development environment MatlabR2016(a). To demonstrate the effectiveness of the proposed function, the proposed algorithm was first tested against other comparison algorithms on a standard test function set. The average values and variances obtained by each algorithm were calculated, and an iteration count-fitness value curve was plotted. Through comparative analysis, the effectiveness of the multi-objective optimization algorithm proposed in this paper was verified.

(4) Test function set

To validate the effectiveness of the multi-objective locust optimization algorithm (MOGOA) proposed in this paper, we first compare the proposed MOGOA with related algorithms such as the global optimization chaotic GOA (divided into CGOA1 and CGOA2 using different chaotic formulas), GA, and GWO. The parameter settings for these algorithms are as follows: population size $N = 60$, iteration count 200, dimension 60, original algorithm $c\_\min = 0.0001$, $c\_\max = 1$. Each algorithm was run independently 100 times in the experiment, and algorithm performance was evaluated using the mean and variance.

The theoretical optimal solutions for the 10 test function sets used in this study are all 0. Therefore, the smaller the final result obtained by the algorithm, the better, and the closer to 0, the better. By comparing the solutions of different functions, the convergence accuracy of different algorithms can be analyzed. The convergence speed of the algorithm can be observed from the fitness value change curve during the iteration process. The faster the iteration curve decreases, the faster the convergence speed of the algorithm. When the iteration curve fluctuates up and down or tends to be parallel, it indicates that the algorithm has fallen into a local optimum. This experimental result can also be used to test the algorithm's ability to escape local optima. Ten standard test function sets were selected, among which functions F1-F6 are single-modal benchmark test functions. This type of test function set has only one global optimal solution and no local optimal solutions, primarily used to test the convergence speed and convergence accuracy of the algorithm. Functions F7–F10 are multi-modal benchmark test functions. Unlike single-modal benchmark functions, multi-modal benchmark test functions have many local optima and are primarily used to test the algorithm's global search capability and ability to escape local optima.

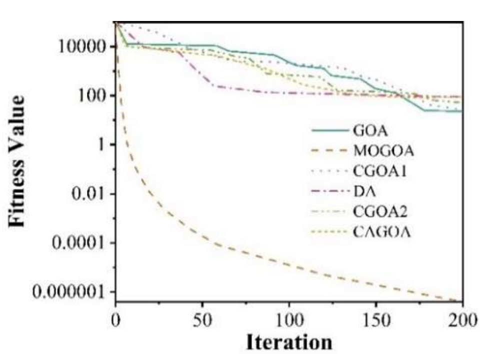
III. A. 2) Experimental Results

Each algorithm was run independently 100 times on different test sets to reduce randomness. Table 1 shows the experimental comparison results between MOGOA and other algorithms. Figure 5 shows the convergence curves of the MOGOA algorithm and other comparison algorithms, where (a) to (j) represent test functions F1 to F10, respectively. From the experimental results in Table 1, it can be seen that DA performs better than other functions in terms of mean and variance on test function 1, but MOGOA outperforms GOA, CGOA1, and CGOA2. This indicates that the GOA algorithm is not as effective as GA in solving certain single-mode benchmark functions, but the algorithm proposed in this paper performs better than other GOA algorithms on test function F1. MOGOA achieves the optimal mean value on test function F7, but its variance is larger than that of CGOA2, indicating that

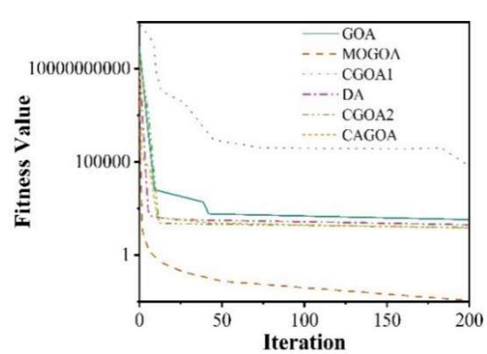
MOGOA's stability is inferior to CGOA2 on this test function set. MOGOA outperforms other algorithms on other test functions, demonstrating its superior convergence and stability. Additionally, as shown in Figure 5, MOGOA converges faster than other algorithms.

Table 1: Test the test results of functions F1-F10

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



(a)F1



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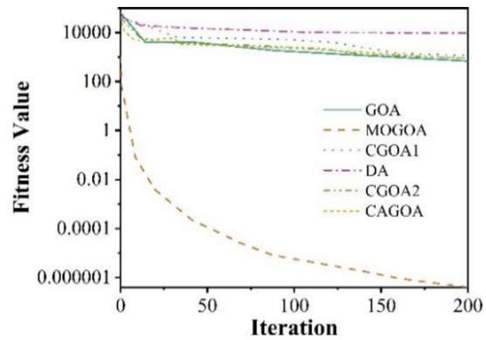
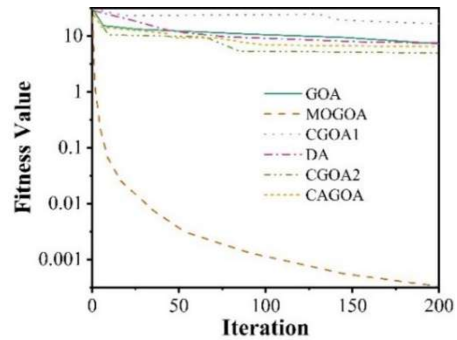
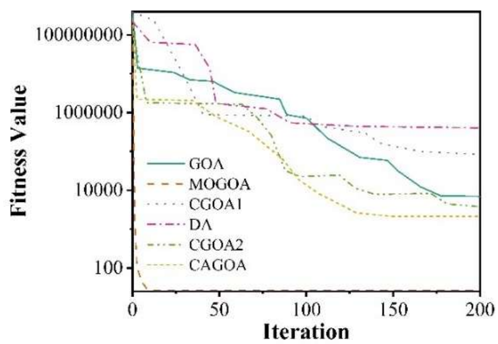


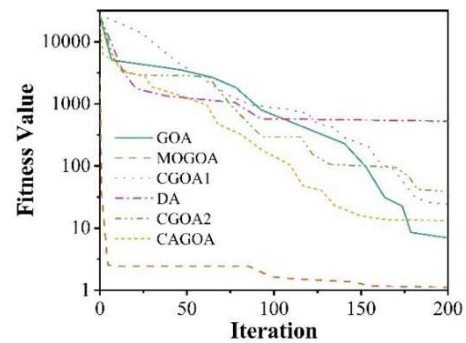
(c)F3



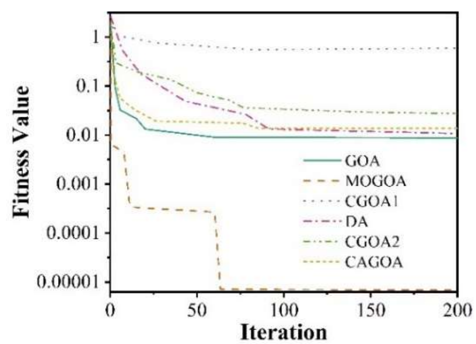
(d)F4



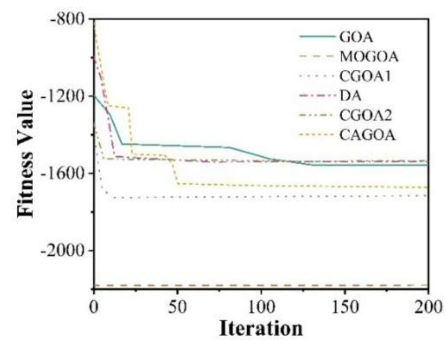
(e)F5



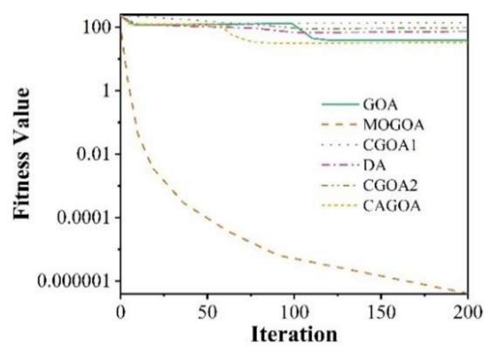
(f)F6



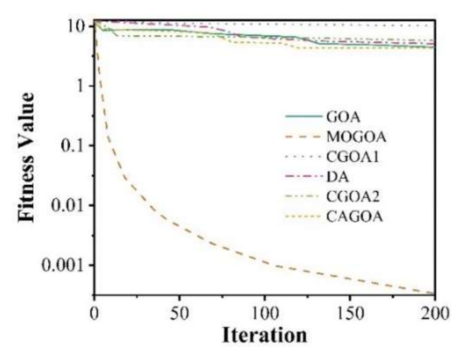
(g)F7



(h)F8



(i)F9



(j)F10

Figure 5: Iterative curves of fitness values for 10 test functions

III. B. Exploring Advertising Placement Strategies from a Multi-Objective Perspective

The preceding section has demonstrated the priority of the multi-objective locust optimization algorithm proposed in this paper. This subsection will utilize MATLAB simulation software to conduct a simulation analysis of the application performance of the multi-objective locust optimization algorithm in AIGC advertising placement strategies.

III. B. 1) 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, making the results have practical reference value. In the specific implementation of advertising placement, solutions should be sought based on real-time data.

Table 2: Sample data

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

III. B. 2) Simulation results

Simulation experiments can provide the final non-inferior solution set and the corresponding positions of the locusts. The positions of the locusts correspond to the specific websites selected, and the non-inferior solution set represents the final results of each objective under the website selection decision. The simulation experiment based on the dual-objective decision-making model of AIGC advertising effectiveness and implementation cost yielded the non-inferior solution set data shown in Table 3. To provide a more intuitive observation and analysis of the results, the data was plotted in the objective space. The distribution of the non-inferior solution set in the objective space is shown in Figure 6. As can be seen from the combined charts, the non-inferior solutions searched by the multi-objective locust optimization algorithm form a Pareto front, achieving excellent results and making the formulated AIGC advertising placement strategy more aligned with actual needs. Compared to single-objective algorithms, the multi-objective locust optimization algorithm is more closely aligned with real-world problems, and its solution results are more valuable for reference. The multi-objective locust optimization algorithm does not yield a single optimal solution but rather a set of non-inferior solutions. From this set, a solution must be selected based on the specific requirements of the problem to serve as the final solution. For AIGC advertising, the weight of general dissemination efficiency is relatively high. For example, if a company prioritizes maximizing dissemination efficiency as its primary objective, it can select a preferred solution from the non-dominated solution set for advertising placement. In this case, the total dissemination efficiency is 3,984, and the total advertising cost is 9,783 yuan (see Table 3). From the non-inferior solution set, it can be observed that as advertising costs increase, communication effectiveness also gradually increases, aligning with actual patterns. This model and algorithm can be used to provide reference for enterprises' AIGC advertising placement decisions.

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

Communication effectiveness	Advertising expenses(yuan)	Communication effectiveness	Advertising expenses(yuan)	Communication effectiveness	Advertising expenses(yuan)
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

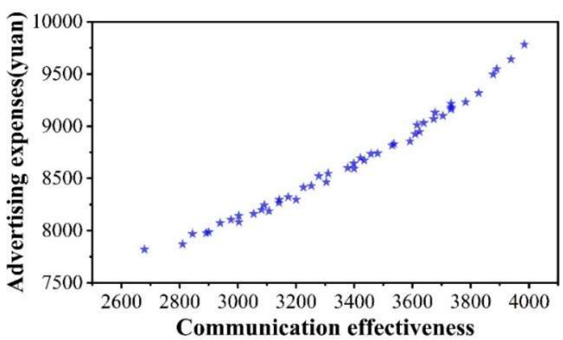


Figure 6: The distribution of Pareto Optimal Set in the target space

IV. Conclusion

To design a development strategy that meets advertising placement requirements, this paper combines multi-objective optimization theory to propose a study on AIGC advertising placement strategies based on the multi-objective locust optimization algorithm. First, a simulation experiment environment is constructed, and algorithm parameters are set. Using MATLAB mathematical simulation software, the actual effectiveness of the AIGC advertising placement strategy research scheme based on the multi-objective locust optimization algorithm is explored. Under the influence of 10 test functions, it was found that MOGOA outperforms other algorithms in other test functions, verifying the convergence and stability of the multi-objective locust optimization algorithm, and providing a solid theoretical foundation for subsequent analysis of the algorithm's practical application effectiveness. In the simulation analysis of the algorithm's practical application performance, the total dissemination effectiveness of AIGC advertising was found to be 3,984, with corresponding costs of 9,783 (yuan), making the AIGC advertising placement strategy more aligned with current trends. This further demonstrates that the multi-objective locust optimization algorithm can provide reference for enterprises' AIGC advertising placement decisions.

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