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Adaptive Clustering-based Multi-modal Multi-Objective Location Optimization Algorithm

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Abstract: To address the issues of insufficient solution diversity, imbalanced multi-objective trade-offs, and poor adaptability to complex constraints in traditional facility location optimization, this paper proposes an Adaptive Clustering-based Multi-modal Multi-Objective Location Optimization Algorithm (ACM-MOLA). The algorithm adopts a multi-modal multi-objective optimization framework, integrating adaptive clustering and local search mechanisms: it dynamically adjusts the number of clusters to achieve refined exploration of the solution space, employs non-dominated sorting and crowding distance to maintain the Pareto optimal frontier, and enhances the local optimization accuracy of high-quality solutions through local search. Comparative results with other multi-modal multi-objective algorithms demonstrate that ACM-MOLA outperforms in terms of both the quantity of Pareto solutions and solution diversity, providing decision-makers with location options that better cover diverse needs, thereby validating the algorithm's effectiveness and practicality.

Keywords: Facility Location; Multi-modal Multi-objective Optimization; Adaptive Clustering; Non-dominated Sorting; Local Search.

1. Introduction

The site selection problem is a core decision-making problem in the fields of supply chain and urban planning. Its essence is to achieve collaborative optimization of multiple objectives such as transportation costs, construction costs, and service quality while meeting demand coverage and resource constraints [1]. With the acceleration of urbanization and the increase in supply chain complexity, traditional location selection algorithms are facing problems such as lack of solution diversity, imbalanced multi-objective trade-offs, and poor constraint adaptability[2]. Designing a good location selection algorithm is of great practical significance for reducing supply chain operating costs and improving urban resource utilization.

The development of multi-objective location selection algorithms can be divided into three generations: the first generation is represented by weighted sum method, which transforms multi-objective into single objective, but the subjectivity of weight setting is strong [3]. The second generation, with NSGA-II and MOEA/D as the core, maintains the Pareto frontier through non dominated sorting or decomposition strategies, significantly improving the diversity of understanding [4, 5]. However, there is still a deficiency of insufficient exploration of multi-modal regions. The third generation is oriented towards multi-modal multi-objective optimization (MMO), focusing on discovering high-quality solutions distributed in different regions. Zhang et al. [6] proposed a clustering based multi-modal algorithm, which divides the solution space through K-means, but the number of clusters is fixed and difficult to adapt to dynamic iterative processes. At present, the combination of multi-modal exploration and clustering strategies is not closely integrated in existing research, and a fixed number of clusters is difficult to adapt to the dynamic changes in the solution space during the iteration process; The synergy between local search and global exploration is insufficient, and most algorithms only perform local optimization after global iteration, which can easily miss opportunities for fine improvement of high-quality solutions.

Based on this, this article proposes a multi-modal multi-objective optimization algorithm for adaptive clustering, which dynamically adjusts the number of clusters with the iteration progress using an adaptive clustering mechanism to achieve dynamic partitioning of the solution space and exploration of multi-modal regions; Build a three-layer optimization framework consisting of global iteration, clustering partitioning, and local enhancement, combined with non dominated sorting and crowded distance maintenance to maintain the Pareto front, effectively identifying different modal regions and searching between multiple local optimal solutions.

2. Related Work

2.1. Theoretical Basis of Multi-Modal Multi-Objective Optimization Algorithm

In practical applications, real-world problems often involve not only multiple conflicting objectives but also multi-modal objective functions. This requires algorithms to not only balance these objectives and identify a set of Pareto-optimal solutions, but also possess robust search capabilities to explore complex search spaces and discover multiple local optima. Such algorithms, designed to ensure solution diversity and comprehensiveness, are known as multi-modal multi-objective optimization algorithms [7].

Consider the logistics distribution center location selection problem as an example. This issue involves multiple objectives such as minimizing transportation costs and optimizing service quality. These objectives often have interdependent relationships. For instance, reducing transportation costs might lead to choosing locations closer to suppliers, but this could extend delivery times and compromise service quality. Multi-modal multi-objective optimization algorithms can effectively balance and select among multiple local optimal solutions through strategic search methods. This process identifies a set of Pareto-optimal solutions that achieve equilibrium across multiple objectives while covering different modal areas. These solutions provide decision-makers with diverse options, enabling them to flexibly choose the most suitable location plans based on actual needs and preferences.

2.2. Location Modeling

Suppose a logistics company plans to establish a new warehouse in a specific region to meet the storage and distribution needs of multiple neighboring cities. When making location decisions, it is essential to identify sites with minimized costs and maximized market demand to ensure optimal warehouse operations. To address the location optimization challenge, this paper constructs a mathematical model for multi-modal multi-objective location optimization as follows:

Let the candidate site set be $C = \{c_1, c_2, \dots, c_n\}$. Select k sites as facility locations, with decision variables $x = (x_1, x_2, \dots, x_\mathrm{n})$ where $x_\mathrm{i} \in \{0,1\}$. $x_\mathrm{i} = 1$ indicates selecting site c_i, while $x_\mathrm{i} = 0$ indicates non-selection. The constraint is $\sum_{i=1}^{n} x_i = k$.

Minimize transportation costs: $f_1(x) = min \sum_{i=1}^{n} d_\mathrm{i} w_\mathrm{i}$, where d_i is the distance between the warehouse and the i-th demand city, and w_i is the demand volume of goods from the i-th demand city.

Minimize construction costs: $f_2(x) = minC_\mathrm{build}$, where C_build represents the warehouse construction cost.

Market demand maximization: $f_3(x) = max \sum_{i=1}^{\mathrm{n}} s_\mathrm{i} q_\mathrm{i}$, where s_i denotes the service level of the warehouse for the i-th demand city, and q_i represents the market demand scale of the i-th demand city.

In this model, there are multiple local optimal solutions in the decision space, and the objective functions are conflicting, which is in line with the characteristics of multi-modal multi-objective optimization problems.

3. ACM-MOLA

3.1. Suppose a Logistic Adaptive Clustering Strategy

Traditional clustering-based multi-modal multi-objective optimization algorithms typically employ fixed cluster quantities, which may struggle to effectively address complex and dynamic facility location problems. The proposed algorithm introduces an adaptive clustering strategy that dynamically adjusts cluster numbers based on population distribution and search progress. During the initial search phase, when solution space exploration is limited, a larger cluster quantity is adopted to extensively explore the solution space and identify potential multi-modal regions. In the mid-search phase, cluster quantities are gradually adjusted according to solution density distribution and objective function value variations within the population. If solutions in a cluster become overly concentrated with similar objective function values, the cluster quantity can be appropriately reduced to avoid getting trapped in local optima. By implementing this adaptive clustering mechanism, the algorithm demonstrates enhanced flexibility in adapting to facility location problem complexities while improving search efficiency. The adaptive adjustment mechanism for cluster quantity (denoted as k) is defined as follows:

$$\mathrm{k}_{\mathrm{t+1}} = \max(\mathrm{k}_{\min}, \min(\mathrm{k}_{\max}, \mathrm{k}_\mathrm{t} + \Delta\mathrm{k})) \quad (1)$$

3.2. A Local Search Strategy Based on Gradient Descent

To enhance the algorithm's search capability in local regions and improve the discovery of local optimal solutions, the improved algorithm introduces a local search mechanism within each cluster. After clustering the population, the algorithm applies a gradient descent-based local search method to optimize individuals within each cluster. The local search update formula is:

$$x_i^{new} = x_i - \eta \cdot \nabla \mathrm{f}(x_i) \quad (2)$$

where η is the learning rate and $\nabla \mathrm{f}(x_i)$ denotes the gradient of the function f at point x_i.

During the search process, the algorithm simultaneously considers the impact of multiple objective functions by applying weighted integration to combine them. This ensures that while optimizing transportation costs, other objectives are not excessively compromised. The local search mechanism enables fine-tuning of solutions within each cluster, thereby improving solution quality and enhancing the overall performance of the algorithm.

3.3. Algorithm Flow

Input: candidate site areas, population size N, maximum evaluation attempts $MaxFEs$, external archive capacity A, local search radius r, crossover probability pc, mutation probability pm.

Output: the set of Pareto optimal solutions in the external Archive.

1.Generate an initial population P of size N randomly and initialize the external archive Archive=∅,and set the iteration count $FEs = N$

2.while (*FEs*<*MaxFEs*)

3. The population P is divided into multiple clusters based on Euclidean distance using an improved adaptive clustering strategy. Calculate the cluster center for each cluster.

4. A gradient descent-based local search method is employed to identify the optimal solution within the predefined range. Calculate the fitness of the new solution. If the new solution is better, update the current individual.

5. Perform global search on the population through genetic operations such as selection, crossover, and mutation.

6. Using non-dominated sorting and crowding distance strategy, select the *N* optimal individuals and store them in the external Archive.

7. end while

4. Experimental Analysis

4.1. Experiment Settings

An e-commerce company plans to establish a new distribution center in a region with multiple major cities, aiming to enhance delivery efficiency and service quality. The region encompasses several key cities, each with distinct characteristics including population size, consumption levels, and order volumes–factors that directly influence the location selection for the distribution center. The input data includes candidate site areas for each city, cargo demand volumes, and market scale metrics.

The experiment features a population size of *N*=800, with a maximum evaluation count of *MaxFEs*=10000, an external archive capacity of A=800, and a local search radius of r=0.15. The genetic algorithm employs crossover probability pc=0.9 and mutation probability pm=0.1. Each algorithm is independently run 30 times to obtain statistical values.

4.2. Comparison Results

The proposed algorithm ACM-MOLA was compared with MMODE [8], DN-NSGAII [9], SS-MOPSO [10], and MO_Ring_PSO_SCD [11], with performance evaluated using three metrics: Hypervolume (HV), Pareto Set Proximity (PSP), and Diversity Index (Spacing).

Table 1. Performance comparison results

Algorithm	HV value	PSP value	Spacing value
ACM-MOLA	0.782 ± 0.031	0.815 ± 0.042	0.123 ± 0.018
MMODE	0.756 ± 0.035	0.788 ± 0.047	0.141 ± 0.021
DN-NSGA-II	0.725 ± 0.038	0.753 ± 0.051	0.157 ± 0.024
SS-MOPSO	0.703 ± 0.041	0.732 ± 0.056	0.138 ± 0.020
MO_Ring_PSO_SCD	0.698 ± 0.045	0.712 ± 0.063	0.169 ± 0.027

The data in Table 1 demonstrate that under identical evaluation conditions, the proposed HV algorithm achieves superior performance across three key objectives: transportation costs, construction costs, and market satisfaction. It exhibits better equilibrium and a broader coverage of non-dominated solutions. The high PSP value indicates that its location schemes are closer to theoretical optimal solutions, with more uniform solution distribution. The smaller Spacing value reflects enhanced diversity. By balancing multiple local optima, the ACM-MOLA algorithm delivers diversified and optimized solutions that better meet enterprises' needs for cost control and service quality improvement, providing a more comprehensive and scientific basis for decision-making.

5. Summary

One of the key advantages of multi-modal multi-objective optimization algorithms in facility location problems lies in their ability to overcome the limitations of traditional algorithms, providing decision-makers with diverse and varied location solutions. The algorithm proposed in this paper dynamically adjusts the number of clusters through an adaptive clustering mechanism during iterations, enhancing the local search mechanism and improving the exploration of local optimal solutions, ultimately yielding a series of diversified location schemes. Future research should focus on practical application studies, implementing the algorithm in real-world enterprise location decisions. This will enable in-depth analysis of challenges encountered during implementation, further refining both the algorithm and location models to enhance their reliability and practicality in real-world applications.

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