Research on the Geographical Rationality of FAI Allocation in Guangzhou Districts Based on Differential Evolution

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Abstract. The allocation of Fixed Asset Investment (FAI) across districts in Guangzhou significantly influences the coordinated development of the regional economy. Particularly under the constraints of geographical adjacency, the rationality of FAI allocation has garnered considerable attention. In this study, we propose a regional layout optimization method based on soft constraints of geographical adjacency to explore the rationality of FAI allocation. This paper constructs a model integrating economic indicators such as GDP, resident population, total retail sales of consumer goods, and FAI. The weights of these indicators are calculated using Gradient Boosting Decision Tree (GBDT) and Principal Component Analysis (PCA). The rationality of FAI allocation in 2022 is analyzed by combining Multilayer Perceptron (MLP) and Differential Evolution (DE). Furthermore, Kepler Optimization Algorithm (KOA) is introduced to model and optimize the decline in FAI in some districts in 2023, thereby enhancing the analytical accuracy. The results indicate that FAI allocation across Guangzhou districts exhibits a certain level of rationality under geographical adjacency constraints. However, districts such as Panyu and Nansha still require optimized investment strategies. This study provides quantitative support for policymakers, contributing to enhanced regional economic resilience and coordinated development.

Keywords: FAI, Geographical Adjacency, Differential Evolution, Kepler Optimization.

1. Introduction

The allocation of Fixed Asset Investment (FAI) across Guangzhou districts is vital for promoting coordinated regional economic development. Rational FAI distribution improves resource allocation efficiency, fosters balanced economic growth, and enhances regional economic resilience. However, achieving equitable distribution remains challenging in complex economic environments. This paper examines the rationality of FAI allocation from the often-overlooked perspective of geographical adjacency.

Traditional data-driven methods and multi-objective optimization models are widely used in regional economic research. However, they often focus on single economic indicators or ignore the impact of geographical adjacency on FAI allocation. Additionally, they tend to overfit multi-dimensional economic data and struggle to adapt to dynamic changes. Despite these limitations, some scholars have examined the role of spatial adjacency in regional economies from various perspectives, providing valuable insights for this study. For example, Hou et al. (2023) investigated the relationship between digital finance and regional economic resilience, demonstrating that digital finance enhances economic resilience by optimizing regional innovation and consumption [1]. Similarly, Huo et al. (2022) linked spatial proximity with spatial networks to analyze the spatial correlation network structure of carbon emissions, revealing that the stability of central positions gradually strengthens over time [2]. Liu et al. (2021) and Liu and Xue (2021) conducted similar studies, analyzing the role of spatial adjacency in regional economic development and highlighting its significance in shaping economic disparities [3-4]. These studies collectively underscore the importance of spatial adjacency in regional economic dynamics. In the realm of optimization algorithms, Avdagic et al. (2022), Qi et al. (2021), Yan (2021), and Yang et al. (2021) pioneered the use of advanced optimization techniques, such as genetic algorithms and differential evolution, to address complex regional allocation problems

[5-8]. Their work provides a robust technical foundation for optimizing regional investment strategies. Additionally, Q. IS et al. (2021) proposed the concept of adjacency constraints when studying factors affecting regional investment potential, further supporting the relevance of geographical adjacency in investment optimization [9].

Despite these advancements, research on geographical adjacency as a critical constraint remains limited, hindering the practical application of investment optimization strategies. To address this gap, this paper constructs a regional layout optimization model that integrates economic indicators and geographical adjacency constraints. By combining multi-layer perceptrons and differential evolution algorithms, the model analyzes the rationality of FAI allocation in Guangzhou in 2022. Additionally, the Kepler optimization algorithm is employed to enhance the model's adaptability to 2023 data changes. The findings provide quantitative support for governments to optimize investment layouts and improve economic resilience.

2. Model Construction

2.1. The structure of MLP-DE

Multilayer Perceptron-Enhanced Differential Evolution (MLP-DE) is a hybrid method combining Multilayer Perceptron (MLP) and Differential Evolution (DE). MLP, a classic artificial neural network, excels in nonlinear fitting, while DE, a population-based global optimization algorithm, is widely applicable across various fields.

Before analyzing the geographical rationality of FAI across Guangzhou districts in 2022, we first construct economic indicators suitable for MLP-DE through the following steps. We developed a mathematical programming model with an objective function ensuring that the sum of predicted economic indicators across all districts matches the actual total economic indicator. The decision variables involve reallocating FAI across 11 districts, with constraints including the principle of gradual progress and the alignment of optimal and actual total FAI.

The economic indicators integrate GDP, resident population, total retail sales of consumer goods, and FAI, evaluating regional economic conditions from four dimensions: economic strength, development potential, consumption capacity, and investment confidence. Due to industrial transformation and upgrading in Guangzhou at the start of the century, which caused significant FAI fluctuations across districts and statistical method changes affecting data continuity, the study uses data from 2006 to 2023, covering the stable post-transformation period to avoid data distortion.

We standardized GDP, resident population, total retail sales of consumer goods, and FAI, and used the latter three to predict GDP. After training the Gradient Boosting Tree (GBT) model, the importance scores for GDP prediction were 0.404545, 0.342058, and 0.253397, respectively. Principal Component Analysis (PCA) was applied to extract main components and reduce dimensionality, with GDP set as the core indicator (weight = 1) and the other features weighted according to their importance scores. The final weights were: GDP (0.488), resident population (0.215), total retail sales of consumer goods (0.169), and FAI (0.128), used to calculate the economic indicators. The results are shown in Table 1.

Table.1. Economic Indicator

Year	Economic indicator
2006	0.000
2007	0.046
2008	0.100
2009	0.153
2010	0.233
2011	0.303
2012	0.363
2013	0.446
2014	0.497
2015	0.566
2016	0.640
2017	0.708
2018	0.746
2019	0.797
2020	0.839
2021	0.937
2022	0.948
2023	1.000

Extracting the FAI from each district of Guangzhou, we construct the feature vector $X = [x_1, x_2, x_3, ..., x_n]$, where n is the number of features, and normalize the data.

$$x'_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \tag{1}$$

where x'_{ij} represents the normalized feature, x_{ij} is the j-th feature of the i-th sample, μ_j and σ_j are the mean and standard deviation of the j-th feature, respectively.

A multilayer perceptron is designed to capture the complex relationships between features and the target variable. The loss function measures the discrepancy between the predicted economic indicator y' and its true value y.

$$L(w,b) = \frac{1}{m}\sum_{i=1}^{m}\left(y_i - f_{MLP}(s(x_i); w, b)\right)^2 + \lambda\left(\sum_{l\in\{50,30,20\}} \left\|w^{(l)}\right\|_F^2 + \left\|b^{(l)}\right\|_2^2\right) \tag{2}$$

where $L(w,b)$ is the loss function, m is the number of samples, y_i is the predicted economic indicator of the i-th sample, f_{MLP} denotes the function of MLP, λ is the regularization parameter, $\left\|w^{(l)}\right\|_F^2$ denotes the squared Frobenius norm of the weight matrix in the l-th hidden layer, and $\left\|b^{(l)}\right\|_2^2$ represents the squared L2 norm of the bias vector in the l-th hidden layer.

(1) Initialize the population by randomly generating individuals, where each individual is represented as a vector p_i, $i = 1, 2, ..., N$.

(2) Mutation is applied to individual p_i.

$$v_i = p_{r1} + Fp_{r2} - Fp_{r3} \tag{3}$$

where v_i represents the generated mutant individual, p_{r1}, p_{r2}, p_{r3} are three distinct individuals randomly selected from the population, and F is the scaling factor, set as a tuple $(0.7,1)$.

(3) p_i becomes the target individual. For the mutant individual v_i and the target individual p_i.

$$u_{ij} = \begin{cases} v_{ij},\ if\ \ rand_j(0,1) \le 0.9\ or\ \ j = j_{rand} \\ p_{ij},\ otherwise \end{cases} \tag{4}$$

where u_i represents the generated trial individual, and j_{rand} is a randomly selected dimension index to ensure that at least one dimension comes from the mutant individual.

(4) The fitness values of the trial individual u_i and the target individual p_i are compared, and the better individual is selected to proceed to the next generation population.

$$L(ij) = \begin{cases} 1,\ if\ \ 0.8 \times regions_{2021}(j) \le u_{ij} \le 1.3 \times regions_{2021}(j) \\ 0,\ otherwise \end{cases} \tag{5}$$

$$p_i(t+1) = \begin{cases} u_i,\ if\ \ CO(u_i) < CO(p_i)\ and\ \sum_{j=0}^{10} L(ij) = 11 \\ p_i,\ otherwise \end{cases} \tag{6}$$

where $L(ij)$ is a binary indicator function that evaluates whether the trial individual u_{ij} satisfies the regional allocation constraints. This ensures that the optimization process adheres to the predefined allocation limits, maintaining solution feasibility.

$$CO(p_i) = \left| f_{MLP}(p_i;\theta) - T \right| + e^6 \times \max\left(0, \left| \sum_{i=1}^{n} p_{ij} - total_{2022} \right| \right) \tag{7}$$

where $f_{MLP}(p_i;\theta)$ means the output of MLP with parameters θ, T is the target economic indicator value, and $total_{2022}$ denotes the total FAI of Guangzhou in 2022. The penalty factor e^6 ensures that a significant penalty is added to the objective function when the constraints are violated, preventing the selection of infeasible solutions during the optimization.

(5) The convergence tolerance is defined as $tol = 0.01$. Steps (2) through (4) are repeated iteratively until the maximum number of iterations (1000) is reached or the change in the objective function during optimization falls below 0.01.

2.2. The structure of MLP-DE-KOA

Multilayer Perceptron-Enhanced Differential Evolution incorporating Kepler Optimization (MLP-DE-KOA) is a hybrid optimization approach designed to enhance the performance of MLP-DE by integrating Kepler Optimization Algorithm (KOA). MLP-DE exhibits sensitivity to initial values and constraints, particularly under conditions where FAI in certain districts experienced significant declines during 2021-2022, limiting its effectiveness. To address this issue, MLP-DE has been improved by incorporating KOA. KOA [10], is a novel optimization technique inspired by the laws of planetary motion and is known for its robust global search capabilities. By integrating KOA, the robustness and adaptability of MLP-DE are significantly enhanced.

The data preprocessing and neural network model construction remain unchanged.

(1) Randomly generate the initial population, where the vector q_i represents a candidate solution.

(2) Evaluate the fitness function of q_i and calculate the quality of each individual.

$$m_i = \left(\left| f_{MLP}(q_i;\theta) - T \right| + e^6 \times \max\left(0, \left| \sum_{i=1}^{n} q_{ij} - total_{2023} \right| \right) + \varepsilon \right)^{-1} \cdot e^{-\frac{\left\| q_i - q_{best} \right\|^2}{2\sigma^2}} \tag{8}$$

where $CO(q_i)$ is the fitness function, T is the target economic indicator value, $total_{2023}$ is the total FAI of Guangzhou in 2023, m_i denotes the quality of the individual, ε is a small positive constant, q_{best} is the current optimal solution, and σ controls the decay rate of the quality.

(3) The acceleration of each individual is computed based on the gravitational force.

$$F_{ij} = G \cdot \frac{m_i m_j (q_j - q_i)}{\left\| q_j - q_i \right\|^2} \tag{9}$$

where F_{ij} represents the gravitational force between q_i and q_j, G is the gravitational constant.

(4) Analogous to the effect of gravitational force on planetary motion, the interaction between individuals is simulated through differential evolution operations.

$$v_i = Fq_{r1} - Fq_{r2} \tag{10}$$

where v_i represents the differential vector used to simulate velocity. q_{r1} and q_{r2} are two randomly selected distinct individuals. The original individual q_i becomes the target individual. The trial individual u_i is generated based on the crossover probability.

$$u_{ij} = \begin{cases} v_{ij},\ if\ \ rand_j(0,1) \le CR\ or\ \ j = j_{rand} \\ q_{ij},\ otherwise \end{cases} \tag{11}$$

where u_{ij} is the value of the trial individual u_i in the j-th dimension, and v_{ij} and q_{ij} are defined similarly. Here, the role of j_{rand} is the same as in the previous model.

$$v_i^{t+1} = 0.9 \times v_i^t + \sum_{j \ne i} F_{ij} \tag{12}$$

where v_i^{t+1} represents the updated differential vector, and v_i^t is the initial differential vector.

(5) The position of the trial individual u_i is adjusted using the updated velocity v_i^{t+1}. Only individuals that satisfy the constraints are allowed to proceed to the next generation population.

$$u_i^{t+1} = u_i^t + v_i^{t+1} \tag{13}$$

$$L(ij) = \begin{cases} 1,\ if\ \ 0.8 \times regions_{2022}(j) \le u_{ij}^{t+1} \le 1.3 \times regions_{2022}(j) \\ 0,\ otherwise \end{cases} \tag{14}$$

$$q_i(t+1) = \begin{cases} u_i^{t+1},\ if\ \ \sum_{j=0}^{10} L(ij) = 11 \\ q_i,\ otherwise \end{cases} \tag{15}$$

(6) After each iteration, the quality of the individuals is updated based on λ.

$$m_i^{t+1} = \lambda m_i^t \tag{16}$$

where λ is a positive number less than 1, representing the decay of quality over iterations.

3. Results

3.1. Results and Analysis Corresponding to MLP-DE

We used MLP-DE model to calculate the optimal values of FAI allocation across various districts for 2022. The variation of predicted economic indicators over iterations is shown in Figure 1.

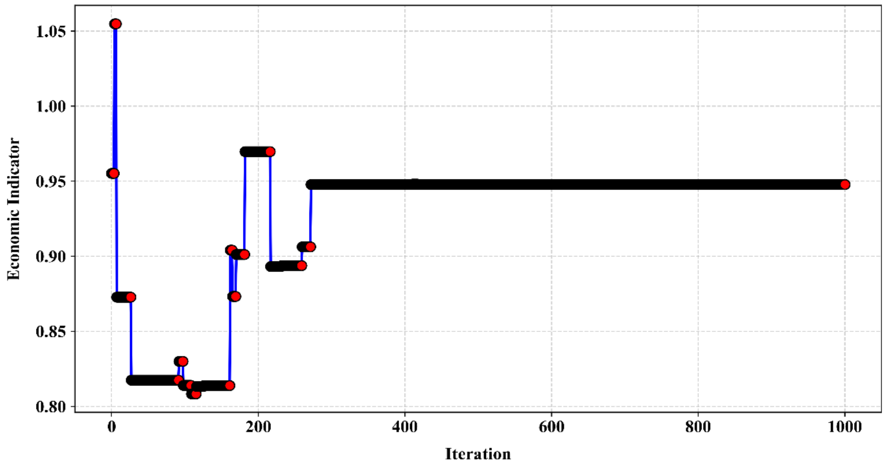

Figure 1. Economic indicator over iterations in 2022

The variation of FAI allocation by districts with the number of iterations is shown in Figure 2.

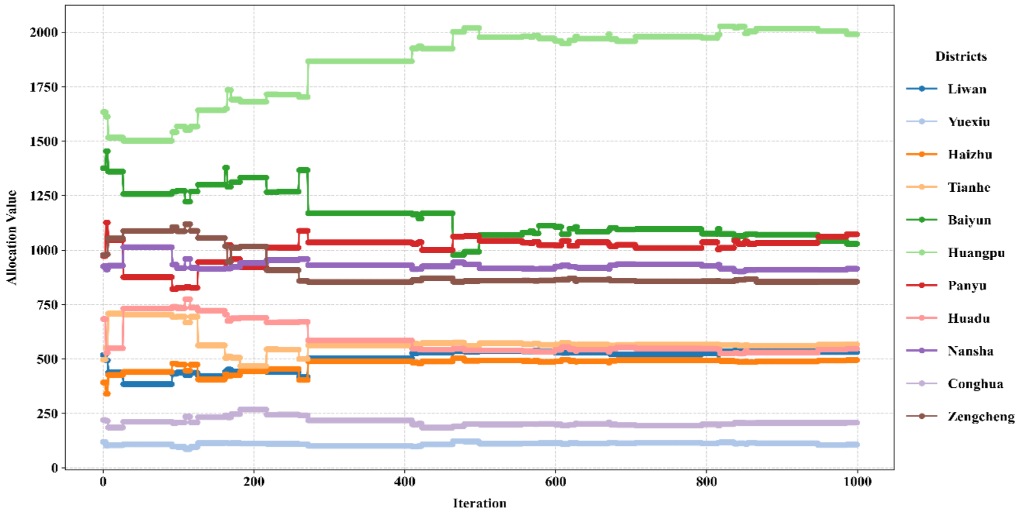

Figure 2. Fixed asset investment allocation by district in 2022

We validated the geographical rationality of FAI allocation, with the results presented in Table 2.

Table.2. Comparison of actual vs optimal by district in 2022

District	Actual allocation	Optimal allocation	Actual/Optimal
Liwan	489.18	531.87	0.920
Yuexiu	104.52	107.35	0.974
Haizhu	478.02	495.56	0.965
Tianhe	586.36	567.90	1.033
Baiyun	1156.64	1029.18	1.124
Huangpu	1920.88	1991.58	0.965
Panyu	737.45	1072.55	0.688
Huadu	573.75	547.29	1.048
Nansha	1217.45	914.67	1.331
Conghua	179.29	208.03	0.862
Zengcheng	877.76	855.32	1.026

We plotted the ratio of actual values to optimal values as a line chart, as shown in Figure 3.

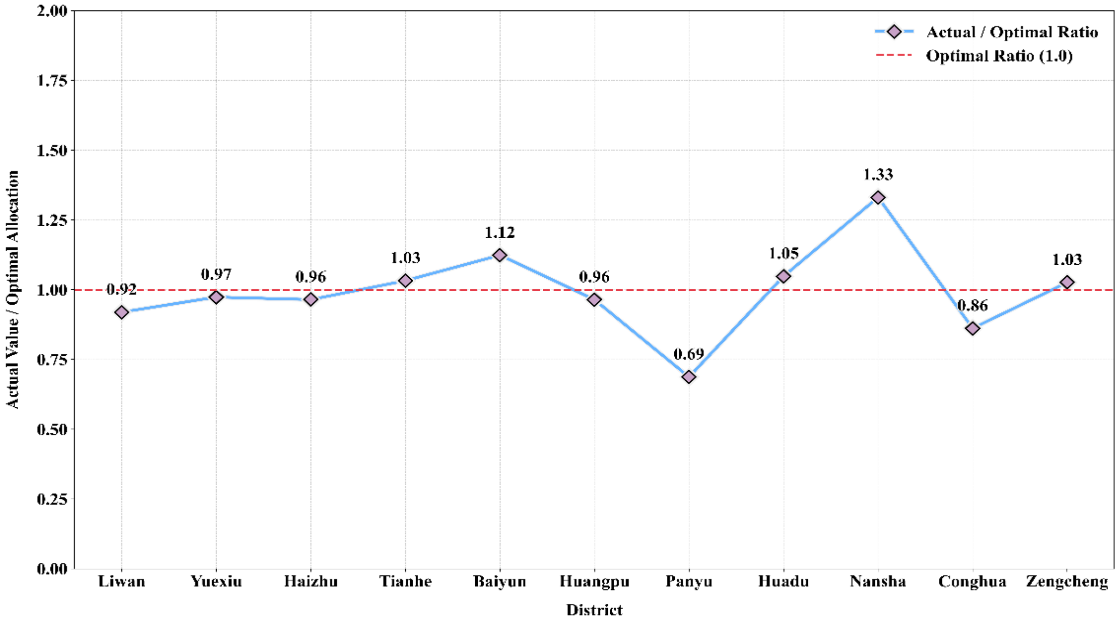

Figure 3. Actual vs optimal allocation ratio by district in 2022

By observing Figure 3, the ratios for Panyu (1/0.69) and Nansha (1/1.3) exceed the constraint range of 80%-130% for the optimal-to-actual values, indicating less reasonable allocation in these districts. Using relevant data, we determined the geographical adjacency relationships and main urban area status, resulting in the adjacency ranking summarized in Table 3.

Table.3. District rank for Geo. Adjacency, GDP, and Pop

District	Geo. Adjacency rank	GDP rank	Pop. rank	Is main urban?
Liwan	1	6	4	Yes
Yuexiu	2	3	10	Yes
Haizhu	3	1	3	Yes
Tianhe	4	5	1	Partially
Baiyun	5	10	8	Yes
Huangpu	6	9	6	No
Panyu	7	8	5	No
Huadu	8	11	11	No
Nansha	9	2	7	No
Conghua	10	4	2	No
Zengcheng	11	7	9	No

By comparing Figure 3 and Table 3, the allocation of Fixed Asset Investment (FAI) across Guangzhou districts in 2022 shows a certain rationality in geographical adjacency, though optimization is still needed. In main urban areas with complex adjacency, such as Tianhe, Yuexiu, and Haizhu, the ratio of actual to optimal FAI values is close to 1, indicating relatively reasonable allocation that meets regional economic demands. As Guangzhou's economic core, the rationality of FAI allocation in these areas supports the city's coordinated development.

However, in districts with simpler geographical adjacency, such as Panyu and Nansha, the ratio of actual to optimal FAI values significantly deviates from 1, indicating less reasonable allocation. This deviation may arise from these districts' unique economic structures, industrial layouts, or policy support, resulting in FAI allocations that do not fully meet their needs. Additionally, while the actual FAI values in main urban areas are close to optimal, they are generally slightly below 1, reflecting insufficient investment. As a key economic pillar of Guangzhou, this FAI shortfall in main urban areas may have constrained the city's rapid economic development in recent years.

3.2. Results and Analysis Corresponding to MLP-DE-KOA

We used MLP-DE-KOA to calculate the optimal values of FAI allocation across various districts in for 2022. The variation of predicted economic indicators over iterations is shown in Figure 4.

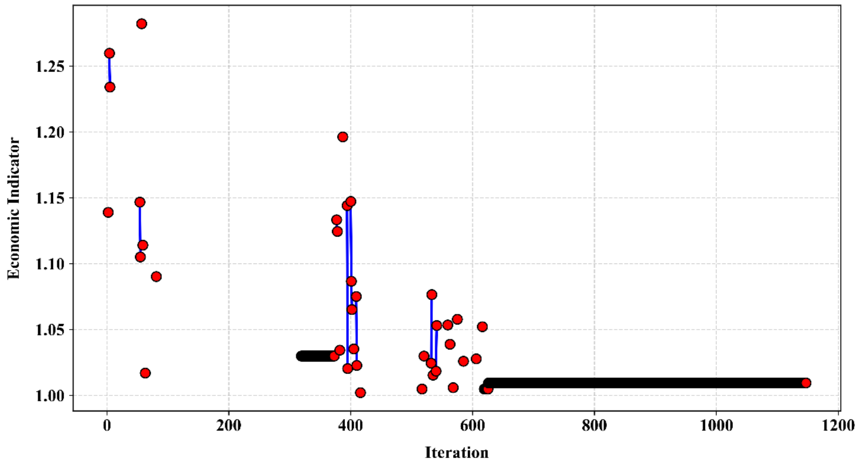

Figure 4. Economic indicator over iterations in 2023

The variation of FAI allocation across districts with the number of iterations is shown in Figure 5.

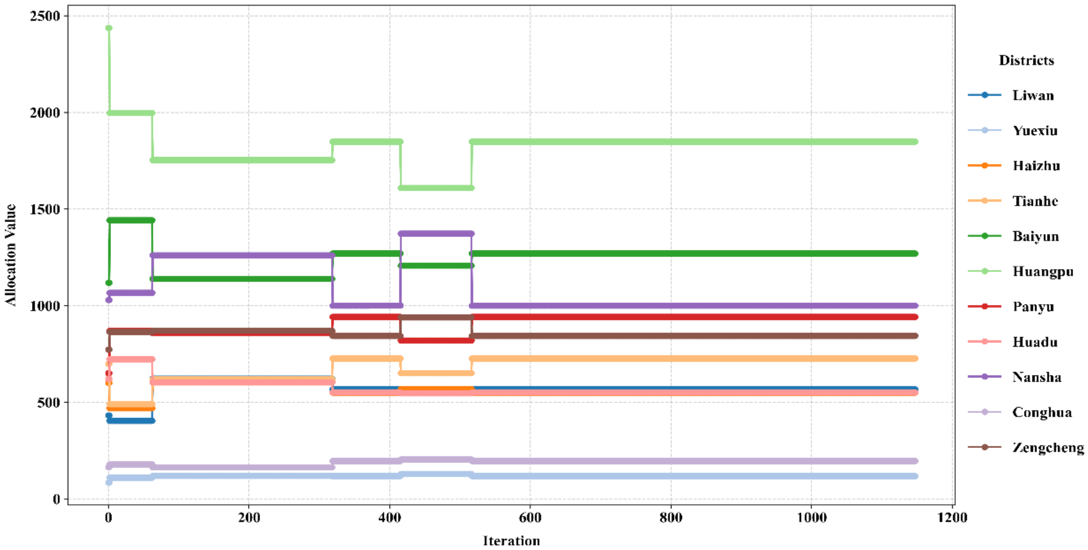

Figure 5. Fixed asset investment allocation by district in 2023

By comparing these optimal values with the actual values, we validated the geographical rationality of FAI allocation, with the results presented in Table 4.

Table.4. Comparison of actual vs optimal by district in 2023

District	Actual allocation	Optimal allocation	Actual/Optimal
Liwan	540.30	568.25	0.951
Yuexiu	115.27	119.17	0.967
Haizhu	535.97	550.64	0.973
Tianhe	703.83	727.83	0.967
Baiyun	1216.55	1270.96	0.957
Huangpu	2000.32	1849.65	1.081
Panyu	811.69	942.36	0.861
Huadu	578.02	551.46	1.048
Nansha	1103.17	1001.07	1.102
Conghua	201.77	197.26	1.023
Zengcheng	816.77	845.01	0.967

To provide a more intuitive representation, we plotted the ratio of actual values to optimal values as a line chart, as shown in Figure 6.

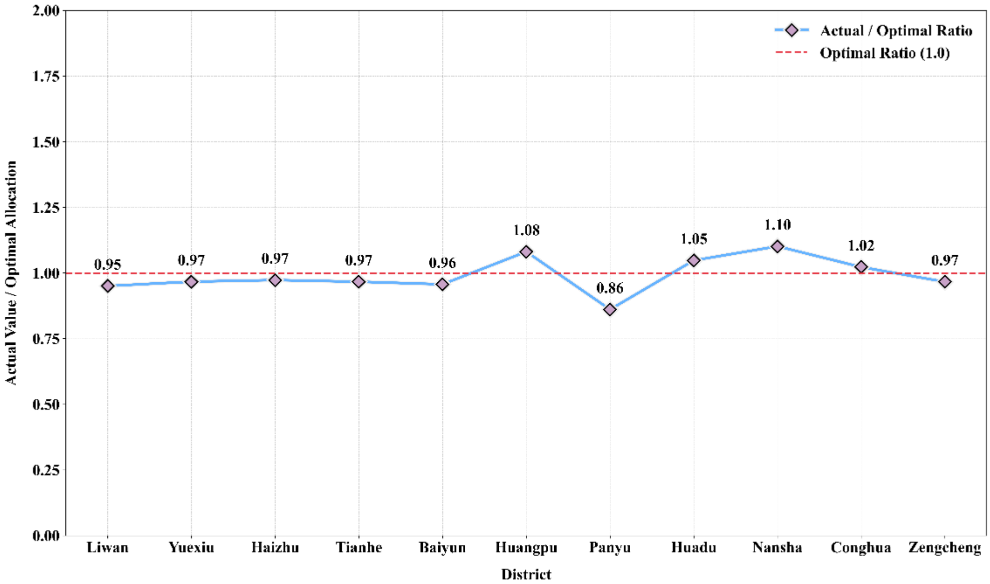

Figure 6. Actual vs optimal allocation ratio by district in 2023

By comparing Figure 6 and Table 3, it can be observed that FAI across various districts of Guangzhou in 2023 also exhibits a certain degree of regularity in terms of geographical adjacency. Specifically, in the main urban areas with complex geographical adjacency, the ratio of actual FAI values to optimal values is close to 1, indicating that FAI allocation in these regions is relatively reasonable and aligns with the expected targets. However, in districts with simpler geographical adjacency, the ratio of actual FAI values to optimal values significantly deviates from 1, suggesting some degree of deviation in FAI allocation. It is noteworthy that although the actual values in the main urban areas are close to the optimal values, they are generally slightly below 1, reflecting a certain insufficiency in FAI in these areas. As the core region of Guangzhou's economic development, the relative insufficiency of FAI in the main urban areas may have imposed certain constraints on the sustained and rapid growth of the city's overall economy.

Furthermore, by comparing the line charts of the ratio of actual to optimal values for 2022 and 2023, it can be seen that the situation in most districts remains relatively stable. However, there are notable fluctuations in some districts, such as Baiyun and Huangpu. These fluctuations may be attributed to changes in local economic policies, industrial restructuring, or shifts in investment priorities.

4. Conclusions and outlooks

In this study, we investigated the geographical rationality of FAI allocation across various districts in Guangzhou. Specifically, we developed an intelligent optimization model based on MLP and DE to validate the geographical rationality of FAI allocation in 2022 and incorporated KOA to optimize FAI allocation for 2023. The results indicate that geographical adjacency significantly influences FAI allocation: in the main urban areas with complex geographical relationships, the ratio of actual FAI values to optimal values is close to 1, suggesting that FAI allocation in these regions is relatively reasonable and contributes to maintaining economic stability in the central urban areas. In contrast, in regions with simpler geographical relationships, such as Nansha District and Panyu District, the ratio deviates from 1, indicating that FAI allocation in these areas still requires further optimization. The significance of this study lies in the fact that the MLP-DE and MLP-DE-KOA models provide new methodological support for analyzing the geographical rationality of FAI allocation, enriching theoretical research in regional economic optimization. The findings offer a scientific basis for governments to formulate FAI allocation policies, helping to achieve efficient resource allocation and promote balanced regional economic development. Moreover, the models established in this study are not only applicable to Guangzhou but can also be extended to other cities or regions, providing references for solving similar problems.

Despite the study's achievements, some limitations remain. The model mainly relies on historical FAI data, which may be incomplete or outdated. It also overlooks key factors like policy changes and industrial adjustments that could affect FAI allocation. Future research could improve the model by integrating real-time data and additional dynamic variables to enhance its accuracy and persuasiveness.

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