Multi-Objective Optimization Information Fusion and Its Applications for Logistics Centers Maximum Coverage

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ABSTRACT

In order to improve the unreasonable distribution of logistics center deployment time, all logistics center algorithms in this paper are regarded as the subject of free "activities," and they are allowed to move freely according to these rules by setting certain moving rules. Simulation results show that the algorithm has good coverage effect and can meet the requirements of logistics centers for coverage effect.

KEYWORDS

Information Fusion, Logistics Centers Maximum Coverage, Multi-Objective Optimization

1. INTRODUCTION

Location selection has always been an important link in the supply chain. The location of logistics center is not only related to the service level of customers, but also directly affects the cost of the whole logistics process, so it has been paid great attention by scholars. At present, the research on location model mainly focuses on MCLP and CCLP. The problem of overlay is a classic problem of traditional location model. It was first proposed by literature and widely used in various fields.

The location problem of large-scale dynamic coverage is solved in detail by simulated annealing algorithm in reference (Regaieg, R., M Koubàa, Ales, Z., & Aguili, T. 2021). The algorithm can meet the service needs of 2500 nodes and 200 logistics hubs, and also fill the problem that previous researches have not paid enough attention to large-scale dynamic coverage. The paper (Aab, A., Ek, A., & Sr, B. 2021) proposes the multi-objective maximum coverage location and multi-objective fuzzy target planning based on the emergency vehicle positioning model. The ultimate goal is to improve service coverage and service level with a short total transportation distance. The paper (Ma, X., Yang, J., Sun, H., Hu, Z., & Wei, L. 2021) proposes the maximum coverage problem when both nodes and paths generate requirements, and establishes two different models for both requirements. Greedy algorithm based on simulated annealing algorithm is used to calculate the secondary maximum coverage position of node requirements, and geometric mathematics is used to calculate path requirements. Finally, the location of mobile service station in Yili County, New York is determined by tracking data of mobile users and mobile users. The paper (Attia, A. M., Al Hanbali, A., Saleh, H. H., Alsawafy, O. G., Ghaithan, A. M., & Mohammed, A. 2021) discusses the maximum coverage problem in the case of negative weight in the network, and proposes an integer programming algorithm for this problem, and implements the algorithm based on ILOG CPLEX software. The data set with 40 maximum coverage problems is solved and tested by two heuristic algorithms, ascending algorithm and simulated annealing algorithm. Reference (Jagadeesh, S., &

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Mu thulakshmi I. 2021) through the use of GIS and the elaboration of partial coverage idea, the traditional coverage model is extended to some extent, and the conclusion is that compared with the traditional coverage model, the new model covers more demand nodes. The paper (Abdel-Basset, M., Mohamed, R., & Mirjalili, S. 2021) propose a method of generating and covering the columns to solve the problem of maximum probability coverage.

The research on the location of maximum coverage in China in the early stage mainly focuses on the classification of the methods used and the reference for foreign scholars. The paper (Zou, F., Yen, G. G., Tang, L., & Wang, C. 2021) divides the covering location into two types: deterministic location model and probability location model. Deterministic location includes set coverage and maximum coverage. Probability location includes probability set coverage model, maximum expected coverage model and maximum availability coverage model. A membrane calculation method based on the non-uniform radius covering location is proposed in the literature (Ursulak, J., & Coulibaly, P. 2021), which is used to locate the fresh agricultural products logistics center. Reference (Shi, C., Wang, M., Yang, J., Liu, W., & Liu, Z. 2021) considers the location of the maximum coverage problem based on time satisfaction. Reference (Hm, A., Hw, B., Ye, T. A., Ran, C. C., & Xz, B. 2021) considers the location efficiency of joint coverage location at the lowest service level. Reference (Tam, N. T., Hung, T. H., Binh, H., & Le, T. V. 2021) according to the disaster degree of the disaster affected area, considering the factors such as the budget cost of the project in the disaster stricken area, the location model covering the largest problem is established to meet the needs of disaster relief and relief materials. Finally, through the actual numerical experiments, the influence area and materials meet different budget cost standards are discussed, Different influences on the number and address of the goods distribution center.

Reference (Leng, L., Jia, H., Chen, A. S., Zhu, D. Z., & Yu, S. 2021) considers all handling tools, products and the process of picking up goods in the warehouse as part of a common logistics. By using location-based service trigger, the location information is seamlessly combined with the warehouse workflow, which makes full use of the convenience of intelligent manufacturing and industry 4.0. Reference (F Shafiee, Kazemi, A., Caghooshi, A. J., Sazvar, Z., & Mahdiraji, H. A. 2021) establishes a multi-level distribution system for specific areas between suppliers and customers in China. The system determines that the method of mixed integer linear multi-level collaborative logistics center is adopted. Meanwhile, the transportation volume and vehicle load rate of transport vehicles are considered in the model. The influence of the model on site selection decision is illustrated according to actual cases. Reference (Naghdi, S., Bozorg-Haddad, O., Khorsandi, M., & Chu, X. 2021) studies location management of location based services using collaborative agents. Each agent learns the depth of a specific customer's mobile mode and predicts the future location of the customer based on the rules learned. All agents coordinate locations by informing the location of mobile objects within the scope of the service. Finally, the comparison of several methods shows that the collaborative location management technology optimizes the location management search method and shortens the search time.

The paper (F Schmid, Winzer, J., Pasemann, A., & F Behrendt. 2021) considers the joint logistics service center in the high-speed service area by using adaptive genetic algorithm, and establishes the location model of multiple logistics centers, including the joint logistics cost of multi suppliers and commodities, inventory cost and construction cost of logistics center. Based on the analysis of the factors affecting the ecological suitability of site selection, the paper introduces the niche suitability model for the first screening, then combines the integer programming to select the alternative scheme for the second time, and finally determines the location scheme of public logistics center. The practice shows that the model can deal with the problem of urban ecological environment and location of joint logistics center. The urban public logistics network system based on B2C and C2C commodities is determined by reference (Liu, R., Yang, P., & Liu, J. 2021). Based on the network structure, the number of secondary logistics centers is determined by the theory of location selection. Then, the location of urban public logistics center is determined by K-means clustering method. Finally,

according to Voronoi diagram theory, the service area division of the city secondary logistics center is determined. The paper (Mirzaee, M., Safavi, H. R., Taheriyoun, M., & Rezaei, F. 2021) proposes the location technology of multi logistics center in public logistics based on analytic hierarchy process. The paper (Wang, R., Wang, Y., Gundersen, T., Wu, Y., & Liu, M. 2021) studies the advantages and disadvantages of logistics center location under the general logistics condition based on depreciation cost. Reference (Fountas, N. A., & Vaxevanidis, N. M. 2021) based on the general logistics location model between different industries based on "soft time window" and "hard time window", in order to better serve different customers' different time demands, the improved particle swarm optimization algorithm and search algorithm are used to solve the nonlinear programming problems.

In the process of logistics center location, it is often necessary to get the support of model or data. The common operational research models and methods include integer programming, dynamic programming, heuristic algorithm and computer technology.

2. RELATED WORKS

2.1 Gravity Method

The centers of gravity method comes from geometry and is often used for the site selection of a single logistics centers. The area to be selected is considered as an object for physical and geometric calculation and the centers of gravity is finally determined as the best location. The centers of gravity method cannot be independently applied in multiple logistics centers due to its disadvantages brought by its natural and simple advantages. However, it can be well used for site selection of multiple logistics centers by combining with other methods, such as systematic clustering.

2.2 Fuzzy Clustering Method

Fuzzy clustering method is a method that first determines the main factors affecting the system, and then makes a comprehensive evaluation index system. It uses multi-layer analysis method and bottom-up thinking to integrate the upper and lower indicators into the index layer. As the input value of fuzzy clustering, it generally combines the final clustering index of TOPSIS method to sort.

2.3 Mixed Integer Programming Method

Mixed integer site selection has always been the best choice for commercial site selection because it can take various costs into account as a specific operational research model. Generally, the objective is to minimize the total cost, and the optimal solution is obtained by considering all kinds of constraints. However, the solving speed of large-scale location problem is relatively slow. Of course, with the upgrading of GPU and other hardware, the calculation speed has been greatly improved, which makes the application of integer programming in location more advantageous.

2.4 Mixed Operational Research Model

Dynamic programming method has always been an important method to solve multi-stage problems. When 0-1 programming is combined in each stage of dynamic programming, the search speed and accuracy are greatly improved.

Double-layer programming method use linear programming method to select the site for the first step, applies the idea of double-layer programming method, and makes a second selection of the site selection results by combining with queuing theory in operational research. This hybrid method has some advantages for large-scale solution.

2.5 Computer Technology

Based on the site selection method of multi-logistics centers based on Witness, the simulation method has the advantages of no two in addressing, and can set the actual constraints existing in the site

selection range, such as rivers and highways, so as to avoid the approximate solution that needs to be carried out when the final selected site is invalid. In addition, GIS (geographic information system) is introduced into the site selection model to make the process of site selection more intuitive and visual, which has more obvious advantages compared with the simulation method. Generally, it should be used in combination with the operational research method.

2.6 Heuristic Algorithm

Heuristic algorithm based on genetic algorithm (GA) is one of the most of the logistics centers location method, but most of the algorithms are mixed to apply, Reference (Singh, S., Agrawal, A., Kodamana, H., & Ramteke, M. 2021) add a multi-objective genetic algorithm analysis evaluation mechanism, in many times after iterative calculation of multiple sets of quality factor analysis has been made to the satisfaction, make the logistics centers location selection more reasonable. Reference (H Wang, Sheng, B., Lu, Q., Yin, X., & Fu, G. 2021) conducted interactive iteration of two genetic algorithms to form hierarchical genetic algorithm and considered evolutionary game to select the location of logistics centers. Reference (Ber Ta Cchini, F., Bilotta, E., Demarco, F., Pantano, P., & Scuro, C. 2021) considered the application of parthenogenetic algorithm in the site selection of multiple logistics centers, but also conducted search on the basis of regional division. Reference (Al-Amin, M., Abdul-Rani, A. M., Ahmed, R., Shahid, M. U., Zohura, F. T., & Rani, M. 2021) proposed a hybrid immune fruit fly optimization algorithm that combines fruit fly optimization algorithm with immune algorithm. By comparing with the simulation results of traditional immune algorithm, the hybrid immune drosophila algorithm is used to solve the problem of location selection of multiple logistics centers, which can quickly converge to the global optimal location model, providing a new way to solve the problem of location selection of multiple logistics centers. Based on the immune algorithm, Reference (Xu, M., Chen, Y., D Wang, Wang, Y., Zhang, L., & Wei, X. 2021) introduced the framework model of multi-population co-evolution, and proposed a multi-population immune co-evolution algorithm. Simulation data experiments also showed that the convergence of global optimization ability of the hybrid algorithm can efficiently conduct site selection. Reference (Mu Zhou, Xinyue Li, Ya Wang, Shanshan Li, Yingyi Ding, and Wei Nie. 2021) comprehensively considered the advantages and disadvantages of grey system theory, particle swarm optimization algorithm, Drezner algorithm, genetic algorithm, immune algorithm, grey analytic hierarchy process and target planning in site selection, combined particle swarm optimization algorithm and immune algorithm, and solved the problem of continuous site selection of logistics centers. The combination of Drezner algorithm and genetic algorithm makes full use of the local search ability of Drezner algorithm and the global optimization ability of genetic algorithm, so that the calculation results can be closer to the global optimal solution. Reference (Mu Zhou, Yanmeng Wang, Zengshan Tian, Yinghui Lian, Yong Wang, and Bang Wang. 2019) mapped the location selection of logistics centers into a clustering process, took the lowest total cost of logistics as the clustering criterion, and defined the transfer probability, list and pheromone updating mode of ants in combination with the behavior pattern of ants clustering objects, so as to realize the location selection algorithm of multi-logistics centers based on ant colony optimization. Some recently proposed algorithms have also been applied to site selection. Reference (Mu Zhou, Yanmeng Wang, Yiyao Liu, and Zengshan Tian. 2019) applied the new heuristic algorithm bat algorithm proposed in 2010 to the process of site selection. The basic idea of bat algorithm originates from the simulation of bat echolocation behavior, and it has good global optimization ability. Reference (Vitor, T. S., & Vieira, J. 2021) based on the gravity search algorithm proposed to apply the mutation strategy of particle aggregation degree to the gravity search algorithm, and used parameters to avoid the problem of early convergence of the gravity search algorithm, and proved the superiority of this algorithm in the location of logistics centers with practical cases.

From domestic and international research trends, more and more with the aid of all kinds of algorithm of location method, the search speed and optimization ability of the algorithm with the development of computer hardware and software are also gradually improve, especially can feel more

and more intelligent algorithm is used for all kinds of social production, for the logistics centers' location in addition to the geometry algorithm and the mathematical model of quantitative, all kinds of heuristic intelligent algorithm is also very suitable for this kind of problem.

3. MAXIMUM COVERAGE LOCATION ALGORITHM BASED ON MULTI - OBJECTIVE OPTIMIZATION

The mathematical model in this paper is mainly to discretize the logistics area into pixel lattice to select the location of the logistics centers. Under this condition of abstract averaging, the logistics centers can be moved according to the set conditions and reach a location with larger coverage after each move. Taking the coverage of logistics centers as the optimization target, the algorithm gradually moves the logistics centers to a more reasonable location by increasing the balance distance between logistics centers, so as to improve the coverage of logistics network. Since this paper does not need to consider the total moving distance of the logistics centers, the movement in the model is just a computer virtual process for our site selection, and the required minimum moving distance is just a constraint on the moving process, without any cost. We focus on the final moving result. The final location of the virtual logistics centers is the location with the highest coverage rate and the location most in line with the expectation.

3.1 Problem Description

In this paper, the coverage of the whole market area in need of service is defined as the ratio R_{area} of the customer area A_{area} and the total market area A_s in need of service that can be economically served by a given logistics centers (the area within the logistics radius is called economic service, and the area beyond the service radius is called uneconomic logistics)

$$R_{area} = \frac{A_{area}}{A_{\circ}} = \frac{P_{COV}(p_{\circ}) \times \Delta x \times \Delta y}{A \times B \times \Delta x \times \Delta y}$$
(1)

3.2 Mathematical Modeling

If the whole logistics area is digitized into individual customers $A \times B$, then the probability $P(p_i, d_j)$ that the i-th customer p_i is served by the j-th logistics centers d_j is defined as

$$P(p_{i}, d_{j}) = \begin{cases} 0 & \text{if} & d(p_{i}, d_{j}) \geq R_{d} + R_{e} \\ e^{-\lambda[d(p_{i}, d_{j}) - R_{d} + R_{e}]^{\beta}} & \text{if} & R_{d} - R_{e} < d(p_{i}, d_{j}) < R_{d} + R_{e} \\ 1 & \text{if} & d(p_{i}, d_{j}) \leq R_{d} - R_{e} \end{cases}$$
 (2)

Where, $d(p_i, d_j)$ is the distance between the i-th customer and the j-th logistics center, R_d is the service scope of the logistics centers.

The logistics centers deployment algorithm based on the balance distance adopts the location selection method of multiple logistics centers' collaborative services. The probability that customer points p_i are served by all logistics centers is:

$$P\left(\mathbf{p}_{i}\right) = 1 - \prod_{j=1}^{N} \left[1 - P\left(p_{i}, d_{j}\right)\right] \tag{3}$$

If there are $A\times B$ customers in the two-dimensional logistics area, and each customer is expressed by area $\Delta x \times \Delta y$, the probability that the i-th customer point can be served by the logistics network is $P\left(\mathbf{p}_i\right)$, when $P\left(p_i,d_j\right) \leq P_{_{\min}}$, $P\left(\mathbf{p}_i\right) = 0$ then the customer point is not served by any logistics centers in the logistics network. When $P\left(p_i\right) = 1$, $P\left(p_i,d_j\right) \geq P_{_{\min}}$ the customer point can be considered to be served by the logistics network. Whether the i-th customer point p_i is served by the logistics centers of the logistics network, i.e

$$P_{\text{coverage}} \left(p_i \right) = \begin{cases} 0 & \text{if} & P(p_i) = 0 \\ 1 & \text{if} & P(p_i) = 1 \end{cases}$$

$$\tag{4}$$

3.3 Algorithm Description

N Logistics centers are randomly assigned in the whole service area, and the node set of logistics centers is $D = \{S_1, S_2, S_3, \dots S_i \dots S_N \}$.

3.3.1 Relevant Assumptions and Conditions

- (1) Each logistics centers can obtain the location information of itself and all other logistics centers;
- (2) Other factors are not considered during the location movement of logistics centers;
- (3) The moving process of logistics centers is divided into z parts;
- (4) In the k-th movement, all logistics centers are moved according to the balanced distance $r=d_z$;
- (5) The logistics centers have the same service radius R_d and communication radius R_c , among which the communication radius is the global coverage radius;
- (6) The requirements of each customer point p_i are the same.

3.3.2 Relevant Symbols

- (1) R_d : Service radius of logistics centers;
- (2) R_c : Communication radius of logistics centers;
- (3) R_a : range of perceived error;
- (4) R_{area} : Logistics coverage rate;
- (5) A_{area} : The total area of customers served by the economy;
- (6) A_s : The total area of customers needing to be served
- (7) P_{\min} : When the lowest perceived probability $P\left(p_i,d_j\right) \geq P_{\min}$, p_i is served in a single logistics centers:
- (8) λ : is the intensity of information p_i released. The stronger the information is, the easier it is to be perceived. According to the characteristics of exponential distribution and the law of gravity, the smaller the value of λ

- (9) β : the perceptive ability parameter of logistics centers is set as 2 in this paper according to the universal gravitation theorem;
- (10) j: number of logistics centers, each logistics centers has a unique number;
- (11) i: customer number, each customer also has a unique number;
- (12) N_a : neighbors' list of logistics centers;
- (13) p_i : the first customer;
- (14) d_i : the first logistics centers;
- (15) $d(S_a, S_b)$: distance between logistics centers and
- (16) Z: The number of times the logistics centers needs to be moved;
- (17) t_{i} : the time length of the first moving process;
- (18) d_k : the balance distance between logistics centers during the first movement;

Among them: $d_1 < d_2 < d_3 < ... < d_k ... < d_k$

3.3.3 Logistics Centers Location Movement Scheme

If the coordinates of any two logistics centers \mathbf{S}_a and S_b are respectively $(x_a, y_a), (x_b, y_b)$, then the distance between the two logistics centers is:

$$d(S_a, S_b) = \sqrt{(x_a - x_b)^2 + (y_a - y_b)^2}$$
 (5)

Within the time period t_k , the repulsion balance distance is d_k , if $d(\mathbf{S}_a, \mathbf{S}_b)$ less than d_k , the two logistics centers need to be moved to reach the balance distance d_k , if $d(\mathbf{S}_a, \mathbf{S}_b) \geq d_k$, the two logistics centers have already met the balance distance, there is no need to move. In the time period t_k , if $d(\mathbf{S}_a, \mathbf{S}_b) \leq d_k$, then the two logistics centers need to be moved to the new coordinate position $(x_a^{\ \ \ \ \ }, y_a^{\ \ \ \ \ })$, $(x_b^{\ \ \ \ \ \ \ \ \ }, y_b^{\ \ \ \ \ \ \ \ })$ meeting the conditions $d(\mathbf{S}_a, \mathbf{S}_b) \geq d_k$. In order to minimize the sum of the moving distance of the two logistics centers, the following formula can be used to calculate:

$$x_{a}' = \frac{d_{k} \left[x_{a} - \frac{1}{2} \left(x_{a} + x_{b} \right) \right]}{2 \sqrt{\left(x_{a} - x_{b} \right)^{2} + \left(y_{a} - y_{b} \right)^{2}}} + \frac{1}{2} \left(x_{a} + x_{b} \right)$$

$$(6)$$

$$y_{a}' = \frac{d_{k} \left[y_{a} - \frac{1}{2} \left(y_{a} + y_{b} \right) \right]}{2 \sqrt{\left(x_{a} - x_{b} \right)^{2} + \left(y_{a} - y_{b} \right)^{2}}} + \frac{1}{2} \left(y_{a} + y_{b} \right) \tag{7}$$

$$x_{b}' = \frac{d_{k} \left[x_{b} - \frac{1}{2} \left(x_{a} + x_{b} \right) \right]}{2 \sqrt{\left(x_{a} - x_{b} \right)^{2} + \left(y_{a} - y_{b} \right)^{2}}} + \frac{1}{2} \left(x_{a} + x_{b} \right)$$
(8)

$$y_{b}' = \frac{d_{k} \left[y_{b} - \frac{1}{2} \left(y_{a} + y_{b} \right) \right]}{2 \sqrt{\left(x_{a} - x_{b} \right)^{2} + \left(y_{a} - y_{b} \right)^{2}}} + \frac{1}{2} \left(y_{a} + y_{b} \right) \tag{9}$$

During the whole moving process, the location of the logistics centers may be beyond the boundary of service scope in the background, which is obviously unreasonable. If the new location is outside the service scope during a movement, the movement will not be carried out this time, that is, the location coordinates of the logistics centers are consistent with the results of the previous movement.

4. ALGORITHM STEPS

- (1) Initialize various parameters and randomly deploy N logistics centers in the service area. Let a=1, b=1, k=1, enter the step (2).
- (2) Every node in the zone broadcasts information when entering the k-th time period t_k , including the ID number and location information of the node. If the node \mathbf{S}_a receives broadcast information from the neighbor node \mathbf{S}_b , update the information in the neighbor list N_a to enter step (3).
- (3) Let S_b is the node N_a with the smallest ID number, and enter step (4).
- (4) According to the information of the nodes S_b in the neighbor table, node S_a calculates the distance $d(S_a, S_b)$ between the node S_a and the neighbor node S_b through equation (5) to enter step (5).
- (5) Compare the equilibrium distance $d(S_a, S_b)$ with the time period d_k . If $d(S_a, S_b) \leq d_k$, calculate the new position coordinates (x_a', y_a') , (x_b', y_b') to be moved to through equations (6) to (9), and enter step (6).
- (6) If the new location of the node to be moved is located outside the monitoring area A, the moving process will not take place, and the node to be moved will not move, entering step (7); otherwise move to the new location and enter step (7).
- (7) If, a = N then turn to step (9); Otherwise, enter step (8).
- (8) If each node \mathbf{S}_b in the neighbor list N_a of the logistics centers \mathbf{S}_a completes the comparison according to the order of node ID number from smallest to largest, then let a=a+1: Otherwise, make $\mathbf{b}=\mathbf{b}+1$, turn to step (4).
- (9) When the k=m period t_m is completed, the algorithm ends; Otherwise, after k=k+1 turning step (2), enter the next node moving period.

5. SIMULATION RESULTS AND ANALYSIS

Matlab software is used to simulate the algorithm, the assumption in the service area $200km \times 200km$ of A random determine N logistics centers, logistics centers service radius $R_d = 50km$, and

Table 1. Coverage effect comparison between the algorithm in this paper and others

N	Random Initial	Gravity Method	Fuzzy Clustering Method	Mixed Integer Programming Method	This Paper Algorithm
10	45%	47%	49%	51%	52%
11	50%	53%	55%	57%	63%
12	55%	58%	61%	66%	71%
13	59%	63%	68%	71%	75%
14	63%	68%	75%	77%	82%
15	66%	72%	74%	79%	85%
16	69%	76%	79%	86%	88%
17	71%	79%	83%	88%	92%
18	73%	84%	87%	90%	95%
19	75%	86%	89%	92%	96%
20	77%	88%	92%	95%	97%

 $\beta=1,\lambda=1$ the communication radius is $100~\rm km$, perceptual error range $R_e=1\rm km$, the moving process of m = $100~\rm times$, the minimum probability of perception $P_{\rm min}=0.8$, the lower the perceived probability lowest customer service to the greater the probability, at the same time, the probability of repeated service is larger, but the stability of the service is not enough, the logistics centers and need quantity will be more, after the test choice under the perception $P_{\rm min}=0.8$ of the probability is more realistic. The coverage of the randomly placed logistics centers is an average of $1000~\rm simulations$. In order to prevent the logistics centers from moving out of the service area A, if the new location of the logistics centers moves to the $20\rm km$ wide edge area inside the service area A, the node of the logistics centers will not move and remain in the original location. When the node density is small, the final balance distance $d_z=R_d$ can obtain the best coverage effect. When the node density is relatively large, the best coverage effect can be obtained when the final balance distance is $d_z=2R_d$. Considering the existence of fixed costs in actual logistics activities, the number of logistics centers will not be too dense, so the number will not be too large $d_z=2R_d=100km$.

The simulation results show that the deployment algorithm of logistics centers in this paper increases the coverage by 20% on average, which means that we can use fewer logistics centers to serve more customers, greatly reducing the cost of logistics. At the same time, it can be seen from the figure above that when N is greater than 13, the marginal effect of coverage improvement gradually approaches to 0. Therefore, under the condition of 90% coverage, it is more reasonable to choose fewer logistics centers for economic consideration.

6. CONCLUSION

The algorithm based on the balance distance has a good effect in the location of the largest coverage logistics center. The disadvantage is that the oscillation time of the algorithm is relatively early, and the subsequent iteration will occupy more computer resources, so it is more suitable for small-scale homogeneous logistics center location.

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120.00% 100.00% —This Paper Algorithm 80.00% Mixed Integer Programming Method 60.00% Fuzzy Clustering Method Gravity Method 40.00% -Random Initial 20.00% 0.00% 5 10 13 15

Figure 1. Coverage effect comparison between the algorithm in this paper and others

Data Availability Statement

The labeled dataset used to support the findings of this study are available from the corresponding author upon request.

Conflict of Interest

The author declare no competing interests.

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