International Journal for Housing Science and Its Applications
Publish August 10, 2025. Volume 46, Issue 4 Pages 4789-4798

https://doi.org/10.70517/ijhsa464322

Optimization Strategy for Port Container Scheduling Based on Improved Clustering Algorithm

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Abstract Optimizing and improving the level of container scheduling as an important means to reduce logistics costs is an important part of port logistics management. In this paper, based on the current container scheduling optimization problem, maximization objective function, and realistic constraint rules, the pre-optimization stage model is designed. At the same time, we use Elbow Mehtod and contour coefficient comprehensive determination method to obtain the optimal number of clusters, combine with improved genetic algorithm, construct improved GA-Kmeans algorithm, and comprehensively propose the container scheduling optimization model based on clustering algorithm. Port E is selected as the experimental object, and under the guidance of the designed container scheduling optimization model based on the clustering algorithm, the time limit of the port vessels' in-port operation is controlled within 1h.

Index Terms improved GA-Kmeans algorithm, container scheduling optimization, pre-optimization stage model, port logistics management

I. Introduction

Container transportation industry is a key link in the social logistics chain and transportation chain, and has an extremely important position in the development of the logistics industry in today's world [1]. The biggest advantage of port containers is the large-scale cargo distribution capacity, which makes port containers the most promising hub of the social logistics chain and value-added service center [2], [3]. With the development of the world economy, the development of the world container transportation industry is gradually accelerated, and the status of container transportation in ocean transportation is becoming more and more important, and the proportion is also higher and higher [4], [5]. Relevant information confirms that the world trade realized by sea transportation has reached more than 2/3 of the total [6].

Due to the surge of container transportation, the contradiction between container transportation demand and terminal capacity gap is highlighted in many ports, and container scheduling becomes critical [7], [8]. At present, the port container production scheduling model is a model that contains two levels of command system and multiple people working together. According to this scheduling model, the staff of each position in accordance with the berthing time and berthing position of the arriving ship, the port reasonably call and distribution of related resources such as equipment, each according to the responsibilities of the division of labor and collaboration, and the planning and scheduling, on-site production scheduling and production meetings are organically integrated to meet the arriving containers loading and unloading, storage and transportation process [9]-[12].

With the accumulation of long-term practice, the terminal production scheduling process gradually formed a set of complete and orderly serial production scheduling process. However, with the growth of port traffic, the defects of traditional container scheduling mode are exposed. A single ship involves container scheduling in thousands of units, and manual scheduling is inefficient, resulting in long standstill time of loading and unloading cranes, and low adaptability to the scheduling needs of suddenly arriving ships [13]-[15]. Therefore, intelligent scheduling system, become the inevitable trend of port logistics container scheduling. And the clustering algorithm has the advantages of processing high-dimensional data, real-time calculation, multi-objective balance, etc., and has emerged in the container scheduling of port logistics [16].

This paper firstly describes the container cargo loading scheduling problem in detail, maximizes the objective function as well as the content of multiple realistic constraint rules. Under this theoretical premise, the definition of the objective function and decision variables as well as the constraints in the pre-optimization stage are explained, and the model of the pre-optimization stage is constructed. Then, the method of determining the number of optimal clusters and the construction process of improved GA-Kmeans clustering algorithm are explained to construct the container scheduling optimization model based on clustering algorithm. Finally, Port E is selected as the research object and the basic situation is sorted out. The proposed model scheduling optimizes the time efficiency of in-port operation and determines the local evaluation function.

II. Container scheduling optimization model based on clustering algorithm

II. A. Container Movement Problem

II. A. 1) Container Scheduling Optimization Problem Description

This paper studies the container is a single box type (using international standard containers) in a variety of goods in the port logistics scheduling optimization problem. That is, for the provision of different types, different sizes and other attributes of a batch of goods, to seek in a single container type of each type of cargo layout mode, so that in the case of limited space in the box as well as in certain performance constraints used in the case of the minimum number of containers, the highest space utilization. The containerized cargo load scheduling problem is described as follows: Given m standard containers, let the width of the box be W, the length of the box be L, and the height be H. Given a batch of N goods (all set to rectangular) set $\{a_1, a_2, \cdots, a_i, \cdots, a_n\}$, the first $i(i=1,2,\cdots,n)$ kind of goods parameter: width of w_i, the length of l_i, the height of h_i. In the process of container scheduling, certain realistic condition constraints should be satisfied between goods and cargo, and between goods and box space, under which the maximization objective function is optimally solved.

The maximization objective function to be achieved by container scheduling under satisfying the constraints of crate performance is equation (1):

$$\max(z_1) = \sum_{i=1}^{n} \frac{l_i \times w_i \times h_i}{L \times W \times H} \tag{1}$$

II. A. 2) Realistic constraint rules

Container constraint rules, i.e., rules that determine the constraints under which goods are loaded in a container vessel. Combined with practical applications, the container scheduling process needs to deal with the reality of loading constraint rules are:

(1) Set the cargo along the height direction for rotational placement, can not be upside down.

(2) The same type of goods can be vertically stacked the maximum number of stacked layers for five layers.

(3) The total load of the loaded goods shall not be higher than the maximum weight that the container can bear.

(4) The gap between the placement of goods with carton expansion package or fill the buffer material, fasteners in advance to leave a gap.

(5) Set up a reserved space to ensure air circulation or make a part of the container space is not loaded with goods.

(6) The same goods are placed next to each other.

II. B. Pre-optimization stage model

Pre-optimization stage is every night according to the ship plan and yard plan to predict the 2nd day of the shore bridge and yard bridge operation, in order to ensure that the yard bridge each period of operation sequence full, lifting equipment operation continuous premise, according to the yard lanes service intensity to arrange the optimal set of trucks to travel the path, to avoid overlapping or cross traffic route, the goal is to make the vehicle in the yard waiting for the shortest time of operation.

Depending on the direction of mission execution, both the shore bridge and the yard are collectively referred to as the source or target yard bridge. The source field bridges are numbered as $1,2,\cdots,T$ and the target field bridges are numbered as $T+1,\cdots,Z$, and all the lifting devices are denoted by points i, j. f_{ij} is the j th operation of lifting equipment i, and h_i is the length of the equipment working period. Each channel is numbered as $1,2,\cdots,M$, and the capacity of each channel is β_m. Assume that the cost of lifting at the yard bridge is $F/$ time slot, the cost of dispatching a truck is $P/$ vehicle, and the cost of transportation from the source yard bridge i to the target yard bridge j is C_{ij}/m. The time for the collector truck to arrive at the target yard bridge j is t_j, and if t_j is earlier than e_j, then increase the waiting cost $C_e \times (e_j - t_j)$. If t_j is later than l_j, then a penalty $C_t \times (t_j - l_j)$ is due.

The objective function (1) is equation (2):

$$\min Z = F\sum_{i=1}^{T} h_i + P\sum_{i=1}^{T}\sum_{j=t+1}^{Z} x_{ijv}\frac{z}{y}vC_{ij} \\ +C_e\sum_{j=t+1}^{Z}\max\{e_j - t_j, 0\} + C_t\sum_{j=t+1}^{Z}\max\{t_j - l_j, 0\} \tag{2}$$

The objective function (1) requires that the total cost of lifting equipment use at the yard bridge, the cost of driving a collector truck, and the cost of waiting and penalties for not meeting the time window be minimized, as in equation (3):

$$\min\sum_{i=1}^{T}\sum_{j=t}^{Z} f_{ij}\times F - h_i \tag{3}$$

The objective function (2) refers to the least amount of overflow of waiting jobs in the yard set of cards in each time period.

The decision variables are defined as in equations (4)-(6):

$$x_{ijv} = \begin{cases} 1, & \text{Service set card } v \text{ transferred from} \\ & \text{lifting equipment } i \text{ to lifting equipment } j \\ 0, & \text{Other} \end{cases} \tag{4}$$

$$y_i^g = \begin{cases} 1, & \text{Task } i \text{ loaded or unloaded by lifting equipment } g \\ 0, & \text{Other} \end{cases} \tag{5}$$

$$\lambda_i = \begin{cases} 1, & \text{Channel } i \text{ is close to the sea area} \\ 0, & \text{Channel } i \text{ is not close to the sea area} \end{cases} \tag{6}$$

The constraints are Eqs. (7)-(14):

$$\sum_{m=1}^{M} y_{wv}^g b_m \le z, \quad \forall v, g \tag{7}$$

$$\sum_{i=1}^{Z}\sum_{v=1}^{K_m} y_{iv}^m = 1, \quad \forall i \tag{8}$$

$$\sum_{i}^{K} x\frac{g}{yv} = \sum_{i=1}^{T}\sum_{j=t+1}^{Z} y_{ij}\frac{g}{v}, \quad \forall j, v, g \tag{9}$$

$$\sum_{j}^{N+M} x\frac{g}{yv} = y\frac{g}{iv}, \quad \forall i, v, g \tag{10}$$

$$\sum_{j=1}^{Z_n} K_j \le 1, \quad j \in Y_n \tag{11}$$

$$\sum_{i=1}^{N} x_{zjv}^h = \sum_{j=t}^{N+M} x_{zjv}^h = 0 \\ z \in \{1, \cdots, N+M\}, \quad h \in \{1, 2, \cdots, K\} \tag{12}$$

$$\sum_{j=1}^{Z}(h_j - t_{ij})K_{ij} + f_i^+ - f_i^- = E_{i'}, \quad i \in K_n \tag{13}$$

$$\sum_{i=1}^{T}\sum_{j=t+1}^{Z} K_{ij} \le \lambda_i, \quad i \in K_n \tag{14}$$

Constraint (7) guarantees that each channel is bounded in terms of capacity for each time period. Constraint (8) guarantees that each collector card waiting for a field channel is serviced. Constraint (9) and constraint (10) guarantee that the collector card is accessed by only 1 lifting device per unit of time. Constraint (11) ensures that 1 collector card is serviced by only 1 lifting device in 1 unit of time. Constraint (12) indicates that a collector card serving a specified box zone can directly reach a specified target box zone. Constraint (13) ensures that the extra time of the source yard crane is consistent with the missing yard crane work capacity of the target box zone. Constraint (14) ensures that the number of fully loaded yard crane equipment waiting in the collector queue does not exceed the number of airlifted transfer crane equipment.

II. C. Construction of Improved GA-Kmeans Algorithm

II. C. 1) Determination of the optimal number of clusters

In this paper, we use Elbow Method and contour coefficient to comprehensively determine the optimal number of clusters of clustering algorithm, in which the Elbow Method selects the rate of reduction of the sum of squared errors within clusters (SSE) with the increase of the number of clusters (RRE) as an indicator of the effectiveness of the clustering.The definitions of RRE and contour coefficient are as follows:

(1) The specific formula for RRE is shown in Eqs. (15)-(16):

$$SSE(K) = \sum_{i=1}^{K}\sum_{x\in G_i} \left|x - g_i\right|^2 \tag{15}$$

$$RRE(K) = SSE(K-1) - SSE(K) \tag{16}$$

Here, K is the number of clusters, G_i denotes the i th class cluster, and g_i denotes the clustering center of the i th class cluster.

(2) Profile coefficient: measures the similarity of each sample to its assigned cluster, and the dissimilarity of that sample to other recent clusters. The specific formula is calculated as equation (17):

$$S = \frac{1}{N_S}\sum_{i=1}^{N_S} \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \tag{17}$$

Here, $b(i)$ is the average distance from sample i to all samples in the nearest other clusters, and $a(i)$ is the average distance from sample i to other samples in the same cluster. The contour coefficient value domain is $[-1,1]$, the closer to 1 indicates that the clustering degree of cohesion and separation are relatively better, i.e., the better the clustering effect.

The specific steps for determining the optimal number of clusters in this paper are as follows:

(1) Choose different number of clusters to cut down the initial container dispatch data generated, calculate the results of RRE and profile coefficient corresponding to different number of clusters respectively, and draw the change curve of RRE and profile coefficient with the number of clusters.

(2) Use the Elbow Method to determine the range of the optimal number of clusters for RRE, and select the largest value of contour coefficient as the final result within the range of the optimal number of clusters.

II. C. 2) Improvement of GA-Kmeans algorithm

In this subsection, a genetic algorithm is used to optimize the initial clustering centers of the K-means clustering algorithm, and a hybrid selection strategy based on the elite retention strategy, tournament selection, and roulette wheel selection is proposed by improving the selection operation of the traditional GA in response to the problem that the traditional GA is prone to immature convergence. The specific design of the improved GA-K-means clustering algorithm in this paper is as follows:

(1) Chromosome coding

In this paper, genetic algorithm is used to optimize the selection of the initial clustering center of K-means clustering algorithm, so this paper adopts integer coding, and the chromosome is structured as equation (18):

$$S = \{s_1, s_2, \cdots, s_K\} \quad s_i = 1, 2, \cdots, N_S \tag{18}$$

Here, S denotes the selected initial clustering center, N_S denotes the number of wind turbine scenes in the initial wind turbine scene set, K denotes that the scene reduction algorithm needs to reduce N_S initial scenes into K classical scenes, and s_i denotes the s_i th wind turbine scene in the initial scene set.

(2) Population initialization

Population initialization is the process of randomly generating an initial population. Firstly, the wind power scenes in the initial scene set are numbered from 1 to N_S. Then randomly select K non-repeating wind power scenes from the initial scene set as an individual, and their numbers form the chromosome of the corresponding individual. Repeat the above operation N_P times to generate the initial population P_0 with the size of N_P, and choose $N_P = 100$ in this paper.

(3) Selection of objective function

K-means clustering algorithm's ultimate goal is to divide a set of data points into K different class clusters, so that each data point belongs to the cluster represented by its nearest clustering center, through iterative optimization, minimize the square distance between the data point and its belonging to the clustering center and thus achieve effective grouping of data. Therefore the objective function chosen in this paper is equation (19):

$$\min f = \min\{SSE\} \tag{19}$$

(4) Crossover operation

Crossover operation mimics the process of genetic recombination in biological inheritance and its main function is to produce new offspring by exchanging chromosome parts of two individuals. This process helps in retaining favorable traits in the parent and produces offspring with better performance. The crossover operation in this paper uses a modified uniform crossover, where one of the two parents of the crossover operation is derived from N_e elite individuals selected using an elite retention strategy, and the other is derived from a traditional crossover individual. Since one parent is derived from an elite retained individual, the improved uniform crossover operation produces better individuals and carries out a substantial improvement in the performance of the search.

(5) Mutation operation

The mutation operation makes the newly generated individuals slightly different from their parents by introducing small random variations in the genes of the individuals, which aims to maintain the diversity of the population and avoid falling into local optimal solutions. In this paper, the mutation operation used is uniform integer mutation, for the mutation point in each gene, with a given probability of mutation in the integer range $[1, N_S]$ to generate a random integer that does not exist in the current gene to replace the original gene value.

(6) Selection Operation

In order to solve the problem that traditional GA is prone to immature convergence, the selection operation of traditional GA is improved, and a hybrid selection strategy based on the elite retention strategy, tournament selection and roulette selection methods is proposed. First, all individuals in the initial population P_t of the generation are crossed and mutated to obtain the population Q_t, and then the population P_t is mixed with the population Q_t to obtain a new population R_t, and the optimal N_e individuals are retained using the elite retention strategy. The other $N_P - N_e$ individuals are obtained using a combination of tournament selection and roulette selection in the following steps:

Step 1: Calculate the mean f_{avg} of the objective function values corresponding to all individuals in the population R_t.

Step 2: Randomly select an odd number (at least 3) of individuals from the population R_t, if more than half of the selected individuals have objective function values greater than f_{avg}, it means that the number of high quality individuals among the remaining individuals may be relatively small, in order to increase the probability that the individual with a larger objective function enters into the next generation, and thus the roulette wheel method is used to randomly select among the selected individuals one individual into the next generation. If more than half of the selected individuals have objective function values less than f_{avg}, the number of high quality individuals among the remaining individuals in the population is relatively large, and in order to ensure that the high quality individuals can enter the next generation with high probability, the individual with the smallest objective function value is selected to enter the next generation.

Step 3: Repeat step 2 until the number of selected individuals meets the requirements.

This method ensures that individuals with smaller objective function values (high-quality individuals) enter the next generation with a greater probability, and at the same time increases the probability that individuals with larger objective function values enter the next generation, and thus effectively maintains population diversity while accelerating the GA convergence rate, thus preventing the occurrence of immature convergence.

(7) Termination conditions

The termination conditions of the algorithm in this paper are: the maximum number of iterations is reached or the value of the objective function does not change within a given number of iterations (100 times in this paper).

The realization flow of the improved genetic algorithm in this paper is shown in Fig. 1.

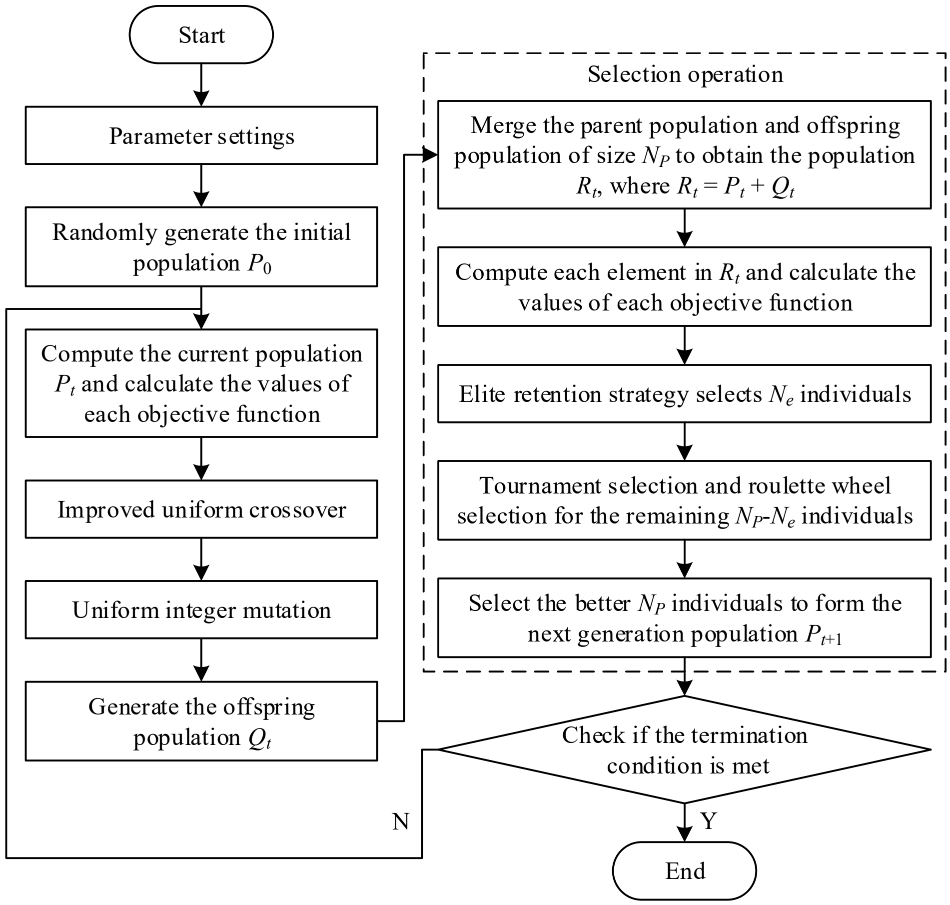

Figure 1: Genetic algorithm process

III. Application analysis of container scheduling optimization model

In this chapter, Port E is selected as the research object, combing its existing logistics box area as well as the operation situation. Combined with the actual situation of Port E, the container scheduling optimization model proposed above is used to carry out the scheduling optimization of container operation, and then analyze the change of the time efficiency of the ship's operation in the port and determine the node local evaluation function.

III. A. Basic information

Known as port E to be unloaded container ships need to unload the amount of containers to be loaded with the amount of containers to be loaded ships need to be loaded are 250, the number of container trucks for the 10 and the provisions of each box area equipped with a field bridge, the import of each box area (1-10) unloading volume and box capacity of the box area is shown in Table 1, the export of each box area (11-20) to be loaded the number of containers is shown in Table 2, the import of the box area to the export of each box area to see the distance See Table 3.

Table 1: The quantity of imported containers and the capacity of each container area

Task	Box area	Unloading volume	Capacity
1-25	1	25	30
25-50	2	25	50
50-75	3	25	30
75-100	4	25	40
100-125	5	25	50
125-150	6	25	30
150-175	7	25	30
175-200	8	25	60
200-225	9	25	50
225-250	10	25	30

Table 2: The number of containers to be loaded in each container area for export

Task	Box area	The number of containers
250-275	11	30
275-300	12	40
300-325	13	30
325-350	14	25
350-375	15	30
375-400	16	50
400-425	17	40
425-450	18	35
450-475	19	25
475-500	20	30

Table 3: The distance from the import container area to the export container area(m)

	1	2	3	4	5	6	7	8	9	10
11	500	600	500	525	500	400	300	325	350	450
12	325	500	300	350	400	300	350	325	450	500
13	225	350	500	525	550	350	375	500	525	600
14	250	525	275	500	500	400	300	300	300	300
15	300	500	250	350	500	325	350	425	450	400
16	425	550	225	325	400	500	300	350	325	400
17	500	425	300	300	525	325	500	500	525	550
18	525	300	350	300	500	300	425	500	550	550
19	325	300	325	400	450	350	500	225	500	250
20	300	250	300	425	300	400	525	550	250	500

In the model, it is assumed that the collector card expects to be serviced within 35min of its arrival. The 30 tasks for which the collector card arrives within 90min in five of the export box areas in this port were selected and the specific data are shown in Table 4.

Table 4: Instance data

Mission number	Box area	Arrival time of the collection card (min)	Task operation time (min)
1	10	2.61	3.5
2	2	35.94	2.5
3	2	32.82	2.0
4	16	86.13	3.5
5	7	66.02	3.0
6	6	28.62	4.5
7	18	36.28	5.5

8	7	10.56	6.0
9	14	74.15	6.5
10	17	12.45	5.5
11	13	20.91	5.0
12	13	52.97	5.5
13	4	48.35	2.5
14	3	1.62	3.5
15	9	36.99	3.0
16	9	48.08	4.5
17	12	61.38	4.0
18	2	4.74	3.0
19	18	67.05	5.0
20	11	36.79	5.5
21	0	2.38	3.5
22	8	40.16	3.5
23	16	29	3.5
24	15	53.07	4.5
25	7	45.97	4.5
26	17	43.81	2.5
27	8	2.51	2.0
28	17	77.25	3.0
29	16	40.92	3.0
30	7	37.18	5.0

III. B. Scheduling optimization of in-port operation timelines

Using the designed scheduling optimization model, based on the actual situation of Port E, a total of 10 in-port operations are optimized for its five vessels (T1-T5). The changes in the time efficiency of the in-port operations of the optimized vessels are shown in Table 5, which shows that the time efficiency of the optimized in-port operations are controlled within 1h, indicating that the algorithm in this paper has a high computational level.

Table 5: The change of ships work effectiveness(h)

Number	T1	T2	T3	T4	T5
1	0.78	0.79	0.76	0.7	0.7
2	0.66	0.66	0.66	0.66	0.66
3	0.95	0.95	0.95	0.95	0.95
4	1	1	1	1	1
5	0.72	0.72	0.72	0.72	0.72
6	0.58	0.58	0.58	0.58	0.58
7	1	1	1	1	1
8	0.98	0.98	0.98	0.98	0.98
9	1	1	1	1	1
10	0.36	0.36	0.36	0.36	0.36

III. C. Evaluation function for nodes

Figure 2 demonstrates the calculation results of each local evaluation function, where the X-axis coordinate is the cluster width, and the Z-axis coordinate is the calculation deviation of the sought solution from the optimal solution. According to the terminal logistics operation flow of containers, the selected evaluation functions are: MWR, LPT, LB. Among the three local evaluation functions, the solution performance of MWR evaluation function is better than that of the other two, and the highest computational error is lower than 20.00% and tends to converge when the cluster width is 15. Accordingly, the local evaluation function is determined to be MWR, and the filtering width is set to 20 and the cluster width to 10 based on its actual performance.

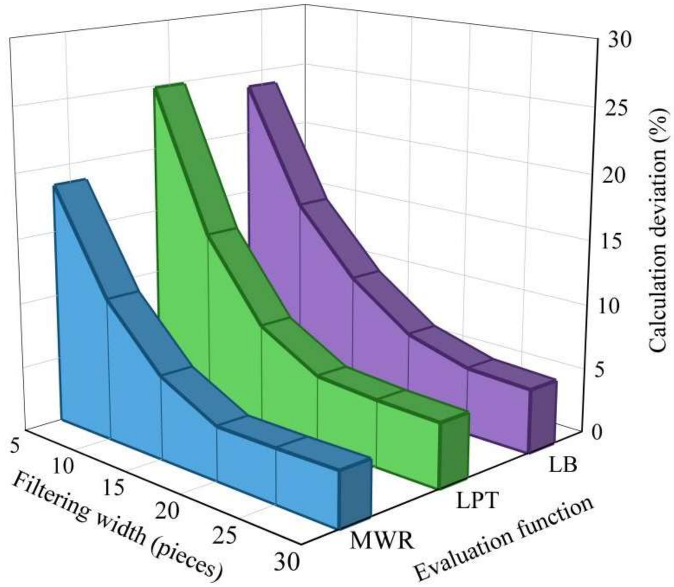

Figure 2: The influence of local evaluation functions on solving deviations

IV. Conclusion

This paper combines the current port logistics container scheduling optimization problems and maximization objective function, constructs the pre-optimization stage model, designs the improved GA-Keans clustering algorithm to solve the objective function under the constraints, and proposes the container scheduling optimization model based on the clustering algorithm. Port E is selected as the experimental object, and the proposed model is used to optimize its container scheduling operation strategy based on the actual situation, and the effect of container scheduling optimization is reflected through the statistics of the time efficiency of the vessels' operation in the port. After optimization, the operating time of vessels in port E is controlled within 1h, which reflects the superior performance of the proposed model in container scheduling optimization. At the same time, based on the logistics operation flow of Port E, MWR is selected as the local evaluation function, and the filtering width is set to 20 and the cluster width is set to 10.

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