IMPROVED ALGORITHM USED FOR DEMAND PREDICTION AND SCHEDULING OPTIMIZATION OF SHARED BICYCLES

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Aiming at the problems of low user satisfaction and high operating cost of shared bicycle systems, the corresponding strategies are proposed from two aspects: demand forecasting and bicycle scheduling path optimization. Firstly, the influences of time, space, and weather factors on shared bicycles' demand are analyzed. The generalized opposition-based learning strategy is introduced into the improved Grey Wolf Optimizer (GWO) algorithm based on dynamic weight allocation and a new control factor to optimize the Back Propagation (BP) neural network. Secondly, taking the total cost of dispatching shared bicycles and user satisfaction as the optimization objectives, establishing the scheduling path optimization model of shared bicycles with multi-scheduling centers, a discrete GWO algorithm based on Large Neighborhood Search (LNS) is proposed for solving. Finally, the effectiveness and efficiency of the proposed methods are verified via simulation.

Keywords: Bicycle-sharing system; Improved GWO algorithm; BP neural network; Demand prediction; Scheduling path optimization

1. Introduction

The rapid development of bicycle-sharing has triggered the problems of “no bicycles available” and “idle vehicles piling up” at a large number of stations[1], and accurately predicting the borrowing/returning capacity of sites and scientific scheduling has become the hot spots of research in related fields.

Many studies have focused on bicycle-sharing scheduling path optimization. Kadri et al. established a static scheduling model with the optimization objective of minimizing the total waiting time in the stations[2]. Yang Jiahui et al[3] abstracted the shared bicycle scheduling problem as a multiple traveling salesman problem (MTSP) with local paths repeated, established a model to minimize the total cost of scheduling. Besides, some scholars have studied the loan/counterweight prediction of shared bicycle sites. Jian et al. developed a Markov model to reasonably predict the number of bicycle borrowing/returning at rental sites considering the return and borrowing rates[4]. Wu Manjin[5] developed

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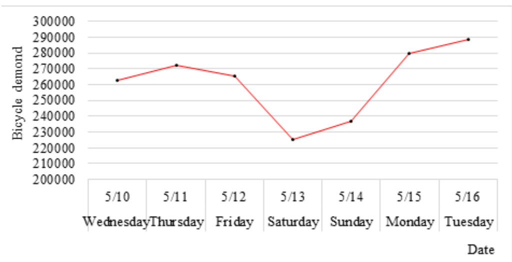
a multi-logit improved model to estimate bicycles' share in total passenger transport and predicted the natural demand for borrowing and returning at stations using historical data.

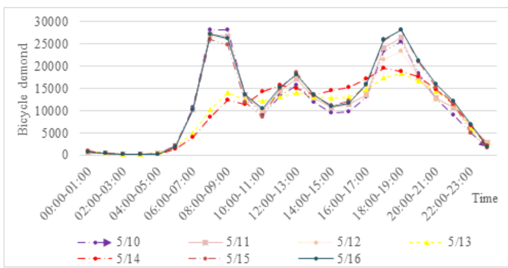
In summary, these studies provided a variety of implementable ideas for shared bicycle scheduling optimization, but the following problems still exist: lacking overall consideration of factors influencing the demand for shared bicycles; focusing on forecasting or scheduling optimization unilateral research; scheduling optimization has the company's cost as the primary goal and lacks research on customer satisfaction. This study establishes the shared bicycles demand prediction and scheduling optimization models for improvement.

2. Data Set Analysis

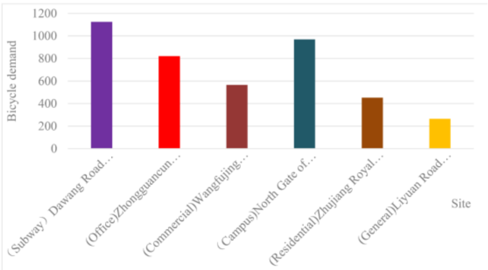
The data in this study came from the 2017 Mobike Cup Algorithm Challenge[6], processed and analyzed by SQL Server. Fig.1 presents the analysis of factors influencing demand for shared bicycles, *a* presents the Daily demand for bicycles, showing the demand was much higher on weekdays than on rest days. *b* showing the bicycle borrowing/returning at each station during the 23:00 to 7:00 interval was negligible. Kong Jing[7] divided bicycle-sharing sites into six categories, as shown in *c*, there were apparent differences in the average daily borrowing and returning volume of each site. For the weather information from 2017/5/10 to 5/24, the demand for shared bicycles varies significantly under different weather conditions as c was shown. In summary, factors (time, space, and weather) have significant effects on the demand for shared bicycles, so the dataset was processed in this study based on an overall consideration of these attributes. we established a shared bicycle borrowing/returning volume prediction model with a single site as the study object and divided the study time from 7:00 to 23:00 into 2h per period, i.e., a total of 8 time periods per day in this study. The date attributes were represented by 0/1, 0 being a day off and 1 being a weekday; the weather attributes were expressed as -1 / 0 / 1, corresponding to rainy, cloudy, and sunny days, the information on the number of shared bicycle borrowing/returning is shown in Table 1.



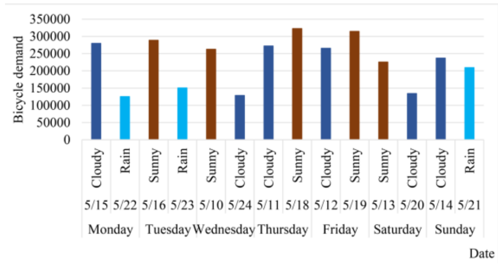
a. Daily demand for bicycles



b. Number of bicycles demand during the week



c. Average daily borrowing and returning demand for each type of site



d. Demand for bicycles with different weather conditions

Fig.1. Analysis of factors influencing demand for shared bicycles

Table 1.

Data set of loan/return volume of the Dawanglu site

date	5/10	5/11	5/12	5/13	5/14	5/15	5/16	5/18	5/19	5/20	5/21	5/22	5/23	5/24
date attribute	1	1	1	0	0	1	1	1	1	0	0	1	1	1
weather attribute	1	0	0	1	0	0	1	1	1	0	-1	-1	-1	0
07:00-09:00	70/101	62/92	60/87	35/32	30/26	58/89	73/105	68/103	75/99	31/30	17/15	40/45	38/48	61/88
09:00-11:00	42/43	30/33	34/35	21/25	16/18	32/34	45/48	43/45	47/43	18/16	9/8	15/17	18/20	30/36
11:00-13:00	45/49	33/39	31/36	23/22	18/17	30/37	46/41	44/46	48/44	17/18	8/9	15/19	17/18	34/33
13:00-15:00	51/49	40/40	43/39	25/28	17/19	42/39	50/43	54/46	56/50	19/17	9/9	21/20	23/19	42/35
15:00-17:00	36/35	23/27	28/25	20/23	13/15	25/26	38/31	35/32	36/34	15/13	7/7	9/13	10/15	26/28
17:00-19:00	135/130	120/116	114/121	40/37	26/23	118/119	138/135	133/132	140/128	23/60	11/14	98/60	103/66	121/117
19:00-21:00	95/80	83/70	80/66	30/26	20/17	79/68	98/83	97/78	96/76	17/34	8/11	55/34	58/32	81/71
21:00-23:00	73/51	57/39	59/37	22/24	11/14	58/38	75/45	74/47	70/53	14/19	7/6	35/19	39/22	58/40

3. Bicycle sharing site borrowing/returning volume prediction model

3.1. Improving GWO algorithm based on multi-policy

The GWO algorithm is an intelligent algorithm proposed by Mirjalili and Lew[8], simulating gray wolves' hunting behavior. For the leadership hierarchy relationship among α、β、σ is not reflected in the hunting process, Guo et al [9] proposed an improved GWO algorithm by introducing a dynamic assignment strategy of weights. However, the above improved GWO algorithm has problems such as failure to guarantee population diversity, insufficient search, and room for improvement in balancing local and global search. In this study, we propose a multi-strategy improved GWO algorithm, i.e., introduce generalized opposition-based learning strategy based on the GWO improved by the dynamic weight assignment strategy, and propose a new control factor to improve the probability of obtaining the global optimal solution.

(1) Generalized opposition-based learning strategy. The existing GWO algorithms use random initialization to obtain the population, which cannot guarantee population diversity. We use a generalized opposition-based learning strategy to improve the population initialization of the GWO algorithm and select

the top N (population size) individuals by randomizing the initial population and the merit ranking of the corresponding inverse population. Without increasing the search space, improve the probability of the algorithm to obtain the global optimum. The generalized opposition-based learning strategy means that the individual x_i=($x_{i,1}$, $x_{i,2}$.....$x_{i,n}$)in the n-dimensional space generates the corresponding reverse solution according to Eq. (1)[10].

$$\widehat{x_{i,j}}=k(a_j+b_j)-x_{i,j}(j=1,2,...,n) \quad (1)$$

where k is a random solution uniformly distributed between (0,1), and the dynamic search range of individual x_i in the *jth* dimension is [a_j, b_j]. If $\widehat{x_{i,j}}$ is beyond the search range, it is randomly generated within [a_j, b_j].

(2) Nonlinear convergence factor. The nonlinear convergence factor a1 (Eq. (1)) is proposed in this study decays slowly in the early iterations and intensifies in the late iterations. Assuming the maximum iterations is 100, Fig. 2presents the variation of control factors, showing a1 is more effective in coordinating the global and local search capabilities through its variation than the linearly decreasing control factor a2 in the GWO algorithm[8] and the non-linearly decreasing control factor a3 in the improved GWO algorithm[9].

$$a1=2^* \cos\left(\frac{it}{it\_max} * \frac{\pi}{2}\right)^{1/2} \quad (2)$$

Where *it* is the current iteration and *it_max* is the maximum iterations.

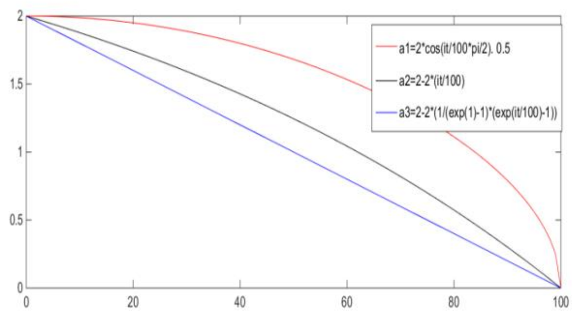


Fig.2. Control factors comparison

3.2 Construction of shared bicycle loan/repayment prediction model

We propose a shared bicycle borrow/return prediction model with the optimized BP neural network based on the multi-strategy improved GWO (MIGWO-BP), as shown in Fig.3.

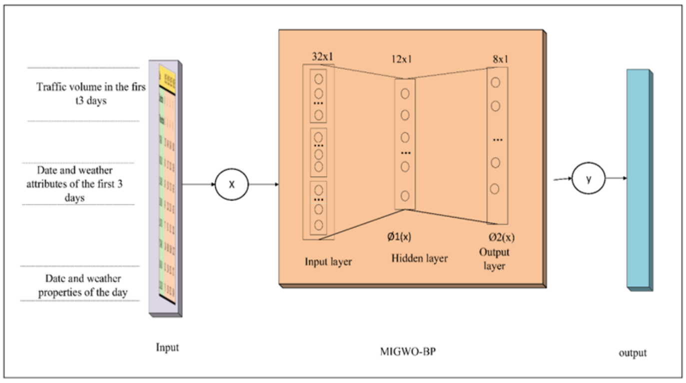


Fig.3. Shared Bicycle loan/repayment prediction model

The borrowing/returning volume data, date and weather attributes of each period of 3 days before the predicted day, date, and weather attributes of the day to be predicted are taken as the original data. The dimensionless processing ensures data are all between (-1,1) (Eq (3)) and then predicted by the model. Finally, the prediction results are obtained by the renormalization processing (Eq. (5)).

$$X=\frac{2\cdot(x\text{-}x_{min})}{x_{max}\text{-}x_{min}}\text{-}1 \tag{3}$$

$$\varphi_1(x)=\frac{1}{arctan(x)+1};\varphi_2(x)=\frac{1}{1+e^{-x}} \tag{4}$$

$$y=\frac{(Y+1)\cdot(y_{max}\text{-}y_{min})}{2}\text{-}1 \tag{5}$$

The BP network structure is 32-12-8, X is the dimensionless data, x is the original data, x_{min} and x_{max} are the minimum and maximum value in the original data, y is the predicted value, Y is the output value of the BP neural network, y_{max} and y_{min} are the maximum and minimum value in the output value.

Other parameters: learning rate is 0.001, training function is traingdx function, performance function is mean square error (MSE), error precision is 1×10^{-5}, Population size is 30, number of iterations is 5, and maximum of training is 5000.

3.2.1. MIGWO-BP

BP neural networks have been widely used due to their excellent stability in solving fitting and classification problems but suffer from the drawback that the selection of initial connection weights and thresholds significantly impacts the training results and cannot be obtained accurately[11]. We use the improved GWO algorithm based on multi-strategy to optimize the initial weights and thresholds of the BP neural network to improve its prediction accuracy. The MIGWO-BP flow chart, as shown in Fig.4.

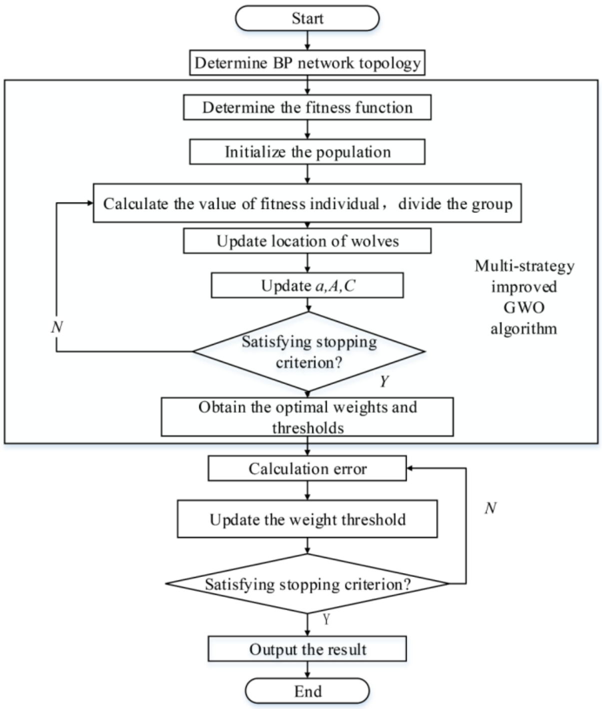


Fig. 4. Flowchart of the MIGWO-BP

Step 1: Determine the BP neural network topology. The number of network layers, nodes, weights, thresholds, maximum training times, transfer function, and training function is determined according to the input/output parameters.

Step 2: Determine the fitness function (the error between the actual and predicted values).

Step 3: Multi-strategy improvement of grey wolf algorithm initialization. Determine the individual dimension, number, maximum iterations, and activity range of wolves according to the weights and the number of thresholds, and generate wolf location information combined with the generalized inverse learning strategy.

Step 4: Calculation of individual fitness values and classification into 4 classes α、β、σ and ω Step 5: Update location information of wolves and parameters A, a, C.

Step 6: Satisfying stopping criterion, namely, reach the number of iterations, output the optimal solution corresponding to the weight threshold, otherwise return Step 4.

Step 7: Using obtained the weights and thresholds as the initial values of the BP neural network.

Step 8: Input testing datasets into the trained model to get the prediction results.

It is worth noting that the MIGWO-BP algorithm is an enhancement of the solution stability of the BP neural network, which can also be applied to solve other problems by adjusting relevant parameters in addition to being applied to predict traffic flow. For example, for the distribution existing fault selection model studied by Zhao Jie[12], the fault selection feature quantity can be used as the input parameter of the MIGWO-BP algorithm to output the fault selection result and achieve accurate judgment of the faulted line. For the intelligent equipment life prediction model proposed by Jian Ma[13], the main environmental stresses that affect the basic error value of intelligent power metering equipment are taken as input parameters, and the basic error value is output to predict the degradation trend of intelligent power metering equipment. The algorithm is also applicable to the settlement of box culverts in large water transfer projects, using internal and external pressure and temperature as input values to predict the settlement of box culvert foundations[11].

3.2.2 Case verification

The model shown in Fig.3 was constructed using MATLAB to predict the borrowing/returning volume of Dawanglu Station in each period on May 24. We split the data into two parts: the training (5/10-5/16 and 5/18-5/23) and testing datasets (5/22-5/24). The effectiveness of the optimized BP neural network model based on the multi-strategy improved GWO algorithm is verified by the borrowed bicycle data of Dawanglu Station. Fig.5 presents the mse curves obtained by the different models, and this model converges to 0.0083 in the 168th generation that significantly best. The results of each model's output compared with the actual situation, this model is closer to the actual results than other models, and the corresponding residual curves fluctuate most smoothly by predicting the borrowing volume, as shown in Fig.6. Based on verifying the validity of the model, it was applied to predict the return volume of the Dwanglu Station on May 24, and the result is shown in Fig 7.

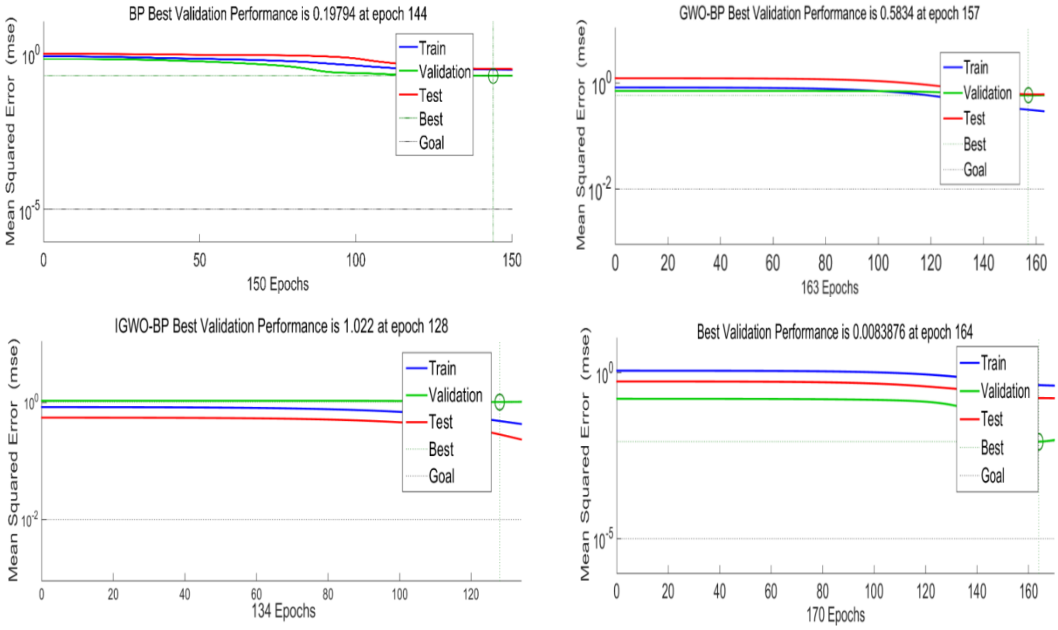


Fig. 5. Mse curves obtained by the different model

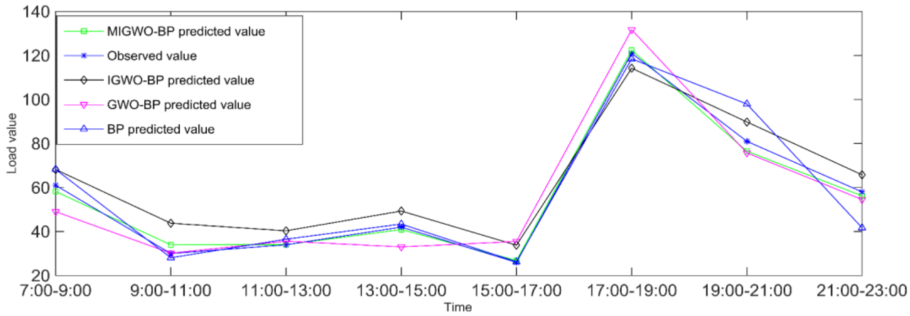


Fig. 6. May 24 borrowing volume forecast results

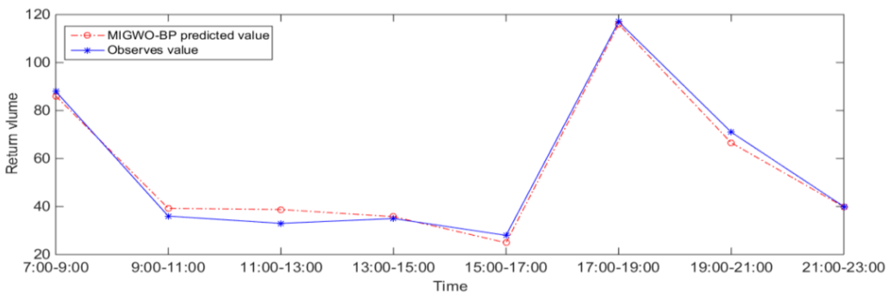


Fig.7. The forecast results of return traffic volume

4. Bicycle-sharing scheduling path optimization model

4.1. Construction of scheduling path optimization model

Based on the demand d_i of shared bicycles obtained by Eq. (6), we propose a bicycle-sharing scheduling path optimization model, and the cost function (Eq (11)) consists of minimizing the cost of dispatching vehicles and maximizing customer satisfaction. Besides, the cost of dispatching vehicles consists of a fixed cost C_f for starting vehicles and a variable cost C_v that changes with the travel time and the operating time for tasks. The penalty cost $p_i(t_i)$ represents the cost that a vehicle i arrive at the station beyond the time window $[tE_i, tL_i]$, and the total scheduling penalty cost C_P is represent customer satisfaction, namely, the lower the penalty cost, the higher the customer satisfaction.

$$d_i = p_i - \left[q_i + \left(a_i - f_i\right)\right] \tag{6}$$

$$C_f = C \cdot \sum_{m=1}^{M} \sum_{j=1}^{N} \sum_{h=1}^{H} x_{mjh} \tag{7}$$

$$C_v = E \cdot \left[\sum_{i=1}^{P} \sum_{j=1}^{P} \sum_{h=1}^{H} x_{ijh} \cdot t_{ij} + \sum_{i=1}^{N} \left(|d_i| + f_i\right) \cdot t\right] \tag{8}$$

$$p_i(t_i) = \begin{cases} MAX & t_i \leq tE_i \\ 0 & tE_i \leq t_i \leq tE_I \\ MAX & t_i \geq tL_i \end{cases} \tag{9}$$

$$C_p = \sum_{i=1}^{N} p_i(t_i) \tag{10}$$

$$Min \quad \alpha \cdot \left(C_f + C_v\right) + \beta \cdot C_p \tag{11}$$

Where p_i and q_i are the demand and return of bicycles at the next stage obtained by the bicycle borrowing/return prediction model, a_i and f_i are the number of shared bicycles and the number of faulty bicycles obtained from the shared bicycle information collection system for this period at the station. M, N, and H are the dispatch center collection, the shared bicycle station collection, and the dispatch vehicle collection, respectively. P is the set of dispatch centers and stations, i.e., $P=M \cup N$, x_{ijh} is a 0-1 variable, when the vehicle h travels from the station (dispatching center) i to station (dispatching center) j is 1, otherwise 0. C is the fixed cost of each vehicle activation, E is the variable cost per unit of time, and f_i is the number of faulty bicycles transferred out of shared bicycle station i. t_{ij} is the travel time of the dispatched vehicle from station i to j, and $t_{ij}=d_{ij}/v$, v is the average speed of the vehicle. MAX is a large enough positive number.

$$\sum_{h=1}^{H} \sum_{j=1}^{N} x_{mjh} \leq H_m \quad \forall m \in \mathrm{M} \tag{12}$$

$$\sum_{i=1}^{M} \sum_{j=1}^{N} x_{ijh} = 0 \quad \forall h \in H \tag{13}$$

$$\sum_{i=1}^{N} x_{mih} = \sum_{j=1}^{N} x_{jmh} \leq 1 \quad \forall m \in M, h \in H \tag{14}$$

$$0 \leq \sum_{\mathrm{i}=1}^{\mathrm{P}} \sum_{\mathrm{j}=1}^{\mathrm{P}} \mathrm{x_{ijh}} \cdot \mathrm{d_{ij}} \leq \mathrm{L} \quad \forall \mathrm{h} \in \mathrm{H} \tag{15}$$

$$0 \leq \sum_{h=1}^{H} \sum_{i=1}^{P} r_{ijh} + \sum_{h=1}^{H} \sum_{i=1}^{P} rf_{ijh} \leq Q \quad \forall i,j \in P, h \in H \tag{16}$$

$$\sum_{h=1}^{H} \sum_{i=1}^{P} r_{ijh} = \sum_{h=1}^{H} \sum_{i=1}^{P} r_{ijh} + d_j \quad \forall j \in N \tag{17}$$

$$\sum_{h=1}^{H} \sum_{i=1}^{P} rf_{ijh} = \sum_{h=1}^{H} \sum_{i=1}^{P} rf_{ijh} + f_j \quad \forall j \in N \tag{18}$$

$$t_j = \sum_{i=1}^{P} \sum_{h=1}^{H} x_{ijh} \cdot \left[t_i + t_{ij} + t \cdot \left(|d_i| + f_i \right) \right] \quad \forall j \in N \tag{19}$$

$$tE_i \leq t_i \leq tL_i \quad \forall i \in N \tag{20}$$

Where d_{ij} is the Euclidean distance between two points, r_{ijh} is the available single load of the dispatching vehicle h on the way from the site i to j, and rf_{ijh} is the number of faulty bicycles loaded on the way of the vehicle h from i to j, t is the time required to transfer a single shared bicycle to/from a station (including the dispatching behavior of available bicycles and faulty bicycles).

Constraint (12) guarantees that dispatched vehicles' demand cannot exceed the number of vehicles in the corresponding center. Constraints (13) and (14) ensure that the vehicle departs from the dispatch center and returns to the original dispatch center after completing its task. Constraint (15) indicates that the dispatching vehicle cannot exceed its maximum mileage L. Constraint (16) guarantees that the number of available （*r*） and faulty (*rf*) bicycles that each vehicle carries could not exceed its capacity Q. Constraints (17) and (18) are available and faulty vehicle flow-conservation, Eq (19) indicates how the time is computed. Constraint (20) ensures compliance with the time window.

4.2. LSN- based discrete GWO (LNS-DGWO)

The GWO cannot be directly employed to deal with the discrete scheduling problem, this study adopts the real number coding, use the OX crossover operation based on a modified discrete search operator, and introduces LNS proposed by David and Stefan[14], to enhance the searchability of the proposed algorithm.

(1) Population initialization. Each wolf as a scheme, taking 6 sites, 1 distribution center, and up to 3 vehicles as an example, the length of the individual is (6+3-1), and the initial solution is generated by the PFIH strategy[15]. Let12378465 as an individual, 7 and 8 represent the center, i.e., the solution includes 2 routes: 0-1-2-3-0,0-4-6-5-0.

(2) Discrete update. After the initial population was selected by the roulette wheel, based on referring to the update method of Equation (22)[16] to realize the leadership of the leading wolf to the candidate wolf, and adopted the OX crossover operator is adopted, and the crossover probability is set to 1 to ensure that each candidate wolf is updated.

$$W_1 = f_1 / \left(f_1 + f_2 + f_3 \right) \quad W_2 = f_2 / \left(f_1 + f_2 + f_3 \right) \quad W_3 = f_3 / \left(f_1 + f_2 + f_3 \right) \tag{21}$$

$$X(t+1)=\begin{cases} F\big(X_k(t),X_\alpha(t)\big),\ rand\leq W_1 \\ F\big(X_k(t),X_\beta(t)\big),W_1\leq rand\leq W_1+W_2 \\ F\big(X_k(t),X_\sigma(t)\big),W_1+W_2\leq rand \end{cases} \tag{22}$$

Where, f_1, f_2 and f_3 are the corresponding fitness values (inverse of the target value) of α, β, and σ, F represents the crossover operation, and $X_k(t)$ represents the discrete scheduling solution corresponding to *the k*th wolf.

(3) LNS algorithm. Wolves are selected as the first several individuals as the population of LNS according to the fitness value after the above update. A removal heuristic removes several sites on the individuals, and if only one path exists for an individual, remove randomly, otherwise remove stations that are closest to each other on different paths. The repair operator is used to fix the destroyed solution by inserting the removed stations based on the principle of maximum fitness, provided that the load, mileage, and time window constraints are satisfied.

It is worth noting that the LNS-DGWO algorithm is solved in a discrete space environment, and by setting the corresponding objective function and constraints, it applies not only to path planning but also to solving other discrete combinatorial optimization problems. For example, the interference resource allocation problem of collaborative enemy-us identification system with secondary radar mechanism proposed by Li Dongsheng[17] and the construction of sitter scheduling problem considering part-time employment constructed by Wang Xiuli[18] realize the reasonable allocation of resources.

4.3.1. Overview of the Instance

There are 2 dispatch centers (Each includes 3 dispatch vehicles, v=40km/h) and 12 bicycle-sharing stations in the operation area. Table 2 presents the parameters of dispatch centers(nodes 1 and 2) and bicycle-sharing sites (nodes 3-14). Table 3 presents the other constraint parameters corresponding to the dispatched vehicles:

Table 2.

Parameters of dispatch centers and bicycle-sharing sites

Node	x_i	y_i	d_i	f_i	tE_i	tL_i
1	93	100	0	0	0	12
2	50	123	0	0	0	12
3	95	110	-15	3	0.2	0.5
4	90	86	-30	2	0.2	0.5
5	65	45	5	2	2.1	2.4
6	75	106	-10	2	0.6	0.9
7	125	117	-17	8	3.1	3.4
8	20	117	-10	8	1.7	2
9	30	149	-23	9	0.7	1

10	36	88	20	0	3.7	4
11	49	65	4	0	2.9	3.2
12	134	163	7	4	1.7	2
13	135	76	-15	5	1.9	2.2
14	104	64	15	3	0.9	1.2

Table 3.

Other constraint parameters

Parameters	values	Parameters	values
Vehicle capacity Q	40	Maximum mileage L	200
Vehicle enablement C	100	The unit time variable cost E	10
The time required to transfer bicycle in/out t	0.005	Maximum penalty cost MAX	50
α/β	0.35/0.65	Removed individuals	3
Population size	100	Number of generations	100

4.3.2. Scheduling optimization results

In this paper, for the constructed bicycle-sharing scheduling path optimizat ion model belongs to the multi-distribution center problem, the stations were assig ned to each center based on the distance nearest assignment method, and the mode l was solved by MATLAB using the LNS-DGWO, the optimal scheduling path is shown in Fig. 8, and the total cost is 226.53. Fig. 9 presents the efficiency of LNS-DGWO, showing the distribution centers 1 and 2 converge in the 10th and 1st gen eration, respectively, and more efficient than GA that converges in the 60th and 2n d generation.

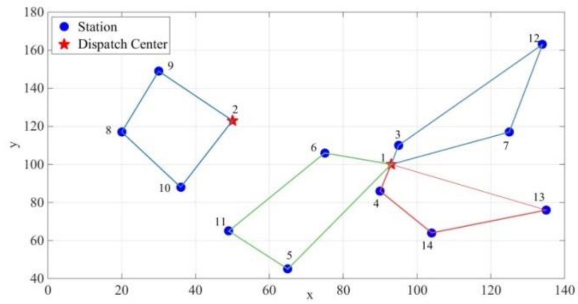


Fig.8. Scheduling path diagram

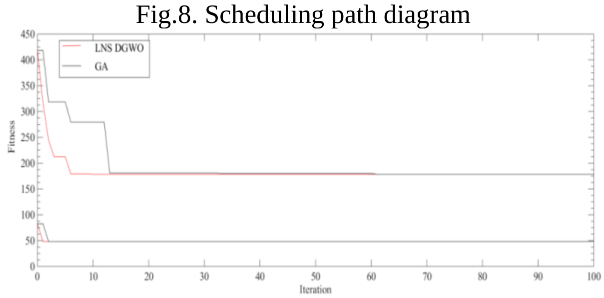


Fig.9. The Efficiency of LNS-DGWO

5. Conclusions

This paper studies demand prediction and scheduling optimization of shared bicycles and establish corresponding models and algorithms. Based on the examples verification and algorithms comparison, the following can be observed: (1) The generalized opposition-based learning strategy is introduced based on random initialization, can expand the population diversity, and the global search and local search ability of the GWO algorithm can be effectively balanced by changing the control factor a; (2) The multi-strategy optimization GWO is applied to determine the initial weights and thresholds of BP neural network, which improves the prediction accuracy compared with BP, GWO-BP, and improved GWO-BP model. (3) The model from both cost and customer satisfaction to make it more realistic, for the model's discreteness, the crossover operator is used to update the individuals, and the LNS strategy is added to improve the probability of obtaining the global optimum, which is efficient than the GA[3]. As for future work, it will be thoroughly considered the factors affecting the demand and the allocation of multiple scheduling centers to build the corresponding models.

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