Research On Emergency Parcel Transfer and Structure Optimization of E-Commerce Logistics Network Based on Multi-Objective Planning

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Abstract. This paper addresses the problem of urgent forwarding and structural optimization of parcels in e-commerce logistics networks. Firstly, based on the historical data of past freight volumes of different routes, this paper predicts the freight volume forecast data of each route by establishing an ARIMA time series forecast model; secondly, a multi-objective optimization model based on genetic algorithm is established to derive the optimal freight volume allocation scheme after the disappearance of route DC5; again, a multi-objective optimization model based on bat algorithm is established to derive the DC9 route Finally, a multi-objective optimization model based on the bat algorithm was developed to derive the route adjustment and cargo allocation scheme after the disappearance of route DC9. This paper concludes that after the cancellation of the DC5 route, the number of routes that are not in normal operation is 23 and the number of logistics paths that are allocated to new cargo is 56 in order to achieve the most balanced route load possible; after the closure of the DC9 route, 21 new roads are opened and 15 roads are closed, which are in a normal flow state and the transhipment is balanced. This paper has more far-reaching applications for multi-objective large-scale NP problems by establishing a multi-objective optimization model based on a heuristic algorithm, which can reduce the solution time of the calculation.

Keywords: ARIMA time series forecasting model, multi-objective optimization model, bat algorithm, genetic algorithm.

1. Introduction

In the context of today's growing e-commerce boom, logistics networks have become one of the key supports for the fast and efficient conduct of e-commerce business and the enhancement of user experience.[1] In an e-commerce logistics network, logistics sites and logistics routes are the key components of the logistics transport process. By accurately predicting the volume of goods to be delivered to each logistics site and route, managers will be able to arrange transport and sorting plans in advance, thereby minimising logistics operating costs and improving operational efficiency. At the same time, in the event of a major emergency resulting in the temporary or permanent closure of a logistics site, the design of a corresponding adjustment plan based on the predicted results and the handling capacity of each logistics site and the transport capacity of the logistics route will ensure the normal and smooth transport of goods.

Accurate forecasting of cargo volumes for individual logistics sites and routes is therefore essential to improve the efficiency of logistics operations, reduce costs and ensure smooth logistics transport.

2. Materials and methods

2.1 Data sources and analysis

This paper uses the 2023 MathorCup Collegiate Mathematical Modelling Challenge C question (http://mathorcup.org/) for analysis and research.

2.2 Data pre-processing

The raw data was analysed and processed. As observations were made and it was found that there were no missing values and the data was raw cargo data for different lines, no further outlier analysis was carried out on the data and all data was considered valid. As the data are all time-series data, they are considered for time-series analysis.

Historical data was fitted to the analysis, and here the data for this route, DC14→DC10, was plotted as an example. At the same time, there is a large variation in the volatility of this data, probably because the volume of cargo carried on this route has increased with the expansion of the company's size and business, so the data is first fitted with a polynomial. From the results of the fitting, the data as a whole showed an upward trend over time, and the ARIMA time series model was considered here for predictive analysis of the data. This is shown in Figure 1.

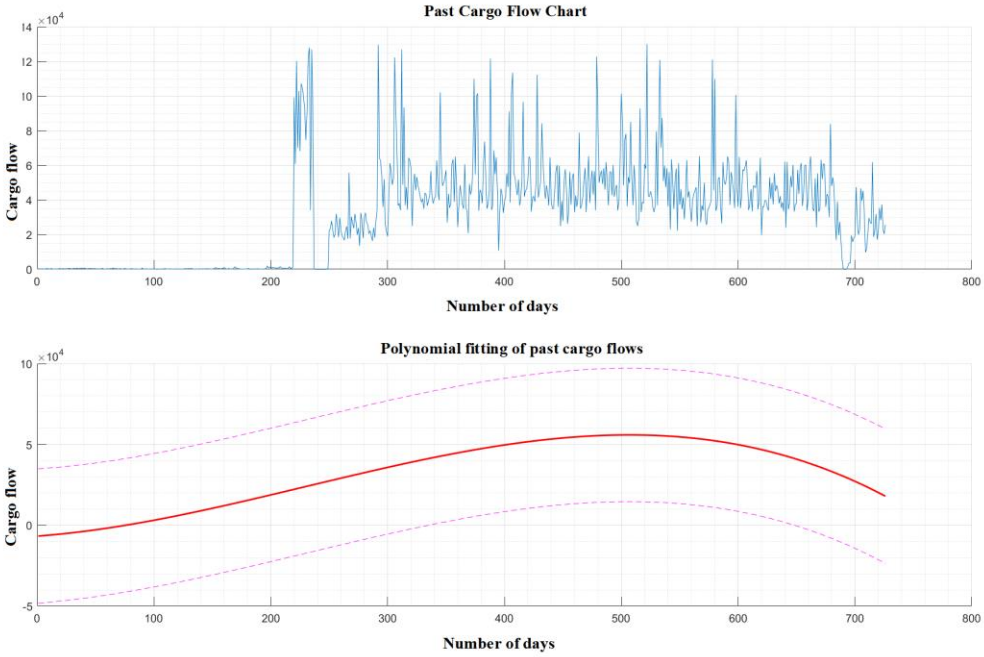

Figure 1. ARIMA time series model analysis for three lines

2.3 Modeling

(1) Creation of a smooth time series model

Smooth in this context refers to broad smoothness, which is characterised by the fact that the statistical properties of the series do not vary with time advection, i.e. the mean and covariance do not vary with time advection [2].

Given a random process fixed $\left\{X_t, t \in T\right\}$ 。 t, X^t is a random variable, let its mean be When μ_t, t varies, this mean is a function of , denoted t $\mu_t = E(X_t)$, is called the mean function of the random process. Fixing t , let the variance of be When X_t σ_t^2。 t varies, this variance is also a function of , denoted t

$$\sigma_t^2 = Var(X_t) = E\left[\left(X_t - \mu_t\right)^2\right] \tag{1}$$

is called the variance function of the stochastic process. The square root of the variance function σ_t is called the standard deviation function of the stochastic process and it represents the deviation of the stochastic process X_t from the mean value function . μ_t

For the stochastic process $\{X, t \in T\}$, take $t, s \in T$, and define its self-covariance function as

$$\gamma_{t,s} = Cov(X_t, X_s) = E\left[\left(X_t - \mu_t\right)\left(X_s - \mu_s\right)\right] \tag{2}$$

To characterize the correlation between $\{X, t \in T\}$ at the moments t and s, it is also possible to standardize $\gamma_{t,s}$, i.e. to define the autocorrelation function

$$\rho_{t,s} = \frac{\gamma_{t,s}}{\sqrt{\gamma_{t,t}}\sqrt{\gamma_{s,s}}} = \frac{\gamma_{t,s}}{\sigma_t \sigma_s} \tag{3}$$

The autocorrelation function $\rho_{t,s}$ is therefore a normalised self-covariance function.

Let the random sequence $\{X_t, t = 0, \pm 1, \pm 2, \cdots\}$ satisfy 1. $E(X_t) = \mu = constant.$

$\gamma_{t+k,t} = \gamma_k (k = 0, \pm 1, \pm 2, \cdots)$ Not related to .t

Then X_t is said to be a smooth random series (smooth time series), or simply a smooth series.

Let the autocovariance function of the smooth series $\{\varepsilon_t, t = 0, \pm 1, \pm 2, \cdots\}$ be

$$\gamma_k = \sigma^2 \delta_{k,0} = \begin{cases} 0, & k \neq 0, \\ \sigma^2, & k = 0, \end{cases} \tag{4}$$

$$\delta_{k,0} = \begin{cases} 1, & k \neq 0, \\ 0, & k = 0, \end{cases} \tag{5}$$

For a sample of a smooth sequence X_t the sample mean of $X_1, X_2, \cdots, X_n$, can be used to estimate the mean of a random sequence

$$\hat{\mu} = \frac{1}{n}\sum_{i=1}^{n} X_i = \bar{X} \tag{6}$$

Let $\{\varepsilon_t, t = 0, \pm 1, \pm 2, \cdots\}$ be zero-mean smooth white noise and $\mathrm{Var}(\varepsilon_t) = \sigma_\varepsilon^2$。 if $\{G_k, k = 0, 1, 2, \cdots\}$ is a series satisfying.

$$\sum_{k=0}^{\infty} |G_k| < +\infty, G_0 = 1, \tag{7}$$

Defining random sequences

$$X_t = \sum_{k=0}^{\infty} G_k \varepsilon_{t-k}, \tag{8}$$

Then X_t is called a random linear sequence. Under conditions, it can be shown that Eq. X_t is a smooth sequence. If the zero-mean smooth sequence X_t can be expressed in the form of Eq. then this form is called the transfer form and $\{G_k, k = 0, 1, 2, \cdots\}$ is called the Green function [3].

Let $\{X_t, t = 0, \pm 1, \pm 2, \cdots\}$ be a zero-mean smooth series and lead to the definition of a partial correlation function in terms of time series forecasting. If the value of $\{X_{t-1}, X_{t-2}, \cdots, X_{t-k}\}$ is known, a forecast is required for X_t. In this case, consider the linear least mean square estimate of X_t from $\{X_{t-1}, X_{t-2}, \cdots, X_{t-k}\}$, i.e. choose the coefficient $\varphi_{k,1}, \varphi_{k,2}, \cdots, \varphi_{k,k}$,

makes it possible to

$$\min \delta = E\left[\left(X_t - \sum_{j=1}^{k} \varphi_{k,j} X_{t-j}\right)^2\right]。 \tag{9}$$

Expanding δ gives

$$\delta = \gamma_0 - 2\sum_{j=1}^{k} \varphi_{k,j}\gamma_j + \sum_{j=1}^{k}\sum_{i=1}^{k} \varphi_{k,j}\varphi_{k,i}\gamma_{j-i} \tag{10}$$

Let $\frac{\partial \delta}{\partial \varphi_{k,j}} = 0, j = 1, 2, \cdots, k$。 yield.

$$-\gamma_j + \sum_{i=1}^{k} \varphi_{k,i}\gamma_{j-i} = 0, j = 1, 2, \cdots, k。 \tag{11}$$

If let $\{X_t, t = 0, \pm 1, \pm 2, \cdots\}$ be a zero mean smooth series satisfying the following model:

$$X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} + \varepsilon_t \tag{12}$$

Where: ε_t is a smooth white noise with zero mean and variance of σ_ε^2 ; X_t is an autoregressive series of order p, abbreviated as an AR(p) series: φ is an autoregressive parameter vector and

$$\varphi = \left[\varphi_1, \varphi_2, \cdots, \varphi_p\right]^T, \tag{13}$$

Notation of arithmetic polynomials

$$\varphi(\mathrm{B}) = 1 - \varphi_1\mathrm{B} - \varphi_2\mathrm{B}^2 - \cdots - \varphi_\mathrm{p}\mathrm{B}^\mathrm{p}, \tag{14}$$

Let $\{X_t, t = 0, \pm 1, \pm 2, \cdots\}$ be a zero mean smooth series satisfying the following model:

$$X_t = \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \cdots - \theta_q\varepsilon_{t-q}, \tag{15}$$

In engineering terms, a smooth white noise generator passes through a linear system and if its output is a linear superposition of white noise then this output obeys the MA model.

For the linear backward shift operator B there is

$$B\varepsilon_t \equiv \varepsilon_{t-1}, B^k\varepsilon_t \equiv \varepsilon_{t-k}, \tag{16}$$

Re-introduction of arithmetic polynomials

$$\theta(\mathrm{B}) = 1-\theta_1\mathrm{B}-\theta_2\mathrm{B}^2-\cdots-\theta_q\mathrm{B}^q, \tag{17}$$

Then equation (11) can be rewritten as

$$X_t = \theta(B)\varepsilon_t \tag{18}$$

ARIMA (p,q) sequence

Let $\{X_t, t=0,\pm1,\pm2,\cdots\}$ be a zero mean smooth series satisfying the following model:

$$X_t-\varphi_1 X_{t-1}-\cdots-\varphi_P X_{t-P}=\varepsilon_t-\theta_1\varepsilon_{t-1}-\theta_2\varepsilon_{t-2}-\cdots-\theta_q\varepsilon_{t-q}, \tag{19}$$

Where: ε_t is a smooth white noise with zero mean and variance of σ_ε^2; X_t is an autoregressive moving average series of order p,q , abbreviated as an ARIMA(p,q) series, which is an AR(p) series when q=0 and an MA(q) series when p=0.

3. Model building and solving

3.1 A multi-objective optimization model based on genetic algorithm for changing the allocation of cargo routes

3.1.1 Model building

(1) Determination of constraints

Based on the analysis above, for any line with a cargo volume of L_{ij} , whose maximum cargo volume is the maximum of its historical data, denoted by $Max(L_{ij})$, the following constraints can be obtained in order to meet the small cumulative daily total of cargo volumes that fail to flow normally, the line's cargo volume must not exceed the historical maximum.

$$L_{ij_{present}} \le Max(L_{ij}) \tag{20}$$

The same in order to meet the relative balance of the line cargo load, it may be worth defining I_i to indicate, with C_{ij} and $C_{i+1,j+1}$ to indicate the load capacity of each line after the allocation of the line, here you can use the relative ratio of any line after the allocation to indicate the degree of balance of the load capacity between this line, so I_i the closer to 1, the more similar the load capacity of its route [4] [5]. I_i The formula for the calculation of

$$I_i=\frac{C_{ij}}{C_{i+1j+1}}\times 100\%, (ij, i+1j+1 \text{represents any adjacent alternative route}) \tag{21}$$

It can also be noted that C_{ij} is also a binary variable, so consider replacing C_{ij}' with its binary value and define it as follows:

$$C_{ij}'\begin{cases}1, L_{ij}\le Max(L_{ij}) \text{indicates that the line has not yet reached its maximum value, can be transported normally}\\ 0, L_{ij}>Max(L_{ij}) \text{indicates that the line allocation exceeds the maximum value, can't be transported normally}\end{cases} \tag{22}$$

Then the following constraints can be obtained.

$$\lim_{i \to i+1} I_i = 1 \tag{23}$$

(2) Determination of the objective function

Based on the above, it is required that after the cancellation of the DC5 route, the cargo on it is allocated in a reasonable way so that the number of routes allocated is as small as possible and the cargo load on each route is relatively balanced. To satisfy this variation, a penalty function $\delta g(x)$ is introduced, for which the range of values is defined as $[-1, 0]$ [6], x denotes the number of routes selected, δ is a penalty factor whose value varies with the increase in the number of routes, for which it is useful to define Z to denote the target value of this objective, which, according to the derivation above, can be derived as

$$Z = \lim_{i \to i+1} I_i + \delta g(x)(x = 1, 2, ..., N) \tag{24}$$

That is, the following objective function can be set

$$\min Z \tag{25}$$

The paper also requires that the cumulative daily total of the volume of goods that fail to flow normally is satisfied to be small, which indicates that the allocation is carried out so as not to exceed the normal set limits as far as possible, and here it is useful to set χ to denote the cumulative daily total of goods that are exceeded, as per the definition above:

$$\chi = \sum L_{ij}(\text{actual}) - \sum L_{ij}(\text{theoretical}) \tag{26}$$

Another objective function can be obtained at this point as

$$\min \chi \tag{27}$$

(3) Multi-objective optimization model for changing the distribution of cargo routes

The following bi-objective multivariate optimization model can be obtained based on the objective function and constraints

$$s.t.\begin{cases} L_{ij_{present}} \le Max(L_{ij}) \\ d_{ij} = \begin{cases} 1, v_{1i} \to v_{2j} \\ 0, \text{no linking relationship} \end{cases} \\ C_{ij} = \frac{L_{ij} + \Delta L_{i \Rightarrow j}}{Max(L_{ij})} \times 100\% \\ I_i = \frac{C_{ij}}{C_{i+1j+1}} \times 100\%, (ij, i+1j+1 \text{ represents any adjacent alternative route}) \\ C_{ij}{}' \begin{cases} 1, L_{ij} \le Max(L_{ij}) \text{indicates that the line has not yet reached its maximum value, can be transported normally} \\ 0, L_{ij} > Max(L_{ij}) \text{indicates that the line allocation exceeds the maximum value, can't be transported normally} \end{cases} \\ \lim_{i \to i+1} I_i = 1 \\ Z = \lim_{i \to i+1} I_i + \delta g(x)(x = 1, 2, \dots, N) \\ \chi = \sum L_{ij}(\text{actual}) - \sum L_{ij}(\text{theoretical}) \end{cases} \tag{28}$$

3.1.2 Model solving

(1) Application of genetic algorithms

Genetic Algorithm (GA) is a computational model of the biological evolutionary process that simulates the natural selection and genetics mechanisms of Darwinian biological evolution. [7] Based on this model, we set the argument variable to real code in coded form, and convert the multi-objective function to single objective function by linear transformation.

$$\min\ w_i \tag{29}$$

The reciprocal of the function value is used as the individual's fitness value. The larger the function, the smaller the fitness value and the better the individual, the better the fitness calculation function is:

$$F = \frac{1}{W} \tag{30}$$

The probability that an individual i will be selected is

$$p_i = \frac{F_i}{\sum_{j=1}^{N} F_j} \tag{31}$$

where F is the fitness value of an individual i; N is the number of individuals in the population.

Since the individuals were coded in real numbers, the crossover operation was performed using the real number crossover method. The crossover of the η chromosome a^* and the 2nd chromosome at the j position was performed as follows

$$\begin{aligned} a_{kj} &= a_{ij}(1-b) + a_{lj}b \\ a_{lj} &= a_{lj}(1-b) + a_{kj}b \end{aligned} \tag{32}$$

where b is a random number in the interval [0,1].

An individual is selected at random from the population by the mutation operation, and a point in the individual is selected for mutation to produce a superior individual. The jth gene of the ith individual is known to undergo mutation by the operation

$$a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{\max}) * f(g), & r \geq 0.5 \\ a_{ij} + (a_{\min} - a_{ij}) * f(g), & r < 0.5 \end{cases} \tag{33}$$

Where $a_{\max}$ is the upper bound of the gene a_{ij} ; $a_{\min}$ is the lower bound of the gene a_{ij} ; $f(g) = r_2(1 - g / G_{\max})^2$, r is a random number, g is the number of current iterations, and $G_{\max}$ is the maximum number of evolutions.

(2) Solution results

Here we set, number of evolutionary generations: 100, population size: 500, crossover probability: 0.6, variation probability: 0.01. The results calculated using the genetic algorithm for DC5 to DC3, for example, are shown in Table 1.

Table 1 Genetic algorithm iteration results

The original route to DC3	Original line goods L_{1DC3} (forecast)	Pre-allocated cargo volumes ΔL_{1DC3}	Current line cargo volume load status C_{ij}'	The degree of balance of load capacity I_i'
DC2-DC3	23	738	0	1.38
DC4-DC3	435	372	1	1
DC5-DC3	146	208	0	2.74
DC7-DC3	54	1247	1	1
DC8-DC3	3533	321	1	1
DC9-DC3	2854	998	1	1
DC10-DC3	469	1430	0	2.69
⋮	⋮	⋮	⋮	⋮
DC70-DC3	63	868	0	1.92
DC71-DC3	247	1328	1	1
DC72-DC3	368	4288	0	3.17
DC73-DC3	4103	65	1	1
DC74-DC3	534	517	1	1
DC76-DC3	612	3508	0	2.28

When DC5 is shut down, the cargo from DC5 to DC3 will be diverted to other routes connected to DC3 besides DC5. We have achieved the distribution of cargo based on the principle of distributing as evenly as possible so that I_i' tends to 1 as much as possible, in which case the cargo diversion on day 1 is shown in the table above. Where C_{ij}' indicates the cargo load status, when C_{ij}' is 0 it means that the logistics is not functioning properly, when C_{ij}' is 1 it means that the route is functioning properly. The table shows that with the allocation rules we have developed, we have achieved as balanced a route load as possible, but also when there is an abnormal flow of routes, in the table the number of abnormal operation 0 is 23, the number of logistics routes being allocated new goods is 56, at this time the load state of the network has been the most balanced.

3.2 A multi-objective optimization model based on the bat algorithm for changing the allocation of cargo routes

3.2.1 Model building

On the basis of the above, the closed logistics site is adjusted to DC9, so no additional changes to the original constraints are required. However, in addition the ontology allows for adjustments to the daily routes, allowing for open or closed routes. For this purpose we have carried out simulations and based on the above simulation results we can obtain a relationship between the load volume c_{ij} and the load carrying efficiency η_{ij} . From this, we can calculate the load efficiency η_{ij} for each day based on the load volume c_{ij} . We consider the load efficiency η_{ij} to be more than 0.3, which gives us a load interval $\left[c_{ij1}, c_{ij2}\right]$ [8].

Therefore, we believe that the load within this range is acceptable; while when the load c_{ij} is greater than c_{ij2} , it is in a high load state, and the simulation results show that the load efficiency is significantly lower than the acceptable load efficiency, so we can open a new road to achieve pressure relief diversion to make the load efficiency in the acceptable range; while when the load c_{ij} is less than c_{ij1} , the path is in a nearly idle state, and the load efficiency is also lower than the acceptable load efficiency. Therefore, we choose to close this route and spread the load on this route to other routes to avoid idle efficiency. On this basis, a value of A_{ij} is used to represent the status of the road. A_{ij} equals 1 for a new route to be opened, A_{ij} equals 0 for the original route to remain unchanged and no route to be closed or opened, and A_{ij} equals -1 for the road to be closed. The following constraints can be obtained:

$$A_{ij}\begin{cases} 1 & c_{ij} \geq c_{ij2} \\ 0 & c_{ij} \in \left(c_{ij1}, c_{ij2}\right) \\ -1 & c_{ij} \leq c_{ij1} \end{cases} \tag{34}$$

3.2.2 For the determination of the objective function

The bi-objective multivariate optimization model is the same as the genetic algorithm

3.2.3 Solving the model

The bat algorithm is one of the modern optimisation algorithms that is used for objective function finding, based on the feature that bat populations use generated sound waves to search for prey and control flight direction to achieve function finding. [9].

(1) Initialize the relevant parameters, the position of the bat x_i , the flight speed v_i , the sound speed A_i , the frequency y_i range, with a target function $F(x_i)(i=1,2,...,n)$.

(2) Varying the solution generated by the pulse frequency and changing the position and flight speed of the bat with the following equation for the speed change:

$$w(t) = w_{\min} + (w_{\max} - w_{\min})\exp(-\rho(\frac{t}{T_{\max}})^2) \tag{35}$$

$$\begin{aligned} y(i) &= y(i)_{\max} + [y(i)_{\max} - y(i)_{\min}]\beta \\ v_i^t &= w(t)v_i^{t\text{-}1} + A_i(x_i^{t-1} - X^*)y(i) \end{aligned} \tag{36}$$

Where $w(t)$ is the momentary variable speed inertia weighting factor, which serves to make the bat's earlier search a reference for the later search, $w_{\max}$ is the maximum value of $w(t)$, $w_{\min}$ is the minimum value of $w(t)$; $1 \leq p \leq T_{\max}$, generally taken as 2, and $T_{\max}$ is the maximum number of iterations; X^* is the optimal solution at the current location; $y(i)$ is a random number whose frequency satisfies a normal distribution, β is a random variable, and $\beta \in [0,1]$. At the start of the run, bats are randomly assigned frequencies in $[y_{\min}, y_{\max}]$.

During flight, the bat's position is replaced by the formula

$$X_i^t = X^* + v_i^t \tag{37}$$

In order to control the position of the bat within the range of the independent variable, this paper sets up boundary condition rules for the situation: if the position of the next this movement is outside the range of the independent variable, then the position of the next this flight is the position projected on the boundary.

(3) Search for a locally optimal solution $F(X_i^{'})$, generate multiple optimal solutions by multiple flights of the bat, conduct a global search at and if a new optimal solution is obtained $F^{'}(X_i^{'}) > F(X_i^{'})$, then accept the solution.

(4) Arrange the positions of all the bats and find the current optimal solution $F^{'}(X_i^{'})$ and the corresponding position, set the current optimal solution to F^{*}, then make all the bats continue to move to the next moment and return to step 2 to recalculate.

(5) End of moment, output: optimal solution.

In the conventional bat algorithm, $w(t)$ is a fixed coefficient, in this question this coefficient is linked to the time t, this parameter is able to avoid the dilemma of local extremes and thus achieve a global search for the best result [10].

After several experiments and tests, the range of inertia weights was finally fixed between $0.4 \sim 0.9$, the size of the number of bats in each space was selected as 2000, the range of frequency was selected as $0 \sim 1$ and the number of spaces was set as 123. The specific results are shown in Table 2.

Table 2 Bat algorithm iteration results

The original route to DC3	Original line goods L_{1DC3} (forecast)	Pre-allocated cargo volumes ΔL_{1DC3}	Current line cargo volume load status C_{ij} '	The degree of balance of load capacity I_i '	State of the road A_{ij}
DC8-DC3	478	0	0	0.98	-1
DC9-DC3	3277	4399	1	1	0
DC10-DC3	2168	998	1	1	0
DC14-DC3	32	1083	1	1	0
DC17-DC3	1376	845	0	1.83	1
DC19-DC3	218	1033	1	1	0
⋮	⋮	⋮	⋮	⋮	⋮
DC67-DC3	738	593	0	1.55	1
DC69-DC3	6173	3491	1	1	0
DC70-DC3	236	908	1	1	0
DC72-DC3	4194	3937	0	1.13	1
DC73-DC3	1024	0	0	0.61	-1
DC74-DC3	763	98	1	1	0

On day 23, for example, when DC9 is shut down, the goods originally destined for DC3 are diverted to other roads outside DC9 and connected to DC3, which, according to the above table, inevitably generates a non-normal flow state under the principle of balanced load distribution. The new road strategy. This is reflected in the table A_{ij} , when A_{ij} is -1 it means that the road is idle and we will close it; when A_{ij} is 1 it means that the road is overloaded and the logistics efficiency is very low and we decide to take diversion measures by opening a new route to divert the traffic; when A_{ij} is 0 it means that the road is within our acceptable transport efficiency range. We have specific tables that show that in the most balanced state, 21 new roads are opened and 15 roads are closed, when they are in normal flow and the number of changes to routes is minimal.

4. Conclusion

Aiming at the problem of emergency parcel transit and structural optimisation of e-commerce logistics networks, this paper **first** establishes an ARIMA time series model for its given route, which can be predicted using ARIMA time series based on its historical freight volume, and carries out residual tests. At the **same time, the** model is constructed step by step using historical data and the accuracy and reliability of the model is measured by forecasting future data. **Secondly**, a multi-objective optimisation model based on genetic algorithm is established to give the route adjustment and cargo allocation scheme after the disappearance of route DC5, determining the number of irregularly operating routes to be 23 and the number of logistics paths being allocated new cargo to be 56, thus achieving route load balancing; **finally**, a multi-objective optimisation model based on bat algorithm is established to give the route adjustment and cargo allocation scheme after the disappearance of route DC9. Finally, a multi-objective optimisation model based on the bat algorithm is developed to give the route adjustment and cargo allocation plan after the disappearance of DC9 route. After closing the DC9 route, 21 new roads are added and 15 roads are closed, which are in the normal flow state at this time, and the number of path changes is the least. Since heuristic algorithms are more flexible in dealing with complex problems, adaptable and scalable, and can find feasible solutions close to the optimal solution by simulating processes in nature, this paper can provide reference ideas for similar problems.

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