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Emergency Parcel Dispatching and Structure Optimization of E-Commerce Logistics Network Based on CCNSGA-II

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Abstract: In order to facilitate managers to arrange transportation and sorting plans in advance, so as to improve operating costs and operating efficiency The logistics site and route are optimized by establishing the emergency dispatching and structure optimization model of e-commerce logistics network parcel. A refined forecasting model based on ARIMA-EBP neural network is constructed to forecast the daily cargo volume of each line from 2023-01-01 to 2023-01-31 A mixed-integer linear programming (MILP) model is established and a co-evolutionary non-dominated sequencing genetic algorithm (CCNSGA-II) is designed to achieve multi-objective optimization with the objective of minimizing the workload and balancing all packets as well as possible.

1. Introduction

E-commerce logistics network is composed of logistics sites (receiving warehouse, sorting center, sales department, etc.) and transportation lines between logistics sites[1]. However, due to the influence of holidays and promotional activities such as "Double Eleven" and "618", the order quantity of e-commerce users will fluctuate significantly, and when emergencies such as epidemics and earthquakes lead to temporary or permanent suspension of logistics sites, the packages handled by them will be urgently divided into other logistics sites. These factors will affect the number of packages transported by each line and the number of packages handled by each logistics site.

2. ARIMA-EBP neural network model

Since the relationship between the volume of each day from 2023-01-01 to 2023-01-31 and 2022-12-31 is not necessarily the same, if only one network structure is used to correct the predicted value, the difference of historical data on the daily volume cannot be considered And ARIMA can not capture all the information in the time series. In this paper, we use ARIMA model to predict the linear part of BP neural network to deal with the nonlinear network, but the whole prediction is divided into linear and nonlinear prediction. If the two parts of prediction are added together, it may lead to the lack of information. Then we build a fine forecasting model based on ARIMA-BP neural network model, and build a neural network forecasting model for every day in a month. After training the models, we integrate them to forecast the freight volume from 2023-01-01 to 2023-01-31.

2.1. Solution of cargo volume prediction based on ARIMA-EBP two-stage algorithm

Because ARIMA can not capture all the information in the time series, we adopt ARIMA model to predict the linear part of the BP neural network [2], but the whole prediction is divided into linear and nonlinear prediction. If the two parts of the prediction add up, it may lead to the lack of information Therefore, BP is used to modify the ARIMA output results [3]. Based on the ARIMA model mentioned above, the predicted value of the cargo volume of the line DCP 1 → DC P 2 on the $\{t, t+1, t+0000000000002, \ldots, t+30\}$day can be: $\{\hat{y}^{ARIMA}_{p1,p2,t}, \hat{y}^{ARIMA}_{p1,p2,t+1}, \hat{y}^{ARIMA}_{p1,p2,t+2}, \ldots, \hat{y}^{ARIMA}_{p1,p2,t+30}\}$.As mentioned above, BP neural network is introduced to modify the predicted value to form a new neural network architecture and mix new models to improve the prediction accuracy.

The pseudocode of the ARIMA-EBP (ARIMA-Ensemble BP neural network) two-stage prediction algorithm proposed in this paper is shown in Table 1:

Table 1: ARIMA-EBP two-stage algorithm flow

Algorithm 1: ARIMA-EBP Two-stage prediction algorithm flow
Input: $Y = \{y_t, y_{t-1}, \cdots, y_1\}$, RD, $F = \{fe_{RD,1}, fe_{RD,2}, \ldots, fe_{RD,m}; fe_{RD+1,1}, fe_{RD+1,2}, \ldots, fe_{RD+1,m}; fe_{RD+2,1}, fe_{RD+2,2}, \ldots, fe_{RD+2,m}; \ldots\}$

Output: $\hat{y}_t$
for $j = RD$ to t do
Prediction of period j+1 to j+31 based on data from period j-RD+1 to period j using ARIMA model, recorded as $\{\hat{y}^{ARIMA}_{j+1}, \hat{y}^{ARIMA}_{j+2}, \hat{y}^{ARIMA}_{j+3}, \ldots, \hat{y}^{ARIMA}_{j+31}\}$
for $k = 1$ to 31 do
$Set_{train,k}(j,:) = [\hat{y}^{ARIMA}_k, fe_{j,1}, fe_{j,2}, \ldots, fe_{j,m}, y_j]$
end
end
for $k = 1$ to 31 do
Training of BP_k using $Set_{train,k}$
Correction of the predicted value of $\hat{y}^{ARIMA}_{t+k}$ using BP_k, recorded as $\hat{y}_{t+k}$
end

In the above algorithm, RD is the historical period referenced in ARIMA prediction are the m features of the input BP neural network. The algorithm trained a total of 31 neural networks to correct the forecast value of ARIMA. When predicting the next month, 31 neural networks were integrated to predict the corresponding period.

As can be seen from Table 1:

We set the input to: Y: to represent a set of time series data including .where the observation is the current time and the observation is the previous time RDF: Represents a matrix with multiple rows and columns where each row contains a set of time series data:

$$F = \{fe_{RD,1}, fe_{RD,2}, \ldots, fe_{RD,m}; fe_{RD+1,1}, fe_{RD+1,2}, \ldots, fe_{RD+1,m}; fe_{RD+2,1}, fe_{RD+2,2}, \ldots, fe_{RD+2,m}$$

Next, for each time step t, the following operation is performed: the period j+1 to period j+31 is predicted using the ARIMA model based on the data of the period j-RD+1 to period j. A set of predicted values is recorded as (DAPMA, DAMA, MA,... yMA) Then for each k (from 1 to 31): use Settrain to train the BPx model Finally, BP neural network is used to modify of ARMA.

3. Mixed Integer Linear Programming (MILP) Model

The model optimization objectives include three items Equation (1) means to minimize the number of lines whose cargo volume changes before and after DC5 is shut down Equation (2) means that the variance of workload in each line is minimized and the workload of each line is as balanced as possible Equation (3) means to minimize the daily cumulative total amount of parcels that fail to flow normally.

$$f_1 = \min \sum_{t=1}^{31} NR_t \tag{1}$$

$$f_2 = \min \sum_{t=1}^{31} Var\ (L_t) \tag{2}$$

$$f_3 = \min \sum_{t=1}^{31} A_t \tag{3}$$

$$NR_t = \sum_{l=1}^{N_t} X_{l,t} \tag{4}$$

In order to achieve the above goals, the constraints of the model need to be defined:

$$\sum_{t=1}^{31} \sum_{l=1}^{IQ_{DC5}} y_{p,DC5,t} = 0,\ \forall p \in ISet_{DC5} \tag{5}$$

$$\sum_{t=1}^{31} \sum_{l=1}^{OQ_{DC5}} y_{DC5,p,t} = 0,\ \forall p \in OSet_{DC5} \tag{6}$$

$$\prod Y_{p1,p2} > 0\ ,\ \forall p1,p2 \in RSet_{DCp} \tag{7}$$

$$y_{p1,p2,t} + INSet_{p,DC5} \leq C_{p1,p2}, \forall p1,p2 \in RSet_{DCp}, \forall p \in ISet_{DC5} \tag{8}$$

$$\sum_{p=1}^{IQ_{DC5}} Z_{DCp} * INSet_{p,DC5} \leq \sum_{p=1}^{IQ_{DC5}} INSet_{p,DC5} \tag{9}$$

$$\Delta y_{p1,p2,t} = \Delta y_{p3,p4,t}, \forall p1,p2,p3,p4 \in RSet_{DCp}, \forall p \in ISet_{DC5} \tag{10}$$

Equations (5-6) indicate that packages cannot flow on the line connected to the logistics field DC5 when it is shut down Equation (7) indicates that the re-planned path affected by DC5 stop must be an existing path Equation (8) indicates that the re-planned path affected by DC5 stop will not overload the path Equation (9) indicates that the re-planned traffic volume does not exceed the affected traffic volume Equation (10) indicates that when the quantity on the fault line is rearranged, it will be transported in the original batch without splitting it.

3.1. Model solving

3.1.1. Multi-objective model based on Pareto

Pareto optimality characterizes the state that each sub-objective of the solution of a problem cannot be optimized at the same time. By using the concept of Pareto optimality, we can solve the problem of individual fitness allocation in multi-objective optimization. The solution that achieves Pareto optimum is called the good or bad solution of the problem. The specific definition is as follows:

$$\begin{cases} \min F = [f_1(x), f_2(x), \dots, f_n(x)] \\ s.t.\, g_i(x) = 0 \quad i = 1, 2, \dots, K \\ h_j(x) \le 0 \quad j = 1, 2, \dots, R \end{cases} \tag{11}$$

Where: x is the solution vector in the solution space E; Is the objective function vector; Is the number of sub-objective functions; It is an equality constraint condition in general form; Is the constraint condition of inequality in general form; K and R are the number of equality and inequality respectively.

For two feasible solutions in E and if any self-function objective is not inferior to the corresponding sub-function objective, that is, if there is such a solution, then it is called the disposable solution of the solution. In the solution of multi-objective programming based on Pareto optimization, the purpose of optimization is to search for the Pareto frontier as complete and evenly distributed as possible as the alternative set; At the same time, the purpose of optimization is to sort the individuals in the alternative scheme set according to certain preferences and principles, and then determine the optimal scheme.

3.1.2. Algorithm Design of CCNSGA-II

The MILP model [4] constructed in this paper includes three objectives. For the equilibrium optimization of the three objectives, this paper selects the large framework of NSGA-II to solve the model NSGA-II algorithm [5] is based on genetic algorithm and Pareto optimal concept The main difference between NSGA algorithm and genetic algorithm is that the fast non-dominant ranking of individuals before the selection operation increases the probability of excellent individuals being retained At the same time, the operation of selection, cross and mutation is used

In addition, the solution requires a daily rescheduling scheme from 2023-01-01 to 2023-01-31.

In CCNSGA-II, each subpopulation determines a one-day rescheduling scheme, and each subpopulation runs k times separately to communicate with each other This is to coordinate the daily volume in and out relationship For example, the quantity of DC1 may be larger than the quantity of DC1 in 2023-01-01, which means that there are inventory goods in DC1. At this time, the seed flow can coordinate the maximum shipment quantity of DC1 in 2023-01-02DC1 In the iteration, each population generates a solution fragment, and after the seed flow, the solution fragments are spliced into a completed solution (i.e., a 31-day rescheduling scheme) to calculate the fitness of the iteration.

3.1.3. Coding and decoding

Based on the characteristics of this problem, matrix coding is adopted in this paper. The code can be expressed as:

$$\begin{bmatrix} y_{DC1,DC1,t} & y_{DC1,DC2,t} & y_{DC1,DC3,t} & \cdots & y_{DC1,DC81,t} \\ y_{DC2,DC1,t} & y_{DC2,DC2,t} & y_{DC2,DC3,t} & \cdots & \vdots \\ y_{DC3,DC1,t} & y_{DC3,DC2,t} & y_{DC3,DC4,t} & \cdots & \vdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ y_{DC81,DC1,t} & y_{DC81,DC2,t} & y_{DC81,DC3,t} & \cdots & y_{DC81,DC81,t} \end{bmatrix} \tag{12}$$

In the code, means the cargo volume of line DCp1 → DCp2 on the t day As mentioned above, a total of 31 populations (12) correspond to the rescheduling problem for 31 days A complete solution can be obtained by splicing the solutions obtained by 31 populations in one solution segment of each population solution problem At this time, the spliced solution can be decoded into a 31-day rescheduling scheme and further solved to obtain three target values.

3.1.4. Knowledge-driven initial solution generation

In the algorithm, the initial solution is often generated randomly. Before the initial population, we estimate the probability so that the initial population is far from the coding space of the global optimal solution. We grasp the distribution range in the space occupied by the optimal solution, and then set the initial population; first randomly generate a certain number of individuals, and then select the best individuals to join the initial population and the number of individuals reaches a predetermined scale. In order to improve the performance of the algorithm, a knowledge-driven initial solution generation strategy is designed in this paper. The algorithm flow is as follows:

Table 2: Knowledge-driven initial population generation pseudocode

```
Algorithm 2: Knowledge-driven initial population generation
Input: NIND
Output: population
for nind = 1 to NIND do
  for s=1 to 81 do //Find every line on DC5
    if There used to be freight on this road
        Set the amount of freight on this line to 0
      if nind ≤ ⌊NIND/3⌋
          Placement of freight on this route on a feasible route with the least amount
      Else if ⌊NIND/3⌋ < nind ≤ ⌊2 * NIND/3⌋
          Splitting the freight on this route to arrange it on feasible routes to make the load of
        each route as balanced as possible
      else
          Random allocation
      end
    end
  end
end
```

As shown in Table 2, the initial population is mainly divided into three parts: the initial solution generation for K1, the initial solution generation for K2, and the random initial solution generation Initial solution generation for K1 and K2 belong to heuristic algorithms, which can easily lead to homogeneity of individuals. Therefore, random initial solutions are used to ensure the diversity of solutions Initial solution generation for K1 and initial solution generation for K2 focus on K1 and K2 respectively to generate initial solutions in the form of multitasks.

When the initial solution is generated in the form of multi-objective, the leading edge solution is {2, 3, 4, 5}; When the initial solution is generated in the form of multi-task, the leading edge solution is {1, 2, 5, 6}.

3.1.5. Cross mutation

Crossover operation groups the original data to evaluate the prediction performance of the model, especially the performance of the trained model on the new data, which can reduce the problem of over-fitting to a certain extent and obtain more effective information from the limited data[6].

Mutation probability is the key control parameter that affects the performance and convergence of the algorithm Large mutation probability is easy to jump out of local extremum to find global optimal solution, but too large mutation probability will make it a random search algorithm On the other hand, if the probability of mutation is too small, it is difficult to produce new individuals, which makes evolution stagnate.

In order to improve the efficiency of mutation in mutation operation, this paper disturbs the altered route caused by DC5 shutdown. Before each mutation, the individual is compared with the original scheduling scheme. Adaptively changing the mutation rate according to the outlier degree of each route for the changed individuals. The formula for calculating the adaptive mutation rate is shown in (13):

$$P_m = M * \frac{|\max(L_t) - \text{average}(L_t)|}{\text{average}(L_t)} \quad (13)$$

Where is the initial variation rate Is the load of the maximum route in the individual Is the average load of routes in an individual It can be seen in the formula that the more unbalanced the route load of individuals, the higher the variation rate; The more balanced the route load, the lower the mutation rate.

3.2. Algorithm solution

Use the algorithm described in 6.2 to solve the model. At the same time, in order to test the performance of the algorithm, the CCNSGA-II designed in this paper is compared with CCNSGA-II without improved initial solution generation strategy. CCNSGA-II without crossover mutation improved strategy, CCNSGA-II without any improved strategy. In order to ensure the fairness of the algorithm, Taguchi method is used to check the parameters and select the best parameters to carry out comparative experiments. The experimental parameters obtained by verification are as follows:

Table 3: Parameter Settings

parameter	numerical value
Population size	20
Crossing rate	0.75
Initial variation rate	0.15

Run 20 times on each algorithm. Each run time is equal to the total number of lines and averages it. The solution results are as figure 1.

In fig. 1, objec1 is the number of changed lines, object 2 is the degree of dispersion, object 3 is the number of unwrapped pieces. We can see that in CNSGA-II algorithm, the number of changed lines in objec1 is the smallest, objec2 is the lowest, and the number of unwrapped pieces in objec3 is the less, the better the optimization effect can be solved At the same time, we can see that CCNSGA-II does not contain improved initial generated solution strategy, does not contain crossover mutation strategy, and does not contain any improved strategy. We can see that CCNSGA-II has a large number of changed lines, a high degree of dispersion and a large number of unwrapped parts, so its optimization effect is not good.

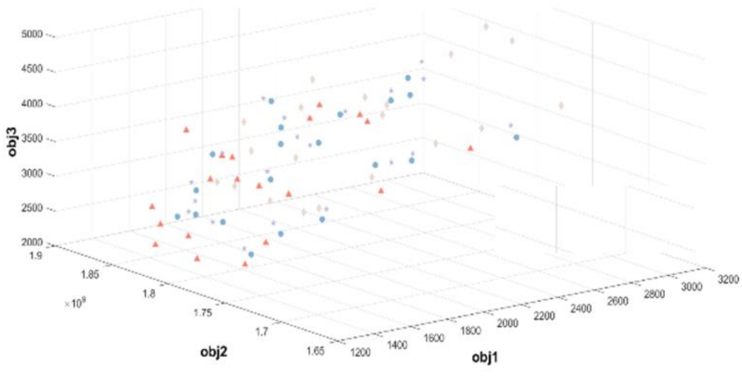

Figure 1: CCNSGA-II algorithm comparison simulation diagram

In order to express the optimization effect of the solution results on each target more clearly, Show the optimization effect on the pairwise target values as follows:

The results show that the number of lines and the degree of dispersion in the case of unwrap invariant show that the improved initial generation solution of CCNSGA-II has the best optimization effect under the condition of crossover mutation improved strategy and improved strategy. We can see that CCNSGA-II has the best optimization effect.

The optimization effect of CCNSGA-II algorithm with improved initial generation solution, crossover mutation and improved strategy and improved strategy is explained by changing the number of unwrapped orders and the number of lines without changing the dispersion degree. We can see that CCNSGA-II has the best optimization effect.

The optimization effect of CCNSGA-II algorithm with improved initial generation solution, crossover mutation, improved strategy and improved strategy is explained by changing the number of unwrapped orders and discrete degree without changing the number of lines. We can see that CCNSGA-II has the best optimization effect.

4. Conclusions

In this paper, an ARIMA-EBP neural network forecasting model is established for line cargo forecasting. The model is modified by EBP neural network based on ARIMA prediction. In addition, training neural networks for the 31-day prediction period and ensemble prediction can further improve the prediction performance of the model. A mixed integer linear programming model is established to optimize the three objectives simultaneously. The performance of the scheduling scheme is balanced among the three objectives. A CCNSGA-II algorithm is designed to solve the MILP model. Experiments show that this algorithm is superior to other algorithms in solving efficiency.

References

[1] Zhang Xiaheng. Collaborative strategy of county and township e-commerce logistics network in China [J]. Research on Technical Economy and Management, 2015 (8): 21-25.

[2] Sha Li, Lin Hui. Spatio-temporal modeling and prediction combined with MLR and ARIMA model [J]. Computer Engineering and Application, 2021, 57 (13): 276-282.

[3] Lan Xuemei, Zhu Jian, Huang Chengming, et al. MATLAB realization of BP network [J]. Microcomputer Application, 2003, 19 (1): 6-8.

[4] Guan Bo and Wang Lijie. Construction of reverse logistics network of third-party return and exchange in C2C e-commerce based on MILP model [J]. Business Economics Research, 2020 (09): 115-118.

[5] Chen Zhiwei and Wang Hongpeng. Research on the construction of seaport-dry port network in Fujian Province based on NSGA-ii algorithm [J]. China Navigation, 2023, 46 (01): 114-119 +126.

[6] Liu Chao, Qi Rongbin, Qian Feng. A new hybrid particle swarm optimization algorithm combining crossover mutation and chaos [J]. Acta Chemical Engineering Sinica, 2010, 61 (11): 2861-2867.