Logistics sorting cargo volume prediction and personnel scheduling optimization based on ARIMA

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ABSTRACT

The development of the e-commerce industry is unstoppable, and logistics is an important part of this industry, and the speed of industry development is largely constrained by the efficiency of logistics sorting. The prediction of cargo volume and personnel scheduling in logistics network sorting centers is one of the core issues in logistics management. With the rapid development of the e-commerce industry, logistics network sorting centers have to handle a large number of packages every day. Accurately predicting cargo volume and arranging personnel scheduling reasonably are of great significance for improving efficiency, reducing costs, and ensuring service quality. Regarding problem one: In order to ensure the stability of the data and the accuracy of predictions, seasonal adjustments and Mahalanobis distance are first used to handle missing and outliers in the data, thereby improving the reliability of subsequent models and the accuracy of predictions. Next, the SARIMS model will be used to predict the cargo volume of the sorting center for the next 30 days, and the ARIMA time series model will be used to predict the hourly cargo volume of the sorting center. Finally, residual testing will be conducted to ensure that the results of the model are more accurate and reliable. Regarding problem two: when predicting the cargo volume for the next 30 days and each hour, it is necessary to first identify the total cargo volume corresponding to the changing route. Then, the proportion of transported goods for each route is calculated using a mathematical model, taking into account factors such as transportation efficiency, cost, and route length, and comprehensively considering the rational allocation of goods. Finally, based on the change rate of the total cargo volume, the final prediction result is revised to make it consistent with reality. Regarding problem three: categorize the problem as a typical integer linear programming problem and use heuristic algorithms to solve it. In order to effectively schedule employees, it is necessary to establish a planning model, define appropriate variables and parameters, and use an objective function and constraints. I hope to achieve a balance of actual hourly efficiency per day while minimizing the total number of person days as much as possible. Regarding problem four: In order to solve the scheduling problem of specific sorting centers, it is necessary to deeply optimize the factory production line settings. The core goal is used to balance cost-effectiveness, rational resource allocation.

Keywords: Seasonal Adjustment, Mahalanobis Distance, ARIMA Time Series Model, Integer Linear Programming, Simulated Annealing Algorithm

1 INTRODUCTION

The prediction of cargo volume in sorting centers is an important research problem in e-commerce logistics networks. Accurate prediction of cargo volume in sorting centers is the basis for subsequent management and decision-making. If managers can predict the cargo volume that each sorting center needs to operate in advance for a period of time, they can arrange resources in advance. There are generally two objectives for cargo volume prediction in this scenario: first, to predict the daily cargo volume of each sorting center based on historical cargo volume, logistics network configuration, and other information; The second is to predict the hourly cargo volume of each sorting center based on historical hourly cargo volume data. Based on the above analysis, the research object could be divided into following four works.

Work 1: Establish a cargo volume prediction model to predict the daily and hourly cargo volume of 57 sorting centers for the next 30 days, and obtain the prediction results.

Work 2: The average cargo volume of each transportation route between sorting centers in the past 90 days is shown in Annex 3. If there are changes in the transportation routes between sorting centers in the next 30 days, as shown in Annex 4. According to attachments 1-4, predict the daily and hourly cargo volume of 57 sorting centers for the next 30 day.

Work 3: Assuming there are 60 formal workers in each sorting center, priority will be given to using formal workers when arranging personnel, and temporary workers will be used if additional personnel are needed. Please establish a model based on the prediction results of work 2, provide the attendance figures for each shift in each sorting center for the next 30 days. On the basis of completing the daily cargo volume processing, it is required to arrange as few person days as possible (for example, if 200 employees are on duty every day for 30 days, the total person days will be 6000), and the actual hourly efficiency of each day should be balanced as much as possible [1].

Work 4: Study the scheduling problem of a specific sorting center. Here, let's take SC60 as an example. Assuming that there are currently 200 formal workers in the sorting center SC60, please establish a model based on the prediction results of work 2 to determine the shift attendance plan for each formal worker and temporary worker for the next 30 days. That is, provide the shift attendance plan for each formal worker in the six shifts per day for the next 30 days, and how many temporary workers need to be hired for each shift, and write it in Table 6 of the results [2]. The attendance rate of each formal worker (the number of days attended divided by the total number of days) cannot exceed 85%, and the number of consecutive attendance days cannot exceed 7 days. On the basis of completing the daily cargo volume processing, it is required to arrange as few people and days as possible, balance the actual hourly efficiency as much as possible, and achieve a balanced attendance rate for formal workers.

2 MODEL ASSUMPTIONS

Based on the actual situation and comprehensive analysis, in order to avoid interference from unnecessary or relatively small factors on the accuracy and rationality of the model, the following assumptions are proposed:

(1) Assuming that historical cargo data is a time series with certain periodicity and seasonality;

(2) Assuming that after deleting or adding new routes, the corresponding amount of goods is allocated according to their proportion;

(3) Assuming that the working hours of all employees are fixed at 8 hours, excluding rest time or other factors;

3 MODEL BUILDING AND ANALYZING

3.1 Model establishing and solving for work one

3.1.1 Work analysis

Work 1 requires the establishment of a cargo volume prediction model to predict the daily and hourly cargo volume of 57 sorting centers for the next 30 days. Firstly, preprocess the data in Annex 1 and Annex 2, check for missing and abnormal values, and handle them appropriately. Standardize data to eliminate dimensional effects. Because many time series data contain seasonal changes, which may mask the true trend of the data, seasonal adjustments are made to eliminate seasonal effects in the data and make the trend more pronounced [3]. Finally, the SARIMA model was used to predict the daily cargo volume of 57 sorting centers for the next 30 days, and the ARIMA model was used to predict the hourly cargo volume.

3.1.2 Model establishing

3.1.2.1 Data preprocessing

Firstly, a visual analysis is conducted on the routes generated by different nodes and the total amount of goods distributed on the nodes. The data is then cleaned, and zero values are added to the missing hourly cargo volume. A Mahalanobis distance model is established for outliers to eliminate errors caused by outliers. The daily cargo volume visualization of some nodes is shown in Fig.1.

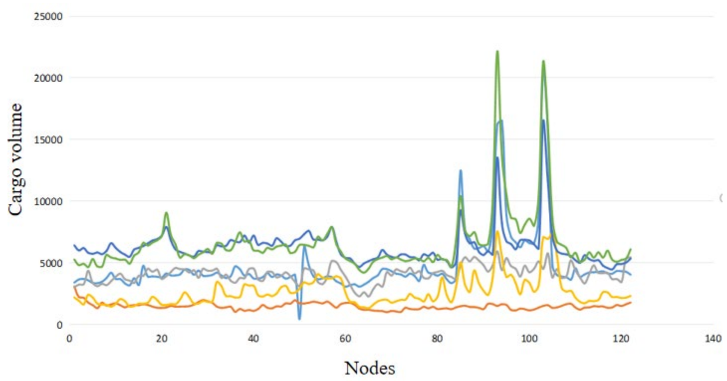

Fig.1 Visualization of the daily trend of average cargo volume at some sorting center points

Definition of Mahalanobis distance: As a distance measurement method, Mahalanobis distance can be understood as an optimization and improvement of Euclidean distance, which specifically solves the problems caused by differences in scale and correlations in various dimensions in Euclidean distance calculation [4].

Mahalanobis distance of individual data:

$$D_M(X) = \sqrt{(x-\mu)^T \sum{}^{-1}(x-\mu)} \tag{1}$$

Mahalanobis distance between data points x and y:

$$D_M(X) = \sqrt{(x-y)^T \sum{}^{-1}(x-y)} \tag{2}$$

Where, Σ is the covariance matrix of multidimensional random variables, μ is the sample mean. If the covariance matrix presents as an identity matrix, it means that the dimensions are independent and identically distributed. In this case, the Mahalanobis distance is essentially equivalent to the Euclidean distance.

3.1.2.2 Seasonal ARIMA model

In certain time series, there are obvious periodic changes that are caused by seasonal changes (including quarterly, monthly, weekly, etc.) or other factors. This type of sequence is called a seasonal sequence. The model that describes such sequences is called a seasonal time series model, represented by SARIMA. Definition of Seasonal Time Series Model: The period of change of seasonal series is represented by s. For quarterly sequences, s=4; for monthly sequences, s=12. Use seasonal differences to eliminate periodic changes. The seasonal difference operator is defined as:

$$\Delta_s = 1 - L^s \tag{3}$$

If the seasonal time series is represented by y, then the seasonal difference is expressed as:

$$\Delta_s y_t = (1 - L^s) y_t = y_t - y_{t-s} \tag{4}$$

For time series containing non-stationary seasonal features, theoretically, they can always be transformed into stationary sequences by implementing a finite number of seasonal and non seasonal differencing treatments. If the total number of observation points in the original sequence is denoted as T, once a seasonal difference (i.e. difference according to seasonal period s) and a non seasonal difference (conventional first-order difference) are performed, it will result in a reduction of s+1 data points in the sequence. Therefore, the length of the transformed sequence will be reduced to T - (s+1).

3.1.2.3 ARIMA time series model

The ARIMA model, also known as the auto-regressive integral moving average model or differential integrated moving average auto-regressive model, is one of the core tools in time series prediction analysis. The basis for constructing this model is that the time series must have stationarity. In other words, it is crucial to ensure that the time series is in a stationary state before applying the ARIMA model for prediction [5]. For non-stationary time series, preprocessing techniques such as differencing can be used to achieve sequence stabilization.

However, in order to obtain the predicted values of the original non-stationary time series, it is necessary to perform an inverse operation, i.e. a restoration step, on the predicted results of the stationary series mentioned above. This usually involves reverse processing of the exponential or differential operations used in the stabilization process, in order to ultimately obtain the true predicted results of the original data. Model of ARIMA(p,d,q) could be written as

$$(y')_t = \alpha_0 + \sum_{p}^{i-1} \alpha_i (y')_{t-i} + \epsilon_t + \sum_{i=0}^{q} \beta_i \epsilon_{t-i} \tag{5}$$

$$y'_t = \delta^d y_t = (1 - L)^d y_t \tag{6}$$

$$(1 - \sum_{i=0}^{p} \alpha_i L^i)(1 - L)^d y_t = \alpha_0 + (1 + \sum_{i=0}^{q} \beta_i L^i)\epsilon_t \tag{7}$$

Where, p represents the lag number (lags) of the time series data used in the time series prediction model, also known as the AR/Auto Regression term; d represents the order at which the temporal data reaches a stable differentiation, also known as the Integrated term, q represents the lag number (lags) of the prediction error used in the prediction model, also known as the MA/Moving average term.

3.1.3 Model solving

3.1.3.1 Rolling prediction of daily cargo volume based on SARIMA

In the process of solving this problem, the daily cargo volume of each sorting center is predicted separately, and the preprocessed data is substituted to solve the problem using the SARIMA cargo volume prediction model. Using Matlab to write a program, analyze the changes in cargo volume of the picking center over the past period of time (August November) with time as the horizontal axis and cargo volume as the vertical axis, and predict the cargo volume for the next month

3.1.3.2 Rolling prediction of hourly cargo volume based on ARIMA

On the basis of daily cargo volume, summarize and visualize the cargo volume data for each hour of 57 sorting centers. Sum up the cargo volume for each hour of the 24 hours of the day and observe the overall hourly trend as shown in Fig.2.

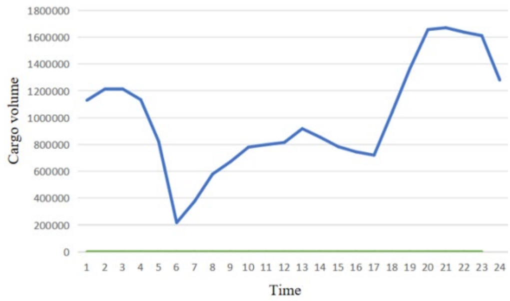

Fig.2 Trend of total hourly cargo volume

The basic idea of ARIMA is as follows: first, perform data preprocessing, including performing stationarity tests on the original time series, and if necessary, use differential operations to make it stationary. Continuing into the model recognition stage, by observing the auto correlation function graph (ACF) and partial auto correlation function graph (PACF), we can effectively infer and determine the appropriate order for constructing the auto regressive model (AR) and moving average model (MA) [6]. Then, in the parameter estimation stage, maximum likelihood estimation and other methods are used to estimate the model parameters, including the auto regressive coefficient, moving average coefficient, and variance of the error term [7]. Afterwards, fit the ARIMA model based on these estimated parameters and perform model diagnosis to check whether the residual sequence conforms to the white noise characteristics. If necessary, adjust the model. Finally, use the fitted model to predict future time series values

3.2 Model establishing and solving for work two

3.2.1 Work analysis

Work 2 requires predicting the daily and hourly cargo volume of 57 sorting centers for the next 30 days after changes in transportation routes. Firstly, match the data in Annex 3 and Annex 4 to find the total cargo volume corresponding to the changing route. Multiply the rate of change with the prediction result in work one as the corrected prediction result. The directed graphs of each route are shown in Fig.3.

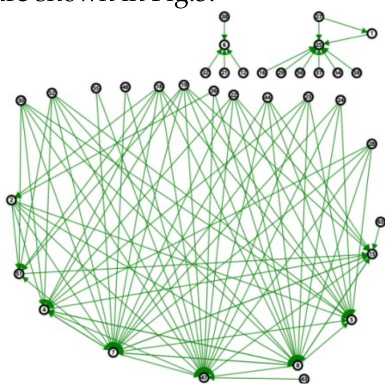

Fig.3 Directed Graph of Each Route

3.2.2 Model establishing

For each changing route, calculate its corresponding total cargo volume. If the changing route corresponds to an average cargo volume of, then the total cargo volume $H_{total,i}$ can be calculated using the following formula:

$$H_{total,i} = \sum_{j=1}^{n} H_{i,j} \tag{8}$$

Where, n is the number of sorting centers on the route, and $H_{i,j}$ is the average cargo volume departing from sorting center j on the route. Summarizing the deleted route after re matching with the newly added route 8. The deleted route after re matching is shown in Table 1, and the newly added route after re matching is shown in Table 2.

Table 1 Routes deleted after matching

Departure sorting center	Arriving at the sorting center	Quantity of goods
SC1	SC25	254
SC2	SC19	356
SC4	SC15	15

Table 2 Newly added routes after matching

Departure sorting center	Arriving at the sorting center
SC5	SC4
SC38	SC6

3.2.3 Model solving

Calculate the proportion of cargo volume on the corresponding route when the transportation route of the sorting center in Attachment 4 changes, as shown in Fig.4.

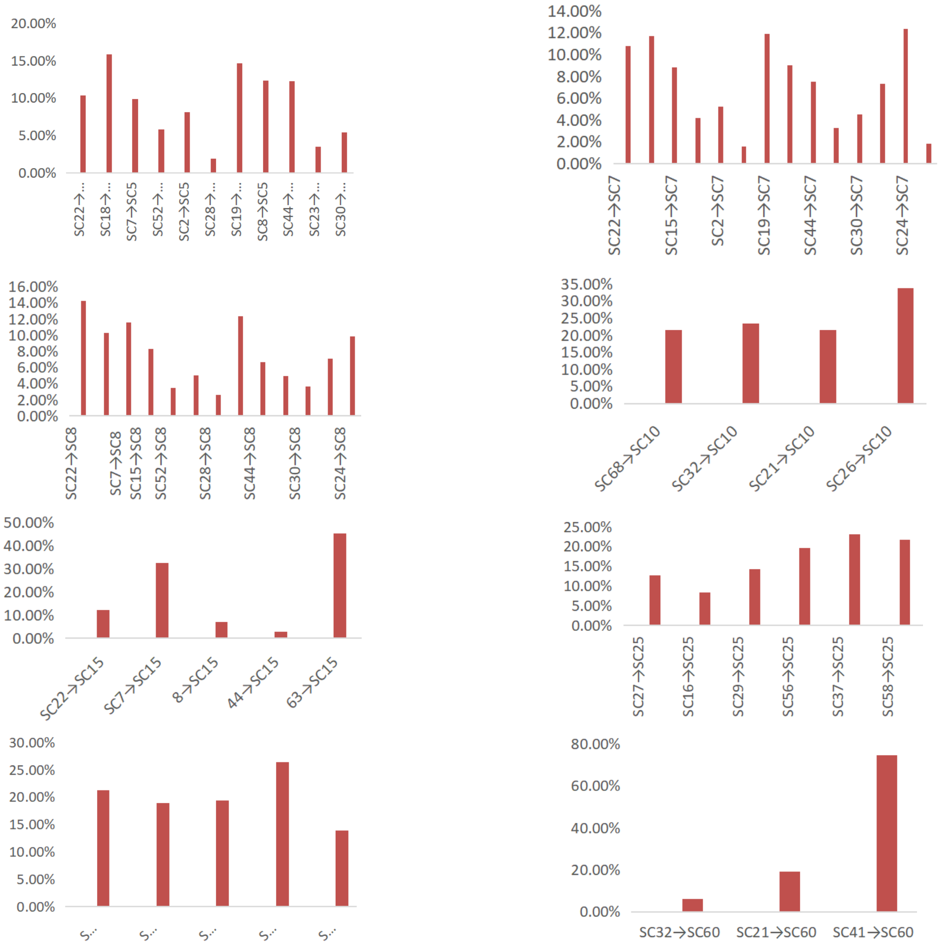

Fig.4 The proportion of goods on the corresponding routes of different picking centers

To calculate the rate of change in cargo volume based on the changes in the route and the total cargo volume $H_{total,i}$ of each route, we first need to allocate the total cargo volume to the corresponding route to the sorting center according to different proportions [8]. If the allocation ratio is set to, the allocated quantity of goods $H_{de,i}$ can be calculated using formula 9.

$$H_{de,i} = H_{total,i} \times p_{ij} \tag{9}$$

According to the distribution of the deleted route cargo volume, the change in cargo volume of the revised route is shown in Fig.4

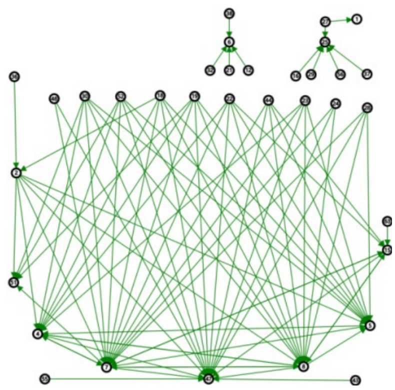

Fig.5 Directed graph of cargo volume for the revised route

To calculate the rate of change, we need to refer to the past cargo volume and the allocated cargo volume. Assuming the average cargo volume of each sorting center in the past is $H_{past,j}$, the rate of change c_j can be calculated using formula 10.

$$c_j = \frac{H_{de,j}}{H_{past,j}} - 1 \tag{10}$$

Where, $H_{de,j}$ is the total amount of goods allocated, $H_{past,j}$ is the average amount of goods in the past sorting center j, and can be used to calculate the sorting center and its corresponding rate of change in goods volume [9]. Finally, we need to apply the rate of change r_j to the prediction result in problem one to obtain the revised prediction result $J_{xiuzheng,j}$.

Assuming the original prediction result is $J_{yuanshi,j}$, the revised prediction result can be calculated using formula 11.

$$J_{xiuzheng,j} = J_{yuanshi,j} \times (1 + r_j) \tag{11}$$

Where, $J_{xiuzheng,j}$ is the corrected predicted cargo volume of sorting center j.

3.3 Model establishing and solving for work three

3.3.1 Work analysis

Work three requires scheduling both formal and temporary workers, minimizing the number of person days arranged, and balancing the actual hourly efficiency as much as possible. Therefore, a planning model is established to solve the scheduling problem of personnel. Firstly, it is necessary to define appropriate variables and parameters, establish a mathematical model of the objective function and constraint conditions, and obtain the optimal attendance arrangement plan by solving the model [10].

3.3.2 Model establishing

Establish a planning model, set constraints and other variables. Based on the known information of the analysis work, we can summarize the known conditions as:

(1) The number of sorting centers is 57.

(2) The number of shifts is 6, and the schedule of shifts is: 00:00-08:00, 05:00-13:00, 08:00-16:00, 12:00-20:00, 14:00-22:00, 16:00-24:00.

(3) Each person (formal or temporary) can only attend one shift per day.

(4) The maximum hourly efficiency for formal workers is 25 packages per hour, while the maximum hourly efficiency for temporary workers is 20 packages per hour.

Based on the above known conditions, we need to minimize the total number of person days, which means that all sorting centers have the lowest total number of people arranged within 30 days [11]. Therefore, the problem is summarized as a typical integer linear programming problem and solved through heuristic algorithms.

Decision variables: Let the number of formal workers and temporary workers attending the kth shift on the jth day of the ith sorting center be, i=1,2,...,57、j=1,2,...,30、k=1,2,...,6, The decision variable is an integer and cannot be a decimal. The cargo volume for the i^{th} sorting center on day j.

Target number of people: Arrange as few people and days as possible

$$\min(\mathrm{P}) = \sum_{\mathrm{i}=1}^{57}\sum_{\mathrm{j}=1}^{30}\sum_{\mathrm{k}=1}^{6} X_{ijk} + \sum_{\mathrm{i}=1}^{57}\sum_{\mathrm{j}=1}^{30}\sum_{\mathrm{k}=1}^{6} Y_{ijk} \tag{12}$$

Constraints:

1) Daily cargo volume processing completed

$$25\sum_{\mathrm{k}=1}^{6} X_{ijk} + 20\sum_{\mathrm{k}=1}^{6} Y_{ijk} \geq a_{ij} \tag{13}$$

2) Each formal worker can only attend one shift per day

$$\sum_{k=1}^{6} X_{ijk} \leq 60 \tag{14}$$

3) The total daily attendance cannot exceed the total number of people in the sorting center (60 formal workers):

$$\sum_{k=1}^{6} \left(X_{ijk} + Y_{ijk}\right) \leq 60 \tag{15}$$

4) Prioritize the use of formal workers

$$\sum_{k=1}^{6} X_{ijk} \geq \sum_{\mathrm{k}=1}^{6} Y_{ijk} \tag{16}$$

5) Try to balance the actual hourly human efficiency as much as possible every day

$$25\sum_{\mathrm{k}=1}^{3} X_{ijk} + 20\sum_{\mathrm{k}=1}^{3} Y_{ijk} \geq \frac{1}{2} a_{ij} \tag{17}$$

$$25\sum_{k=4}^{6} X_{ijk} + 20\sum_{k=4}^{6} Y_{ijk} \geq \frac{1}{2}a_{ij}$$

6) Decision variables are integers and cannot be decimals

The decision variables represent the cargo volume of the ith sorting center in the kth shift on the jth day. These variables are integers, not decimals [12]. In MATLAB, the boundaries and types of variables can be set to ensure that they are integers. In summary, the integer programming model for minimizing the number of days of personnel arrangement is:

$$\min P = \sum_{i=1}^{57}\sum_{j=1}^{30}\sum_{k=1}^{6} X_{ijk} + \sum_{i=1}^{57}\sum_{j=1}^{30}\sum_{k=1}^{6} Y_{ijk} \tag{18}$$

$$\text{s.t.}\begin{cases} 25\sum_{k=1}^{6} X_{ijk} + 20\sum_{k=1}^{6} Y_{ijk} \geq a_{ij} \\ \sum_{k=1}^{6} X_{ijk} \leq 60 \\ \sum_{k=1}^{6}\left(X_{ijk} + Y_{ijk}\right) \leq 60 \\ \sum_{k=1}^{6} X_{ijk} \geq \sum_{k=1}^{6} Y_{ijk} \\ 25\sum_{k=1}^{3} X_{ijk} + 20\sum_{k=1}^{3} Y_{ijk} \geq \frac{1}{2}a_{ij} \\ 25\sum_{k=4}^{6} X_{ijk} + 20\sum_{k=4}^{6} Y_{ijk} \geq \frac{1}{2}a_{ij} \end{cases} \tag{19}$$

3.3.3 Model solving

Firstly, we defined the coefficient vector F of the objective function, the inequality constraint matrix A, the right-hand vector b, and the lower bound variable b. Defining the coefficient vector F of the objective function is crucial for determining the objective we want to minimize or maximize. This vector reflects the contribution of each decision variable to the objective function and is the core indicator of our optimization process. The inequality constraint matrix A and the right-hand vector limit the range of decision variables, ensuring that our solution satisfies the constraints in practical situations [13]. By using the intlinprog function in MATLAB, we can solve the overall planning problem. This function is based on an internal integer linear programming algorithm, which can find the optimal integer solution in a reasonable time, thereby improving our decision-making efficiency and quality. By organizing the data, we can better understand and analyze the optimal solution for each date, thereby providing reliable reference for future decision-making and planning.

3.4 Model establishing and solving for work four

3.4.1 Work analysis

To study the scheduling problem of a specific sorting center, taking SC1 as an example, it is necessary to optimize the production line configuration of a factory to maximize production efficiency, while considering cost, resource allocation, and employee satisfaction. We will build a multi-objective optimization model, use simulated annealing methods, and display the optimal solutions and their impacts in different aspects through various visualizations.

3.4.2 Model establishing

Build an optimization model and solve it using simulated annealing algorithm. The concept of simulated annealing algorithm originated from the physics theory proposed by Metropolis et al., which cleverly drew on the phenomenon of structural changes during the heating and cooling process of solid materials and applied it to solve complex combinatorial optimization problems. The core mechanism of this method can be divided into three main stages:

(1) Heating process. Similar to heating a solid to a high temperature state, this stage in the algorithm means endowing the system with greater "randomness" or "exploratory" in the initial stage. Raising the "temperature" of the system essentially increases the possibility of random movement of the solution in the search space, allowing the solution to move away from the existing stable state (i.e. local optimum) and even overcome the potential barrier that originally hindered reaching the global optimum.

(2) Isothermal process. In the simulated annealing algorithm, this stage corresponds to the process of maintaining thermal equilibrium with the environment. In mathematical models, this means conducting a series of random sampling attempts at a fixed temperature. According to the Metropolis criterion, even if the newly generated solution is temporarily inferior to the current solution in the objective function sense, there is still a certain probability of acceptance. This way, the algorithm can not be completely limited to the local optimal solution in the search space, but has the opportunity to cross the local minimum region.

(3) Cooling process. As the simulated annealing process progresses, the system begins to gradually "cool down" by gradually reducing the control parameters (simulated temperature). This process gradually narrows the exploration scope of the algorithm, making it more inclined to retain high-quality solutions until they finally stabilize in a lower energy state (manifested as a state with a smaller objective function value in optimization problems), thus potentially finding the global optimal solution or a solution close to the local optimal solution.

3.4.3 Model solving

Adopting simulated annealing process. Based on the similarity between the annealing process of solid materials and general combinatorial optimization problems. Simulated annealing algorithm is based on probability algorithm, which involves heating a solid to a sufficiently high temperature and gradually cooling it down. Construct the optimal solution for finding the objective function in the solution space, and obtain the global optimal solution through the local optimal final iteration process. Mainly consider the following three processes:

(1) Iteration process:

Through computer simulation, continuously determine acceptable solutions and ultimately determine the optimal solution. Each iteration goes through the following three steps:

1) Determine new solution: After multiple iterations, the original data is randomly shuffled and changed differently in each iteration process.

2) Cost function difference. Let this iteration be the result of the (=1,2,3,...) th iteration, denoted as, and let the solution generated by the -1st iteration be. In step 1), it has been calculated through random simulation, and the cost function difference can be determined as

$$\Delta f = f_l - f_{l-1} \tag{20}$$

3) Acceptance criteria. Determine the acceptance level of the new path, use computer

simulation to generate uniformly distributed random numbers on [0,1], and determine the acceptance probability of the iterative process.

$$P = \begin{cases} 1 & \Delta f < 0 \\ exp(-\Delta f \; / \; T) & \Delta f \geq 0 \end{cases} \tag{21}$$

When Δf<0, the objective function difference in this iteration is negative and the distance is shortened, a new path is accepted; Otherwise, the iteration results cannot be fully accepted, and it is considered acceptable to accept the new path with probability $exp(-\Delta f \; / \; T)$. In computer simulation of random numbers, if the random number $h \leq exp(-\Delta f \; / \; T)$, it is considered acceptable.

4 CONCLUSION

The Mahalanobis algorithm is not affected by dimensionality and performs multivariate outlier search. The Mahalanobis distance between two points is independent of the measurement unit of the original data, and the Mahalanobis distance can also eliminate the interference of correlation between variables.

The ARIMA model performs well in revealing and predicting trends, seasonality, and random fluctuations contained in time series data, especially for stationary time series, where the model often provides accurate prediction results. And the model application is relatively simple, only requiring endogenous variables without the need for other exogenous variables. When applying the ARIMA model to predict time series data, the basic prerequisite is that the processed data series must exhibit stationarity characteristics. If the data itself is in a non-stationary state, the ARIMA model will find it difficult to effectively capture the underlying patterns.

The advantage of simulated annealing algorithm lies in its relative insensitivity to initial setting conditions, demonstrating strong robustness and adaptability. Has strong robustness. The quality of the optimal solution found using simulated annealing algorithm largely depends on the number of iterations set. When the number of iterations is increased, the search process becomes more in-depth and comprehensive. Although the required time is correspondingly extended, the optimal solution obtained from this is usually more accurate and reliable. On the contrary, if a smaller number of iterations is chosen, although it can shorten the calculation time, it also increases the risk of missing the global optimal solution, which may lead to less than ideal results.

5 ACKNOWLEDGEMENTS

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REFERENCES

[1] Zhai, J., & Cao, J. (2016). A combined prediction model based on time series ARIMA and BP neural network. *Statistics and Decision Making*, 04: 29-32.

[2] Chen, S. J. (2017). A Logistics sorting system based on multi AGV scheduling. *Shenzhen University*.

[3] Yang, C. X., Huang, H., & Dai, Y. C. (2017). Research and implementation of key technologies for 3D visualization of distribution networks based on CIM. *Electric Power Science and Engineering*, 33(05): 6-10.

[4] Gong, B. B. (2021). Prediction of natural gas imports in China based on GA-ELM model. *China University of Petroleum*.

[5] Wang, G. N., & Tang, X. P. (2022). Research on rural emergency logistics distribution path based on simulated annealing and floyd optimization algorithm. *Software Engineering*, 25(12): 9-12.

[6] Yang, J., Yang, X. D., & li, L. S. (2022). Optimization of stacker crane path based on genetic simulated annealing algorithm. *Logistics Technology*, 41(08): 119-123.

[7] Xu, B., & Wang, Q. D. (2023). A fault-tolerant method for AUV collaborative localization based on Mahalanobis distance and neural network assistance. *Chinese Command and Control Society*.

[8] Ding, Y. M., Zhang, X. Q., & Zhang, X. Q. (2024). Active distribution network operation optimization considering linearized power flow constraints. *Shandong Electric Power*, 51(03): 36-44.

[9] Zhang, B. (2024). Research on logistics distribution optimization model and solution algorithm based on integer linear programming. *China Storage and Transportation*, 03: 008-015.

[10] Li, Z. Y., Xu, Y., & Han, X. T. (2024). Application of quantum computing technology in decision optimization of new power systems. *Power System Automation*, 48(06) :62-73.

[11] Wang, L., Jiang, S., & Mao, Y. (2024). Lithium-ion battery state of health estimation method based on trategy. E*nergy Reports*, 112877-2891.

[12] Saranya, S., Anusha, P., & Chandragandhi, S. (2024). Enhanced decision-making in healthcare cloud-edge networks using deep reinforcement and lion optimization algorithm. *Biomedical Signal Processing and Control*, 92105963.

[13] Gómez, A., & Xie, W. (2024), A note on quadratic constraints with indicator variables: convex hull description and perspective relaxation. *Operations Research Letters*, 52107059.