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Optimization Strategy for Storage Location Allocation in Air Cargo Warehouse Area

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Abstract. Facing rapid growth in air cargo demand within the global supply chain and limitations of traditional storage location allocation methods, this study proposes an intelligent optimization strategy for storage location allocation. The strategy considers key factors like flight schedules, cargo collection and delivery data, cargo terminal topology, and in-and-out paths. It intelligently allocates each cargo batch to the most suitable location, assigning more flights' cargo to locations near the exit, thereby reducing cargo handling distance and offloading time, and enhancing operational efficiency and cargo handling capacity in the air freight sector. The algorithm, based on the latest optimization theories and techniques, seeks optimal solutions under various constraints. The model and algorithm's effectiveness is validated through simulation experiments using actual flight data. The results indicate that, compared to traditional strategies, the optimized strategy reduces response time by 62%.

1.Introduction

Air freight plays a critical role in the global supply chain, facing complex challenges in storage location optimization and allocation. With the rapid growth in demand for air cargo, existing logistics infrastructure is no longer sufficient to handle the increasing volume of freight, especially in terms of efficient and intelligent storage location management. Traditional storage location allocation methods rely on static rules and manual experience, which exhibit clear limitations when dealing with a variety of cargo, flight uncertainties, and urgent takeoff times. These limitations not only affect the responsiveness of the warehouse management system but also impact the efficiency of the entire supply chain.

Existing research focuses on enhancing picking efficiency by reducing the distance traveled during the picking process, making the minimization of picking distance the core objective function in storage location allocation issues. Kim et al. [1] conducted research on storage location allocation problems in automated warehouses. By applying heuristic algorithms to the issue of picking paths within the warehouse, they optimized the machine's travel route to achieve the shortest path. Dukic and Oluio [2] compared different picking strategies and storage location allocation methods through simulation experiments to determine the best combination of approaches. Chuang et al. [3] proposed a two-phase Clustering-Assignment Problem Model (CAPM), which includes a cargo clustering model and a model for allocating cargo clusters to warehouse zones, using a Z-shaped path based on the frequency of cargo orders for storage location allocation and evaluating the model's effectiveness based on the picking distance under a Z-shaped path strategy. Dijkstra and Roodbergen [4] explored storage location allocation issues in manual picking systems, proposing formulas for expected picking distances based on common picking strategies and establishing a model aimed at minimizing these distances. Zhang et al. [5] proposed a storage location allocation model that integrates the Demand Correlation Pattern (DCP), focusing on minimizing the picking distance under an S-shaped path. Aboelfotoh et al. [6] aimed to optimize the static order batching problem (OBP) involving multiple pickers. This issue entails optimally assigning a set of customer orders into batches under specific capacity constraints, with the objective of minimizing the total travel distance. This approach is crucial for enhancing the efficiency of order picking processes. Li et al. [7] explored heuristic methods for assigning Stock Keeping Units (SKUs) to individual slots in a distribution center. These heuristics aim to assign frequently ordered SKUs to slots near the input/output points and SKUs often ordered together to adjacent slots, effectively reducing the travel distance of order pickers in the distribution center. Yücel et al. [8] proposed a multi-period two-dimensional vehicle loading and dispatching problem, which involves developing a transportation plan from a single origin to a single destination. The objective is to minimize the total vehicle usage and penalty costs, with constraints based on the due dates of orders, compatibility of orders loaded on the same vehicle, compatibility between orders and vehicles, as well as the area and weight capacity of the vehicles. A Mixed-Integer Linear Programming model was established for this purpose. Muharni et al. [9] employed the ant colony

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optimization method to design effective and efficient material handling movement routes, aiming to minimize the material handling transfer costs.

These studies apply heuristic algorithms, intelligent optimization algorithms, and other mathematical models and optimization techniques to seek optimal storage location allocation solutions in automated warehouses and manual operation systems. Through simulation experiments and real data analysis, detailed explorations of storage location allocation for single and composite operation modes have been conducted, thereby identifying the best picking strategies and storage location allocation models. The research involves various optimization goals, including shelf stability, in-and-out efficiency, and minimization of the picking path, all aimed at meeting the modern retail industry's needs for multiple-item, small-batch orders.

However, due to the specificity of air cargo transportation, the process from storage to retrieval involves first transporting cargo to the security check entrance and then allocating them to appropriate storage locations for retrieval within a specified time, requiring high efficiency and rapid response throughout the process. This area still has room for further in-depth research and exploration, necessitating not only the handling and analysis of dynamic flight and cargo flow data but also the ability to intelligently adjust storage location allocations to adapt to rapidly changing operational conditions.

From a supply chain perspective, the optimization of storage location allocation is directly related to the efficiency of cargo storage and retrieval, thereby affecting the speed and cost of the entire cargo circulation. The application of intelligent storage location allocation strategies not only improves the efficiency of warehouse operations but also reduces the risk of cargo loss and misoperation through refined management, thereby enhancing the overall quality of air freight services.

In this context, this paper proposes an air cargo warehouse storage location allocation optimization strategy that combines data analysis and optimization algorithms. This strategy takes into account various factors such as flight schedules, cargo collection and delivery data, cargo terminal topology, storage location attribute data, and cargo in-and-out paths. Applying the latest optimization theories and techniques, it aims to improve operational efficiency and cargo turnover speed in the warehouse area. This not only enhances the overall quality of air cargo services but also provides valuable theoretical and practical insights for logistics management and the aviation industry, promoting the development of the air cargo sector towards more environmentally friendly and sustainable directions.

2.Air Cargo Warehouse storage location Allocation Optimization Strategy

2.1. Problem Description and Symbol Definition

To enhance the operational efficiency of the air cargo warehouse area, a storage location allocation strategy needs to be designed. When cargo are stored, the best storage location must be assigned based on the specifications of the cargo and the departure time of the pre-arranged flight for the cargo. Given are the flight schedule, cargo terminal topology, storage location attribute data, and the time, process, and path of cargo storage and retrieval. The objective of this strategy is to minimize the distance for cargo storage and retrieval, ensuring efficient transfer of cargo to the departure gate in accordance with the scheduled flight cargo retrieval time. This approach aims to guarantee timely flight departures, avoid operational delays, maximize the utilization rate of the air cargo warehouse area, and expedite cargo turnover, achieving automated and refined storage location allocation.

To establish a mathematical model, input variables are defined as shown in Table 1.

Table 1. Definition of Input Variables.

Variable Symbol	Description
$F = \{i \mid 1,2,...,n_f\}$	Set of flights to be allocated, with the total number of flights being n_f
ST_i	Cargo storage time of flight i , $i \in F$
RT_i	Cargo retrieval time of flight i , $i \in F$
$G = \{k \mid 1,2,...,n_g\}$	Set of storage locations, with the total number of locations being n_g
$P_k = (x, y)$	Coordinates of storage location k , $k \in G$
d_k	Instance from storage location k to the out-storage gate, $k \in G$

The decision variable is defined as x_{ik}, which is set to $x_{ik} = 1$ if the cargo of flight i is allocated to storage location k, otherwise $x_{ik} = 0$. Consequently, the solution to the storage location allocation model can be expressed as a 0-1 matrix, as depicted in Table 2.

Table 2. Matrix Representation of Storage Location Allocation Decision Variables.

F \ G	1	2	3	4	…	n_g
1	0	0	1	0		0
2	0	1	0	0	…	0
3	1	0	0	0		0
⋮	0	0	0	0		0
n_f	0	0	0	1		0

Each row in the matrix illustrates the allocation result for a flight, with a single column marked as 1 to indicate the final assigned storage location for that flight. Each column corresponds to a storage location, and the flights that are marked with a 1 in a column comprise the final sequence of flights allocated to that storage location.

2.2.Optimization Model

The objective function of the model is to minimize the total distance of cargo out-storage. When storing cargo, storage locations closer to the warehouse exit should be chosen as much as possible to reduce the distance and time of cargo handling, thereby improving the efficiency of cargo storage and retrieval. Therefore, allocating the cargo of more flights to storage locations closer to the out-storage gate is the optimization goal of the model.

The actual allocation of storage locations in a warehouse is quite complex. For the purpose of modeling and solution, this paper simplifies the problem with the following assumptions:

(1) All goods arrive according to their scheduled inbound time and must be processed and transferred before their outbound time.

(2) Storage location allocation considers only a single exit point, meaning all goods are eventually transferred out of the warehouse through this exit.

(3) The storage location allocation strategy prioritizes ensuring the timely departure of flights, avoiding delays caused by improper storage location allocation.

The expression of the objective function is shown as Equation (1).

$$F = \min \sum_{i=1}^{n_f} \sum_{k=1}^{n_g} x_{ik} d_k \tag{1}$$

The constraints of the model are as follows:

$$\sum_{k=1}^{n_g} x_{ik} = 1, \forall i \in F \tag{2}$$

$$x_{ik} + x_{jk} \le 1, \text{if} (ST_i < RT_j \text{ and } RT_j < RT_i), \forall i, j \in F, i \ne j, k \in G \tag{3}$$

$$x_{ik} \in \{0,1\}, \forall i \in F, \forall k \in G \tag{4}$$

Constraint (2) states that the cargo of each flight must be allocated to exactly one storage location.

Constraint (3) stipulates that flights with conflicting cargo storage times are not permitted to be allocated to the same storage location.

Constraint (4) is the binary variable constraint.

2.3.Algorithm Design

Based on the allocation rules, a greedy algorithm approach is utilized, aiming to assign as many flights as possible to storage locations closer to the dispatch area. The allocation is guided by the following rules:

(1) Sort the flights according to their Cargo Retrieval Time.

(2) For each flight, start the search from the nearest storage location and find a storage location that doesn't conflict with the occupancy times of already allocated flights. Then, compare the distances of available storage locations, selecting the nearest for allocation. If distances are identical, compare the time interval between the storage location and the previous flight, choosing the one with the smallest interval.

Allocating based on Cargo Retrieval Time, as per the first rule, avoids the limitations seen in scenarios like Fig. 1, where allocation based on Cargo Storage Time might only accommodate a few flights. This approach increases the number of flights allocated to storage locations near the dispatch area. The second rule ensures that, while maintaining the usage interval of a storage location, the interval between adjacent flights at the same location is minimized. This reduces idle time at storage locations, thereby enhancing the utilization rate of storage locations near the dispatch area.

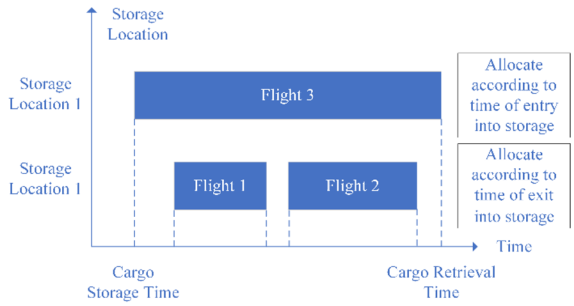

Fig. 1. Difference in Flight Allocation Sorting Methods.

3.Case Analysis

The experiment employed a warehouse instance from a particular airport to test the optimization model. This warehouse comprises 30 storage locations, along with a single path leading to the only exit. Each location is defined by unique coordinates and its distance to the exit. The experimental data selected includes flight data for goods arriving at the port on October 22, 2023.

3.1.Simulation Data

The available flight data includes cargo storage time, retrieval time, origin, and flight number, as shown in Table 3.

Table 3. Flight Data.

Storage Time	Retrieval Time	Origin	Flight Number
2023-10-22 07:15:00	2023-10-22 08:36:00	Chengdu	3U8691
2023-10-22 07:52:00	2023-10-22 09:05:00	Kunming	8L9801
2023-10-22 08:08:00	2023-10-22 10:05:00	Chongqing	JD5608
2023-10-22 08:22:00	2023-10-22 09:15:00	Kunming	MU5921
2023-10-22 08:28:00	2023-10-22 09:29:00	Kunming	MU5925
…	…	…	…
2023-10-22 23:10:00	2023-10-22 23:55:00	Zhengzhou	PN6445
2023-10-22 23:40:00	2023-10-23 11:40:00	Wuhan	8L9824
2023-10-22 23:45:00	2023-10-23 11:45:00	Guangzhou	JD5131

2023-10-22 23:45:00	2023-10-23 11:45:00	Shijiazhuang	JD5658
2023-10-22 23:55:00	2023-10-23 11:55:00	Beijing	JD5215

3.2.Simulation of Warehouse Structure

The simulation warehouse structure of a certain airport's cargo area, as shown in Fig. 2, represents storage locations with coordinates *(x, y)*. The efficiency of cargo movement is related to the distance from these locations to the in-and-out gates of the warehouse; locations closer to the exit are given higher priority.

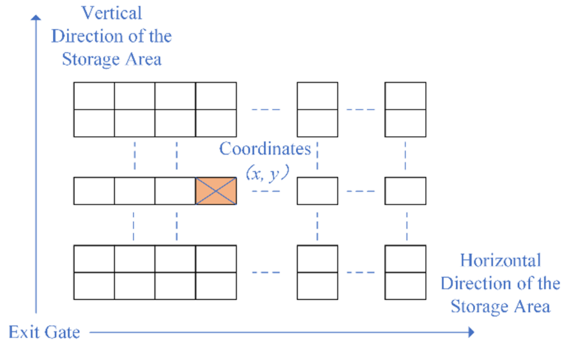

Fig. 2. Warehouse Simulation Diagram.

3.3.Optimization Results of Storage Location Allocation

The optimized results of the storage location allocation are depicted in the Gantt chart as shown in Fig. 3.

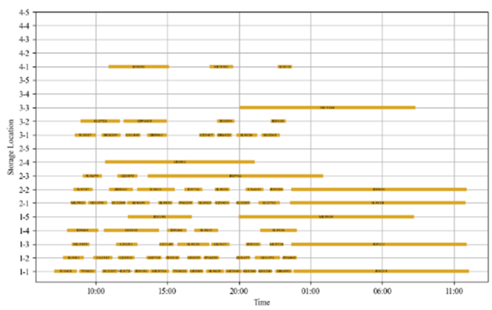

Fig. 3. Gantt Chart of Allocation Results.

3.4.Efficiency Comparison

In specific efficiency comparison experiments, the optimized strategy for allocating flight storage locations demonstrated a significant reduction in average time compared to the traditional methods based on static rules and manual experience. On the same computational environment and dataset, the average response time of the optimized strategy was reduced by 62% compared to the original strategy, illustrating the high efficiency of the greedy algorithm in handling large datasets. Additionally, the reduction in manual intervention with the optimized strategy also decreased the error rate due to human factors, thereby further enhancing the reliability and stability of the storage location allocation process.

4.Conclusions

This study constructs an optimization model for storage location allocation in air cargo warehouses, aiming to allocate more flights' cargo to locations closer to the exit, thereby shortening the distance for cargo offloading and enhancing operational efficiency. Theoretically, the model broadens the research perspective of storage location allocation, introducing new constraints and objective functions, enhancing its adaptability and flexibility in dealing with real-world issues. Practically, the proposed strategies and algorithms provide effective decision support tools for air cargo warehouse management. Simulation experiments using actual flight and warehouse data from a specific airport validate the superiority of the proposed air cargo warehouse storage location allocation optimization strategy.

Despite the achievements, this study has some limitations. For instance, the model assumes flight delays and cargo handling times are deterministic. Future research could consider introducing random factors to further improve the robustness of the model.

Acknowledgments

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References

1. B.I. Kim, S.S. Heragu, R.J. Graves, et al., IEEE Trans. Robot. Autom. **19**, 991-1001 (2003).
2. D. Dukic, D. Oluio, Stroj Vestn-J Mech E **50**, 2 (2004).
3. Y.F. Chuang, H.T. Lee, Y.C. Lai, Comput. Ind. Eng. **63**, 1171-1177 (2012).
4. A.S. Dijkstra, K.J. Roodbergen, Transp. Res. Part E Logist. Transp. Rev. **102**, 38-59 (2017).
5. R.Q. Zhang, M. Wang, X. Pan, Comput. Ind. Eng. **129**, 210-219 (2019).
6. A. Aboelfotoh, M. Singh, G. Suer, Procedia Manuf. **39**, 1464-1473 (2019).
7. X. Li, G. Hua, A. Huang, et al., Transp. Res. Part E Logist. Transp. Rev. **144**, 102158 (2020).
8. E. Yücel, F.S. Salman, G. Erdoğan, Eur. J. Oper. Res. **302**, 954-969 (2022).
9. Y. Muharni, L. Herlina, B. Kurniawan, et al., J. Industrial Servicess **7**, 289-294 (2022).