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Collaborative truck-robot routing problem with meal delivery for the elderly on the personalized needs

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A B S T R A C T

With the development of a new generation of information technology, smart elderly care plays an important role in promoting the construction of elderly care services. The emerging application tools provide door-to-door meal service for urban elderly groups, solving meal problems for special and ordinary elderly with different priority levels and penalty costs of violating time windows. Based on this, considering the personalized needs of the elderly group, this study examines the route optimization problem of cooperative delivery of elderly meals by trucks and robots, and builds a mixed integer programming model to minimize the total cost of the system. For large-scale problems, this study designs an improved adaptive large neighbourhood search algorithm that incorporates simulated annealing algorithm and artificial bee colony algorithm to avoid falling into local optimality. Experiments have proved feasibility and effectiveness of the algorithm and proposed the corresponding management insights from the aspects of delivery efficiency and service quality.

1. Introduction

With the increasing population aging, the government proposes smart elderly care to promote the construction of elderly care services (Beijing: Health Commission, Ministry of Civil Affairs, Ministry of Industry and Information Technology, 2021). Smart elderly care can be realized through information technologies such as the Internet, the Internet of Things, and big data, providing high-quality elderly living in their later years. What's more, many cities have set up community canteens for the convenience of the elderly who choose to take care of themselves at home, providing them with affordable and healthy meals and obtaining subsidies from the government (Zhang et al., 2017; Jensen, 2020; Nkurunziza et al., 2023). Moreover, meals on wheels are available for the elderly and disabled (Lin et al., 2022a). Considering the nutritional needs and therapeutic dietary requirements of the elderly, the state has issued official documents to formulate reasonable dietary guidelines and introduced registered dietitian intervention to achieve personalized management to reduce the risk of related diseases (Zanden et al., 2015; Clancy et al., 2021; Fleury et al., 2021; Juckett et al., 2022). Ullevig et al. (2018) tested the nutritional intake changes of the elderly through the nutritional assessment form and found that the nutritional status of the elderly who received meals was significantly improved. Meal delivery for the elderly can meet their nutritional needs in some ways, but problems in delivery still exist. The reason is that the delivery communities still have truck-restricted areas, where only staff can deliver meals to the door. Ensuring the temperature and integrity of elderly meals is difficult with a long supply process. Delivery by trucks and robots can save more than 20% of the cost compared with pure truck delivery (Heimfarth et al., 2022; Ostermeier et al., 2023). During the peak period of the COVID-19 pandemic, delivery robots can reduce contact between customers and drivers, reducing the risk of infection (Chen et al., 2021a, 2021b; Srinivas et al., 2022). In fact, delivery robot robots have been applied in residential areas (Liping, 2018). In California and other areas, KiwiBot and Starship robots are already

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providing food delivery services to customers (Korosec, 2020a(b)). Therefore, this study considers collaborative truck-robot vehicle routing problems and makes use of the advantages of fast speed and high efficiency of truck and robot thermal insulation without regional restrictions to jointly deliver meals for the elderly. To sum up, considering the personalized needs of the elderly, this study examines collaborative truck-robot routing problems. The contributions of this study are mainly as follows. (1) The delivery of meals for the elderly is considered based on the study of collaborative truck-robot routing problems. Considering the particularity of the delivery objects, the elderly are divided into ordinary and special elderly corresponding to different priorities (Abdelbasset et al., 2022) and penalty costs of violating time windows. Considering the personalized needs of the elderly group, registered dietitians are introduced to provide personalized meals according to the physical conditions and dietary preferences of the elderly. (2) The delivery mode considers the collaborative delivery of trucks and robots. The trucks wait for the robots to return or continue to the next community service center, which improves the delivery efficiency to a certain extent. (3) The improved adaptive large neighborhood search algorithm (IALNS) is used to solve the vehicle routing problem for elderly meals. In addition, the simulated annealing algorithm and artificial bee colony algorithm are added to reduce the possibility of falling into the local optimal solution to obtain high-quality solutions.

The rest of the paper is organized as follows. Section 2 presents a literature review of related problems. Section 3 formally and mathematically presents the two-echelon vehicle meal routing problem and model construction considering the individual needs of the elderly. Section 4 introduces the IALNS. Section 5 details the computational experiments carried out in this paper and draws managerial insights. Section 6 presents conclusions and the future research directions emerging from this study.

2. Literature review

2.1 Research on elderly meals and robot delivery

Considering the particularity of the elderly group, the quality and delivery requirements of the elderly meals are strict. The elderly have high requirements for the freshness and quality of food itself, and its finished products are usually soft and warm, which should not only be rich in certain nutritional elements, but also provide good sensory experience (Aguilera, 2022; Walker-Clarke et al., 2022). Hence, the delivery of meals for the elderly has high requirements. The current meal delivery mode for the elderly has changed from self-delivery to outsourcing and volunteer delivery (Lin et al., 2022b). The first echelon is delivered by truck to the parking lot and the second echelon is delivered by volunteers or staff, and elderly meal delivery is a two-echelon delivery problem. However, outsourcing and volunteer delivery make it difficult to ensure the quality of elderly meals and the continuity and stability of delivery. With the sudden increase in demand for elderly meals and the rapid development of information technology, the traditional delivery mode has gradually changed to intelligence, making the efficient delivery of meals for the elderly a reality. Compared with drones, robots have large storage space and operation range and carry out multiple deliveries in one trip. Robots are greatly adaptable to changing weather conditions and complex traffic environments (Jennings & Figliozzi, 2019) and the delivery of meals for the elderly is less affected by weather and traffic. Ostermeier et al. (2021) pointed out that the robot drove on the sidewalk at the speed of pedestrians, and the minimum delivery speed was 6 km/h without causing noise pollution, so it is safe to deliver elderly meals in the community. From the robot design perspective, food delivery robots with a suspension damping structure can ensure the shock absorption and stability of special complex terrain (Jiang et al., 2022), thereby reducing the loss of meals for the elderly. In addition, the Starship robot is equipped with sensors and tracking systems, including cameras and GPS, to ensure real-time positioning in the delivery process. Robots are also equipped with microphones and speakers (Hoffmann & Prause., 2018), which can communicate with the elderly to achieve the links determined by customers. Law et al. (2021) found that the GoCart food delivery robot can not only flexibly avoid obstacles, but also ensure cold and hot food through a case study. Multiple compartments of the robot can reduce cross-contamination of food and facilitate cleaning simultaneously. From the characteristics of robots, they meet the high requirements for elderly meal delivery.

2.2 Research on two-echelon vehicle routing problem

The two-echelon vehicle routing problem is a variant of vehicle routing problem, involving the two-echelon delivery network. The first echelon is mainly delivered by trucks from the main warehouse to various delivery centers, and the second echelon is delivered by small vehicles from the delivery center to customers. Common small vehicles include drones and autonomous robots (Perboli et al., 2021; Yu et al., 2022; Imran et al., 2023; Moradi et al., 2023). In the joint delivery of trucks and drones, relevant scholars mostly take the shortest delivery time as the goal. Luo et al. (2017) considered that drones visit areas that cannot be reached by ground vehicles and established an integer programming model to study the two-echelon cooperative delivery problem. Then Poikonen and Golden (2020) considered the impact of parcel weight on the energy consumption of drones to study the routing problem of single truck and multiple drones. Jeong et al. (2019) considered the impact of the no-fly area of drones and the total amount of parcels on energy consumption, establishing a mathematical model to study the mixed delivery path problem. Yin et al. (2023) considered the uncertain needs of disaster relief, establishing a robust optimization model to study the delivery of relief materials. Rave et al. (2023) considered the location of drone sites and fleet planning, establishing a mixed integer programming model to study the last mile delivery problem. The joint delivery modes of trucks and robots are mainly the mothership and two-tier models (Srinivas et al., 2022). In the mothership model, trucks and robots can serve customers. Chen et al. (2021a) studied the vehicle routing problem with time window constraint and delivery robot to achieve the shortest delivery time. Simoni et al. (2020) explored the impact of different characteristics of robots and operating environments on efficiency, establishing an integer programming model to study the last mile problem of urban logistics. In the two-tier model, trucks act as mobile warehouses and launch robots, with only robots serving customers. In the two-tier model, most scholars aim at the minimum delivery cost. With the goal of minimizing the number of trucks and the total transportation cost of trucks and robots, Yu et al. (2020) studied the two-echelon vehicle route delivery problem in which trucks do not need to wait for robots to return at the same drop-off point, considering that there are multiple entrances and exits in the actual backgrounds. Based on the electronic procurement and delivery system, Liu et al. (2021) studied the two-tier network routing problem consisting of warehouses, satellites and customers, considering environmental effects and customer satisfaction in addition to transportation costs. Heimfarth et al. (2022) proposed the hybrid of trucks and robots with robot warehouses, considering the properties of goods and customer preferences, to minimize the sum of distance costs, time costs, and waiting costs of trucks and robots. Ostermeier et al. (2023) considered the increasing number of trucks to serve many customers to avoid delayed delivery caused by the increasing demand and time window requirements.

2.3 Algorithm solutions of two-echelon vehicle routing problem

In the existing research on the two-echelon vehicle routing problem, two main solving algorithms exist: exact and heuristic algorithms (Sluijk et al., 2023). The exact algorithm mainly includes branch-cutting and decomposition algorithms. Considering the constraints of the flight range and loading capacity of aircraft, Wang & Sheu (2019) established a mixed integer programming model and developed a branch and price algorithm. Liu et al. (2018) used branch and price algorithms to solve capacity-limited vehicle routing problems considering group constraints. Marques et al. (2020) proposed an improved branch cut price algorithm to solve the delivery problem with up to 300 customers and 15 delivery centers. Heuristic algorithms are often used to solve large-scale problems, including genetic algorithms, neighborhood search, simulated annealing, and artificial bee colonies. Imran et al. (2023) studied the last mile problem of joint delivery of autonomous vehicles and drones and used the greedy algorithm to reduce the delivery time of large-scale instances. Heimfarth et al. (2022) studied the delivery problem with robot warehouses and optimized the routes of single trucks and robots through an improved general variable neighborhood search algorithm. Ostermerier et al. (2023) considered the problem of multi-truck and multi-robot joint delivery and proposed a new neighborhood search algorithm to solve the multi-truck and multi-robot scheduling problem. Considering the capacity constraints of trucks and drones, Kitjacharoenchai et al. (2020) used the heuristic algorithm for drone-truck route construction and large neighborhood search to solve large-scale problems. Wu et al. (2022) developed an improved variable neighborhood descent algorithm and combined simulated annealing and tabu search algorithms to study contactless parcel delivery. Chen et al. (2021a) proposed an adaptive large neighborhood search algorithm (ALNS) to solve the robot delivery problem with time windows. Yu et al. (2022) designed an IALNS based on pickup and delivery problems of trucks and robots and verified the effectiveness of the algorithm through real cases.

As mentioned above, many research results exist on the two-echelon vehicle routing problem and meal delivery for the elderly. However, only a few exist to combine robots with elderly meal delivery, and few pay attention to the high requirements and immediacy characteristics of elderly meals. In addition, it can be seen from the above literature that robot delivery of meals for the elderly not only ensures the quality of meals for the elderly, but also improves the delivery efficiency of meals for the elderly. From the particularity of the elderly meal delivery and the characteristics of the robot, robot meal delivery for the elderly is a feasible delivery scheme. Therefore, this study establishes a mathematical model based on the particularity of the elderly meals and considers their personalized needs. The study also introduces registered dietitians to catering, designs the vehicle routing problem with multiple trucks and multiple robots coordinating delivery. The ALNS adds the measure of the effect of operators and adaptively selects good operators to destroy and repair the solutions to obtain high-quality solutions and solves it through an IALNS.

3. Problem description and model

3.1 Problem statement

In this study, the collaborative delivery problem of trucks and robots is examined, in which food preparation and delivery are mainly targeted at the elderly population in the community. The meal delivery process consists of two echelons, as shown in Fig. 1. First, trucks carrying robots start from the central kitchen and arrive at the community service centers. Then, the robot carrying the elderly meals starts from the community service center and delivers meals to the elderly groups in need. Among them, the robot should meet with the truck at the corresponding delivery center after the completion of the food delivery. Considering the personalized needs of the elderly, who are divided into special and ordinary elderly people with two different priorities, their sensitivity to the arrival time of meals is different. This study assumes that different elderly people have different priorities, and the higher the sensitivity to the arrival time, the higher the priority. In addition, the cost of registered dietitians is introduced to make reasonable meal plans according to the needs of the elderly. If the robot delivers the food in advance or on time, there is no waiting and no cost loss. If the robot delays the delivery, there will be a certain penalty. Table 1 shows related parameters. This study proposes the following hypotheses: (1) Assume that catering and delivery services meet all the requirements of the elderly, and each elderly person can only be served by one robot; (2) The time consumed by robot startup and battery replacement is ignored; (3) The fuel consumption cost of the truck is independent of the number of robots loaded; (4) The power consumption cost of the robot is independent of the number of meals loaded.

3.2 Mixed integer programming model

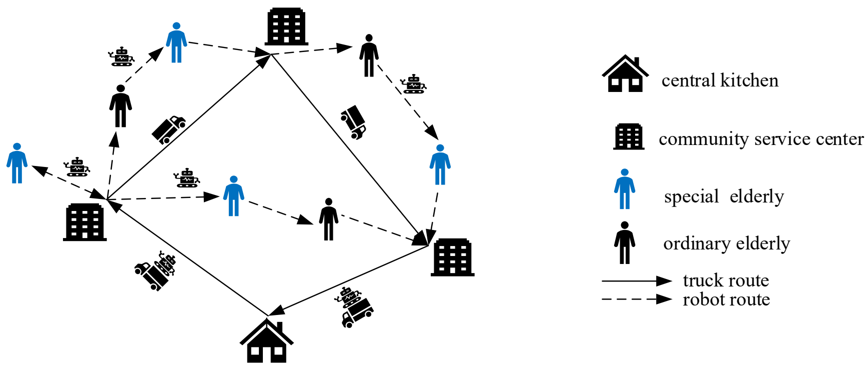

Fig. 1. Example of collaborative delivery of elderly meals by trucks and robots

Table 1
Notation descriptions

Notation	Description
F_T	Set of trucks, $F_T = \{1,2,3, \dots k, \dots K\}$, k represent any truck, K is the maximum number of trucks
F_{kD}	Set of robots belonging to the *kth* trucks, L is the maximum number of robots assignable to the truck, $F_{kD} = \{(k,1),(k,2),(k,l) \dots,(k,L)\}$
F_D	Set of all robots, $F_D = F_{1D} \cup F_{2D} \cup, \dots, \cup F_{KD} = \{(1,1) \cup (1,2), \dots,(k,l), \dots,(K,L)\}$
O	Sets of truck stopping nodes, $O = \{0,1, \dots, 0'-1, 0'\}$,0 and $0'$ represent the starting point and the end point of the truck, being the location of the central kitchen; $O_- = \{0,1, \dots 0'-1\}$ represent the start point and all community service centers; $O_+ = \{1, \dots, 0'\}$represent the end point of the truck and all community service centers; $O_0 = \{1, \dots, 0'-1\}$ represent all community service centers
C	Set of elderly people in need nodes, $C = \{1,2, \dots, c\}$, c represent the maximum number of elderly people
N	Set of nodes, $N = C \cup O$
$d_{i,j}^k$	Distance that truck travels from i to j, $i,j \in O, i \neq j$
$d_{i,j}^{k.l}$	Distance that robot travels from i to j, $i,j \in N, i \neq j$
V_T	The speed of the truck
V_D	The speed of the robot
$c_{i,j}^k$	Transportation costs per unit of distance of truck, $i,j \in O, i \neq j$
$c_{i,j}^{k,l}$	Transportation costs per unit of distance of robot, $i,j \in N, i \neq j$
$[0, b_i]$	Service time window of the elderly people，b_i represent the latest time for the elderly to receive their meals, $i \in C$
θ_i	Different priority levels corresponding to the elderly people in need, $i \in C$
B_i	Penalty costs per unit of time for the elderly people, $i \in C$
W_i^k	Time when the truck arrives at the node, $k \in F_T, i \in O$
$W_i^{k,l}$	Time when the robot arrives at the node, $(k,l) \in F_D, i \in N$
q_i	Meal weight of the elderly people, $i \in C$
Q	The maximum capacity of the robot
c_f^k	Fixed costs of the truck
$c_f^{k,l}$	Fixed costs of the robot
a	The unit cost of a registered dietitian serving an elderly person
p	The cost of making meals for the elderly
G	Government's unit subsidy for meals for the elderly
M	An arbitrarily large constant number
A_1	Truck routes, $A_1 = \{(i,j) \mid i \in \{0\}; j \in O_0\} \cup \{(i,j) \mid i,j \in O_0, i \neq j\} \cup \{(i,j) \mid i \in O_0, j \in 0'\}$
A_2	Robot routes, $A_2 = \{(i,j) \mid i \in O_0, j \in C\} \cup \{(i,j) \mid i,j \in C, i \neq j\} \cup \{(i,j) \mid i \in C, j \in O_0\}$
$x_{i,j,k}$	If arc(i,j) in A_1 is traveled by the *kth* truck, and 0 if otherwise.
$y_{i,j}^{k,l}$	If arc(i,j) in A_2 is traveled by the *lth* robot belonging to the *kth* truck, and 0 if otherwise.

Objective function

$$\min Z = \sum_{k\in F_T}\sum_{(i,j)\in A_1} c_{i,j}^k\, d_{i,j}^k x_{i,j,k} + \sum_{k\in F_T} c_f^k \sum_{j\in O_0} x_{0,j,k} + \sum_{(k,l)\in F_D}\sum_{(i,j)\in A_2} c_{i,j}^{k,l} d_{i,j}^{k,l} y_{i,j}^{k,l} + \sum_{(k,l)\in F_D} c_f^{k,l} \sum_{j\in C}\sum_{i\in O_0} y_{i,j}^{k,l} + \sum_{(k,l)\in F_D}\sum_{i\in C} \theta_i B_i \cdot \left(\max\{0, W_i^{k,l} - b_i\}\right) y_{i,j}^{k,l} + c(a+p-G) \tag{1}$$

subject to:

$$\sum_{(i,j)\in A_1} x_{i,j,k} \le 1, \quad \forall j \in O_+, k \in F_T \tag{2}$$

$$\sum_{i\in O_0} x_{i,0',k} = \sum_{j\in O_0} x_{0,j,k}, \forall k \in F_T \tag{3}$$

$$\sum_{(i,j)\in A_1} x_{i,j,k} - \sum_{(j,i)\in A_1} x_{j,i,k} = 0, \forall j \in O_0, k \in F_T \tag{4}$$

$$\sum_{k\in F_T}\sum_{(k,l)\in F_{kD}}\sum_{i\in N} y_{i,j}^{k,l} = 1, \forall j \in C \tag{5}$$

$$\sum_{i\in N} y_{i,j}^{k,l} - \sum_{i\in N} y_{j,i}^{k,l} = 0, \forall j \in C, (k,l) \in F_D \tag{6}$$

$$\sum_{j\in C} y_{i,j}^{k,l} \le 1, \forall i \in O_-, \forall k \in F_T, (k,l) \in F_D \tag{7}$$

$$\sum_{i\in C} y_{i,j}^{k,l} \le 1, \forall j \in O_+, \forall k \in F_T, (k,l) \in F_D \tag{8}$$

$$2y_{i,j}^{k,l} \le \sum_{m\in O_O, m\ne i} x_{i,m,k} + \sum_{m\in O_0, m\ne i} x_{m,i,k}, \forall i \in O_0, j \in C, (k,l) \in F_D \tag{9}$$

$$\sum_{i\in C} q_i \sum_{j\in N} y_{i,j}^{k,l} \le Q, \forall (k,l) \in F_{kD}, k \in F_T \tag{10}$$

$$W_i^k + \frac{d_{i,j}^k}{V_T} - W_j^k \le M\left(1 - x_{i,j,k}\right), \forall (i,j) \in A_1, k \in F_T \tag{11}$$

$$W_i^{k,l} + \frac{d_{i,j}^{k,l}}{V_D} - W_j^{k,l} \le M\left(1 - y_{i,j}^{k,l}\right), \forall i \in O_0, j \in C, (k,l) \in F_D \tag{12}$$

$$x_{i,j,k} \in \{0,1\}, \forall (i,j) \in A_1, k \in F_T \tag{13}$$

$$y_{i,j}^{k,l} \in \{0,1\}, \quad \forall (i,j) \in A_2, (k,l) \in F_D \tag{14}$$

The objective function (1) minimizes the total cost of the system, including the transportation cost and fixed cost of trucks; the transportation cost and fixed cost of robots; the time window penalty cost caused by different priorities of the elderly in need; the cost of registered dietitians; the cost of making meals for the elderly and government subsidies. Constraint (2) implies that the truck departs from and arrives at the community service center no more than once and reaches the central kitchen no more than once. Constraints (3) and (4) indicate that the number of trucks leaving the central kitchen equals the number of trucks returning to the central kitchen. Constraints (5) and (6) assure each elderly person in need can only be visited once. Constraints (7) and (8) indicate the robot leaves the truck at most once at node i and returns to the truck at most once at node j. Constraint (9) makes the robot start or return from the truck. Constraint (10) indicates that the weight of the elderly meal on each robot route does not exceed the capacity of the robot. Constraint (11) represents the time of arrival of the truck to j is not less than the time of arrival of the truck to i plus the time from i to j. Constraint (12) ensures that the time when the robot arrives at j is not less than the time when the robot arrives at i plus time from i to j. Constraints (13) and (14) represent decision variables (0,1).

4. Improved adaptive large neighborhood search algorithm

The two-echelon vehicle routing problem is an NP-hard problem (Hemmelmayr et al., 2012; Yildirim & Kuvvetli Y, 2021). This study examines the collaborative delivery of meals for the elderly by trucks and robots, which is also an NP-hard problem, because it considers factors such as time window penalty cost generated by different priorities on the personalized needs of the elderly. This model is based on IALNS, and simulated annealing algorithm is used to judge whether the operator is updated, and artificial bee colony algorithm is added to monitor the iterative process. When the operator falls into the local optimal solution, perturbations are added to create new solutions in order to find the optimal solution.

4.1 First feasible solution

In this study, an initial solution construction method for cooperative delivery of trucks and robots is proposed. Let S_1 be the elderly set, S_2 be the community service center set, S_3 be the robot path set, S_4 be the selected community service center set, and S_5 be the truck path set.
Step1: With the robot capacity as constraint and the transportation cost as the goal, the elderly people in need are clustered to form different areas.
Step2: After forming different areas, the community service center returned by the robot is selected with the truck capacity as the constraint and the transportation cost as the goal. Thus, the selected community service center set S_4 and the robot paths set S_3 are obtained.
Step3: After the robot path is formed, the selected community service center S_4 is clustered to minimize the transportation cost, and the truck path set S_5 is obtained.

After the above steps, a collaborative truck-robot path satisfying the constraints can be constructed.

Table 2
First feasible solution flow

Algorithm 1: Initialization
1: Initialization: S_3,$S_4 \leftarrow \emptyset$
2: Input: Coordinate information, capacity constraints, cost, etc
3: Cluster S_1
4: $S_3, S_4 \leftarrow$ determine the return node of the robot
5: $S_5 \leftarrow$ cluster S_4
6: Initial solution$\leftarrow$ combine S_3 and S_4
7: Output S

4.2 Destroy operators

The destroy operator will be used to obtain the solution destruction. In addition to the existing operators of random operator and greedy operator, we specifically design the path destroy operator.

The random destroy operator randomly destroys nodes from the path. This operator can increase the diversity of solutions, thereby avoiding premature convergence of the algorithm during the search process.

The greedy destroy operator records all possible cases before executing the destroy task and chooses the node that has the greatest impact on the total cost of the objective function system to destroy.

The path destroy operator randomly selects a robot path destroy, which can improve the possibility of reducing the number of trucks while ensuring the diversity of solutions (considering that the transportation cost of robots is much smaller than that of trucks'). Given that the number of community service centers is often much smaller than the number of elderly people, the effect of randomly destroying a truck path is very limited, and the robot path destroy operator is only designed in this study.

4.3 Repair operators

The repair operator is used to repair the destroyed solution. We still use three operators and have made improvements to the operators based on the model. The randomness of the random repair operator is relatively strong. An elderly node is randomly selected from the damaged library and inserted into the path satisfying constraints to ensure the search diversity of solutions and reduce the probability of the algorithm falling into the local optimal solution. Greedy repair selects the node that has the least impact on the total cost of the objective function system to repair until all the old people are inserted or no more old people can be inserted in the path satisfying constraints. Path repair operator repairs the robot path. If the path destroy operator is selected in the destroy stage, another robot path is selected for repair to ensure the effect of the path destroy operator. Otherwise, a path is selected at random to repair the fault.

4.4 Adaptive mechanism

We adopt the method of selecting destroy-repair operators adaptively proposed by Ropke and Pisinger (2006). The scoring formula as follows： $w_{mi} = w_{m(i-1)}(1-r) + \frac{s_{mi}}{t_m}$, where r is the reaction coefficient, $r \in [0,1]$, t_m is the number of times that the m^{th}operator is adopted, s_{mi} is the sum of the i stage scores of the m^{th} operator. Score situations are divided into three cases: (1) It is the optimal solution so far; (2) It is better than the previous solution; (3) It is not the optimal solution but is received by the simulated annealing acceptance criterion.

4.5 Update judgment of solution

According to the new solutions obtained by the destroy and repair operators, the acceptance criterion of the simulated annealing solution is adopted. Moreover, the acceptance probability of the new solution is proposed, $P = e^{\frac{f(X_{opt})-f(X_{iter})}{T}}$, where $f(X_{iter})$ represents the newly solved objective function value of $Xiter$, and $f(X_{opt})$represents the currently solved objective function value. T represents the current temperature value of simulated annealing, and T increases with iteration, $T = \rho T$, $\rho > 1$ (Kirkpatrick et al., 1983; Černý, 1985). To further avoid falling into the local optimal solution, this study adopts the idea of scout bees in the artificial bee colony algorithm to monitor the change of the solution. When the iteration exceeds a certain limit *limit* and the total cost of the system is not changed, scout bees will abandon the solution of this iteration and add disturbance to obtain a new solution. Yu et al. (2020) suggested that three different perturbation operators are added to carry out perturbation, including changing the number of community service centers, changing the routes of robots, and damaging repair and reconstruction. The perturbation operator can greatly change the neighborhood of the solution, which is conducive to escaping from the local optimal solution. However, the calculation is relatively complicated and should not be added in every iteration. Therefore, the combination of scouting bees and perturbation operators can effectively reduce the computational complexity and improve the efficiency of the algorithm. The route plan of the elderly meal is obtained through the above steps.

Table 3
Improved adaptive large neighborhood search algorithm flow

Algorithm2: Improved adaptive large neighborhood search algorithm
Input: Maximum iteration: $iter_{max}$; Time limit: t_{max}; Simulated annealing temperature: T; Operator score; Cooling efficiency; Numbers of scouting bees M and scouting bee upper limit *limit*; Initial Solution X_0, $X_{opt} = X_0$
While $iter < iter_{max}$ && $t < t_{max}$
Roulette wheel selects destroy operators
Destroy operator destroys the path, and the dam aged point is recorded as pool
Roulette wheel selects repair operators
Repair operator repairs the path
Output X_{iter}
If X_{iter} is currently optimal, the corresponding operator scores W_1
If X_{iter} is the optimal of this inner iteration, the corresponding operator scores W_2
Simulated annealing is used to select whether to accept the solution, and the acceptance probability is updated as $P = e^{\frac{f(X_{opt})-f(X_{iter})}{T}}$
If is accepted as the new solution
set M=0 to restart
$X_{opt} = X_{iter}$
The corresponding operator scores W_3
Else
set M=0 to restart the monitoring process of the Scout Bee;
Endif
If M>*limit*
The scout bee initiates the disturbance to destroy the current solution
set M=0 to restart the monitoring process of the Scout Bee;
Endif
End While
Output: X_{opt}

5. Computational study

5.1 Data description

This study selects CPLEX to solve the mathematical model and uses MATLAB2022b programming to realize algorithms. Running on 12th Gen Intel(R) Core (TM) i7-1255U@ 1.70GHz 16GBRAM, Windows11 operating system computers, CPLEX uses version number 12.6.3. Dellaert et al. (2019) pointed the generating examples method that the coordinates of the elderly and community service center are randomly generated in a circular area with a radius of 10 km. Moreover, the location of the central kitchen is the origin of the coordinates. Considering the practical background of delivering meals for the elderly in the community, this study sets the number of elderly people in need within a relatively reasonable range (up to 60 users). It is assumed that each truck can load a maximum of 4 robots and the capacity of the robot is between 0 and 25 kg. Different types of trucks and robots have different speeds. This study selected that the speed of the truck is set between 15 and 25 km/h and that of the robot is between 5 and 10 km/h. In this study, numerical values within the range are selected for simulation. Also pointed out that the unit distance cost of the truck is set at 3 yuan /km, and the unit distance cost of the robot is 0.3 yuan /km, mainly considering that the battery consumption of the robot is lower than that of the truck. It is assumed that the fixed cost of the robot is 5 yuan and the fixed cost of the truck is 50 yuan. The elderly group is divided into ordinary and special elderly and assumes that their time window is between 0 and 10000 s. In terms of food delivery time, the penalty cost per unit time is set as 1 yuan. The special elderly are more sensitive to time than the ordinary elderly. Hence, the penalty coefficient of delayed food delivery for the special elderly is set as 0.7, whereas that of the ordinary elderly is set as 0.3. Considering the difference in economic level between regions, this study assumes that the difference between the unit price of meals and the cost of registered dietitians and the government subsidy is 5 yuan.

5.2 Validity testing

In Tables (4-7), Obj indicates total cost of the system (unit: yuan), and T indicates the running time (unit: second). For example, 3-6 indicates that the number of community service centers is 3 and the number of elderly people in need is 6. $Gap1 = \frac{Obj_{GA}-Obj_{CPLEX}}{Obj_{GA}}$, which indicates the Obj gap between the genetic algorithm (GA) and CPLEX. $Gap2 = \frac{Obj_{ALNS}-Obj_{CPLEX}}{Obj_{ALNS}}$, which indicates the Obj gap between the ALNS and CPLEX. $Gap3 = \frac{Obj_{IALNS}-Obj_{CPLEX}}{Obj_{IALNS}}$, which indicates the Obj difference between the IALNS algorithm and CPLEX. Gap4=$\frac{Obj_{IALNS}-Obj_{GA}}{Obj_{IALNS}}$, which indicates the Obj difference between the IALNS and GA. $Gap5 = \frac{Obj_{IALNS}-Obj_{ALNS}}{Obj_{ALNS}}$, which indicates the Obj difference between the IALNS algorithm and ALNS.

Eight groups of numerical experiments are carried out in this part aiming at small-scale instances. CPLEX, GA, ALNS, and IALNS were used to compute the same data. Tables 4 and 5 list the results of small-scale instances and the comparison of running times. As shown in Table 4, the solution results of GA, ALNS and IALNS are close to the exact solution of CPLEX, with a difference of 0%-1.36%. In addition, the error between the solution of IALNS, ALNS, and GA and the exact solution of CPLEX is within 0.64%, 0.85%, and 1.36%. The performance of IALNS is slightly better than that of ALNS and GA on small-scale instances, which proves the effectiveness of the IALNS algorithm. In general, when the number of community service centers increases, the solution time of CPLEX will increase, because the increase in the number of community service centers means that the first echelon of optimization will be longer, resulting in an increase in the search time. As the number of community service centers increases, the impact on the total cost of the system is uncertain and will be affected by the geographical location of the additional community service centers.

Table 4
Comparison of results of small-scale instances

Instance	OBJ_CPLEX	OBJ_GA	OBJ_ALNS	OBJ_IALNS	Gap1	Gap2	Gap3
3-4	108.05	108.05	108.05	108.05	0.00%	0.00%	0.00%
3-6	123.67	123.67	123.67	123.67	0.00%	0.00%	0.00%
3-8	130.51	131.95	130.51	130.51	1.09%	0.00%	0.00%
3-10	148.26	148.59	148.29	148.26	0.22%	0.02%	0.00%
4-4	106.99	106.99	106.99	106.99	0.00%	0.00%	0.00%
4-6	118.72	119.26	119.35	119.26	0.45%	0.53%	0.45%
4-8	131.79	133.61	132.07	131.79	1.36%	0.21%	0.00%
4-10	143.48	145.00	144.71	144.40	1.05%	0.85%	0.64%

Table 5
Running time comparison of small-scale instances

Instance	T_CPLEX	T_GA	T_ALNS	T_IALNS
3-4	9.03	2.11	2.53	4.18
3-6	10.13	2.28	3.01	5.03
3-8	28.86	3.09	3.41	10.29
3-10	1766.30	3.83	3.79	11.78
4-4	10.75	3.75	3.09	7.66
4-6	30.59	4.68	3.27	8.83
4-8	75.91	6.92	5.45	10.41
4-10	7214.66	7.41	6.97	12.32

For large-scale instances, the running time of CPLEX is too long and the effect is not good. When the number of community service centers is 4 and the number of elderly people in need is 10, the running time has exceeded 3600 seconds. Therefore, if the number of elderly people served exceeds 30, this study assumes that it is a large-scale calculation example, and Tables 6 and 7 show the results. Eight sets of numerical experiments are constructed in this part to further evaluate the performance of IALNS on large-scale instances. The results of the algorithm comparison show the difference in performance of GA, ALNS, and IALNS. In this study, an improvement is made based on ALNS. The values of Gap4 and Gap5 are both less than zero, and Gap5 is less than Gap4, thereby proving the effectiveness of IALNS for ALNS optimization and IALNS for GA optimization. As shown in Tables 6 and 7, IALNS can obtain high-quality solutions and optimize the total cost of the system. However, the solution time of IALNS is worse than that of ALNS and GA. Using simulated annealing algorithm and artificial bee colony algorithm reduces the possibility of falling into the local optimal solution, so the solution time is likely to increase. In short, the IALNS designed in this study has evident advantages in solving the quality of the solution and is suitable for solving the elderly meal delivery problem of large-scale instances.

Table 6
Comparison of results of large-scale instances

Instance	OBJ_GA	OBJ_ALNS	OBJ_IALNS	Gap4	Gap5
4-30	352.04	342.48	334.74	-5.17%	-2.31%
4-40	386.77	385.72	362.98	-6.55%	-6.26%
4-50	465.05	457.73	432.81	-7.45%	-5.76%
4-60	557.03	545.56	512.13	-8.77%	-6.53%
5-30	306.02	305.03	297.94	-2.71%	-2.38%
5-40	390.68	387.99	376.48	-3.77%	-3.06%
5-50	479.88	470.98	444.02	-8.08%	-6.07%
5-60	553.00	551.77	517.76	-6.81%	-6.57%

Table 7
Running time comparison of large-scale instances

Instance	T_GA	T_ALNS	T_IALNS
4-30	43.05	83.74	92.31
4-40	70.23	96.93	139.87
4-50	111.43	143.47	188.91
4-60	134.17	204.68	276.47
5-30	67.34	88.62	121.84
5-40	81.24	132.99	169.69
5-50	121.27	181.10	259.13
5-60	161.11	252.84	324.68

5.3 Sensitivity analysis

This study randomly selects a large-scale and small-scale instance for sensitivity analysis to obtain some management sights. The sensitivity analysis of this study is based on experimental analysis of robot speed, robot capacity and time window width for the elderly.

5.3.1 Sensitivity analysis on robot speed

The speed of the robot plays a very important role in overall delivery efficiency. This studies the robot speed of 5, 6, 7, 8, 9 and 10 km/h respectively, and explores the impact of speed on total cost of the system when other conditions remain unchanged. Observing instance 4-10 and 5-40 in Fig. 2, it is found that with the increase of robot speed, the total cost of the system first decreases continuously and then becomes stable. When the robot speed is increased from 5km/h to 10km/h, the total cost of the system has been reduced by more than 20%, especially for large-scale instances. When the speed increases to a certain degree, it means that the time of the elderly is almost met, so there is no penalty cost, and the total cost of the system changes little. To optimize the total cost of the system, the speed of the robot can be appropriately increased, to improve delivery efficiency, but it should be set within a relatively reasonable range.

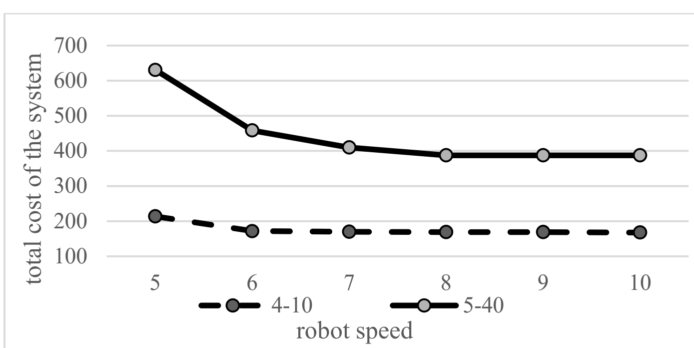

Fig. 2. Sensitivity analysis on robot speed

5.3.2 Sensitivity analysis on robot capacity

The capacity of the robot affects the number of senior meals loaded, which affects the total cost of the system. When the robot capacity is 5, 10, 15, 20 and 25kg respectively, the influence of the robot capacity on total cost of the system is explored when other conditions are unchanged. By observing examples 4-10 and 5-40 in Fig. 3, it is found that with the increase of robot capacity, total cost of the system continues to decrease. However, in 4-10, when the robot capacity is increased from 20kg to 25kg, the total cost of the system remains unchanged, indicating that when the robot capacity is 20kg, the needs of 10 elderly people have been met. Therefore, when the demand is small, the selected robot capacity should consider the number of users and the weight of the meal, which does not mean that the larger the robot capacity, the better, so as not to cause a waste of resources. When the demand is large, robot delivery with larger capacity can be selected, thus reducing the total cost of the system.

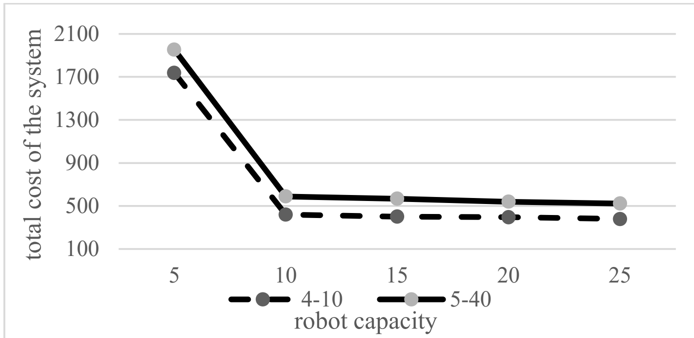

Fig. 3. Sensitivity analysis on robot capacity

5.3.3 Sensitivity analysis on time window width for the elderly

The user's time window affects the penalty cost and thus the total cost of the system. When the user time window is 1000, 1500, 2000, 2500 and 3000 s respectively, the influence of the user time window on total cost of the system is explored when other conditions are unchanged. Through the observation of examples 4-10 and 5-40 in Fig. 4, it is found that the total cost of the system continuously decreases with the increase of the user time window. Therefore, when the user's time window is tight, the robot speed can be appropriately improved to achieve early or on-time delivery of meals, thereby reducing the time window penalty cost.

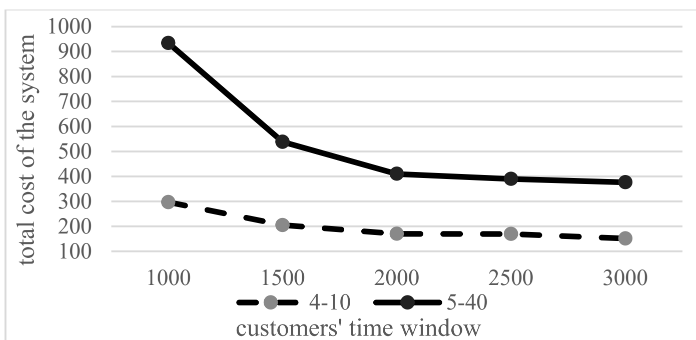

Fig. 4. Sensitivity analysis on customers' time window

6. Conclusion and future work

In the context of smart elderly care, this study researches the vehicle routing problem of collaborative delivery by trucks and robots on personalized needs of the elderly meals. The main contributions are as follows: (1) Elderly people are divided into ordinary elderly and special elderly and corresponding punishment coefficients for different time windows and introducing registered nutritionists to provide dietary guidance for the elderly. This study enriches the research topics related to intelligent delivery, and also provides practical guidance for elderly meal delivery. (2) In delivery, trucks and robots work together, with trucks waiting in place for robots to return or trucks converging at the corresponding community service center, which improves delivery efficiency. (3) An IALNS is designed to solve the problem, adding simulated annealing algorithm and artificial bee colony algorithm to improve the optimal solution. The rationality and effectiveness of the algorithm are verified by numerical experiments. With the continuous advancement of smart elderly care, the collaborative delivery of trucks and robots not only reduces costs and improves efficiencies, but also relieves the pressure on the elderly meals to a certain extent. However, elderly people are a special vulnerable group, and the delivery of elderly meals is a very complex problem. The physical condition and dietary needs of elderly people may suddenly change, and delivery is a real-time dynamic process. It is difficult to obtain the accurate location of the elderly, which may involve spatial dimensions. Therefore, this study considers that the delivery of elderly meals is a relatively static process, and the position of the elderly is in a plane coordinate system.

With the intensification of aging and the increase in demand for elderly meals, elderly meal delivery is an urgent problem that needs to be solved, and it is also an interesting research topic with certain scientific value. In future studies, the dynamic process can be studied, such as considering the changes in the needs of the elderly, road congestion, and other emergencies, and discuss how to solve sudden problems through intelligent technologies, such as big data to adjust the path in real time. In addition, the pension problems faced by the elderly are not only food delivery, but also drug needs, daily shopping, and others, which can consider the combination of different models of robots for delivery. The goal of smart elderly care is to improve the quality of life of the elderly, and customer satisfaction can be considered as an objective function.

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