Robust Optimization of the Hub Location Problem for Fresh Agricultural Products With Uncertain Demand

SHUXIA LI[ID], WANKE HAN[ID], AND LIPING LIU[ID]

School of Business, East China University of Science and Technology, Shanghai 200237, China

Corresponding author: Wanke Han (y30211344@mail.ecust.edu.cn)

ABSTRACT Traditional hub location problems are usually based on deterministic circumstances. However, many uncertain factors can cause demand to vary in the long run, which increases the difficulty of strategic hub location planning. The hub location problem for fresh agricultural products is studied considering the perishability of the products and the uncertainty of customer demands. An uncertain demand variable is described by an affine function of the nominal mean and several independent uncertainty sources and is further adjusted by the deterioration rate. An uncapacitated robust hub location model for fresh agricultural products with uncertain demand is first established and solved using the Lagrangian relaxation approach. Then, a robust optimization model for the corresponding capacitated hub location problem is given. A numerical study based on the Australian Post data set (AP20) shows that the deterioration rate of fresh agricultural products, the uncertainty of demand and the degree of conservatism of decision makers all have significant impacts on the total transportation profit. Furthermore, the capacitated model yields more profit than the uncapacitated model because it allows the effects of the deterioration rate and uncertainty to be moderated through flow reallocation. The proposed models are useful for helping decision makers determine the locations and capacities of hubs for fresh agricultural products in accordance with different risk preferences.

INDEX TERMS Hub location, uncertain demand, capacity constraint, fresh agricultural products, robust optimization.

I. INTRODUCTION

With the improvement of living standards, people's requirement for a higher quality of fresh agricultural products is growing, and the demand for timely and efficient transportation of fresh agricultural products is also markedly increasing. The Food and Agricultural Organization (FAO) reported that approximately half of fruits and vegetables are lost or wasted across the global supply chain [1], and the loss of fresh agricultural products during transportation in China is approximately 20% to 30% [2]. To overcome traffic obstructions and allow agricultural products to be distributed outside of their villages of origin, hub-and-spoke network design is applied in the agricultural product transportation system,

The associate editor coordinating the review of this manuscript and approving it for publication was Mauro Gaggero[ID].

and determining the optimal hub locations for fresh agricultural products has become an important issue for realizing efficient transportation and guaranteeing people's daily supplies [3]–[5].

Fresh agricultural products usually have a short shelf life, and the quality and freshness of the products depend on the delivery process and environmental temperature [6]–[8]. Hence, it is critical to consider the effect of product perishability in the network planning process [9]–[11]. De Keizer *et al.* [12] proposed a new mixed-integer linear programming model for the heterogeneity of quality attenuation of vulnerable products. Chen *et al.* [13] proposed a new transportation model for fresh products that have different vulnerability values. Vorst *et al.* [14] proposed a new mixed-integer linear programming model and a mixed optimization simulation method for a variety of consumable products from

different places of departure, and they designed a logistics network in accordance with the quality requirements of consumable products. Orjuela-Castro *et al.* [15] proposed a mixed-integer linear programming model based on multiproduct and multigradient transportation systems to design a transportation network for vulnerable food in mountainous areas of developing countries.

For the sake of time savings, quite a few studies on transportation for fresh products have explored the application of straight-through networks to achieve efficient distribution within cities. However, for areas where transportation is inconvenient, a straight-through network is not suitable because of the high distribution cost. In addition, with the deepening of research on "first- and last-mile delivery" in recent years, hub networks have been found to be more advantageous in terms of integration and economics of scale [16]–[20]. Therefore, it is of great research value to design a hub-and-spoke transportation network for fresh agricultural products. In previous related research, the location strategy has always been the core of network design. Traditional hub location models have been studied in depth for more than 30 years due to their wide range of application [21], [22]. Macioszek *et al.* [23] introduced methods of determining the locations of logistics centres in transport networks, and more complete reviews of hub location strategies have been presented by Alumur *et al.* [24] and Campbel *et al.* [25].

However, the application of traditional deterministic models may lead to dramatic cost growth in certain cases with high uncertainty. The demand for fresh agricultural products is difficult to predict because it is related to not only the time-varying freshness of the products [26] but also changes in the economy, policy, population, competition, seasonal disturbances, etc. Therefore, the uncertainty that exists in a hub network for fresh agricultural products should be fully considered. The most widely used methods for solving the hub location problem with uncertain demand are stochastic programming and robust optimization. Stochastic programming, first proposed by Wilson [27], can adjust the solution in accordance with various parameter changes when the distributions of the uncertain parameters are known. Thus, decision makers can minimize the total expected cost and obtain the optimal solution within the operational range. Marufuzzaman [28] established a two-stage stochastic programming model for the design and management of biodiesel supply chains. Yang [29] introduced a stochastic programming model to address hub location and flight route planning under seasonal demand variations in the Taiwanese air freight market. Yeh [30] presented a bilevel mathematical program to solve the problem of timberland supply chain network design and considered parametric uncertainty in the two-stage model. Rostami [31] considered the single-allocation hub location problem under demand uncertainty and proposed a challenging variable-allocation case in which the allocation of spokes to hubs can be altered after uncertainty is realized.

Robust optimization is a supplement to stochastic optimization when it is difficult to obtain reliable probability distributions of the uncertain parameters. It uses uncertain-but-bounded data to treat uncertainty in real situations and aims to solve the minmax cost or regret optimization problem in the worst case [32], [33]. Since the robust solution remains applicable to the long-term hub location problem as demands vary over time, robust optimization has aroused the interest of many researchers. Nikoofal and Sadjai [34] proposed a robust optimization approach to obtain a robust linear model for the p-median network design problem with uncertain edge lengths, where uncertainty is characterized by given intervals. Bertsimas and Sim [35] and Merakl *et al.* [36] established a robust optimization model for the intermodal hub location problem under polyhedral demand uncertainty. Shan *et al.* [37] performed similar work in which a depot location problem for an inland transportation system was investigated considering uncertain demand, and they also adopted a robust price approach to obtain a robust counterpart. Yin *et al.* [38] developed a novel distributionally robust optimization model with an ambiguous chance constraint to solve the uncapacitated single-allocation p-hub median problem and discussed the safe approximation of the ambiguous chance constraint in two types of computable ambiguity sets. Boukani *et al.* [39] used a robust optimization method to solve the capacitated single- and multiple-allocation location problems with fixed setup cost and capacity uncertainty. Gabrel *et al.* [40] applied a 2-stage robust formulation to solve the location transportation problem with uncertain demand, and they presented the first extensive computational analysis of a particular recourse problem for the location transportation problem. Peng *et al.* [41] integrated two independent multiplicative uncertainties of demand and transportation cost and introduced two uncertainty budget parameters to formulate a robust facility location model. According to this study, the demand uncertainty has a stronger impact on the total cost than the transportation cost uncertainty does.

In addition to considering the uncertainty of demand, the limited capacity of the hubs is also an important factor worth considering when making strategic decisions regarding hub locations. The capacity limitations of the hubs affect flow in the traffic network, thus causing changes in the original transport paths and total cost, which makes the problem more complicated. Yeh and Rostami [30], [42] assumed the capacity to be infinite, thereby avoiding the influence of capacity limitations. Turgut [43] presented a branch-and-bound algorithm and a heuristic procedure for partitioning the set of solutions on the basis of the hub locations to solve the capacitated hub-and-spoke network design problem. Ghazaleh, Ambrosino *et al.* [44] presented a mixed-integer linear programming model for a capacitated multiple-hub location problem and illustrated the application prospects of this kind of model. Ahmadi, Puerto and Serper [13], [14], [45] considered capacity constraints and demand uncertainty simultaneously. Merakl *et al.* [46] included capacity constraints in their model and devised two different Benders decomposition algorithms to solve the

capacitated multiple-allocation hub location problem with hose demand uncertainty. Tapia-Ubeda *et al.* [47] proposed a novel generalized Benders-decomposition-based solution approach to solve a joint inventory location problem with a stochastic inventory capacity constraint, and their new solution approach ensured good global optimality. Hu *et al.* [42] established a stochastic programming model to account for the uncertainty in the single distribution hub location problem and then extended this model to a second-order mixed-integer cone programming model that took capacity constraints into consideration. To realize the proposed model, they used piecewise tangent approximation and piecewise linear approximation techniques and obtained a near-optimal solution.

In summary, to the best of our knowledge, there is still a lack of literature on fresh agricultural product transportation that concurrently addresses the issues of location, uncertainty, and hub capacity. This paper focuses on the location problem for fresh agricultural products, takes demand uncertainties and capacity constraints into consideration, and establishes a robust location optimization model for fresh agricultural product hubs.

The main contributions of this paper can be summarized as follows: 1) Research on the application of hub-and-spoke networks in the transportation of fresh food is further expanded. 2) A new robust hub location model for fresh agricultural products with capacity limitations is established, and the perishability aspect of fresh agricultural products is fully considered. 3) An uncertainty budget is introduced to control the changes in random variables, which can be beneficial for helping decision makers establish trade-offs between network robustness and cost during the planning process.

This paper is organized as follows. The problem is described, and mathematical models are provided, in Section II. In Section III, a numerical experiment is proposed, and the applications of the two models are presented and compared. Some discussions are presented to illustrate the main results and managerial implications of this work in Section IV. Finally, conclusions and future research are discussed in Section V.

II. PROBLEM DESCRIPTION AND MODEL DESIGN
The hub network studied in this paper is a complete graph composed of hub nodes and nonhub nodes, and there is no direct connection between any two nonhub nodes. Each hub collects fresh agricultural products from other nodes and transports them to the next hub. In this way, the network can achieve economies of scale. In the following proposed model, the total profit depends on the unit price, the quantity of products that can be sold, and the variable and fixed costs of transportation. The notations for the main parameters and variables are shown in Table 1.

The freshness of and the final profit from fresh agricultural products are directly related to the transportation time. Under the assumption that the temperature and transportation speed

TABLE 1. Definitions of parameters.

Parameters	Definitions
N	Set of nodes, $N = \{1, 2, \cdots, n\}$
i, j, k, l	Node indices, $i, j, k, l \in N$
d_{ij}	Distance between i and j
χ	Unit transportation cost of carriers in the collection stage
α	Unit transportation cost of carriers in the transshipment stage
δ	Unit transportation cost of carriers in the distribution stage
c_{ijkl}	Unit transportation cost of carriers from i to j through hubs k and l, $c_{ijkl} = \chi d_{ik} + \alpha d_{kl} + \delta d_{lj}$; when $k = l$, $d_{kl} = 0$
F_k	Fixed construction cost k of hubs
$\widetilde{f}_{ij}$	Uncertain transportation demand flow from i to j
$\overline{f}_{ij}$	Mean flow from i to j
θ	Deterioration rate
L_{ijkl}	Distance from i to j
p_i	Unit value of fresh agricultural products at node i
Q_k	Capacity of hub k
Ω	Uncertainty budget for adjusting the degree of conservatism of the robust solution
$\widetilde{u}_m$	Primitive uncertainty variable that is independently and symmetrically distributed in accordance with certain assumptions
b_{ijm}	Weight of the m-th random variable $\widetilde{u}_m$
Variables	
z_{ik}, z_{jl}	Binary variables indicating whether nonhub node i or j is assigned to hub node k or l, respectively
z_{kk}, z_{kl}	Binary variables indicating whether to establish hub k and whether a connection path exists between hubs k and l
x_{ijkl}	Binary variable indicating whether the transportation path between i and j passes through k and l

are constant, the functional relationship between freshness and time can be transformed into a functional relationship between freshness and transportation distance. Referring to reference [48], the deterioration rate θ is introduced, and the product freshness after transportation can be expressed as $(1 - \theta)^{L_{ijkl}}$; thus, the final unit value of the delivered product is $p_i(1 - \theta)^{L_{ijkl}}$.

Considering the economic situation, policy changes, technical improvements, weather conditions and even competition among enterprises domestically and abroad, many uncertain factors may affect transportation demands. Following reference [48], each uncertain demand flow is assumed to consist of a known mean value and several independent random variables and is accordingly expressed as an affine function as follows:

$$\widetilde{f}_{ij} = \overline{f}_{ij} + \sum_{m=1}^{M} b_{ijm} \widetilde{u}_m, \quad \forall i, j \in N \tag{1}$$

In this function, $\overline{f}_{ij}$ represents the mean flow from i to j, and b_{ijm} represents the weight of the m-th random variable $\widetilde{u}_m$. $\widetilde{u}_m$ is an initial random variable that is independent and obeys a symmetrical distribution, and it satisfies the following three assumptions:

i. $E(\widetilde{u}_m) = 0, \forall m$;

ii. $\|\widetilde{u}_m\|_\infty = \max\{|\widetilde{u}_1|, |\widetilde{u}_2|, \cdots, |\widetilde{u}_m|\} \leq 1$;

iii. the $\widetilde{u}_m, \forall m$, are independent of each other.

A. ROBUST LOCATIONS OF FRESH AGRICULTURAL PRODUCT HUBS WITHOUT CAPACITY CONSTRAINTS UNDER UNCERTAIN DEMAND

Taking the total profit as the objective function, a single-allocation-based hub location model without capacity constraints is defined as follows:

$$Max \sum_i \sum_j \sum_k \sum_l p_i \widetilde{f}_{ij} (1 - \theta)^{L_{ijkl}}$$

$$- \sum_i \sum_j \sum_k \sum_l c_{ijkl} \widetilde{f}_{ij} x_{ijkl} - \sum_k F_k z_{kk} \quad (2)$$

$$s.t. \sum_k z_{ik} = 1, \quad \forall i \quad (3)$$

$$z_{ik} \le z_{kk}, \quad \forall i, k \quad (4)$$

$$\sum_k x_{ijkl} = z_{jl}, \quad \forall i, j, l \quad (5)$$

$$\sum_l x_{ijkl} = z_{ik}, \quad \forall i, j, k \quad (6)$$

$$L_{ijkl} = d_{ik} z_{ik} + d_{kl} z_{kl} + d_{jl} z_{jl} \quad (7)$$

$$z_{ik}, x_{ijkl} \in \{0, 1\} \quad (8)$$

Objective function (2) maximizes the total profit, which is the price of the products minus the sum of the transportation costs and fixed costs. The model is constructed in accordance with the single-allocation mode of the hub location problem, and accordingly, constraint (3) ensures that each nonhub node is directly connected to only one hub node. Constraint (4) indicates that a hub needs to be selected and established before a nonhub node can be assigned to that hub node for transportation. Constraints (5) and (6) indicate that a transportation path from i to j through hubs k and l must exist when nonhub node i is assigned to hub node k and nonhub node j is assigned to hub node l. Constraint (7) indicates that the distance from i to j is determined by the intermediate nodes the path between them passes through. Constraint (8) restricts the decision variables to binary variables.

The random variables of uncertain demand appear only in the objective function, and the constraints do not contain expressions involving random variables, so the objective function of the robust location problem can be expressed as the following minimization problem:

$$\max_{x,z} \min_{\|\widetilde{u}\|_2 \le \Omega} \{ \sum_i \sum_j \sum_k \sum_l p_i (\bar{f}_{ij} + \sum_m b_{ijm} \widetilde{u}_m)(1 - \theta)^{L_{ijkl}}$$

$$- \sum_i \sum_j \sum_k \sum_l c_{ijkl} x_{ijkl} (\bar{f}_{ij} + \sum_m b_{ijm} \widetilde{u}_m) - \sum_k F_k z_{kk} \}$$

$$(9)$$

or

$$\max_{x,z} \{ \sum_i \sum_j \sum_k \sum_l p_i \bar{f}_{ij} (1 - \theta)^{L_{ijkl}}$$

$$- \sum_i \sum_j \sum_k \sum_l c_{ijkl} x_{ijkl} \bar{f}_{ij} - \sum_k F_k z_{kk}$$

$$+ \min_{\|\widetilde{u}\|_2 \le \Omega} \{ \sum_i \sum_j \sum_k \sum_l \sum_m p_i (1 - \theta)^{L_{ijkl}} b_{ijm} \widetilde{u}_m$$

$$- \sum_i \sum_j \sum_k \sum_l \sum_m c_{ijkl} x_{ijkl} b_{ijm} \widetilde{u}_m \} \} \quad (10)$$

By introducing the robust optimization strategy, a robust optimal solution can be obtained for the worst case. Consequently, the obtained solution might be overly conservative. To avoid this situation, the random variables are assumed to belong to an ellipsoid set $U = \{\widetilde{u}_m, \|\widetilde{u}\|_2 \le \Omega\}$, where Ω is called the uncertainty budget. By adjusting the value of the uncertainty budget, the decision maker can change the degree of conservatism of the robust optimal solution. Accordingly, the relationship between the probability of uncertainty protection (pr) and the uncertainty budget can be described by the following function [49]:

$$pr = 1 - \exp(-\Omega^2 / 2) \quad (11)$$

The degree of conservatism of the solution increases with an increase in the uncertainty budget. However, the maximum value of the uncertainty budget is still far less than that in the worst case, which is represented by $\sqrt{m}$.

To transform the model into a solvable form, the minimization problem in the objective function must be considered separately. Let the minimization part be represented by S, which can be expressed as follows:

$$S = \min_{\|\widetilde{u}\|_2 \le \Omega} \{ \sum_i \sum_j \sum_k \sum_l \sum_m p_i (1 - \theta)^{L_{ijkl}} b_{ijm} \widetilde{u}_m$$

$$- \sum_i \sum_j \sum_k \sum_l \sum_m c_{ijkl} x_{ijkl} b_{ijm} \widetilde{u}_m \} \quad (12)$$

Furthermore, let $Z = p_i (1 - \theta)^{L_{ijkl}} - c_{ijkl} x_{ijkl}$; then,

$$S = \sum_i \sum_j \sum_k \sum_l \sum_m Z b_{ijm} \widetilde{u}_m \quad (13)$$

The Lagrange relaxation method is used to solve the minimization problem. Once the optimal values of the random variables $\widetilde{u}_m$ have been obtained, the robust programming problem can be rewritten as a quadratic conic programming problem [48]. With δ denoting the Lagrange multiplier and $\|\widetilde{u}\|_2 \le \Omega$, we can obtain the following form of Lagrange's function:

$$L(\widetilde{u}_m, \delta) = \sum_i \sum_j \sum_k \sum_l \sum_m Z b_{ijm} \widetilde{u}_m - \delta(\Omega - \|\widetilde{u}\|_2)$$

$$(14)$$

The gradient of the above formula is then obtained as follows:

$$\frac{\partial L}{\partial \widetilde{u}_m} = \sum_i \sum_j \sum_k \sum_l Z b_{ijm} - \delta(\frac{\widetilde{u}_m}{\|\widetilde{u}\|_2}) = 0 \quad (15)$$

$$\frac{\partial L}{\partial \delta} = \Omega - \|\widetilde{u}\|_2 = 0 \quad (16)$$

According to formulas (15) and (16), if the Lagrange multiplier δ is positive, then the optimal value of the uncertainty

budget Ω is

$$\Omega = \|\widetilde{u}\|_2 \qquad (17)$$

Correspondingly, the optimal value of the random variable $\widetilde{u}_m$ and its length can be expressed as

$$\widetilde{u}_m = \frac{\|\widetilde{u}\|_2}{\delta} \sum_i \sum_j \sum_k \sum_l Zb_{ijm} \qquad (18)$$

$$\|\widetilde{u}\|_2 = \frac{\Omega}{\delta} \sqrt{\sum_m \left(\sum_i \sum_j \sum_k \sum_l Zb_{ijm}\right)^2} \qquad (19)$$

Thus, the optimal value of the Lagrange multiplier is

$$\delta = \sqrt{\sum_m \left(\sum_i \sum_j \sum_k \sum_l Zb_{ijm}\right)^2} \qquad (20)$$

After integrating formulas (18)–(20), the optimal value of the random variable $\widetilde{u}_m$ can be expressed as follows:

$$\widetilde{u}_m = \Omega \frac{\sum_i \sum_j \sum_k \sum_l Z}{\sqrt{\sum_m \left(\sum_i \sum_j \sum_k \sum_l Z\right)^2}} \qquad (21)$$

Therefore, the objective function can be determined by formula (22):

$$S = \Omega \sqrt{\sum_m \left(\sum_i \sum_j \sum_k \sum_l Z\right)^2} \qquad (22)$$

By substituting the determined form of the minimization problem into the external maximization problem, the uncertain objective function given in (9) can be expressed as the following counterpart:

$$\max\left\{\sum_i \sum_j \sum_k \sum_l p_i \overline{f}_{ij}(1-\theta)^{L_{ijkl}}\right.$$
$$- \sum_i \sum_j \sum_k \sum_l c_{ijkl} x_{ijkl} \overline{f}_{ij}$$
$$\left.+ \Omega \sqrt{\sum_m \left(\sum_i \sum_j \sum_k \sum_l Z\right)^2} - \sum_k F_k z_{kk}\right\} \qquad (23)$$

B. ROBUST LOCATION PROBLEM FOR FRESH AGRICULTURAL PRODUCT HUBS WITH CAPACITY CONSTRAINTS UNDER UNCERTAIN DEMAND

When fresh agricultural products are transported through hubs, the capacity constraints of the cold chain warehouses will directly affect the hub locations. To address this scenario, Q_k is taken to represent the capacity of hub k, and additional capacity constraints are added as follows:

$$\sum_i \sum_j z_{ik} \widetilde{f}_{ij} \leq Q_k z_{kk}, \quad \forall k \qquad (24)$$

There are several uncertain variables in these constraint; however, the method proposed above for dealing with the uncertain parameters in the objective function is not suitable for uncertain variables in constraints. Therefore, this section

refers to the research of Bertsimas and Sim [35] and uses parameters to control the probability of violating a capacity constraint caused by changes in the random variables. Thus, the uncertain model is transformed into a deterministic model that is easy to solve in order to analyse the influence of different levels of uncertain demand on the locations of the hubs:

$$\min \boldsymbol{cx} \qquad (25)$$
$$s.t. \, \boldsymbol{Ax} \leq \boldsymbol{b} \qquad (26)$$
$$\boldsymbol{1} \leq \boldsymbol{x} \leq \boldsymbol{u} \qquad (27)$$

Under the assumption that the matrix A contains uncertain data, the following equation describes an uncertain data set:

$$U = \{A \in R^{m*n} | a_{ij} \in [\overline{a}_{ij} - \widehat{a}_{ij}, \overline{a}_{ij} + \widehat{a}_{ij}] \forall i, j, \sum_{(i,j) \in J} \frac{|a_{ij} - \overline{a}_{ij}|}{\widehat{a}_{ij}} \leq \Gamma\} \qquad (28)$$

As indicated above, for each i and j, every element a_{ij} in matrix A varies in an interval centred at $\overline{a}_{ij}$ with radius $\widehat{a}_{ij}$. The parameter Γ is called the robust price, which is used to weigh the possibility of violating a constraint and its effect on the objective function. The value of the robust price Γ determines the variable ranges of the uncertain parameters. For example, when $\Gamma = 0$, the random variables cannot deviate at all from their means, corresponding to the planning problem in a deterministic environment. Therefore, the uncertain linear programming problem addressed in this paper can be reformulated into a robust linear programming problem of the following form:

$$\min \boldsymbol{cx} \qquad (29)$$
$$s.t. \sum_i \overline{a}_{ij} x_j + u_i \Gamma_i + \sum_{j \in J_i} g_{ij} \leq b_i, \forall i \qquad (30)$$
$$u_i + g_{ij} \geq \widehat{a}_{ij} y_j, \quad \forall i, j \qquad (31)$$
$$-\boldsymbol{y} \leq \boldsymbol{x} \leq \boldsymbol{y} \qquad (32)$$
$$\boldsymbol{l} \leq \boldsymbol{x} \leq \boldsymbol{u} \qquad (33)$$
$$\boldsymbol{g} \geq 0, \quad \boldsymbol{u} \geq 0, \boldsymbol{y} \geq 0 \qquad (34)$$

$\boldsymbol{g}$ and $\boldsymbol{u}$ are both double variable vectors.

Considering that the robust price Γ controls the possibility of constraint violation, we can modify the level of immunity of the robust optimization model to adjust the robust price, that is, to ensure that an uncertain parameter change will not violate a constraint. In the uncertain data set U, solutions obtained from the robust linear model have a high probability of being feasible solutions, which can be illustrated as follows.

If $\eta_{ij} = \frac{|a_{ij} - \overline{a}_{ij}|}{\widehat{a}_{ij}}$ $(i = 1, 2, \ldots, m; j = 1, 2, \ldots, n)$ are independent of each other and symmetrically distributed in the interval [-1,1], then when $0 \leq \gamma_{ij} \leq 1$,

$$p\left\{\sum_{j=1}^n \gamma_{ij} \eta_{ij} \geq \Gamma_i\right\} \leq B(n, \Gamma_i) \qquad (35)$$

and

$$B(n, \Gamma_i) = \frac{1}{2^n}\{(1-\mu)\sum_{l=\lfloor v \rfloor}^{n}\binom{n}{l} + \mu\sum_{l=\lfloor v \rfloor+1}^{n}\binom{n}{l}\}$$

$$= \frac{1}{2^n}\{(1-\mu)\binom{n}{l} + \mu\sum_{l=\lfloor v \rfloor+1}^{n}\binom{n}{l}\} \quad (36)$$

$$v = \frac{\Gamma_i + n}{2}, \mu = v - \lfloor v \rfloor \quad (37)$$

Therefore, the robust price can be used to control the variation range of the uncertain demand, and the planning problem can be transformed into a problem of analysing the robust location strategy under different robust prices.

To ensure that any given vector x^* satisfies the constraints under uncertain demands, the maximum protection value $\beta_k(x^*, \Gamma_k)$ should be set on the left side of the constraint formula. When $\Gamma = 0$, no random variable should deviate from its mean value, so the maximum protection value $\beta_k(x^*, \Gamma_k)$ is 0. At this time, all uncertain constraints can be restrained, and the robustness of the system is weak. Once the protection value has been established, the linear programming problem can be obtained by solving the following linear programming problem:

$$\beta_k(z^*, \Gamma_k) = \max \sum_i \sum_j z_{ik}^* \tilde{f} v_{ijk} \quad (38)$$

$$s.t. \sum_i \sum_j \sum_k v_{ijk} \leq \Gamma_k, \quad \forall k \quad (39)$$

$$0 \leq v_{ijk} \leq 1, \quad \forall i, j, k \quad (40)$$

Γ_k is the robust cost corresponding to the k-th constraint. This shows that the $|N|^2$ coefficients f_{ij} include $\lfloor \Gamma_k \rfloor$ coefficients within their variable ranges, and there is a coefficient f_{kt_k} that changes to $(\Gamma_k - \lfloor \Gamma_k \rfloor)\hat{f}_{kt}$.

The dual problem of (38)–(40) for the linear programming problem is

$$\min \sum_{i \in N} \sum_{j \in N} g_{ijk} + \Gamma_k u_k \quad (41)$$

$$s.t. u_k + g_{ijk} \geq z_{ik}^* \sum_m b_{ijm}, \quad \forall i, j, k \quad (42)$$

$$g_{ijk} \geq 0, \quad \forall i, j, k \quad (43)$$

$$u_k \geq 0, \quad \forall k \quad (44)$$

Therefore, solving for the maximum protection value $\beta_k(x^*, \Gamma_k)$ is equal to solving the dual problem given by (41)–(44).

Constraint (24) is equivalent to constraints (45) and (46).

$$\sum_i \sum_j z_{ik}\bar{f}_{ij} + \sum_i \sum_j g_{ijk} + \Gamma_k u_k \leq Q_k z_{kk}, \quad \forall k \quad (45)$$

$$u_k + g_{ijk} \geq z_{ik}^* \sum_m b_{ijm}, \quad \forall i, j, k \quad (46)$$

$$g_{ijk} \geq 0, \quad \forall i, j, k \quad (47)$$

$$u_k \geq 0, \quad \forall k \quad (48)$$

III. NUMERICAL EXPERIMENT

As a numerical example, 20 postal subsets (denoted by AP20) were generated from the Australian Post data set (AP200) by integration to be used for analysis. The setup cost of every selected node in the subset can be obtained from OR-Library, and the transportation distance and demand flow between each pair of nodes can be obtained through the data integration process. And the derived data of AP20 does not correspond to the actual currency or distance. The transportation costs per unit distance and per unit flow during the processes of collection and distribution are assumed to be 3 and 2, respectively, that is, $\chi = 3$, and $\delta = 2$. The unit transportation cost in the transshipment stage is set to $\alpha = 1$. For the uncertainty of the demand, it is assumed that the demand is affected by four independent random variables, with corresponding weights b_{ijm}. To reduce the calculation time, we assume that the weights can be expressed as $b_{ijm} = b_m \bar{f}_{ij}$, where b_m is a constant coefficient in the range [0,1]. For high, medium and low demand uncertainty levels, $b_m \in \{0.3, 0.6, 0.9\}$ and $b_{ijm} \in \{0.3\bar{f}_{ij}, 0.6\bar{f}_{ij}, 0.9\bar{f}_{ij}\}$, respectively. In this paper, Ω is set to 0, 0.5, and 1 for example analysis, and the range of the robust prices is set to [0, 100].

In contrast to the deterministic strategy, the robust optimal location strategy always considers the worst case when analysing relevant parameters. Therefore, the traffic flows in the hub network are exaggerated. To make the obtained network more stable, more hubs are always chosen to be established under the robust optimal strategy to achieve traffic balance to the greatest extent possible, and the total cost increases correspondingly. In this case, the uncertainty budget and the robust price influence the uncertain transportation demands for products with different deterioration rates. For further analysis, the number of hubs is set to a fixed value of 5, and the research is conducted under two situations: with capacity restrictions and without capacity restrictions.

A. WITHOUT CAPACITY RESTRICTIONS

For three levels of demand uncertainty, low, medium and high, CPLEX is used for numerical experiments, and the results for the robust locations of the hubs under different demands are obtained as shown in Table 2.

Table 2 shows that regardless of the level of demand uncertainty, the location strategy for the hub nodes is the same when $\Omega = 0$. This is because $\Omega = 0$ means that the decision makers do not consider the demand uncertainty in the transportation system and the optimal locations thus will not be affected by external demand fluctuations. In addition, different robust location strategies yield the same location results. For example, under low demand uncertainty and a deterioration rate of $\theta = 0.005$, the optimal locations are 2, 3, 4, 11, and 18 whether the given uncertainty budget is $\Omega = 0.5$ or $\Omega = 0$. Similarly, under medium demand uncertainty, the optimal locations are 3, 4, 7, 11, and 18 whether the uncertainty budget is $\Omega = 0.5$ or $\Omega = 1$. This is because the flow changes caused by different robust control

TABLE 2. Hub location results and profits for different demand situations under an uncertainty budget.

	Low demand uncertainty					
	$\Omega = 0$		$\Omega = 0.5$		$\Omega = 1$	
Deterioration rate	Locations of hubs	Profit	Locations of hubs	Profit	Locations of hubs	Profit
0.005	2, 3, 4, 11, 18	67,672	2, 3, 4, 11, 18	48,423	3, 4, 7, 11, 18	19,982
0.006	3, 4, 5, 11, 18	17,378	3, 4, 7, 11, 18	3,095	3, 4, 7, 11, 18	-10,016
0.007	3, 4, 7, 11, 18	-8,709	1, 3, 4, 11, 18	-19,751	3, 4, 7, 11, 18	-33,273
	Medium demand uncertainty					
	$\Omega = 0$		$\Omega = 0.5$		$\Omega = 1$	
Deterioration rate	Locations of hubs	Profit	Locations of hubs	Profit	Locations of hubs	Profit
0.005	2, 3, 4, 11, 18	67,672	3, 4, 7, 11, 18	19,982	3, 4, 7, 11, 18	-11,535
0.006	3, 4, 5, 11, 18	17,378	3, 4, 7, 11, 18	-10,016	3, 4, 7, 11, 18	-36,239
0.007	3, 4, 7, 11, 18	-8,709	3, 4, 7, 11, 18	-30,016	3, 4, 7, 11, 18	-55,391
	High demand uncertainty					
	$\Omega = 0$		$\Omega = 0.5$		$\Omega = 1$	
Deterioration rate	Locations of hubs	Profit	Locations of hubs	Profit	Locations of hubs	Profit
0.005	2, 3, 4, 11, 18	67,672	3, 4, 7, 11, 18	4,223	1, 3, 4, 11, 18	-35,992
0.006	3, 4, 5, 11, 18	17,378	3, 4, 7, 11, 18	-23,128	1, 3, 4, 11, 18	-57,420
0.007	3, 4, 7, 11, 18	-8,709	3, 4, 7, 11, 18	-44,332	1, 3, 8, 11, 18	-92,562

strategies are relatively small at the middle and low demand uncertainty levels and may not be sufficient to change the optimal locations of the hubs. If the robustness of the hub network is good, a slight change in traffic will not affect the final locations of the hubs, and a small adjustment in the transportation paths can also lead to the optimal results. Moreover, when $\Omega = 0.5$, the optimal locations under the medium and high demand uncertainty levels are the same, that is, 3, 4, 7, 11, and 18, which shows that the robust location strategy with $\Omega = 0.5$ exhibits good stability under medium and high demand uncertainty.

On the other hand, the demand uncertainty and the robust strategy have a considerable impact on the profit of the hub network, as shown in Fig. 1. When the demand is deterministic, the location model does not need to consider the risk of increasing demand. Thus, when the uncertainty budget Ω is 0, the hub network obtained based on the deterministic model can always yield more profit than that obtained based on the robust model, which considers uncertain demand. In other words, in the case that uncertain demand is considered, the profit is reduced. Moreover, with an increase in the uncertainty budget Ω, the profit of the hub network further decreases. This is caused by the nature of the robust strategy, which requires an additional payoff to address the fluctuation in demand. Decision makers can achieve a certain degree of robustness by controlling the degree of conservatism of the robust optimal solution by adjusting the uncertainty budget. If the decision makers cannot afford a higher demand risk, they can adopt a higher uncertainty budget to realize a more stable robust location strategy; then, the hub network will better be able to bear demand fluctuations. Nevertheless, when the decision makers choose a specific robust strategy, the optimal performance of this strategy will be different under different demand fluctuations, and the profit under relatively low demand uncertainty will be higher. This is because the fluctuation in demand is an uncontrollable external factor, and specific robust strategies differ in different demand realization environments.

Notably, the deterioration rate of fresh agricultural products is another important factor in determining the hub locations. The perishable nature of fresh agricultural products results in high timeliness requirements for the hub network, with an effect equivalent to that of increasing demand. Therefore, under a certain level of demand uncertainty and a certain robust strategy, as the deterioration rate increases, the profit will decrease substantially. For example, under low demand uncertainty and an uncertainty budget of $\Omega = 0.5$, as the deterioration rate rises from 0.005 to 0.006 to 0.007, the profit will drop from 48,423 to 3,095 to -19,750, respectively.

B. WITH CAPACITY RESTRICTIONS

The above research shows that the uncertainty of demand has a considerable impact on the hub locations of the fresh agricultural product network. In fact, demand uncertainty not only affects the final location results but also makes the traffic flows in the network uncertain. Additionally, in reality, the traffic flow through a hub is limited by the capacity of that hub. If the influence of such capacity limitations is incorporated into the hub location problem when the flows are already uncertain, the uncertainty in the network will be further enlarged, and the locations and traffic allocation of the hubs will, in turn, be affected.

An increase in the deterioration rate will sharply decrease the profit of the hub network. When $\theta = 0.007$, the profit cannot reach a positive value, even under certain demand. Therefore, this paper takes $\theta = 0.005$ and $\theta = 0.006$ as examples to discuss the influence of robust prices under capacity constraints on the robust locations of fresh agricultural product hubs under uncertain demand.

When the deterioration rate is $\theta = 0.005$, the results for the robust locations of the fresh agricultural product hubs under the dual effects of an uncertainty budget and a robust price are as shown in Table 3. Similar to the case of the location model without capacity restrictions, the robust optimal location strategy changes in response to an increase in demand uncertainty, and the profit decreases with increasing demand
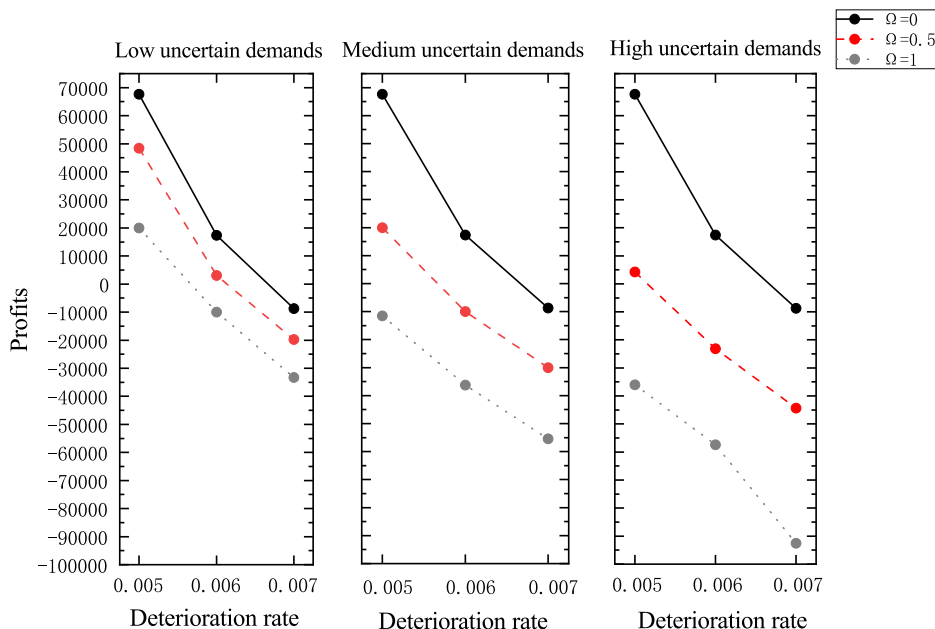
FIGURE 1. Sensitivity analysis of the profit of the robust locations determined without capacity restrictions based on the deterioration rate under different levels of demand uncertainty.

uncertainty, while the optimal location results and the profit remain unchanged under certain demand ($\Omega = 0$). When capacity constraints are taken into consideration, to ensure that the traffic flow increase caused by uncertain demand does not exceed the capacity limit of any hub with a certain probability, additional costs must be paid to maintain the robustness of the hub network. A relatively large robust price Γ makes it less likely that the flow through a hub will violate the corresponding constraint. Thus, a greater payoff is needed, which may lead to decreased profit. For example, in the case of low demand uncertainty, when $\Omega = 0.5$, the robust price increases from 25 to 50; the optimal locations are adjusted from 2, 4, 6, 11, and 19 to 2, 4, 5, 10, and 18; and the profit decreases from 63,496 to 48,567. However, as the robust price continues to be adjusted higher, the optimal location scheme and its profit do not change further because the robust price appears only in the constraints in this model. Once the robust price has increased to a sufficient extent, most of the $\Gamma_k u_k$ values in the constraints become zero; therefore, the result and the hub network do not change further. For the case of medium demand uncertainty, the optimal locations and the profit in Table 3 never change because the robust price has not increased sufficiently.

If the deterioration rate θ is further increased to 0.006, although the profit of the obtained hub network becomes negative in most cases of medium and high demand uncertainty, the trends of variation are basically the same, as shown in Fig. 2.

Furthermore, a comparison of the results for the robust hub locations with and without capacity constraints indicates that adding capacity constraints can reduce the extra cost incurred

to ensure the robustness of the system. Taking the robust location strategy with an uncertainty budget of $\Omega = 0.5$ as an example, the profit of the hub network without capacity constraints is compared with that of the hub network with capacity constraints under a robust price of $\Gamma = 100$. As shown in Fig. 3, when the deterioration rate is 0.005 or 0.006, the profit with capacity constraints is higher than that without capacity constraints. When the level of demand uncertainty increases from low to medium and high, the profits of the robust hub network decrease by 59% and 79%, respectively, in the case of $\theta = 0.005$ without capacity constraints. Under the condition with capacity constraints, the profits decrease by only 39% and 63%, respectively, because the capacity restrictions affect the flow distribution for fresh agricultural product transportation and the utilization rates of the hubs are adjusted through reasonable route planning. Therefore, the profit is increased compared with that predicted without capacity constraints.

However, the deterioration rate of perishable fresh agricultural products also has a substantial impact on the profit of the hub network, somewhat weakening the effectiveness of the capacity constraints. For example, when $\theta = 0.006$ and the level of demand uncertainty changes from medium to high, the profit of the hub network without capacity restrictions drops by 131%. With capacity restrictions, the profit decreases by approximately 140%, a slightly greater decrease than that without capacity restrictions. This shows that the effect of adjusting the flows via capacity restrictions under uncertain demand is limited, illustrating why it is necessary to comprehensively consider both the deterioration rate of fresh agricultural products and the

TABLE 3. Location selection schemes and corresponding profits for different demand situations under the influence of an uncertainty budget and a robust price.

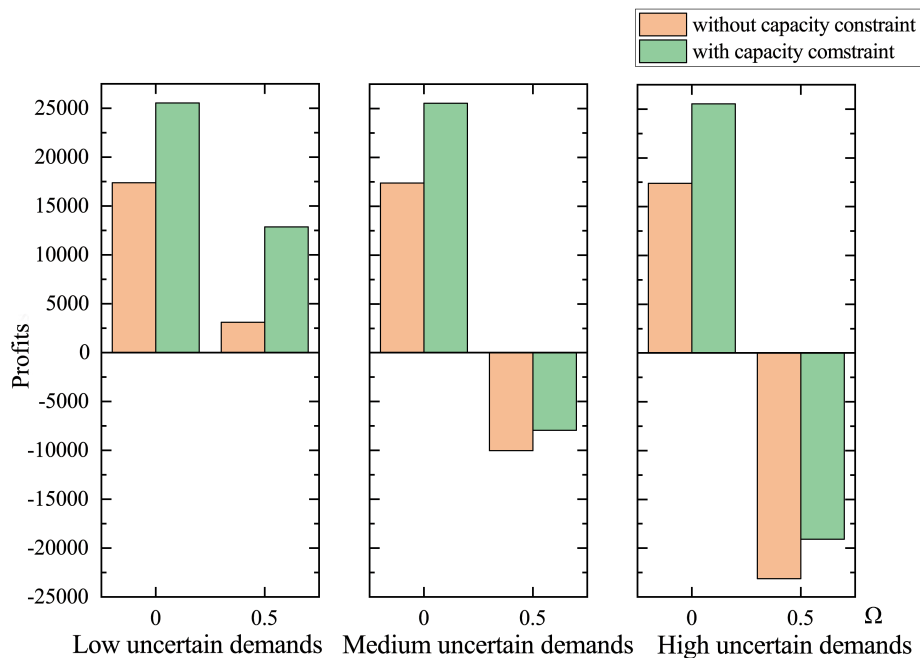|	Low demand uncertainty				
	$\Omega = 0$			$\Omega = 0.5$	
Robust price	Locations of hubs	Profit		Locations of hubs	Profit
0	2, 3, 4, 11, 18	70,294		2, 4, 6, 11, 19	63,496
25	2, 3, 4, 11, 18	70,294		2, 4, 6, 11, 19	63,496
50	2, 3, 4, 11, 18	70,294		2, 4, 5, 10, 18	48,567
75	2, 3, 4, 11, 18	70,294		2, 4, 5, 10, 18	48,567
100	2, 3, 4, 11, 18	70,294		2, 4, 5, 10, 18	48,567
	Medium demand uncertainty				
	$\Omega = 0$			$\Omega = 0.5$	
Robust price	Locations of hubs	Profit		Locations of hubs	Profit
0	2, 3, 4, 11, 18	70,294		2, 4, 5, 11, 18	29,705
25	2, 3, 4, 11, 18	70,294		2, 4, 5, 11, 18	29,705
50	2, 3, 4, 11, 18	70,294		2, 4, 5, 11, 18	29,705
75	2, 3, 4, 11, 18	70,294		2, 4, 5, 11, 18	29,705
100	2, 3, 4, 11, 18	70,294		2, 4, 5, 11, 18	29,705
	High demand uncertainty				
	$\Omega = 0$			$\Omega = 0.5$	
Robust price	Locations of hubs	Profit		Locations of hubs	Profit
0	2, 3, 4, 11, 18	70,294		1, 3, 4, 11, 18	14,265
25	2, 3, 4, 11, 18	70,294		1, 3, 4, 11, 18	14,265
50	2, 3, 4, 11, 18	70,294		1, 3, 4, 11, 18	14,265
75	2, 3, 4, 11, 18	70,294		1, 3, 4, 11, 18	14,265
100	2, 3, 4, 11, 18	70,294		2, 4, 5, 11, 18	10,843

FIGURE 2. Comparison of transshipment profits for fresh agricultural products with and without capacity constraints under uncertain demand ($\Gamma = 100$).

uncertainty of demand when determining a robust control strategy.

IV. RESULTS AND DISCUSSION

In this work, a hub-and-spoke network designed for the transportation of fresh agricultural products was proposed, and the influence of uncertain parameters on network hub locations was explored. In addition, because the capacities of the network hubs directly affect the robustness of the system

and the choice of transportation routes, this paper presented the construction of robust location models for fresh agricultural product hubs with and without capacity constraints and compared and analysed the results obtained using the two models. Some discussions of the main results and managerial implications of this work are as follows:

First, in the traditional design of transportation networks for fresh agricultural products, decision makers usually apply straight-through transportation networks to
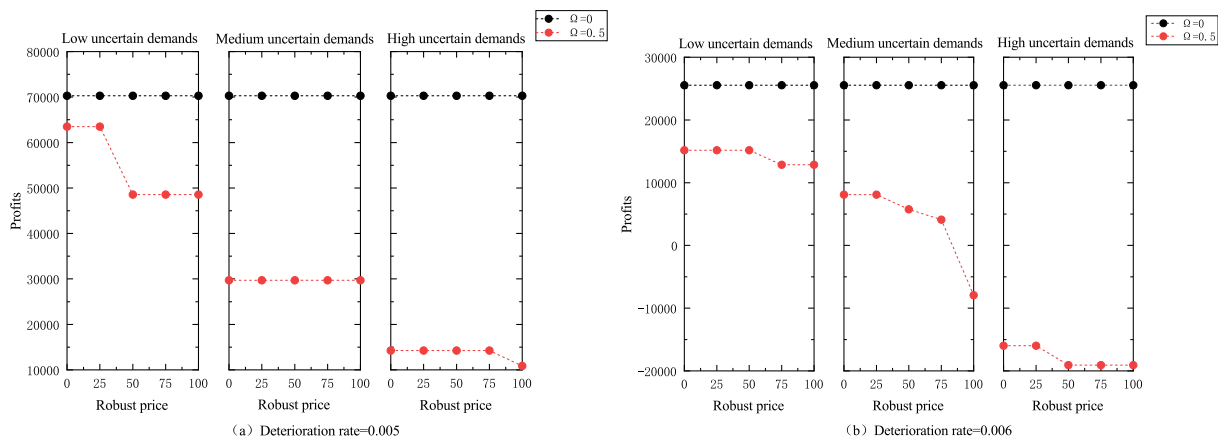
FIGURE 3. Sensitivity analysis of profit of robust hub locations with capacity restrictions based on a robust price under different levels of demand uncertainty.

reduce transshipment times [50], [51]. However, for covering transportation demands from scattered rural areas, a hub location strategy can provide more convenient transportation and enable the realization of economies of scale for agricultural products leaving villages and entering cities. To this end, this paper established a hub location model for a transportation network for fresh agricultural products in order to contribute to the literature on the application of hub-and-spoke networks in the transportation of goods with time requirements.

Second, the demands for fresh agricultural products will fluctuate with changes in weather, the season and other factors, so the demand uncertainty needs to be fully considered and discussed [11]. This paper used an uncertainty budget to control the changes in random variables and then analysed the influence of the uncertainty budget on the optimal hub locations in the network. The results show that a robust control strategy for the hub locations is beneficial to improve the robustness of the network. However, if the decision makers are overly conservative, the control cost may be too high to make a profit. In such a case, the decision makers should improve the accuracy of their demand forecasts or increase their tolerance to demand risk to reduce the uncertainty budget and obtain a higher profit.

Third, since the flow through a hub will be affected by the hub capacity in real life, this paper introduced capacity restrictions and further explored the resultant amplified uncertainty in fresh agricultural product transportation. The results showed that adding capacity restrictions can reduce the extra cost incurred to ensure the robustness of the system to a certain extent, but the effect is limited because the perishable characteristics of fresh agricultural products will simultaneously weaken the effect of the capacity restrictions to a certain extent. Therefore, decision makers need to consider these effects comprehensively and adopt suitable robust control strategies.

From the above analysis, we can extract the following managerial implications: 1) Hub-and-spoke networks can be applied for the transportation of fresh agricultural products,

and for scattered areas such as rural areas, decision makers should consider using hub-and-spoke networks instead of traditional straight-through networks to achieve economies of scale. 2) Setting a reasonable uncertainty budget is of great importance for network hub location optimization. A higher budget is beneficial to improve the robustness of the network, but decision makers also need to consider the cost and seek a suitable trade-off between a more stable network and sufficient profit. 3) Adding capacity constraints to the hubs in a fresh agricultural product transportation network will influence the flow distribution for transportation but is beneficial for rational route planning and the improvement of hub utilization; consequently, the profit will often be increased compared with the case without capacity constraints. 4) Whether or not capacity constraints are imposed, the decay rate of fresh agricultural products will have a great influence on the profit of the transportation network, so reducing and controlling the product decay rate should be one of the priority issues of concern for decision makers.

V. CONCLUSION

The increased consumption of fresh agricultural products presents new challenges for the hub location problem. In view of the perishability of fresh agricultural products and the uncertainty of their demand, this paper established robust hub location optimization models with and without capacity constraints, which are helpful for improving the level of logistics network design, especially with respect to fresh agricultural product transportation. In addition, the Lagrange relaxation method was used to solve the problem, and a numerical experiment based on an Australian data set showed that the deterioration rate of fresh agricultural products and the uncertainty of demand both greatly affect the profit of fresh agricultural product transportation.

In addition, several directions of research should be explored in the future. Intelligent algorithms and other optimization methods should be considered to solve large-scale real-world problems with improved computational efficiency.

Moreover, in the real transportation process for fresh food, the loading capacity limitations of different vehicle types, the integrated transportation of multicategory products with different deterioration rates, and cooperative hub selection for multiple fresh agricultural product enterprises are also topics worth studying.

REFERENCES

[1] NB Statistics. *Key Facts on Food Loss and Waste*. Accessed: Dec. 16, 2021. [Online]. Available: https://data.stats.gov.cn/

[2] *Development Report of Cold Chain Logistics in China*, CCLPC China Fed. Logistics, NERCFAPL Purchasing, CLT Assoc., Beijing, China, 2016.

[3] M. M. Musavi and A. Bozorgi-Amiri, "A multi-objective sustainable hub location-scheduling problem for perishable food supply chain," *Comput. Ind. Eng.*, vol. 113, pp. 766–778, Nov. 2017.

[4] Y. Esmizadeh, M. Bashiri, H. Jahani, and B. Almada-Lobo, "Cold chain management in hierarchical operational hub networks," *Transp. Res. E, Logistics Transp. Rev.*, vol. 147, Mar. 2021, Art. no. 102202.

[5] F. Sgroi and G. Marino, "Environmental and digital innovation in food: The role of digital food hubs in the creation of sustainable local agri-food systems," *Sci. Total Environ.*, vol. 810, Mar. 2022, Art. no. 152257.

[6] E. B. Tirkolaee, S. Hadian, G. Weber, and I. Mahdavi, "A robust green traffic-based routing problem for perishable products distribution," *Comput. Intell.*, vol. 36, no. 1, pp. 80–101, Feb. 2020.

[7] C.-I. Hsu, S.-F. Hung, and H.-C. Li, "Vehicle routing problem with time-windows for perishable food delivery," *J. Food Eng.*, vol. 80, no. 2, pp. 465–475, 2007.

[8] A. Osvald and L. Z. Stirn, "A vehicle routing algorithm for the distribution of fresh vegetables and similar perishable food," *J. Food Eng.*, vol. 85, no. 2, pp. 285–295, Mar. 2008.

[9] S. Daroudi, H. Kazemipoor, E. Najafi, and M. Fallah, "The minimum latency in location routing fuzzy inventory problem for perishable multi-product materials," *Appl. Soft Comput.*, vol. 110, Oct. 2021, Art. no. 107543.

[10] M. Biuki, A. Kazemi, and A. Alinezhad, "An integrated location-routing-inventory model for sustainable design of a perishable products supply chain network," *J. Cleaner Prod.*, vol. 260, Jul. 2020, Art. no. 120842.

[11] B. D. Song and Y. D. Ko, "A vehicle routing problem of both refrigerated-and general-type vehicles for perishable food products delivery," *J. Food Eng.*, vol. 169, pp. 61–71, Jan. 2016.

[12] M. de Keizer, R. Akkerman, M. Grunow, J. M. Bloemhof, R. Haijema, and J. G. A. J. van der Vorst, "Logistics network design for perishable products with heterogeneous quality decay," *Eur. J. Oper. Res.*, vol. 262, no. 2, pp. 535–549, Oct. 2017.

[13] G. Ahmadi, S. A. Torabi, and R. Tavakkoli-Moghaddam, "A bi-objective location-inventory model with capacitated transportation and lateral trans-shipments," *Int. J. Prod. Res.*, vol. 54, no. 7, pp. 2035–2056, Apr. 2016.

[14] J. Puerto, A. B. Ramos, A. M. Rodríguez-Chía, and M. C. Sánchez-Gil, "Ordered median hub location problems with capacity constraints," *Transp. Res. C, Emerg. Technol.*, vol. 70, pp. 142–156, Sep. 2016.

[15] J. A. Orjuela-Castro, L. A. Sanabria-Coronado, and A. M. Peralta-Lozano, "Coupling facility location models in the supply chain of perishable fruits," *Res. Transp. Bus. Manage.*, vol. 24, pp. 73–80, Sep. 2017.

[16] E. Macioszek, "First and last mile delivery—Problems and issues," in *Advanced Solutions of Transport Systems for Growing Mobility*, G. Sierpiński, Ed. Cham, Switzerland: Springer, 2018, pp. 147–154.

[17] Y. Choi, P. M. Schonfeld, Y.-J. Lee, and H.-S. Shin, "Innovative methods for delivering fresh food to underserved populations," *J. Transp. Eng., A, Syst.*, vol. 147, no. 1, Jan. 2021, Art. no. 04020140.

[18] F. Borghetti, C. Caballini, A. Carboni, G. Grossato, R. Maja, and B. Barabino, "The use of drones for last-mile delivery: A numerical case study in Milan, Italy," *Sustainability*, vol. 14, no. 3, p. 1766, Feb. 2022. [Online]. Available: https://www.mdpi.com/2071-1050/14/3/1766

[19] E. Macioszek, "Freight transport planners as information elements in the last mile logistics," in *Integration as Solution for Advanced Smart Urban Transport Systems*. Cham, Switzerland: Springer, 2019, pp. 242–251.

[20] J. Qin, S. Luo, D. Yi, H. Jiang, and J. Zhang, "Measuring cluster-based spatial access to shopping stores under real-time travel time," *Sustainability*, vol. 14, no. 4, p. 2310, Feb. 2022.

[21] D. L. Bryan and M. E. O'Kelly, "Hub-and-spoke networks in air transportation: An analytical review," *J. Regional Sci.*, vol. 39, no. 2, pp. 275–295, May 1999.

[22] E. Lee, "Spatial analysis for an intermodal terminal to support agricultural logistics: A case study in the upper great plains," *Manage. Res. Rev.*, vol. 38, no. 3, pp. 299–319, Mar. 2015.

[23] E. Macioszek, *The Principles and Methods of Locating Logistics Centers in Transport Networks*. Cham, Switzerland: Springer, 2021, pp. 149–162, doi: 10.1007/978-3-030-71771-1_10.

[24] S. Alumur and B. Y. Kara, "Network hub location problems: The state of the art," *Eur. J. Oper. Res.*, vol. 190, no. 1, pp. 1–21, 2008.

[25] J. F. Campbell and M. E. O'Kelly, "Twenty-five years of hub location research," *Transp. Sci.*, vol. 46, no. 2, pp. 153–169, May 2012.

[26] V. Yakavenka, I. Mallidis, D. Vlachos, E. Iakovou, and Z. Eleni, "Development of a multi-objective model for the design of sustainable supply chains: The case of perishable food products," *Ann. Oper. Res.*, vol. 294, nos. 1–2, pp. 593–621, Nov. 2020.

[27] J. M. Wilson, "Introduction to stochastic programming," *J. Oper. Res. Soc.*, vol. 49, no. 8, pp. 897–898, 1998.

[28] M. Marufuzzaman, S. D. Eksioglu, and Y. Huang, "Two-stage stochastic programming supply chain model for biodiesel production via wastewater treatment," *Comput. Oper. Res.*, vol. 49, pp. 1–17, Sep. 2014.

[29] T.-H. Yang, "Stochastic air freight hub location and flight routes planning," *Appl. Math. Model.*, vol. 33, no. 12, pp. 4424–4430, Dec. 2009.

[30] K. Yeh, C. Whittaker, M. J. Realff, and J. H. Lee, "Two stage stochastic bilevel programming model of a pre-established timberlands supply chain with biorefinery investment interests," *Comput. Chem. Eng.*, vol. 73, pp. 141–153, Feb. 2015.

[31] B. Rostami, N. Kämmerling, J. Naoum-Sawaya, C. Buchheim, and U. Clausen, "Stochastic single-allocation hub location," *Eur. J. Oper. Res.*, vol. 289, no. 3, pp. 1087–1106, Mar. 2021.

[32] D. Serra and V. Marianov, "The p-median problem in a changing network: The case of Barcelona," *Location Sci.*, vol. 6, nos. 1–4, pp. 383–394, May 1998.

[33] I. Averbakh and O. Berman, "Minmax regret median location on a network under uncertainty," *INFORMS J. Comput.*, vol. 12, no. 2, pp. 104–110, May 2000.

[34] M. E. Nikoofal and S. J. Sadjadi, "A robust optimization model for p-median problem with uncertain edge lengths," *Int. J. Adv. Manuf. Technol.*, vol. 50, nos. 1–4, pp. 391–397, Sep. 2010.

[35] D. Bertsimas and M. Sim, "The price of robustness," *Oper. Res.*, vol. 52, no. 1, pp. 35–53, Feb. 2004.

[36] M. Meraklı and H. Yaman, "Robust intermodal hub location under polyhedral demand uncertainty," *Transp. Res. B, Methodol.*, vol. 86, pp. 66–85, Apr. 2016.

[37] W. Shan, Z. Peng, J. Liu, B. Yao, and B. Yu, "An exact algorithm for inland container transportation network design," *Transp. Res. B, Methodol.*, vol. 135, pp. 41–82, May 2020.

[38] F. Yin, Y. Chen, F. Song, and Y. Liu, "A new distributionally robust p-hub median problem with uncertain carbon emissions and its tractable approximation method," *Appl. Math. Model.*, vol. 74, pp. 668–693, Oct. 2019.

[39] F. H. Boukani, B. F. Moghaddam, and M. S. Pishvaee, "Robust optimization approach to capacitated single and multiple allocation hub location problems," *Comput. Appl. Math.*, vol. 35, no. 1, pp. 45–60, Apr. 2016.

[40] V. Gabrel, M. Lacroix, C. Murat, and N. Remli, "Robust location transportation problems under uncertain demands," *Discrete Appl. Math.*, vol. 164, pp. 100–111, Feb. 2014.

[41] C. Peng, J. Li, L. Ran, and X. Cao, "Robust facility location model with two multiplicative uncertainties," *Syst. Eng. Theory Pract.*, vol. 37, no. 12, pp. 3170–3181, 2017.

[42] Q.-M. Hu, S. Hu, J. Wang, and X. Li, "Stochastic single allocation hub location problems with balanced utilization of hub capacities," *Transp. Res. B, Methodol.*, vol. 153, pp. 204–227, Nov. 2021.

[43] T. Aykin, "Lagrangian relaxation based approaches to capacitated hub-and-spoke network design problem," *Eur. J. Oper. Res.*, vol. 79, no. 3, pp. 501–523, Dec. 1994.

[44] D. Ambrosino and A. Sciomachen, "A capacitated hub location problem in freight logistics multimodal networks," *Optim. Lett.*, vol. 10, no. 5, pp. 875–901, Jun. 2016.

[45] E. Z. Serper and S. A. Alumur, "The design of capacitated intermodal hub networks with different vehicle types," *Transp. Res. B, Methodol.*, vol. 86, pp. 51–65, Apr. 2016.

[46] M. Meraklı and H. Yaman, "A capacitated hub location problem under hose demand uncertainty," *Comput. Oper. Res.*, vol. 88, pp. 58–70, Dec. 2017.

[47] F. J. Tapia-Ubeda, P. A. Miranda, and M. Macchi, "A generalized benders decomposition based algorithm for an inventory location problem with stochastic inventory capacity constraints," *Eur. J. Oper. Res.*, vol. 267, no. 3, pp. 806–817, Jun. 2018.

[48] M. Shahabi and A. Unnikrishnan, "Robust hub network design problem," *Transp. Res. E, Logistics Transp. Rev.*, vol. 70, pp. 356–373, Oct. 2014.

[49] N. Gülpınar, D. Pachamanova, and E. Çanakoğlu, "Robust strategies for facility location under uncertainty," *Eur. J. Oper. Res.*, vol. 225, no. 1, pp. 21–35, Feb. 2013.

[50] J. Chen, T. Fan, and F. Pan, "Urban delivery of fresh products with total deterioration value," *Int. J. Prod. Res.*, vol. 59, no. 7, pp. 2218–2228, Apr. 2021.

[51] B. S. Onggo, J. Panadero, C. G. Corlu, and A. A. Juan, "Agri-food supply chains with stochastic demands: A multi-period inventory routing problem with perishable products," *Simul. Model. Pract. Theory*, vol. 97, Dec. 2019, Art. no. 101970.

WANKE HAN was born in Taiyuan, Shanxi, China, in 2000. She received the B.S. degree in logistics engineering from Shanghai Maritime University, in 2021. She is currently pursuing the M.S. degree in management science and technology with the East China University of Science and Technology, Shanghai. Her research interests include vehicle routing problem, logistic network design, and the multi-objective optimization.

SHUXIA LI was born in Shiyan, Hubei, China, in 1975. She received the B.S. degree in mechanical engineering from the Hubei University of Automobile Technology, in 1996, the M.S. degree in mechanical engineering from Chongqing University, in 1999, and the Ph.D. degree in mechanical engineering from the Huazhong University of Science and Technology, in 2005. Since 2005, she has been an Assistant Professor and an Associate Professor with the School of Business, East China University of Science and Technology, Shanghai. Her research interests include modeling and optimization of logistics systems, scheduling theories and methods, and sustainable transportation.

LIPING LIU was born in Linchuan, Jiangxi, China, in 1973. She received the Ph.D. degree in management from Shanghai Jiao Tong University, in 2008. She has been an Assistant Professor and an Associate Professor with the School of Business, East China University of Science and Technology, since 2002. Her research interests include multimodal transportation of hazmat and logistics supply chain management.

• • •