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Robust Optimization of a Distribution Network Location-Routing Problem Under Carbon Trading Policies

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ABSTRACT Taking carbon emissions into account in decision-making on distribution network operations contributes to achieving the goal of promoting energy conservation and emissions reduction. The focus of this paper is to research multicapacity hierarchical location-routing robust optimization in distribution network design under carbon trading policies. First, this problem is described as a mixed integer nonlinear programming model. Then, based on strong duality theory, the nonlinear model is transformed into a linear robust equivalent model. Finally, GUROBI software is used for numerical calculation and analysis. The results suggest the following: carbon trading policies have a carbon abatement effect; with a decrease in the carbon emissions cap and an increase in carbon trading prices, carbon emissions undergo a ladder-like downward trend; uncertain fluctuations in freight units will influence the optimal decision-making patterns of enterprises; and making more vehicles available will reduce carbon emissions. The government should set a reasonable carbon emissions cap according to market conditions. Enterprises could adopt robust control parameters on the basis of their decision-making preferences and consider the impact of carbon trading policy in formulating and adjusting an optimal decision-making scheme.

INDEX TERMS Carbon emissions, carbon trading, green location-routing problem, robust optimization.

I. INTRODUCTION

China, the world's largest emitter of CO2, is facing increasing pressures to conserve energy and reduce emissions. Controlling carbon emissions and promoting sustainable development have become important policy objectives of the Chinese government [1]. Currently, feasible regulation measures of carbon emissions reduction include carbon emissions trading policies and carbon tax policies. Some studies have examined the trend of China's carbon emission reduction regulation policies. Some studies believe that the implementation of the carbon tax in the short term and carbon trading in the long term is more in line with the future situation of China [2]. More studies believe that carbon tax and carbon trading are not opposite in nature, and the comprehensive application of the two is a better choice for environmental regulations [3]. The parallel and comprehensive application of carbon trading and a carbon tax together should be considered [4]. The carbon tax can be introduced when an appropriate opportunity arises while actively promoting the carbon emissions trading mechanism [5]. Although there are some differences in researchers' views, there is a consensus that carbon trading policies will play an important role for some time to come. China was one of the first countries to conduct research on

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and practice carbon emissions permit trading. In 2013, China initiated its first carbon emissions trading pilot projects in seven provinces and cities. In December 2017, taking the power generation industry as a pilot setting, China launched a national carbon emissions trading system. Carbon emissions trading is also an internationally recognized means to promote carbon emissions reduction. Practices adopted in the United States, the United Kingdom, Australia and other countries have proven that carbon emissions trading policies have positive effects on carbon emissions reduction [6]. The China Carbon Pricing Survey of 2015 co-published by the China Carbon Forum (CCF) and International Consulting Firm (ICF) projects that China's carbon emissions will peak in 2030. Thus, the next decade will be a critical period for China's carbon abatement trajectory. China must accelerate its establishment of a national carbon emissions trading market, promote a deterrent mechanism for emissions, and urge enterprises to accelerate green transformation [7].

Location and routing decisions about the operation of distribution networks also concern CO_2 emissions, which have a direct impact on the environment. Over the past decade, the impact of environmental issues in the context of optimization has been studied extensively (Koç [8]). Under carbon trading policies, a government regulates enterprises to adjust location and inventory decision-making by controlling CO_2 emissions and eventually cutting carbon emissions. Therefore, carbon trading is likely to affect the distribution network of enterprises in terms of location and inventory decision-making. Based on the implementation of China's carbon trading policies, our aim is to analyze sustainability issues with the location-routing problem (LRP) under carbon trading policies and to provide some insights.

In examining the green facility location problem (GFLP), researchers have gradually shifted from focusing on economic factors to considering both economic and environmental factors. For instance, Zhang *et al.* [9] proposed a method for determining the optimal location and scale of a logistics park based on the bi-level programming model while considering both economies of scale and the impact on the design of logistics networks. The design of a supply chain network considering CO_2 emissions was also examined by Elhedhli and Merrick [10]. The model established by the authors is a nonconvex optimization problem, a type of problem that is difficult to solve directly. Therefore, a Lagrange relaxation algorithm was designed to decompose the original problem into several single-resource volumetric FLP to produce a solution, and the calculation gap was measured as less than 1%. Considering carbon emissions factors, Xiao *et al.* [11] considered the location-allocation problem involved in the design of a four-level reverse logistics network, constructed a mixed integer linear programming model, and used LINGO software to solve the model. Xiao *et al.* [11] expanded multilevel multicommodity FLP on the basis of carbon emissions trading prices and procurement costs and analyzed the impact of different carbon trading prices on supply chain costs and allocation. Yang and Lu [13] compared the location-allocation problem of multicapacity facilities under four different carbon emissions policies, established corresponding mixed integer linear programming models, and conducted a numerical calculation of models with CPLEX software. The above works do not consider routing decision-making.

Unlike the traditional vehicle routing problem (VRP), the green vehicle routing problem (GVRP) takes into account negative externalities such as CO_2 emissions and reduces costs and carbon emissions by optimizing the operation scheme. Fuel consumption models and calculation methods of traffic emissions and energy consumption have been used to describe environmental factors that should be considered in GVRP modeling. The GVRP was first introduced by Erdoğ̆an and Miller-Hooks [14]. The authors proposed a mixed-integer-linear programming (MILP) formulation and two heuristics. Lin *et al.* [15] and Demir *et al.* [16] summarized related models and algorithms of the GVRP. In terms of modeling approaches, GVRPs can be categorized into 3 types: deterministic GVRP (DGVRP), the stochastic GVRP (SGVRP), and the robust GVRP(RGVRP). **(i) *The DGVRP***. The DGVRP has been most widely studied by previous researchers. Kara *et al.* [17] first expanded the capacitated vehicle routing problem (CVRP) and investigated the CVRP with minimal energy consumption, which was described as an integer linear programming model. The proposed model is solved by CPLEX. Assuming that carbon emissions are related to time and loads, the transmission ratio is defined as the main factor that affects vehicle emissions in addition to factors of distance, load and velocity. Ashtineh and Mir [18] studied the GVRP with alternative fuels by establishing a mixed integer programming model and evaluated the economic and environmental performance of alternative fuels in a VRP. Macrina *et al.* [19] incorporated velocity, acceleration, deceleration, load and other factors into the comprehensive energy consumption model, designed a GVRP model of a hybrid fleet that includes electric vehicles and traditional diesel locomotives, and developed an embedded large neighborhood search heuristic algorithm. Atashi *et al.* [20] investigated the time-dependent green weber problem (TD-GWP). Montoya *et al.* [21] proposed a multispace sampling heuristic for the GVRP. The pollution-routing problem (PRP) was developed as a successful application of the GVRP and was coined by Bektaé and Laporte [22]. The time window constraints of consumers are usually taken into account in the PRP. Raeesi and Konstantinos [23] presented a multiobjective PRP with a time window while considering the objective function of minimum vehicle rental costs, minimum total fuel consumption and the shortest routing time. Demir *et al.* [24] designed the dual-objective PRP model with the goal of minimizing total fuel consumption and achieving the shortest routing time and developed the corresponding adaptive neighborhood search algorithm. Andelmin and Bartolini [25] modeled the GVRP as a set partition problem and proposed an accurate algorithm. Franceschetti *et al.* [26]

TABLE 1. Features of the GLRP.

Reference	Solution method	Objective	Emission model	Type of VRP	Modeling approach
Govindan et al. [44]	Heuristic	Multi	Factor	LRPTW	Deterministic
Koç et al. [45]	Exact and heuristic	Single	CMEM	HLRP1	Deterministic
Toro et al. [46]	Exact	Multi	Macroscopic	CLRP	Deterministic
Tricoire and Parragh [47]	Exact and heuristic	Multi	Factor	HLRP2	Deterministic
Dukkanci et al. [48]	Exact and heuristic	Single	CMEM	LRPTW	Deterministic
Tang et al. [49]	Heuristic	Single	CMEM	CLRP	Deterministic
Koç et al. [8]	Heuristic	Single	MEET	LRPTW	Deterministic
Wang et al. [50]	Heuristic	Single	MEET	CLRP	Deterministic
Leng et al. [51]	Heuristic	Single	CMEM	LRPTW	Deterministic
Leng et al. [52]	Heuristic	Multi	CMEM	LRPTW	Deterministic
Leng et al. [53]	Heuristic	Multi	CMEM	LRPTW	Deterministic
Shen et al. [54]	Heuristic	Multi	Factor	CLRP	Fuzzy
Our Study	Exact	Single	Factor	CLRP	Robust and stochastic

studied a PRP with time-varying speed while considering that traffic congestion significantly limits vehicle speeds and increases carbon emissions. The method of separable convex programming was designed by Fukasawa *et al.* [27] to solve the PRP, while a branch-and-bound algorithm was defined by Dabia *et al.* [28] to solve the PRP. In addition, Poonthalir and Nadarajan [29], Li *et al.* [30], Qin *et al.* [31], and Shen *et al.* [32] also researched the green VRP from different perspectives. **(ii)** ***SGVRP***. Some researchers have also studied the SGVRP. Çimen and Soysal [33] investigated a time-dependent GVRP with stochastic vehicle speeds and proposed an approximate dynamic programming algorithm. Hsueh [34] and Feng *et al.* [35] presented a GVRP with stochastic traffic speeds. Hwang and Ouyang [36] showed that a GVRP with random congestion states on each link follows an independent probability distribution. Rabbani *et al.* [37] developed a stochastic time-dependent capacitated GVRP model. The authors designed a simulated annealing (SA) algorithm for the proposed model. **(iii)** ***SGVRP***. A robust VRP (RVRP) was introduced by Bertsimas and Simchi-Levi [38] for the SVRP and was applied when the probability distribution of an uncertain parameter was unknown. Few studies have been conducted on the RGVRP. Eshtehadi *et al.* [39] adopted robust optimizations, such as the soft worst case, the hard worst case and chance constraints, and provided a PRP with demand and travel time uncertainty. Tajik *et al.* [40] presented a robust PRP with pickup and delivery and introduced a new robust counterpart of the mixed integer linear programming model to manage uncertainty. Eshtehadi *et al.* [41] also illustrated a robust PRP. The authors presented an adaptive large neighborhood search for the model under demand uncertainty. The above works do not consider location decision-making.

The location-routing problem (LRP) involves the integration of the FLP and VRP. The basic LRP solves problems associated with determining the location of a facility and with dispatching a vehicle fleet from a facility to provide services to a given set of customers while minimizing location and routing costs (Drexl and Schneider [42], Prodhon and Prins [43]). The FLP and VRP affect and restrain each other, and classic LRP research works prove that the integrated optimization of the two could reduce system costs and promote scientific decision-making (Drexl and Schneider [42]). To the best of our knowledge, only a few studies (Table 1) have been conducted on the Green LRP (GLRP). The GLRP was first studied by Govindan *et al.* [44]. To minimize total costs and environmental impact, a two-objective two-stage LRP model with time windows was established, and a hybrid multi-objective optimization algorithm combining particle swarm optimization with adaptive neighborhood searching was designed [44]. While incorporating fuel consumption and CO_2 emissions into system costs, Koç *et al.* [45] studied the LRP in relation to urban logistics and proposed a new adaptive large neighborhood search heuristic algorithm. Toro *et al.* [46] proposed a new model for calculating greenhouse gas emissions generated from vehicle routing and studied a capacity-constrained LRP considering environmental impacts. Their research suggests that using more vehicles could enhance fuel economy and thus lower emissions, while emissions can also be reduced by enabling more vehicles on short routings and prioritizing high-demand customers. The green city hub location routing problem (GCHLRP), with the objective of minimizing the cost of strategic investments and pollution by using CO_2 emissions as an indicator, was studied by Tricoire and Parragh [47]. Dukkanci *et al.* [48] studied the green LRP with capacity limitation on the basis of the classic LRP and PRP. Tang *et al.* [49] discussed the influence of a customer's limited 'carbon behavior' preferences on the joint optimization of location-routing inventory. With the goal of minimizing the total system cost, including the cost of fuel and CO_2 emissions, Koç *et al.* [8] studied the GLRP with time widows (GLRPTW) and developed an adaptive large neighborhood search metaheuristic. A GLRP in a cold chain logistics system with low composite costs is constructed based on fixed costs, transportation, propagation, damage, and carbon emission costs in Wang *et al.* [50]. The authors constructed a hybrid genetic algorithm to solve the model. Leng *et al.* [51] studied the GLRP considering simultaneous pickup and delivery and hard time windows. Leng *et al.* [52] proposed a multiobjective regional low-carbon LRP. The authors sought to minimize service durations, client waiting times, and total costs. A novel hyperheuristic (HH) method for addressing a bi-objective model of the GLRP was defined by Leng *et al.* [53]. Most examined GLRPs have been deterministic. Only Shen *et al.* [54] considered fuzzy parameters in studying the GLRP. The authors studied a fuzzy demand and open GLRP model for emergency logistics. The objective function included the minimum delivery time, total costs and carbon emissions, and the authors designed a hybrid two-stage algorithm to deal with the model.

In conclusion, several studies have been conducted on carbon emissions in supply chain operation optimization and have made some progress; however, the following questions still need to be addressed: (1) As carbon trading becomes an increasingly discussed topic in political and academic circles, what influence does carbon trading have on the distribution network location-routing decision-making of companies in supply chains? How should governments set carbon caps? How can enterprises make more favorable decisions under the influence of carbon trading policies? Existing research does not provide answers to these questions. (2) Previous studies on the GLRP are mainly based on deterministic optimization. Only one study has examined the GLRP under fuzzy requirements [54]. To the best of our knowledge, there has been little research on the stochastic optimization and robust optimization of the GLRP. Previous research on the GVRP mainly focuses on deterministic and stochastic optimization, and research on the RGVRP has been rare. Stochastic optimization is more practical than deterministic optimization, but it still has limitations. First, it is difficult to determine representative scenarios and their probability or the probability distribution function of uncertain parameters. Second, the decision-making objective of minimizing expected costs in stochastic optimization is difficult to use to reflect the risk preferences of decision-makers. Third, most stochastic optimization models use mixed-integer nonlinear programming, which must be solved by a heuristic or meta-heuristic algorithm; thus, a global optimal solution is difficult to obtain. However, robust optimization remedies the limitations of stochastic optimization modeling to some extent [55]. On the basis of the traditional supply chain distribution network LRP (DNLRP), this paper introduces a box-indeterminate set and two uncertain level parameters to describe unit freight uncertainty and establishes a multi-capacity-level LRP robust optimization model considering carbon trading policies and carbon emissions. Based on strong duality theory, the mixed integer nonlinear programming model is transformed into the linear robust equivalent model, and the model's optimal solution is calculated with GUROBI software. Finally, through numerical calculation and a sensitivity analysis of key parameters, implications for management are obtained to provide decision-making references for governments and enterprises. In summary, we know the following: (i) Carbon trading will play an increasingly important role in the policy level of environmental regulation, so it is necessary to consider the impact of carbon trading policies when making LRP decisions. (ii) At present, research on the GLRP is based on deterministic optimization, so it is necessary to consider the uncertainty of key parameters in studying the robust GLRP. These two points are the main motivations behind this paper. The contributions of our study can be summarized as follows: (i) We formally define the GLRP under carbon trading policies. (ii) We propose a mixed integer linear programming formulation for the GLRP, and we reformulate the GLRP with a well-known robust approach. (iii) We carry out a sensitivity analysis on key parameters and provide management insights.

The remainder of this paper is structured as follows. Section II presents the studied problem settings and descriptions and a mathematical formulation. Computational experiments are presented in Section III followed by conclusions in Section IV.

II. METHODOLOGY

A. PROBLEM DESCRIPTION

An optimization design problem of a three-level distribution network will be solved. The network consists of several factories, distribution centers and demand points. The location and scale of factories are determined. Candidate distribution centers have capacity limitations, and multiple capacity levels are available. In a multi-capacity-level FLP, in addition to the decision-making variable of the facility location, the capacity level also belongs to the set of decision-making variables [13]. Through the overall optimization of facility locations, quantities and capacities, imbalances between facility resources and customer needs can be reduced. The location and demand of demand points are known, and each demand point is met by only one vehicle [56], [57]. Vehicles also have capacity limitations, with only one vehicle on each itinerant routing, and each vehicle needs to return to the distribution center after completing the distribution task. Carbon emissions generated from distribution networks are based on the locations and operation of distribution centers, transportation/distribution from factories to distribution centers, and distribution from centers to demand points.

The following decisions need to be made: (1) determine the locations, number and capacity levels of open distribution centers; (2) determine the distribution of freight volumes, including the freight volume transported from factories to distribution centers and from distribution centers to demand points; and (3) determine the distribution routing from distribution centers to demand points.

B. EXPLANATIONS OF PARAMETERS AND VARIABLES

The sets are as follows

I Set of distribution centers
M Set of factories
J Set of demand points
V Set of transport vehicles
K Set of capacity levels

The parameters are as follows

f_{ik} Construction cost allocation of establishing a distribution center with capacity level k in candidate distribution center i
h_j Demand at demand point j
γ_{ik} Unit operatio cost of establishing a distribution center with capacity level k at candidate location i
c_{ik} Maximum capacity of establishing a distribution center with capacity level k at candidate location i
d_{mi} Transportation distance from factory m to distribution center i
b_{mi}, b_{lj} Freight of per unit product and per unit distance
c Vehicle idling cost of per unit distance
c_0 Fixed departure cost per vehicle
d_{lj} Transportation distance from node i to node j
cap_v Maximum carrying capacity of vehicle v
H A large number

Decision variables

q_{mi} Number of products transported from factory m to distribution center i
q_{lj} Number of products transported from node l to node j
x_{ljv} If vehicle v travels from node l to node j, this variable takes the value 1, and otherwise it takes the value 0
X_{ik} If a distribution center with capacity level k is established at node i, this variable takes the value 1, and otherwise it takes the value 0

C. BASIC MODEL OF THE DNLRP

The basic model of the DNLRP is written as Model I. Model I is as follows:

$$\begin{aligned}\min Z_1 = &\sum_{i\in I}\sum_{k\in K} f_{ik}X_{ik} + \sum_{i\in I}\sum_{k\in K}\gamma_{ik}c_{ik}X_{ik} \\ &+ \sum_{m\in M}\sum_{i\in I} b_{mi}d_{mi}q_{mi} + \sum_{l\in(I\cup J)}\sum_{j\in J} b_{lj}d_{lj}q_{lj} \\ &+ \sum_{i\in I}\sum_{j\in J}\sum_{v\in V} cd_{ji}x_{jiv} + \sum_{i\in I}\sum_{j\in J}\sum_{j\in V} c_0x_{ijv} \end{aligned} \tag{1}$$

$$\text{Subjective to} \sum_{l\in(I\cup J)}\sum_{j\in J} h_jx_{ljv} \le cap_v,\ v\in V \tag{2}$$

$$\sum_{l\in(I\cup J)}\sum_{v\in V} x_{ljv} = 1, \quad \forall j\in J \tag{3}$$

$$\sum_{i\in I}\sum_{j\in J} x_{ijv} \le 1, \quad \forall v\in V \tag{4}$$

$$\sum_{l\in(I\cup J)} x_{ljv} - \sum_{l\in(I\cup J)} x_{jlv} = 0, \quad \forall j\in J, v\in V \tag{5}$$

$$\sum_{m\in M} q_{mi} \ge \sum_{j\in J} q_{ij}, \quad \forall i\in I \tag{6}$$

$$\sum_{l\in I+J, l\ne r} q_{lr} - \sum_{j\in J, j\ne r} q_{rj} = h_r, \quad \forall r\in J \tag{7}$$

$$\sum_{k\in K} X_{ik} \le 1 \tag{8}$$

$$\sum_{m\in M} q_{mi} \le \sum_{k\in K} c_{ik}X_{ik}, \quad \forall i\in I \tag{9}$$

$$\sum_{j\in J} q_{ij} \le \sum_{k\in K} c_{ik}X_{ik}, \quad \forall i\in I \tag{10}$$

$$q_{mi} \le H\sum_{k\in K} X_{ik}, \quad \forall m\in M, i\in I \tag{11}$$

$$q_{lj} \le H\sum_{v\in V} x_{ljv}, \quad \forall j\in J, l\in(I\cup J) \tag{12}$$

$$x_{ijv} \le \sum_{k\in K} X_{ik}, \quad \forall i\in I, j\in J, v\in V \tag{13}$$

$$x_{ijv} = 0, \quad \forall i\in I, j\in I, v\in V \tag{14}$$

$$\sum_{j\in J} x_{ijv} = \sum_{j\in J} x_{jiv}, \quad \forall i\in I, v\in V \tag{15}$$

$$X_{ik} \in (0,1), \quad \forall i\in I, k\in K \tag{16}$$

$$x_{llv} \in (0,1), \quad \forall j\in J, l\in(I\cup J), v\in V \tag{17}$$

The objective function (1) refers to the minimum total cost of the system, in which the first item is the facility construction cost, the second item is the operation cost of the distribution center, the third item is the transportation cost from the factory to the distribution center, the fourth item is the transportation cost from the distribution center to the demand point, the fifth item is the vehicle idling cost, and the sixth item is the fixed departure cost. Constraint (2) is the capacity constraint of a vehicle. Formula (3) ensures that only one vehicle is serving any demand point. Constraint (4) requires that each vehicle serves at most one distribution center. Formula (5) indicates that a vehicle cannot stay at a node. Constraint (6) denotes that the quantity of products transported into the distribution center must not be less than the quantity transported out of the distribution center. Formula (7) ensures that the demands of all demand points are met. Constraint (8) shows that each distribution center has at most one capacity level. Constraints (9) and (10) are capacity limitations placed on inbound and outbound transportation to and from the distribution center, respectively. Constraints (11)-(13) denote that the distribution center performing the task must be open. Formula (14) states that a vehicle cannot travel from one distribution center to another, reducing the search scale of the solution space. Formula (15) denotes that each routing starts and ends at the same distribution center. Formulas (16) and (17) are binary variable constraints.

D. THE DNLRP MODEL UNDER CARBON TRADING POLICIES

Under carbon trading policies, carbon emissions rights are traded in the market as a commodity. Each enterprise has a certain emissions cap, and when an enterprise's emissions do not exceed its emissions cap, the saved emissions can be sold to other enterprises; conversely, when emissions from an enterprise exceed its emissions cap, the emissions balance must be purchased from other enterprises. Therefore, carbon trading policies will affect enterprise costs and carbon emissions. Referring to the carbon footprint parameter setting method provided in [13], the distribution network LRP model under carbon trading policies is built as model II. In model II, a carbon trading mechanism was added to analyze the impact of carbon trading policies on the design of distribution networks. Compared with model I, the objective function (18) of model II increases the transaction cost of carbon emissions and adds a carbon emission constraint (19).

$\widehat{f}_{ik}$ Construction carbon emissions allocation for establishing a distribution center with capacity level k in candidate distribution center i

$\widehat{\gamma}_{ik}$ Per unit operational emissions from distribution center i with capacity level k

$\widehat{b}$ Per unit emissions of transportation

$\widehat{c}$ unit emissions of transportation

L Emissions caps

e^+ Externally purchased emissions

e^- Emissions for sale

p Carbon trading price

Model II is as follows.

$$\begin{aligned}\min Z_2 = &\sum_{i\in I}\sum_{k\in K} f_{ik}X_{ik} + \sum_{i\in I}\sum_{k\in K}\gamma_{ik}c_{ik}X_{ik} \\ &+ \sum_{m\in M}\sum_{i\in I} b_{mi}d_{mi}q_{mi} \\ &+ \sum_{l\in(I\cup J)}\sum_{j\in J} b_{lj}d_{lj}q_{lj} \\ &+ \sum_{i\in I}\sum_{j\in J}\sum_{v\in V} cd_{ji}x_{jiv} \\ &+ \sum_{i\in I}\sum_{j\in J}\sum_{v\in V} c_0 x_{ijv} + p(e^+ - e^-) \end{aligned} \tag{18}$$

$$\begin{aligned}\sum_{i\in I}\sum_{k\in K}\widehat{f}_{ik}X_{ik} + \sum_{i\in I}\sum_{k\in K}\widehat{\gamma}_{ik}c_{ik}X_{ik} + \sum_{m\in M}\sum_{i\in I}\widehat{b}d_{mi}q_{mi} \\ + \sum_{l\in(I\cup J)}\sum_{j\in J}\widehat{b}d_{lj}q_{lj} \\ + \sum_{i\in I}\sum_{j\in J}\sum_{v\in V}\widehat{c}d_{ji}x_{jiv} + (e^- - e^+) = L \end{aligned} \tag{19}$$

Constraints (2)-(17) are also established.

Equation (18) is the objective function, indicating the minimum total system costs under carbon trading policies. Constraint (19) refers to the carbon emissions constraint, which is that a certain emissions cap L is granted to each enterprise under carbon trading policies. The enterprise arranges production on the basis of emissions cap L. If the actual emissions are greater than L, then the enterprise has to buy e^+ units of emissions from outside sources. If the actual emissions are less than L, the enterprise can sell e^- units of emissions to outside sources. The costs incurred by carbon trading $p(e^+ - e^-)$ are included in the total system costs.

E. ROBUST OPTIMIZATION MODEL OF THE DNLRP UNDER CARBON TRADING POLICIES

In real conditions, due to the impacts of congestion, oil price fluctuations, labor cost changes and other factors, the unit freight b_{lj} and b_{mi} exhibit obvious uncertainties. Therefore, based on the nominal model II, considering the indeterminacy of the unit freight, the box-indeterminate set is introduced to depict unit freight b_{lj} and b_{mi}, and the robust optimization method is used to establish the robust LRP optimization model of distribution network optimization design under carbon trading policies [58].

We define the unit freight as $\tilde{b}_{lj} \subseteq [b_{lj} - a_{lj}u_{lj}, b_{lj} + a_{lj}u_{lj}]$, the unit freight of the nominal model as b_{lj}, and the disturbance quantity of the freight in $a_{lj} = \varepsilon_l b_{lj}$ as a_{lj}, where ε_l is the disturbance ratio and u_{lj} is the indeterminate factor. The disturbance ratio ε_l can be obtained based on historical data and statistical methods and can also be estimated based on causal analysis, time series prediction and other methods. $U_1 = \left\{ : \sum_{l\in I+J}\sum_{j\in J} u_{lj} \leqslant \Gamma_1, 0 \leqslant u_{lj} \leqslant 1 \right\}$, where Γ_1 represents the indeterminate level parameter of the unit freight and is used to objectively measure the degree of conservatism in the constraints. In addition, Γ_1 reflects the risk preferences of decision-makers such that the larger Γ_1 is, the more conservative the model is. Γ_1 is equal to 0, which means that the decision-maker is not risk-averse at all. The decision-maker chooses the indeterminate level parameter Γ_1 according to his risk preference to minimize the total cost of the system. In practical decision-making scenarios, group decision-making and other methods can also be used to determine the indeterminate level parameter Γ_1 and the disturbance ratio ε_l to avoid the knowledge limitations and idiosyncratic traits of individual decision-makers and promote the scientificization of decision-making. Because indeterminacy exists only in the objective function, robust LRP optimization model III of the box-indeterminate set is formulated. The robust optimization model III takes into account the uncertain fluctuation of unit freight b_{lj} and reflects the risk aversion of decision-makers.

Model III is as follows:

$$\begin{aligned}\min Z_3 = &\sum_{i\in I}\sum_{k\in K} f_{ik}X_{ik} + \sum_{i\in I}\sum_{k\in K}\gamma_{ik}c_{ik}X_{ik}\\ &+\sum_{m\in M}\sum_{i\in I} b_{mi}d_{mi}q_{mi}\\ &+\sum_{l\in(I\cup J)}\sum_{j\in J} b_{lj}d_{lj}q_{lj}\\ &+\sum_{i\in I}\sum_{j\in J}\sum_{v\in V} cd_{ji}x_{jiv}\\ &+\sum_{i\in I}\sum_{j\in J}\sum_{v\in V} c_0x_{ijv}\\ &+p(e^+ - e^-)\\ &+\max_{u\in U_1}\sum_{l\in(I\cup J)}\sum_{j\in J}(b_{lj}+a_{lj}u_{lj})d_{lj}q_{lj} \end{aligned} \tag{20}$$

Additionally, constraints (2)-(17) and (19) are established.

The objective function (20) represents the minimum total system costs that increase the uncertain transportation cost from distribution centers to demand points on the basis of equation (18).

When $\Gamma_1 = 0$, the robust LRP optimization model III of the box indeterminate set is equivalent to the nominal model II. Objective formula (20) of model III contains the inner layer maximization problem (21), which can be transformed into a robust equivalent model that is easier to solve by means of the strong duality theory.

$$\begin{aligned}&\max_{u\in U_1}\sum_{l}\sum_{j}(b_{lj}+a_{lj}u_{lj})d_{lj}q_{lj}\\ &\quad=\sum_{l}\sum_{j} b_{lj}d_{lj}q_{lj} + \max_{u\in U_1}\sum_{l}\sum_{j} a_{lj}u_{lj}d_{lj}q_{lj}\end{aligned} \tag{21}$$

The linear programming problem with inner layer maximization is as follows.

$$\max_{u\in U_1}\sum_{l}\sum_{j} a_{lj}u_{lj}d_{lj}q_{lj} \tag{22}$$

Conditional on

$$\rho_{lj}+\theta_1 \geqslant a_{lj}d_{lj}q_{lj},\quad \forall l\in I+J,\ j\in J \tag{23}$$
$$\rho_{lj},\theta_1 \geqslant 0,\quad \forall l\in I+J,\ j\in J \tag{24}$$

According to the strong duality principle, the problem is equivalent to (25), in which θ and ρ_{lj} are dual variables.

$$\min \rho_{lj} + \Gamma_1\theta_1 \tag{25}$$

Conditional on

$$\rho_{lj}+\theta_1 \geqslant a_{lj}d_{lj}q_{lj},\quad \forall l\in I+J,\ j\in J \tag{26}$$
$$\rho_{lj},\theta_1 \geqslant 0,\quad \forall l\in I+J,\ j\in J \tag{27}$$

Equation (25) is the objective function of the dual problem of the inner maximization problem. Equation (26) and equation (27) are the constraints of the dual problem of the inner maximization problem.

Then, formula (21) and formula (25) are substituted into formula (20), and the nonlinear robust model is transformed into the deterministic linear robust equivalent model IV.

Model IV is as follows:

$$\begin{aligned}\min Z_4 = &\sum_{i\in I}\sum_{k\in K} f_{ik}X_{ik} + \sum_{i\in I}\sum_{k\in K}\gamma_{ik}c_{ik}X_{ik}\\ &+\sum_{m\in M}\sum_{i\in I} b_{mi}d_{mi}q_{mi}\\ &+\sum_{l\in(I\cup J)}\sum_{j\in J} b_{lj}d_{lj}q_{lj}\\ &+\sum_{i\in I}\sum_{j\in J}\sum_{v\in V} cd_{ji}x_{jiv}\\ &+\sum_{i\in I}\sum_{j\in J}\sum_{v\in V} c_0x_{ijv}\\ &+p(e^+ - e^-)+\sum_{l\in(I\cup J)}\sum_{j\in J} b_{lj}d_{lj}q_{lj}\\ &+\sum_{l\in(I\cup J)}\sum_{j\in J}\rho_{lj}+\Gamma_1\theta_1 \end{aligned} \tag{28}$$

At the same time, constraints (2)-(17), (19), (26), and (27) are established.

Thus, the objective function (28) is equivalent to equation (20), which also represents the minimum total system costs.

Similarly, if unit freight $\tilde{b}_{mi} \subseteq [b_{mi} - a_{mi}\mu_{mi}, b_{mi} + a_{mi}\mu_{mi}]$, then b_{mi} is the unit freight of the nominal model, a_{mi} is the disturbance quantity of the freight, $a_{mi} = \varepsilon_m b_{mi}$, where ε_m is the disturbance ratio, and μ_{mi} is the indeterminate factor. $U_2 = \left\{: \sum\sum \mu_{mi} \leq \Gamma_2, 0 \leq \mu_{mi} \leq 1\right\}$, where Γ_2 represents the indeterminate level parameter of the unit freight. The linear equivalent model V of the robust LRP optimization problem with two kinds of indeterminate freight parameters is formulated. Model V is a mixed integer linear programming model, which can be solved by GUROBI, CPLEX and other operations research software.

Model V is as follows:

$$\begin{aligned}\min Z_5 = &\sum_{i\in I}\sum_{k\in K} f_{ik}X_{ik} + \sum_{i\in I}\sum_{k\in K}\gamma_{ik}c_{ik}X_{ik}\\ &+\sum_{m\in M}\sum_{i\in I} b_{mi}d_{mi}q_{mi}\\ &+\sum_{l\in(I\cup J)}\sum_{j\in J} b_{lj}d_{lj}q_{lj}\\ &+\sum_{i\in I}\sum_{j\in J}\sum_{v\in V} cd_{ji}x_{jiv}\\ &+\sum_{i\in I}\sum_{j\in J}\sum_{v\in V} c_0x_{ijv}\\ &+p(e^+ - e^-)+\sum_{l\in(I\cup J)}\sum_{j\in J} b_{lj}d_{lj}q_{lj}\\ &+\sum_{l\in(I\cup J)}\sum_{j\in J}\rho_{lj}+\Gamma_1\theta_1 \end{aligned}$$

$$+\sum_{m\in M}\sum_{i\in I} b_{mi}d_{mi}q_{mi} + \sum_{m\in M}\sum_{i\in I}\tau_{mi} + \Gamma_2\theta_2 \tag{29}$$

It is conditional on

$$\tau_{mi} + \theta_2 \geqslant a_{mi}d_{mi}q_{mi}, \quad \forall m \in M,\ i \in I \tag{30}$$

$$\tau_{mi}, \theta_2 \geqslant 0, \quad \forall m \in M,\ i \in I \tag{31}$$

Additionally, constraints (2)-(17), (19), (26), and (27) are established.

The objective function (29) minimizes the total system costs, which increases the uncertain transportation cost from factories to distribution centers on the basis of equation (28). Similarly to equation (26) and equation (27), equation (30) and equation (31) are constraints of the dual problem of the corresponding inner maximization problem.

F. ROBUST OPTIMIZATION MODEL OF THE DNLRP WITH STOCHASTIC DEMAND UNDER CARBON TRADING POLICIES

A scenario-based two-stage stochastic programming model was established. Assume that the demands were stochastic and involved different scenarios. Under real conditions, the demand scenarios were reflected in off-season and peak-season product sales. Let S denote the set of scenarios, where $s \in S$, ω_s represents the probability of scenario s, and h_{js} indicates the demand at demand point j under scenario s. Clearly, location decision-making was not related to the scenarios (because a distribution center needed to be established before the scenario occurred), and routing decision-making was related to the scenarios (because routing decision-making was related to scenario-based demand). Therefore, the location variable X_{ik} remained unchanged while the transportation volume q_{mis}, q_{ljs} and vehicle routing variable x_{ljvs} included the subscript s. Model VI is as follows:

$$\min Z_6 = \sum_{i\in I}\sum_{k\in K} f_{ik}X_{ik} + \sum_{i\in I}\sum_{k\in K}\gamma_{ik}c_{ik}X_{ik} + \sum_{l\in(I\cup J)}\sum_{j\in J}\rho_{lj} + \Gamma_1\theta_1 + \sum_{m\in M}\sum_{i\in I}\tau_{mi} + \Gamma_2\theta_2$$
$$\sum_{s\in S}\omega_s \left(\begin{array}{l} \sum_{m\in M}\sum_{i\in I}\sum_{s\in S} b_{mi}d_{mi}q_{mis} \\ + \sum_{l\in(I\cup J)}\sum_{j\in J}\sum_{s\in S} b_{lj}d_{lj}q_{ljs} \\ + \sum_{i\in I}\sum_{j\in J}\sum_{v\in V}\sum_{s\in S} cd_{ji}x_{jivs} \\ + \sum_{i\in I}\sum_{j\in J}\sum_{v\in V}\sum_{s\in S} c_0 x_{ijvs} \\ + p\sum_{s\in S}(e_s{}^+ - e_s{}^-) \\ + \sum_{l\in(I\cup J)}\sum_{j\in J}\sum_{s\in S} b_{lj}d_{lj}q_{ljs} \\ + \sum_{m\in M}\sum_{i\in I}\sum_{s\in S} b_{mi}d_{mi}q_{mis} \end{array} \right) \tag{32}$$

$$\sum_{l\in(I\cup J)}\sum_{j\in J} h_{js}x_{ljvs} \leqslant cap_v, v \in V,\ s \in S \tag{33}$$

$$\sum_{l\in(I\cup J)}\sum_{v\in V} x_{ljvs} = 1, \quad \forall j \in J,\ s \in S \tag{34}$$

$$\sum_{i\in I}\sum_{j\in J} x_{ijvs} \leqslant 1, \quad \forall v \in V,\ s \in S \tag{35}$$

$$\sum_{l\in(I\cup J)} x_{ljvs} - \sum_{l\in(I\cup J)} x_{jlvs} = 0, \quad \forall j\in J, v\in V,\ s\in S \tag{36}$$

$$\sum_{m\in M} q_{mis} \geqslant \sum_{j\in J} q_{ijs}, \quad \forall i \in I,\ s \in S \tag{37}$$

$$\sum_{l\in I+J, l\neq r} q_{lrs} - \sum_{j\in J, j\neq r} q_{rjs} = h_{rs}, \quad \forall r \in J,\ s \in S \tag{38}$$

$$\sum_{k\in K} X_{ik} \leqslant 1 \tag{39}$$

$$\sum_{m\in M} q_{mis} \leqslant \sum_{k\in K} c_{ik}X_{ik}, \quad \forall i \in I,\ s \in S \tag{40}$$

$$\sum_{j\in J} q_{ijs} \leqslant \sum_{k\in K} c_{ik}X_{ik}, \quad \forall i \in I, s \in S \tag{41}$$

$$q_{mis} \leqslant H\sum_{k\in K} X_{ik}, \quad \forall m \in M, i \in I,\ s \in S \tag{42}$$

$$q_{ljs} \leqslant H\sum_{v\in V} x_{ljvs}, \quad \forall j\in J, l\in(I\cup J),\ s\in S \tag{43}$$

$$x_{ijvs} \leqslant \sum_{k\in K} X_{ik}, \quad \forall i\in I, j\in J, \mathrm{v} \in V,\ s \in S \tag{44}$$

$$x_{ijvs} = 0, \quad \forall i\in I, j\in I, v\in V,\ s \in S \tag{45}$$

$$\sum_{j\in J} x_{ijvs} = \sum_{j\in J} x_{jivs}, \quad \forall i \in I, \mathrm{v} \in V,\ s \in S \tag{46}$$

$$x_{ljvs} \in (0,1), \quad \forall j \in J, l \in (I\cup J), v \in V,\ s \in S \tag{47}$$

$$\rho_{lj} + \theta_1 \geqslant a_{lj}d_{lj}q_{ljs}, \quad \forall l \in I+J, j \in J,\ s \in S \tag{48}$$

$$\rho_{lj}, \theta_1 \geqslant 0, \quad \forall l \in I+J,\ j \in J \tag{49}$$

$$\tau_{mi} + \theta_2 \geqslant a_{mi}d_{mi}q_{mis}, \quad \forall m \in M, i \in I,\ s \in S \tag{50}$$

$$\tau_{mi}, \theta_2 \geqslant 0, \quad \forall m \in M,\ i \in I \tag{51}$$

$$X_{ik} \in (0,1), \quad \forall i \in I, k \in K \tag{52}$$

$$\sum_{i\in I}\sum_{k\in K}\widehat{f}_{ik}X_{ik} + \sum_{i\in I}\sum_{k\in K}\widehat{\gamma}_{ik}c_{ik}X_{ik} + \sum_{m\in M}\sum_{i\in I}\sum_{s\in S}\widehat{b}d_{mi}q_{mis} + \sum_{l\in(I\cup J)}\sum_{j\in J}\sum_{s\in S}\widehat{b}d_{lj}q_{ljs} + \sum_{i\in I}\sum_{j\in J}\sum_{v\in V}\widehat{c}d_{ji}x_{jivs} + e_s{}^- - e_s{}^+ = L, \quad \forall s \in S \tag{53}$$

The objective function (32) represents the minimum total system cost and further integrates the transportation costs and their fluctuating values under different random demand

TABLE 2. Related parameters of demand points in group 1.

Demand point	X-axis	Y-axis	Demand (tons)	Demand point	X-axis	Y-axis	Demand (tons)
1	80	12	1	16	70	75	1.3
2	31	18	2.2	17	100	40	1.1
3	53	24	0.9	18	7	9	2
4	16	42	2.1	19	44	13	1.4
5	60	5	1.6	20	10	95	2.2
6	26	91	2.3	21	97	96	1
7	66	95	0.8	22	0	58	1.1
8	69	49	1.4	23	78	6	0.9
9	75	49	0.8	24	82	23	0.9
10	45	34	2.3	25	87	35	2.1
11	8	90	0.7	26	8	82	1.6
12	23	37	2	27	40	1	1.6
13	92	11	2	28	26	4	0.9
14	15	78	2.1	29	80	17	2.1
15	83	39	0.8	30	43	65	1.7

TABLE 3. Related parameters of candidate distribution centers in group 1.

Candidate Distribution Center	X-axis	Y-axis	Candidate Distribution Center	X-axis	Y-axis
1	91	73	9	14	18
2	18	65	10	86	37
3	26	45	11	62	63
4	14	55	12	35	78
5	13	29	13	51	8
6	87	75	14	40	93
7	58	19	15	7	78
8	55	69			

TABLE 4. Distribution center-related parameters at different capacity levels.

Capacity k (tons)	f_{ik} (CNY/d)	γ_{ik} (CNY)	$\widehat{f}_{ik}$ (ton /d)	$\widehat{\gamma}_{ik}$(ton /d)
200	50	0.15	879.75	1.026
300	70	0.04	1583.55	0.855

scenarios based on equation (29). Constraints (35)-(38), (40)-(48), and (50) all contain the subscript parameters of scenario s, which are the expressions of the corresponding constraints in model V under scenario s. The other constraints of model VI are the same as those of model V.

III. NUMERICAL CALCULATION AND ANALYSIS

A. PARAMETER VALUES

The robust optimization problem of the distribution network LRP under carbon trading policies is a new, integrated decision-making problem that lacks standardized examples. In this paper, two groups of examples are provided. According to the scale of demand points, 5 examples are designed for each group. Group 1 adopts the distribution network structure cited in [59], which includes 2 factories, 15 candidate distribution centers and 30 demand locations. Factory coordinates are [16, 24] and [80, 80], respectively, and related parameters of other network nodes are shown in Table 2 and Table 3. Carbon footprint parameters, vehicle load parameters and demand parameters are drawn from [13] and [49], and robust control parameters are drawn from [58]. Additionally, according to the characteristics of the example described in this paper, the values of relevant parameters are given as follows: The maximum number of vehicles available is $|V| = 6$. According to the 2018 freight rates of the China Post Group and distribution enterprises, including China Post, China National Materials Storage and Transportation Corporation, and SF Express, we can assume that the freight per unit of product and per unit of distance is $b_{mi} = b_{lj} = 0.02$ CNY/ton-km. According to the standards of the China Development Gateway, the per-unit amount of transportation emissions is $\widehat{b} = 0.3$ tons/km, and the per-unit amount of emissions generated from vehicle idling is $\widehat{c} = 4$ tons/km. The cost of vehicle idling per unit of distance is $c = 0.04$ CNY, the fixed departure cost per vehicle is $c_0 = 40$ CNY/vehicle, the maximum carrying capacity of a heavy-duty semi-trailer is $cap_v = 150$ tons, the carbon trading price is $p = 0.06$ CNY/ton, and the indeterminate level parameters are $\Gamma_1 = \Gamma_2 = 1$, $\varepsilon_l = \varepsilon_m = 0.05$. Table 4 shows the capacity level of the distribution center and construction cost allocation, per-unit operation cost, carbon emissions allocation and per-unit operational emissions allocation parameters. The parameters of group 2 were moderately improved on the basis of group 1 to test the reliability of model VI (i.e., the two-stage stochastic programming model). We assume three types of demand, corresponding to the off season, normal season and peak season.

TABLE 5. Distribution center-related parameters at different capacity levels.

Num.	Demand point	Open Distribution Center [level]	Routing	Carbon emissions (ton)	Target Value (CNY)
1	10	⑤[1]	⑤-4-6-7-⑤/⑤-10-8-9-3-⑤/⑤-2-5-1-⑤	5023.76	423.40
2	15	⑤[2]	⑤-4-14-11-6-7-⑤/⑤-12-10-8-9-15-3-⑤/⑤-2-5-1-13-⑤	7821.60	667.00
3	20	⑤[1] ⑥[1]	⑥-16-7-⑥/⑤-2-19-5-3-⑤/⑤-12-18-⑤/⑥-9-8-10-⑥/⑥-15-1-13-17-⑥/⑤-4-14-11-20-6-⑤	9021.19	925.68
4	25	⑤[2] ⑥[1]	⑥-21-7-16-⑥/⑥-9-8-15-25-24-17-⑥/⑤-4-14-11-20-6-⑤/⑤-12-10-3-⑤/⑤-18-22-⑤/⑤-2-19-5-23-1-13-⑤	11623.34	1142.90
5	30	⑤[2] ⑥[2]	⑤-12-10-3-5-⑤/⑥-15-25-24-29-1-23-13-⑥/⑤-4-14-26-11-20-6-22-⑤/⑥-21-7-30-⑥/⑥-16-8-9-17-⑥/⑤-2-19-27-28-18-⑤	14280.7	1378.38

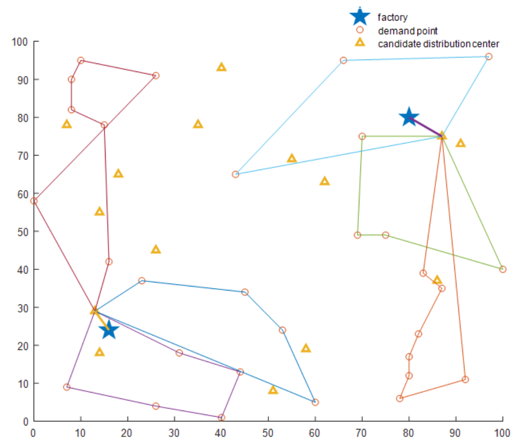

FIGURE 1. Results of location-routing decision making (Example 5 of group 1).

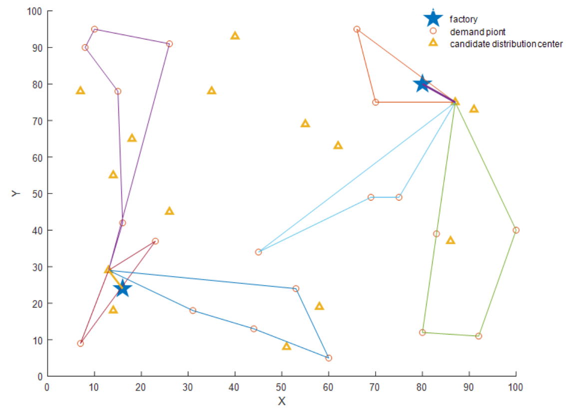

FIGURE 2. Result of location-routing decision making (Example 3 of group 1).

Under scenario 2, the demand of demand points is generated randomly and evenly in the range [200 350], and then it expands downward and upward by 20% to obtain the demand of scenarios 1 and 3, respectively. Candidate distribution centers, demand points and factories were generated randomly in the coordinate plane of 100*100. In group 2, parameters such as the location of various nodes and demand point requirements are randomly generated to make the network structure, and examples can be extended more in the general setting. The settings of other parameters were the same as those of group 1.

It was found that the main network structure parameter affecting the target value is the number of demand points. Therefore, according to the number of demand points, five calculation examples with different scales in each group were set, and the carbon emissions cap L applied to the calculation examples of different scales was set as 5000, 6000, 7000, 8000 and 9000.

B. CALCULATION RESULTS

The solver GUROBI 8.0.1 was used to calculate the model. The calculation results of five examples tested on group 1 are shown in Table 5, and the location-routing decision-making results of two examples are shown in Figures 1 and 2.

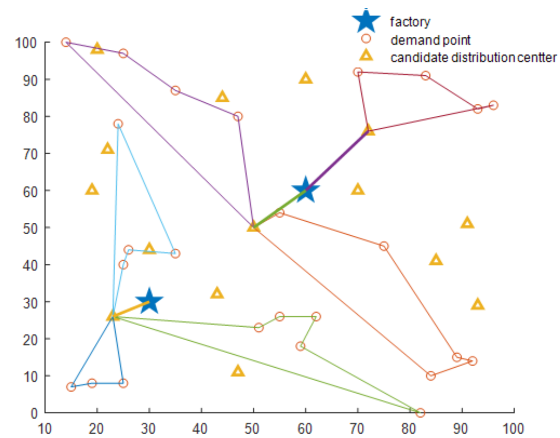

FIGURE 3. Result of location-routing decision making under scenario 1 (Example 4 of group 2).

Figures 3 to 5 reflect location-routing decision making under three different demand scenarios for Example 4 of group 2.

C. THE IMPACT OF CARBON TRADING POLICIES

To analyze the impact of carbon trading policies on enterprise decision-making, the LRP model I without considering carbon trading policies and the LRP model II considering carbon

TABLE 6. Comparisons of LRP decision-making results considering and not considering carbon trading policies for group 1.

Numerical Example		Open Distribution Center [level]	Routing	Carbon Emissions (ton)	Total Cost (CNY)	Location and operation costs (CNY)	Carbon emissions cost (CNY)
10 demand points	Model I	⑤[1]	⑤-4-10-8-9-7-6-⑤/⑤-2-3-5-1-⑤	5326.10	432.29	412.72	19.57
	Model II	⑤[1]	⑤-4-6-7-⑤/⑤-10-8-9-3-⑤/⑤-2-5-1-⑤	5023.76	420.02	418.60	1.42
15 demand points	Model I	⑤[2]	⑤-4-14-11-6-7-⑤/⑤-2-3-5-1-13-⑤/⑤-12-10-8-9-15-⑤	7916.28	668.48	553.50	114.98
	Model II	⑤[2]	⑤-4-14-11-6-7-⑤/⑤-12-10-8-9-15-3-⑤/⑤-2-5-1-13-⑤	7821.60	663.38	554.08	109.30
20 demand points	Model I	⑤[2] ⑥[1]	⑥-16-7-⑥/⑤-18-2-19-5-⑤/⑤-4-14-11-20-6-⑤/⑥-9-8-15-17-⑥ ⑤-12-10-3-1-13-⑤	9913.80	943.03	768.20	174.83
	Model II	⑤[1] ⑥[1]	⑤-2-19-5-3-⑤/⑤-4-14-11-20-6-⑤ ⑤-12-18-⑤/⑥-9-8-10-⑥/⑥-16-7-⑥/⑥-15-1-13-17-⑥	9021.19	921.45	800.18	121.27
25 demand points	Model I	⑤[2] ⑥[1]	⑥-21-7-16-⑥/⑥-9-8-15-25-24-17-⑥/⑤-4-14-11-20-6-⑤/⑤-12-10-3-⑤/⑤-18-22-⑤/⑤-2-19-5-23-1-13-⑤	11772.99	1141.58	915.20	226.38
	Model II	⑤[2] ⑥[1]	⑥-21-7-16-⑥/⑥-9-8-15-25-24-17-⑥/⑤-4-14-11-20-6-⑤/⑤-12-10-3-⑤/⑤-18-22-⑤/⑤-2-19-5-23-1-13-⑤	11623.34	1137.91	920.51	217.40
30 demand points	Model I	⑤[2] ⑥[2]	⑥-21-7-16-⑥/⑥-15-25-24-29-1-23-13-⑥/⑤-12-4-14-26-11-20-6-22-⑤/⑤-18-28-27-5-⑤/⑤-2-19-3-10-30-⑤ ⑥-9-8-17-⑥	14382.76	1376.16	1053.19	322.97
	Model II	⑤[2] ⑥[2]	⑤-12-10-3-5-⑤/⑥-15-25-24-29-1-23-13-⑥/⑤-4-14-26-11-20-6-22-⑤/⑥-21-7-30-⑥/⑥-16-8-9-17-⑥/⑤-2-19-27-28-18-⑤	14280.70	1370.41	1053.57	316.84

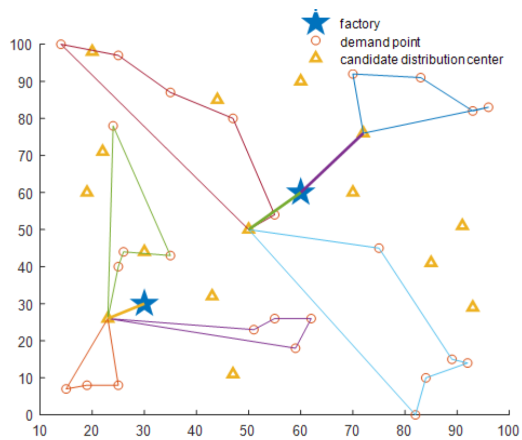

FIGURE 4. Result of location-routing decision making under scenario 2 (Example 4 of group 2).

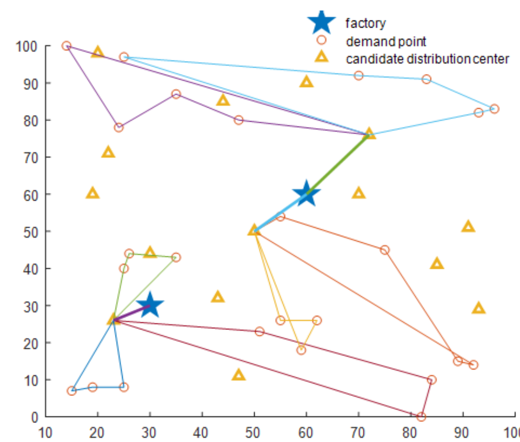

FIGURE 5. Result of location-routing decision making under scenario 3 (Example 4 of group 2).

trading policies were calculated and compared. The results are shown in Table 6 and Figure 6. In this study, the carbon emissions cost was defined as the carbon trading cost, and when carbon emissions costs were found to be negative, this reflected the generation of corporate profits by selling carbon trading rights. Costs other than carbon emissions were defined as location and operation costs. It should be noted that the calculation results of model I do not include carbon emissions and carbon emissions costs. By calculating the optimal solution of model I and substituting it into model II, carbon emissions, carbon emissions costs and actual total costs of the decision-making solution determined under carbon trading policies were obtained. The computational results show that carbon trading policies can effectively reduce the carbon emissions of enterprises, with carbon emissions reduction ratios of 5.68%, 1.20%, 9.00%, 1.27% and 0.71%. As seen from Table 6 and Figure 3, although location and operation costs were lower under the decision-making scheme not considering carbon trading policies (model I), the influence of carbon trading policies was neglected, resulting in an increase in carbon emissions costs and total costs for enterprises, and increases in proportions of the total cost were recorded as 2.84%, 0.76%, 2.29%, 0.32% and 0.42%. Therefore, carbon trading policies had a distinct carbon emission-abating effect.

TABLE 7. Comparisons of LRP decision-making results considering and not considering carbon trading policies for group 2.

Numerical Example	Without carbon trading policies				With carbon trading policies			
	Carbon Emissions (ton)	Total Cost (CNY)	Location and operation costs (CNY)	Carbon emissions cost (CNY)	Carbon Emissions (ton)	Total Cost (CNY)	Location and operation costs (CNY)	Carbon emissions cost (CNY)
10	6752.71	715.37	610.21	105.16	7010.52	725.16	604.53	120.63
15	10045.72	1033.42	790.68	242.74	10149.47	1037.95	788.98	248.97
20	13085.49	1394.25	1029.12	365.13	13492.03	1414.54	1025.02	389.52
25	16907.19	1755.54	1221.11	534.43	17097.27	1763.56	1217.72	545.84
30	18982.4	2005.23	1406.29	598.94	19314.27	2024.28	1392.42	631.86

TABLE 8. Sensitivity analysis of p (p unrelated to L) for group 1.

$p^{(CNY/ton)}$	Carbon emissions (ton)	Location and operation costs (CNY)	Carbon emissions cost (CNY)	Total Cost (CNY)	Ratio
0	**5326.1**	**412.72**	**0.00**	**412.72**	**-**
0.001	5326.1	412.72	0.33	413.04	1250.67
0.01	5326.1	412.72	3.26	415.98	126.56
0.02	**5071.1**	**416.12**	**1.42**	**417.54**	**293.04**
0.03	5071.1	416.12	2.13	418.26	195.36
0.04	5071.1	416.12	2.84	418.97	146.52
0.05	5071.1	416.12	3.56	419.7	116.89
0.06	**5023.76**	**418.60**	**1.42**	**420.02**	**294.79**
0.07	5023.76	418.60	1.66	420.26	251.68
0.08	5023.76	418.60	1.90	420.50	220.22
0.09	5023.76	418.60	2.14	420.74	195.75
0.1	5023.76	418.60	2.38	420.98	176.18
0.2	**5019.56**	**419.22**	**3.91**	**423.13**	**107.16**
0.3	5019.56	419.22	5.87	425.09	71.44
0.4	5019.56	419.22	7.82	427.04	53.58

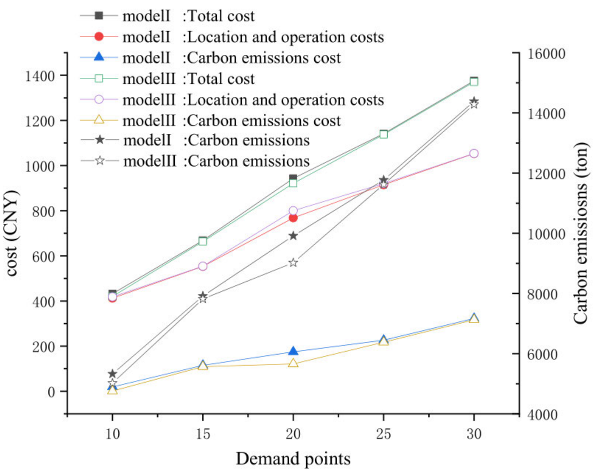

FIGURE 6. Influence of carbon trading policies on LRP decision-making for group 1.

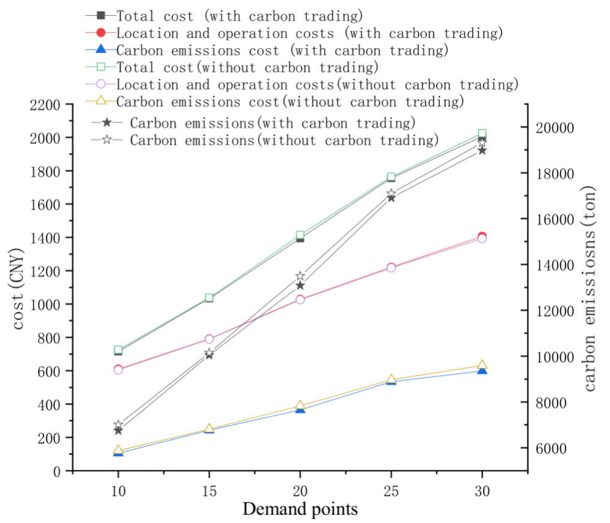

FIGURE 7. Influence of carbon trading policies on LRP decision-making for group 2.

For enterprises, considering the impact of carbon trading policies during location-routing operation decision-making could reduce total system costs. Table 7 and Figure 7 show the calculation results of the second set of examples consistent with group 1. The results show that in a stochastic demand environment, carbon trading policies also reduce carbon emissions, which would prompt enterprises to alter their optimal decision-making.

D. SENSITIVITY ANALYSIS OF CARBON TRADING PRICE P AND EMISSIONS CAP L

Under carbon trading policies, two factors influenced enterprise decision-making, carbon trading prices p and emissions caps L. First, the impact of changes in p on the decision-making results was analyzed. To eliminate the impact of freight rate changes on the results, the sensitivity of p was analyzed based on model II. Taking the 10-demand-point network as an example, the calculation results are shown in Table 8. As seen from Table 8 and Figure 8, higher carbon trading prices could constrain enterprises from reducing carbon emissions. However, with an increase in p, carbon emissions exhibit a ladder-like downward trend. For instance, when p increased from 0 to 0.02,

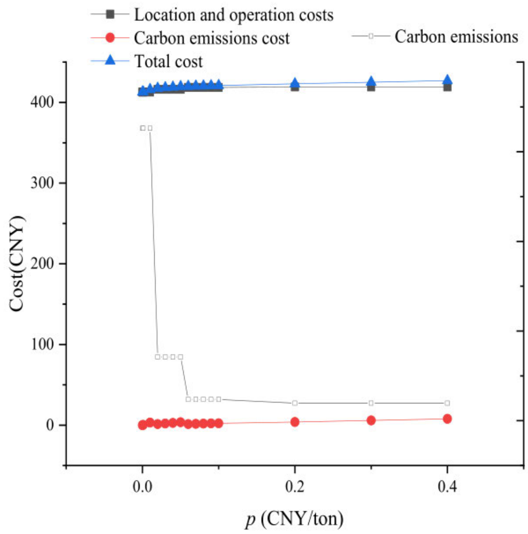

FIGURE 8. Cost structure and carbon emissions under different values of p (p unrelated to L) for group 1.

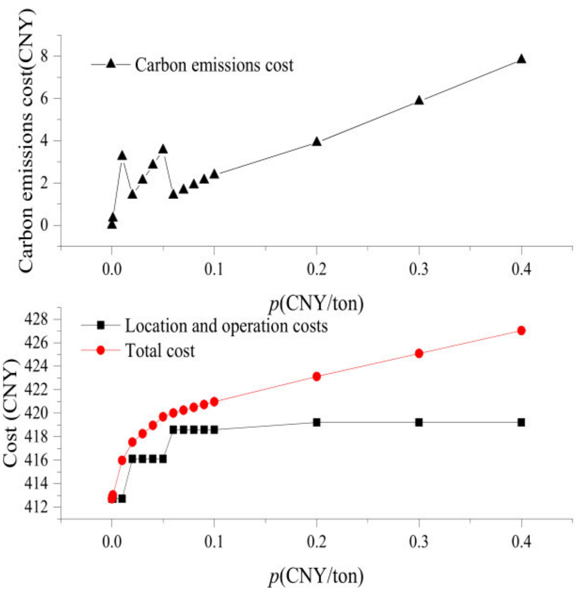

FIGURE 9. Cost variation under different values of p (p unrelated to L) for group 1.

carbon emissions reduced by 255 tons. When p increased from 0.02 to 0.06, carbon emissions decreased by 47.34 tons. Table 8 and Figure 9 show that optimal decision-making by an enterprise remains unchanged within a certain range of p values. For example, when p increased from 0.02 to 0.05, optimal decision-making did not change until the price increased to 0.06. Within this interval, even if p increased, enterprises would only increase production costs and not reduce carbon emissions. Nevertheless, when p increased to a certain threshold, the carbon emissions cost increased significantly. Meanwhile, it was necessary for enterprises to adjust their optimal decision-making and to reduce carbon emissions and carbon emissions costs to minimize system costs.

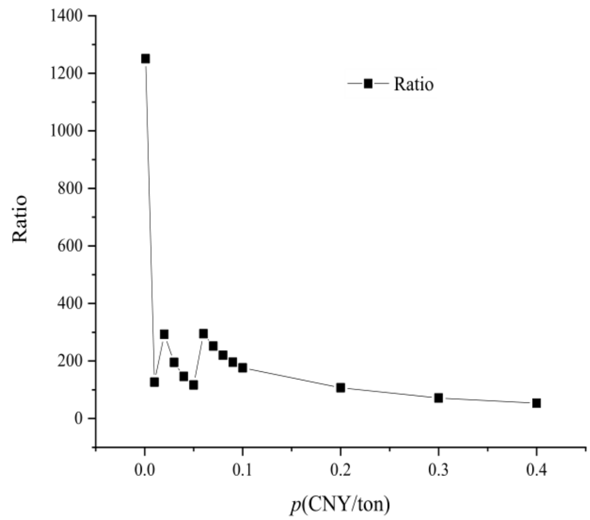

FIGURE 10. Ratio of location and operation costs to carbon emissions costs (p unrelated to L) for group 1.

Regarding cost structure trends, within a certain range of p, the carbon emissions cost and total system cost progressively increased because the optimal decision-making results remained unchanged as well as carbon emissions and location and operation costs. When p exceeded the threshold and the optimal decision-making results changed, carbon emissions costs temporarily fell. Because the decrease in carbon emissions cost is less than the increase in location and operation costs, the total cost of the system increased. Then, the optimal decision-making results and location and operation costs remained unchanged, and the carbon emissions cost and total cost of the system continued to increase until p exceeded the next threshold, and the optimal decision-making results changed again. As shown in Figure 10, the ratio curve of location and operation costs/carbon emissions costs fluctuated in a wave-like manner.

The results of our sensitivity analysis of the carbon emissions cap L are shown in Table 9 and demonstrate that L had little influence on carbon emissions and optimal decision-making under carbon trading policies. This occurred because the difference in

$$L - \left[\begin{array}{l} \sum_{i\in I}\sum_{k\in K}\widehat{f}_{ik}X_{ik} + \sum_{i\in I}\sum_{k\in K}\widehat{\gamma}_{ik}c_{ik}X_{ik} \\ + \sum_{m\in M}\sum_{i\in I}\widehat{b}d_{mi}q_{mi} + \sum_{l\in(I\cup J)}\sum_{j\in J}\widehat{b}d_{lj}q_{lj} \\ + \sum_{i\in I}\sum_{j\in J}\sum_{v\in V}\widehat{c}d_{ji}x_{jiv} + (e^{-} - e^{+}) \end{array}\right]$$

could be adjusted by carbon trading, and the carbon emissions cost was much greater than location and operation costs; thus, optimal decision-making and carbon emissions remained unchanged. However, this reflects decision-making under conditions in which the carbon trading price p was independent of the emissions cap L. Actually, carbon trading prices p fluctuated with different emissions caps L. Therefore, we next

TABLE 9. Sensitivity analysis of L (p unrelated to L) for group 1.

p	L	Carbon emissions (ton)	Location and operation costs (CNY)	Carbon emissions cost (CNY)	Total cost (CNY)
p=0.06	1000	5023.76	418.60	241.42	660.02
	5000	5023.76	418.60	1.42	420.02
	10000	5023.76	418.60	-298.58	120.02
p=0.12	1000	5023.76	418.60	482.85	901.45
	5000	5023.76	418.60	2.85	421.45
	10000	5023.76	418.60	-597.15	-178.55

TABLE 10. Sensitivity analysis of L (p related to L) for group 1.

L (ton)	Carbon emissions (ton)	Location and operation costs (CNY)	Carbon emissions cost (CNY)	Total cost (CNY)
1000	5019.56	419.22	728.82	1148.04
2000	5019.56	419.22	482.04	901.26
3000	**5023.76**	**418.60**	**279.2**	**697.80**
4000	5023.76	418.60	119.04	537.64
5000	5023.76	418.60	2.24	420.84
6000	5023.76	418.60	-71.19	347.41
7000	**5071.10**	**416.12**	**-98.83**	**317.29**
8000	5071.10	416.12	-86.58	329.54
9000	**5326.10**	**412.72**	**-28.95**	**383.77**
9300	5326.10	412.72	-5.47	407.25

analyzed the impact of p on enterprise decision-making when it was related to L. It is assumed that p and L were linearly related and $p = 0.203 - 2.168 * 10^{-5} * L$. For carbon trading, the lower the emissions cap L, the stricter the government's emission constraints on enterprises, and the more the government wants enterprises to reduce emissions. When the price of carbon trading is higher, the cost of purchasing emissions for enterprises is higher, which can also constrain enterprises in terms of reducing emissions. Therefore, under this assumption, we adjusted L and then changed p and thus constrained enterprises to reduce emissions from both policy and market perspectives. The assumption guaranteed p within a reasonable range of [0, 0.203]. The objective function of model II was then transformed into formula (54).

$$\begin{aligned}\min Z_2 = &\sum_{i\in I}\sum_{k\in K} f_{ik}X_{ik} + \sum_{i\in I}\sum_{k\in K}\gamma_{ik}c_{ik}X_{ik}\\ &+\sum_{m\in M}\sum_{i\in I} b_{mi}d_{mi}q_{mi}\\ &+\sum_{l\in(I\cup J)}\sum_{j\in J} b_{lj}d_{lj}q_{lj}\\ &+\sum_{i\in I}\sum_{j\in J}\sum_{v\in V} cd_{ji}x_{jiv}\\ &+\sum_{i\in I}\sum_{j\in J}\sum_{v\in V} c_0x_{ijv}\\ &+(0.203-2.168*10^{-5}*L)*(e^{+}-e^{-}) \quad (54)\end{aligned}$$

Then, under the condition that the carbon trading price p is related to the emissions cap L, what was the impact of L on enterprises' decision-making? Table 10 shows the results of our sensitivity analysis of L. Figures 11 and 12 show the cost structure and carbon emissions under different L and p values, respectively. It can be observed that with an increase

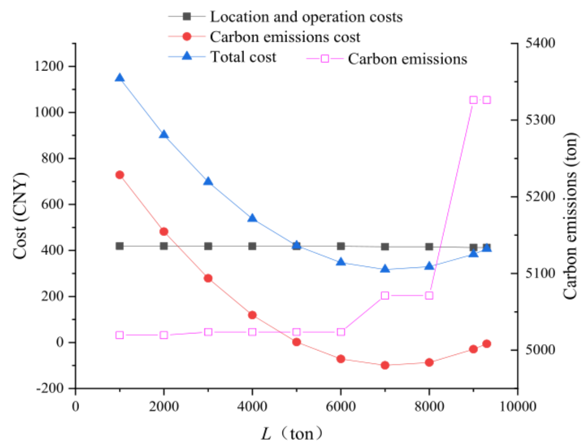

FIGURE 11. Cost structure and carbon emissions under different L values (p related to L) for group 1.

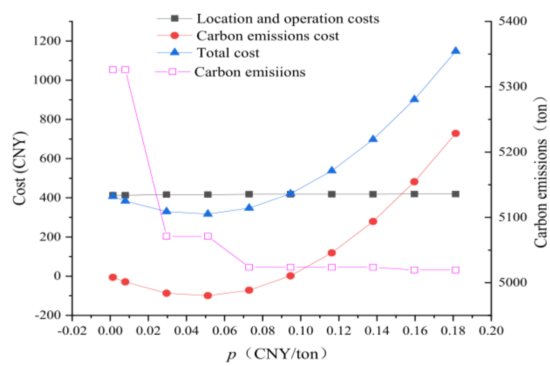

FIGURE 12. Cost structure and carbon emissions under different p values (p related to L) for group 1.

in L, p progressively decreased, enterprises adjusted optimal decision-making accordingly, and carbon emissions followed a ladder-like upward trend. The results given in Table 10,

TABLE 11. Decision-making results based on combinations of different robust control parameters for group 1.

Γ	ε	Open Distribution Center [level]	Routing	Carbon Emissions (ton)	Target Value (CNY)
0	-	⑤[1]	⑤-4-6-7-⑤/⑤-10-8-9-3-⑤/⑤-2-5-1-⑤	5023.76	420.02
1	0.05	⑤[1]	⑤-4-6-7-⑤/⑤-10-8-9-3-⑤/⑤-2-5-1-⑤	5023.76	423.40
	0.06	**⑤[1]**	**⑤-4-6-7 -⑤/⑤-2-3-⑤-1-⑤/⑤-10-8-9-⑤**	**5071.10**	**424.02**
	0.1	⑤[1]	⑤-4-6-7 -⑤/⑤-2-3-⑤-1-⑤/⑤-10-8-9-⑤	5071.10	426.44
3	0.04	⑤[1]	⑤-4-6-7-⑤/⑤-10-8-9-3-⑤/⑤-2-5-1-⑤	5023.76	424.86
	0.05	**⑤[1]**	**⑤-4-6-7 -⑤/⑤-2-3-⑤-1-⑤/⑤-10-8-9-⑤**	**5071.10**	**426.07**
	0.06	⑤[1]	⑤-4-6-7 -⑤/⑤-2-3-⑤-1-⑤/⑤-10-8-9-⑤	5071.10	427.21
5	0.03	⑤[1]	⑤-4-6-7-⑤/⑤-10-8-9-3-⑤/⑤-2-⑤-1-⑤	5023.76	425.08
	0.04	**⑤[1]**	**⑤-4-6-7 -⑤/⑤-2-3-5-1-⑤/⑤-10-8-9-⑤**	**5071.10**	**426.71**
	0.05	⑤[1]	⑤-4-6-7 -⑤/⑤-2-3-⑤-1-⑤/⑤-10-8-9-⑤	5071.10	428.30

Notes: $\Gamma = \{\Gamma_1,\ \Gamma_2\}\ \&\Gamma_1 = \Gamma_2, \varepsilon = \{\varepsilon_l,\ \varepsilon_m\}\ \&\varepsilon_l = \varepsilon_m$

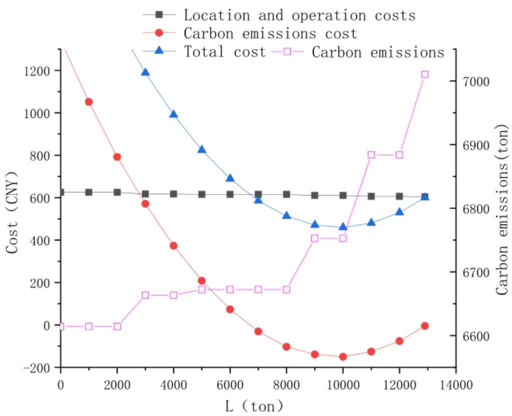

FIGURE 13. Cost structure and carbon emissions under different L values (p related to L) for group 2.

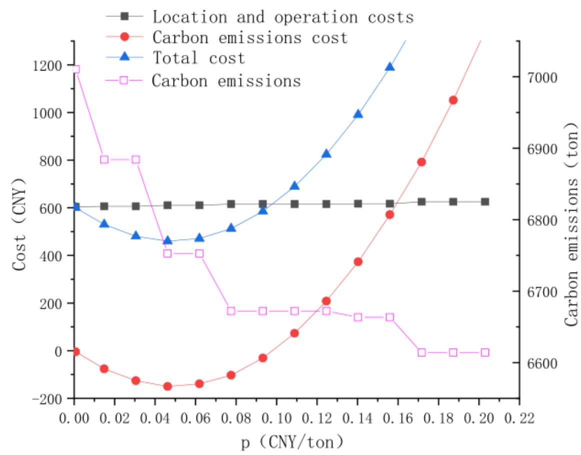

FIGURE 14. Cost structure and carbon emissions under different p values (p related to L) for group 2.

Figure 11, and Figure 12 show that the amplitude of fluctuations in location and operation costs were small, and the increase in total costs of the system mainly occurred due to the increase in carbon emissions costs. Meanwhile, the optimal decision-making of enterprises remained unchanged within a certain range of L and p fluctuations. This phenomenon indicates that although carbon trading policies had carbon abatement effects as a whole, this effect was shaped by market conditions. Therefore, the government should set a reasonable carbon emissions cap to adjust market prices according to market conditions and encourage enterprises to alter their optimal decision-making and reduce carbon emissions to achieve the optimal carbon abatement effect.

Figures 13 and 14 show the cost structure and carbon emissions of model VI under different L and t p values, respectively. Their graphic features are similar to those shown in Figures 11 and 12. This indicates that the above conclusion is valid for the two-stage stochastic programming model.

E. SENSITIVITY ANALYSIS OF ROBUST CONTROL PARAMETERS

Finally, the sensitivity of robust control parameters was analyzed. Taking the 10-demand-point network as an example, linear robust optimization models V and VI were solved by changing the indeterminate level parameters Γ_1 and Γ_2 and the disturbance ratios ε_l and ε_m of the unit freight; the optimal decision-making results for combinations of different robust control parameters are shown in Tables 11 and 12. The bolded text in Tables 11 and 12 shows how the optimal location-inventory decision-making results changed. The results show that the greater the indeterminate level parameter and disturbance ratio, the more obvious the change in the optimal decision-making results. For instance, in Table 11, when the indeterminate level parameter Γ was valued at 1 and the disturbance ratio ε was valued at 0.05, the optimal decision-making results did not change, but when the disturbance ratio was valued at 0.06, the optimal decision-making result changed; when the combination of robust control parameters included $\Gamma = 5$ and $\varepsilon = 0.04$, the optimal solution changed. In addition, an increase in the indeterminate level parameter and disturbance ratio would lead to an increase in the total cost of the system.

Therefore, the indeterminate fluctuation of the unit freight and other parameters affects the optimal decision-making of enterprises. Because the multi-capacity-level location of distribution centers reflects a strategic decision-making problem, once a facility was established, it was difficult to change within a short period of time. Therefore, when an enterprise

TABLE 12. Decision-making results based on combinations of different robust control parameters for group 2.

Γ	ε	Open Distribution Center [level]	Routing: scenario 1	Routing: scenario 2	Routing: scenario 3	Carbon Emissions (ton)	Target Value (CNY)
0	-	④[1], ⑧[1]	④-10-8-④/④-9-2-3-④/⑧-7-1-5-⑧/⑧-4-6-⑧	⑧-7-3 ⑧/④-2-9-④/④-10-8-④/⑧-1-5-⑧/⑧-4-6-⑧	⑧-7-3-⑧/④-2-9-④/④-10-8-④/⑧-1-5-⑧/⑧-4-6-⑧	6752.71	711.06
1	0.1	④[1], ⑧[1]	4-10-8-④/④-9-2-3-④/⑧-7-1-5-⑧/⑧-4-6-⑧	⑧-7-3 ⑧/④-2-9-④/④-10-8-④/⑧-1-5-⑧/⑧-4-6-⑧	⑧-7-3 ⑧/④-2-9-④/④-10-8-④/⑧-1-5-⑧/⑧-4-6-⑧	6752.71	719.69
	0.2	④[1], ⑧[1]	④-10-8-④/④-9-2-3-④/⑧-7-1-5-⑧/⑧-4-6-⑧	⑧-7-3 ⑧/④-2-9-④/④-10-8-④/⑧-1-5-⑧/⑧-4-6-⑧	⑧-7-3 ⑧/④-2-9-④/④-10-8-④/⑧-1-5-⑧/⑧-4-6-⑧	6752.71	728.31
	0.5	④[1], ⑧[1]	④-10-8-④/④-9-2-3-④/⑧-7-1-5-⑧/⑧-4-6-⑧	⑧-7-3 ⑧/④-2-9-④/④-10-8-④/⑧-1-5-⑧/⑧-4-6-⑧	⑧-7-3-⑧/④-2-9-④/④-10-8-④/⑧-1-5-⑧/⑧-4-6-⑧	6752.71	754.2
	0.6	④[1], ⑧[1]	④-10-8-④/④-9-2-3-④/⑧-7-1-5-⑧/⑧-4-6-⑧	⑧-7-3-⑧/④-2-9-④/④-10-8-④/⑧-1-5-⑧/⑧-④-6-⑧	⑧-7-3-⑧/④-2-9-④/④-10-8-④/⑧-1-5-⑧/⑧-4-6-⑧	6752.71	762.82
	0.7	**④[1], ⑧[1]**	**⑧-7-1-5-⑧/④-10-8-④/⑧-4-6-⑧/④-9-2-3-④**	**④-2-9-④/⑧-4-6-⑧/⑧-7-3-⑧ / ⑧-1-5-⑧/④-2-9-④**	**④-9-2-3-④/⑧-7-⑧/④-10-8-④/⑧-4-6-⑧/⑧-1-5-⑧**	**6771.01**	**771.12**
	0.9	④[1], ⑧[1]	⑧-7-1-5-⑧/④-10-8-④/⑧-4-6-⑧/④-9-2-3-④	④-2-9-④/⑧-4-6-⑧/⑧-7-3-⑧ / ⑧-1-5-⑧/④-2-9-④	④-9-2-3-④/⑧-7-⑧/④-10-8-④/⑧-4-6-⑧/⑧-1-5-⑧	6771.01	787.27
3	0.1	④[1], ⑧[1]	④-10-8-④/④-9-2-3-④/⑧-7-1-5-⑧/⑧-4-6-⑧	⑧-7-3-⑧/④-2-9-④/④-10-8-④/⑧-1-5-⑧/⑧-4-6-⑧	⑧-7-3-⑧/④-2-9-④/④-10-8-④/⑧-1-5-⑧/⑧-4-6-⑧	6752.71	728.08
	0.2	④[1], ⑧[1]	④-10-8-④/④-9-2-3-④/⑧-7-1-5-⑧/⑧-4-6-⑧	⑧-7-3-⑧/④-2-9-④/④-10-8-④/⑧-1-5-⑧/⑧-4-6-⑧	⑧-7-3-⑧/④-2-9-④/④-10-8-④/⑧-1-5-⑧/⑧-4-6-⑧	6752.71	745.09
	0.3	**④[1], ⑧[1]**	**⑧-4-6-⑧/ ④-10-8-④/⑧-7-1-5-⑧/④-2-9-3-④**	**④-2-9-④/⑧-1-5-⑧/⑧-7-3-⑧/⑧-4-6-⑧/④-10-8-④**	**④-2-9-④/⑧-1-5-⑧/⑧-7-3-⑧/⑧-4-6-⑧/④-10-8-④**	**6756.35**	**762.07**
	0.5	④[1], ⑧[1]	⑧-4-6-⑧/ ④-10-8-④/⑧-7-1-5-⑧/④-2-9-3-④	④-2-9-④/⑧-1-5-⑧/⑧-7-3-⑧/⑧-4-6-⑧/④-10-8-④	④-2-9-④/⑧-1-5-⑧/⑧-7-3-⑧/⑧-4-6-⑧/④-10-8-④	6756.35	795.77
5	0.1	④[1], ⑧[1]	④-10-8-④/④-9-2-3-④/⑧-7-1-5-⑧/⑧-4-6-⑧	⑧-7-3-⑧/④-2-9-④/④-10-8-④/⑧-1-5-⑧/⑧-4-6-⑧	⑧-7-3-⑧/④-2-9-④/④-10-8-④/⑧-1-5-⑧/⑧-4-6-⑧	6752.71	732.88
	0.2	**④[1], ⑧[1]**	**⑧-4-6-⑧/ ④-10-8-④/⑧-7-1-5-⑧/④-2-9-3-④**	**④-2-9-④/⑧-1-5-⑧/⑧-7-3-⑧/⑧-4-6-⑧/④-10-8-④**	**④-2-9-④/⑧-1-5-⑧/⑧-7-3-⑧/⑧-4-6-⑧/④-10-8-④**	**6756.35**	**754.55**
	0.5	④[1], ⑧[1]	⑧-4-6-⑧/ ④-10-8-④/⑧-7-1-5-⑧/④-2-9-3-④	④-2-9-④/⑧-1-5-⑧/⑧-7-3-⑧/⑧-4-6-⑧/④-10-8-④	④-2-9-④/⑧-1-5-⑧/⑧-7-3-⑧/⑧-4-6-⑧/④-10-8-④	6756.35	819.1
	0.9	④[1], ⑧[1]	⑧-4-6-⑧/ ④-10-8-④/⑧-7-1-5-⑧/④-2-9-3-④	④-2-9-④/⑧-1-5-⑧/⑧-7-3-⑧/⑧-4-6-⑧/④-10-8-④	④-2-9-④/⑧-1-5-⑧/⑧-7-3-⑧/⑧-4-6-⑧/④-10-8-④	6756.35	905.16

is making a location-routing integration decision, it should fully consider the indeterminacy of the unit freight and other parameters and seek more robust decision-making results

F. CHARACTERISTICS OF ROUTING SOLUTIONS

In analyzing the characteristics of routing solutions and their quantities, it was found that enabling more vehicles could reduce emissions (Tables 5 and 6); enabling more vehicles on short routings and prioritizing high-demand customers could also reduce emissions. For instance, the last two routings of the 15-demand-point numerical example shown in Table 5 reduced carbon emissions through the post-distribution low-demand customer location 3. This conclusion echoes those given in literature [41]. This was observed because enabling more vehicles, reducing routing lengths and prioritizing high-demand customers can reduce the average load while vehicles are in motion and thus reduce carbon emissions. However, it is clear that enabling more vehicles would increase operation costs; hence, enterprises need to enable vehicles in a more realistic manner to balance operation costs with carbon emissions costs.

IV. CONCLUSION

Carbon trading will have a significant impact on LRP decisions for distribution networks. In a real-world distribution network, operating parameters such as unit freight are uncertain. The research on the uncertain green DNLRP has more practical application value. Based on the traditional LRP of supply chain distribution networks, a multi-capacity-level robust optimization GLRP of distribution network design under carbon trading policies was studied in this paper. This is the main theoretical contribution of our investigation. Based on mixed integer nonlinear programming, the corresponding mathematical model was constructed. The nonlinear model was transformed into a linear robust equivalent model by means of strong duality theory, and calculations and numerical analysis were carried out using the solver GUROBI. In the calculations of the GLRP, we conducted different sensitivity analyses by changing some key parameters, including the carbon trading price p, the emissions cap L, and robust control parameters.

Overall, our results show that when considering carbon emissions and carbon trading policies, adding "green" factors to the objective function does affect the optimal solution. From the results of this paper, we can draw management insights. First, carbon trading policies have a carbon abatement effect. For governments, carbon trading is a more effective measure for reducing carbon emissions. For enterprises, carbon emissions trading might make it possible for them to increase carbon emissions costs and secure additional benefits from the reduction of carbon emissions. Therefore, enterprises should fully consider the impact of carbon trading policies on their decision-making. Second, with a decrease in carbon emissions caps and an increase in carbon trading prices, carbon emissions undergo a ladder-like downward trend. When carbon trading prices relate to emissions caps, the amplitudes of fluctuations in location and operation costs are small, and fluctuations in the total system cost are mainly due to the variation in carbon emissions costs. Therefore, from a macrocontrol perspective, the government should set a reasonable carbon emissions cap according to the scale and structure of the market to avoid excessively increasing the burden on enterprises while also encouraging enterprises to alter their optimal decision-making and reduce carbon emissions to achieve the optimal carbon abatement effect. For enterprises, to reduce location and operation costs as well as total system costs, it is necessary to find the threshold of carbon trading prices under current conditions and maintain the original optimal decision-making without exceeding the threshold or even to increase emissions by an appropriate amount when the threshold is not exceeded. Conversely, low carbon emissions and low carbon trading costs should be pursued to reduce overall costs. As a result, governments and enterprises need to work together to achieve a balance between economic and environmental benefits, leading to a win-win situation. Third, the indeterminate fluctuation of the unit freight will influence the optimal decision-making of enterprises. Because the indeterminate level parameter in the robust optimization model measures the conservatism of decision-makers to some extent, in practice, decision-makers can choose appropriate robust control parameters according to their preference and risk aversion and then determine decision schemes for distribution networks to provide a reference for government decision-making. The multi-capacity-level location of distribution centers is a strategic decision-making problem. Once established, the distribution centers are difficult to change over a short period of time. Therefore, when an enterprise designs a network, enterprises should fully consider the indeterminacy of various parameters and seek a robust decision-making solution. Although robust optimization cannot achieve the optimal solution in a deterministic scenario, considering critical uncertain information at the network design stage can significantly reduce future emergency costs. Finally, making more vehicles available while giving priority to locations with high demand on short routings could reduce emissions. Therefore, when the carbon trading price does not exceed the threshold, it is advisable to enable more vehicles and prioritize high-demand customer locations to reduce carbon emissions costs and total costs. Conversely, fewer vehicles should be permitted to reduce location and operation costs.

This study is limited in that it does not take into account the time window constraints of the client or vehicle speeds. Further research can introduce time windows and vehicle running speeds to further study the GLRP under carbon trading policies. Another avenue for further research would involve integrating inventory decision-making into LRP decision-making and studying location-inventory-routing problems. More indeterminate parameters, such as supply, can also be taken into account in researching the robust GLRP optimization model under multiclass indeterminate parameters.

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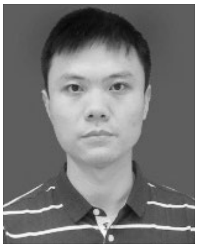

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