MATHEMATICAL MODELS AND OPTIMIZATION ALGORITHMS FOR LOW-CARBON LOCATION-INVENTORY-ROUTING PROBLEM WITH UNCERTAINTY

By

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This thesis considers the low carbon Location-Inventory-Routing Problem (LIRP) by addressing the challenges of demand uncertainty through the application of stochastic and fuzzy methods. Multi-objective mathematical models are developed to solve the conflict between total supply chain cost, carbon emission cost, and customer satisfaction in logistics management. This thesis also aims to solve the low-carbon LIRP model with uncertainty factors such as carbon trading, customer demand, shortages, and soft time windows using advanced algorithms. Three LIRP models involving multiple distribution centers and periods are proposed. The first model is a fuzzy chance-constrained programming model that considers factors such as cost, out-of-stock inventory, carbon trading mechanisms, and fuzzy customer demand. The other two models are bi-objective mixed integer nonlinear programming models with soft time window constraints developed to minimize costs and maximize customer satisfaction under uncertain demand, which include stochastic and fuzzy demand, respectively. Given the NP-Hard nature of the three models proposed in this thesis, two metaheuristic algorithms have been developed. A hybrid Particle Swarm Optimization-Bacterial Foraging Algorithm is developed for solving the single objective LIRP model. Furthermore, an improved non-dominated sorting genetic algorithm with an elite strategy II (IMNSGA-II) has been developed to solve the two bi-objective models, surpassing existing literature's algorithms such as Pareto Envelope-based Selection Algorithm II (PESA-II) and NSGA-II. Empirical validation using benchmark dataset and real-world data from three logistics companies in China demonstrates significant improvements in supply chain efficiency and cost reduction. When compared to the Supply Chain Guru X (SCGX) software, the proposed algorithms offer higher practical applicability.

Keywords: Fuzzy, Low-Carbon, Location-Inventory-Routing Problem, Stochastic, Uncertainty.

SDG: GOAL 9: Industry, Innovation, and Infrastructure, GOAL 12: Responsible Consumption and Production, GOAL 13: Climate Action.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

MODEL MATEMATIK DAN ALGORITMA PENGOPTIMUMAN MASALAH KARBON RENDAH LOKASI-INVENTORI-PENGHALAAN DENGAN KETIDAKPASTIAN

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Tesis ini mempertimbangkan Masalah Lokasi-Inventori-Penghalaan (MLIP) rendah karbon dengan menangani cabaran ketidakpastian permintaan melalui aplikasi kaedah stoka dan kabur. Model matematik berbilang objektif dibangunkan untuk menyelesaikan konflik antara jumlah kos rantaian bekalan, kos pelepasan karbon dan kepuasan pelanggan dalam pengurusan logistik. Tesis ini juga bertujuan untuk menyelesaikan model MLIP karbon rendah dengan faktor ketidakpastian seperti perdagangan karbon, permintaan pelanggan, kekurangan, dan tetingkap masa lembut menggunakan algoritma lanjutan. Tiga model MLIP yang melibatkan pelbagai pusat pengedaran dan tempoh dicadangkan. Model pertama ialah model pengaturcaraan terhad peluang kabur yang mempertimbangkan faktor seperti kos, inventori kehabisan stok, mekanisme perdagangan karbon dan permintaan pelanggan kabur. Dua model lain ialah model pengaturcaraan tak linear integer bercampur bi-objektif dengan kekangan tetingkap masa lembut yang dibangunkan untuk meminimumkan kos dan memaksimumkan kepuasan pelanggan di bawah permintaan yang tidak menentu, yang masing-masing termasuk permintaan stokastik dan kabur. Memandangkan sifat NP-Hard bagi ketiga-tiga model yang dicadangkan dalam tesis ini, dua algoritma metaheuristik telah dibangunkan. Satu algoritma hibrid pintar pengoptimuman kawanan zarah-algoritma mencari makan bakteria dibangunkan untuk menyelesaikan model MLIP dengan objektif tunggal. Tambahan pula, algoritma genetik pengisihan tidak didominasi yang dipertingkatkan dengan strategi elit II (IMNSGA-II) telah dibangunkan untuk menyelesaikan dua model dwi-objektif, mengatasi algoritma kesusasteraan sedia ada seperti Algoritma Pemilihan berasaskan Sampul Pareto II (PESA-II) dan NSGA-II. Pengesahan empirikal menggunakan set data penanda aras dan data dunia sebenar daripada tiga syarikat logistik di China menunjukkan peningkatan ketara dalam kecekapan rantaian bekalan dan pengurangan kos. Jika dibandingkan dengan perisian Supply Chain Guru X (SCGX), algoritma yang dicadangkan menawarkan kebolehgunaan praktikal yang lebih tinggi.

Kata Kunci: Kabur, Rendah Karbon, Masalah Lokasi-Inventori-Penghalaan, Stokastik, Ketidakpastian.

SDG: MATLAMAT 9: Industri, Inovasi dan Infrastruktur, MATLAMAT 12: Penggunaan dan Pengeluaran Bertanggungjawab, MATLAMAT 13: Tindakan Memerangi Perubahan Iklim.

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LIST OF ABBREVIATIONS

LIRP	Location-Inventory-Routing Problem
TW	Time Window
DCs	Distribution Centers
CS	Customer Satisfaction
LIP	Location-Inventory Problem
LRP	Location-Routing Problem
IRP	Inventory-Routing Problem
NSGA-II	Non-dominated Sorting Genetic Algorithm with Elite Strategy II
IMNSGA-II	Improved NSGA-II
MOPSO	Multi-objective Particle Swarm Optimization
MINLP	Mixed Integer Nonlinear Programming
MILP	Mixed Integer Linear Programming
PSO-BFA	Particle Swarm Optimization Bacterial Foraging Algorithm
FRV	Fuzzy Random Variable
STW	Soft Time Window
TSCC	Total Supply Chain Cost
PF	Pareto Front
GD	Generational Distance
HV	Hypervolume
IGD	Inverted Generational Distance
CPF	Coverage over Pareto Front
PD	Pure Diversity
PESA-II	Pareto Envelope-based Selection Algorithm II
CLSC	Closed-loop Supply Chain
GSCM	Green Supply Chain Management
ECLS	E-commerce Logistics System
HSC	Hazmat Supply Chain

PPLN	Perishable Products Logistics Network
CCLN	Cold Chain Logistics Network
ESSC	Environmentally Sustainable Supply Chain
HUSC	Humanitarian Supply Chain
HEL	Healthcare Logistics
MOP	Multi-objective Programming
CP	Capacity Planning
DC	Distribution Center
RL	Reverse Logistics
MS	Multi-stages
SC	Shortage Cost
TC	Transportation Cost
TP	Total Profit
CEEI	CO2 Emission and Environmental Impacts
HOFV	Homogeneous Fleet of Vehicles
HEFV	Heterogeneous Fleet of Vehicles
ICRP	Inventory Control Replenishment Policy
PSI	Positive Social Impacts
SCR	Supply Chain Risks
TTD	Total Traversed Distance

CHAPTER 1

INTRODUCTION

1.1 Overview

To improve the financial performance and market edge of businesses, the logistics service network is a crucial component in the orchestration of supply chain operations. In logistics, achieving a balance between benefits and costs is a central challenge posed by the Location-Inventory-Routing Problem (LIRP). Achieving an optimal operational state for the logistics system requires a delicate equilibrium, making it essential to approach the study of the LIRP from a comprehensive, systemic viewpoint.

With the intensification of global warming, people's concerns about the increase in carbon dioxide emissions are growing. The logistics supply chain, as a major source of air pollution and greenhouse gas emissions, has become a key focus for governments and large companies committed to reducing their environmental impact. Therefore, LIRP considering low carbon emissions is of great significance.

When evaluating decision factors for the LIRP model, it is important to consider certain uncertainties. These may include stochastic or fuzzy demand, inventory shortages stemming from various uncertain factors, and variability in delivery times due to the potential for transportation disruptions.

1.2 Research Background

This section will further analyze the related concepts and theories of the LIRP in an uncertain environment with low carbon.

1.2.1 LIRP Modeling

The primary focus of the LIRP integrated optimization model is to minimize the overall expenses of the system while ensuring that all resource constraints are met. The total cost of the system typically includes location, transportation, and inventory costs. Location cost refers to the expenses associated with constructing and operating an open distribution center over a specific period. Transportation cost encompasses the total expenditure required for moving goods between different nodes within the system. Inventory cost represents the combined expenses related to ordering, holding, and potential losses due to stockouts at each node with inventory. If carbon emission cost is considered, the total system cost should also include the cost due to carbon emission.

System resource constraints usually include: (i) constraints related to distribution centers (DCs)' location, such as the number of DCs, and capacity constraints; (ii) inventory-related constraints, such as inventory capacity and backorder constraints; (iii) constraints related to the distribution path, such as vehicle carrying capacity, service time window (TW), road network flow constraints; and (iv) constraints related to the service, such as service level, service time constraints. In addition to considering supply capacity, demand, and other relevant constraints and decision variables of the system, various limitations and variable configurations are also taken into account in the integrated optimization of LIRP.

Hence, the fundamental structure of the mathematical model for LIRP which is summarized from Le and Lee (2013) is as follows:

$$\min Z = f(x) = C_L + C_I + C_T + C_{carbon}$$

$$\text{s.t.} \begin{cases} \text{Constraints associated with location selection} \\ \text{Constraints related to inventory} \\ \text{Constraints associated with the distribution path} \\ \text{Constraints related to the service} \\ \text{Other constraints} \\ \text{Set variable} \end{cases}$$

In this fundamental model structure, the primary aim is to minimize the overall cost of the system. Here, Z denotes the total system cost, and $f(x)$ represents the total system cost function, which encompasses various components such as location cost (C_L), inventory cost (C_I), transportation cost (C_T), and carbon emission cost (C_{carbon}). Furthermore, it is possible to integrate and optimize service time elements to address multi-objective problems. These may include maximizing customer satisfaction (CS) or enhancing system reliability and punctuality while simultaneously minimizing the total supply chain cost (TSCC). Additionally, if there is a need to modify or adjust the objective function along with certain constraints, corresponding modifications can be made accordingly.

Generally, the definition of a multi-objective optimization problem aiming to minimize an objective value can be found in previous research by Prieto and Gomez (2021). Let $x = (x_1, x_2, \ldots, x_n)^T$ represent the decision variable in a problem. The decision space is denoted as Ω, and $F : \Omega \to \theta \subseteq R^m$ represents a set of real-valued objective functions that map from the dimensional decision space Ω to the m dimensional objective space θ. The objective space is referred to as R^m, while the feasible objective solution of the problem is denoted by $\{F(x) \mid x \in \Omega\}$ Prieto and Gomez (2021).

$$\min F(x) = (f_1(x), f_2(x), \ldots, f_m(x))^T$$
$$\text{s.t.} \begin{cases} \text{Constraints} \\ x \in \Omega \end{cases}$$

1.2.2 Calculation Methods of Carbon Emissions

There are three methods available for calculating carbon emissions, and their application should be based on a thorough analysis of the specific problem at hand. The three methods are as follows:

1. Method one: the relevant carbon emission coefficient is determined, and the carbon emission per unit product distance from the factory to the potential DCs as well as from the potential DCs to the customer is set (Ning and Chan, 2007).

   In the study conducted by Ning and Chan (2007), they examined the emissions of carbon monoxide (CO), hydrocarbon (HC), and nitric oxide (NO) from liquefied petroleum gas vehicles in real-world on-road conditions. By calculating the emission factors of CO, HC, and NO in vehicle exhaust based on standard engine parameters, and converting them into CO_2 emission factors through equations (1.1)-(1.3). The coefficients in the equations are determined through regression analysis of overall liquefied petroleum gas vehicle emissions data.

$$\begin{aligned} Q_1 =& 2.8910 \times 10^{-2} - 8.1472 \times 10^{-4} V + 8.3816 \times 10^{-6} V^2 \\ & - 3.2957 \times 10^{-4} a + 1.4195 \times 10^{-4} a^2, \end{aligned} \tag{1.1}$$

$$\begin{aligned} Q_2 =& 1.3143 \times 10^{-3} - 2.8063 \times 10^{-5} V + 2.1527 \times 10^{-7} V^2 \\ & + 4.7141 \times 10^{-5} a + 1.1609 \times 10^{-6} a^2, \end{aligned} \tag{1.2}$$

$$
\begin{aligned}
\ln Q_3 = & -6.3117 - 1.0142 \times 10^{-1} V + 1.3014 \times 10^{-3} V^2 \\
& + 5.9183 \times 10^{-1} a - 1.6699 \times 10^{-2} a^2,
\end{aligned} \tag{1.3}
$$

where, Q_1 is the volume concentration ratio of CO to CO_2, Q_2 is the volume concentration ratio of HC to CO_2, Q_3 is the volume concentration ratio of NO to CO_2, V represents the vehicle's instantaneous velocity in kilometers per hour, and a represents the vehicle's acceleration/deceleration.

Subsequently, the emission factors for CO_2 in grams per kilometer can be computed within the context of real-world vehicle operation, taking into account instantaneous vehicle velocity and changes in acceleration/deceleration:

$$
Q = Q_1 + Q_2 + Q_3. \tag{1.4}
$$

2. Method two: the fuel efficiency for each unit of distance ρ at customer node (i, j) is directly linked to the vehicle load Q_X, as shown by Xiao et al. (2012). This correlation can be represented mathematically as follows:

$$
\rho(Q_X) = a(Q_0 + Q_X) + b. \tag{1.5}
$$

It is essential to calculate the fuel consumption per unit distance in both unloaded (ρ_0) and fully loaded conditions, taking into account the dead weight (Q_0) and maximum load capacity (Q_k) of the distribution vehicle.

$$
\rho_0 = aQ_0 + b, \tag{1.6}
$$

$$
\rho^* = a(Q_0 + Q_k) + b, \tag{1.7}
$$

obtain

$$
a = \frac{\rho^* - \rho_0}{Q_k}. \tag{1.8}
$$

In summary, it is possible to formulate the calculation of a vehicle's fuel efficiency per unit distance as $\rho(Q_X)$:

$$\rho(Q_X) = \rho_0 + \frac{\rho^* - \rho_0}{Q_k} Q_X. \tag{1.9}$$

The production of carbon emissions is a result of fuel combustion, and the fuel consumption of the distribution vehicle depends on both its distance traveled and its cargo capacity.

The total carbon emissions, denoted as Q_c, for the distribution of section (i, j) node can be computed using the following method:

$$Q_c = \rho(Q_{ij})\omega d_{ij} = (\rho_0 + \frac{\rho^* - \rho_0}{Q_k} Q_{ij})\omega d_{ij}. \tag{1.10}$$

3. Method three: the calculation of route carbon emission is complex, but the carbon emission mainly comes from fuel consumption in the process of transportation/distribution. Therefore, Demir et al. (2011) has undergone testing and modifications by Boriboonsomsin and Barth (2008). The integrated emission measurement model involves the calculation of fuel consumption followed by the computation of carbon emissions based on the fuel volume. Assuming that the vehicle accelerates to a certain speed and then keeps a constant speed in the transportation or distribution process, the basic formula of fuel consumption GF can be obtained as follows.

$$GF = [\zeta + \beta_1 R_T v + \beta_2 a^2 v / 1000] \frac{v^2 + as}{a}. \tag{1.11}$$

In Equation (1.11), ζ represents the idling fuel consumption constant. β_1 represents the engine fuel efficiency factor at constant speed, while β_2 represents the fuel consumption factor for acceleration. v is the velocity, a is acceleration, and s is the running distance. R_T stands for traction, and traction is the force or pull that displaces the truck. It should be noted that if the vehicle is stalled, the idle fuel consumption is 0, and if there is no acceleration, $a = 0$. R_T is calculated as follows:

$$R_T = f_1 + f_2 v^2 + Wa/1000 + WGg10^{-5}. \tag{1.12}$$

In Equation (1.12), f_1 represents the resistance value related to rolling resistance. f_2 represents the drag value related to the aerodynamic drag. W is the total mass including the dead weight of the vehicle. G represents the road slope value, and G is negative when going downhill. g represents the acceleration due to gravity. It should be noted that the speed v in the equation is the final running speed of the vehicle, and the speed is not required to accelerate from 0. R_T is discussed further below:

(i) If the traction $R_T \leq 0$, in which case the fuel consumption is the fuel consumption rate during idling, i.e:

$$GF = \zeta t_s. \tag{1.13}$$

In Equation (1.13), t_s represents the residence time of the vehicle such as loading and unloading at DC, and $GF = 0$ if the vehicle is flared out $\zeta = 0$.

(ii) If the traction force is 0, and if there is acceleration during vehicle operation, then the fuel consumption is:

$$GF = [\zeta + \beta_1(f_1 + f_2 + Wa/1000 + WGg10^{-5}) + \beta_2 Wa^2/1000]\sqrt{2s/a}. \tag{1.14}$$

In Equation (1.14), s is the distance accelerated by the vehicle.

(iii) If the traction force is 0, and if the vehicle is moving at a constant speed, the fuel consumption is

$$GF = [\zeta + c_1 v + c_2 v]\frac{s'}{v}. \tag{1.15}$$

In Equation (1.15), c_1 represents the fuel consumption coefficient due to rolling resistance, c_2 represents the fuel consumption coefficient due to air resistance, and $s^{'}$ is the distance of constant speed forward.

In summary, the measurement formula for carbon emissions in transportation/distribution is as follows:

$$CE_R = \theta GF. \quad (1.16)$$

1.2.3 Customer Satisfaction Function

The calculation of the CS function is divided into two cases, which can be determined based on either the delivery time or the delivery distance of goods. In the case of logistics transportation within the same city, the CS function based on time is employed when the customer specifies the delivery time range in hours. Conversely, for long-distance transportation scenarios, where the customer expects the transportation time range to be measured in days, the CS function based on distance is utilized. These two calculations are performed as follows:.

Case 1: Time-based CS function..

According to the proposed approach by Shu et al. (2021) assumed that the expected delivery TW of customers is $[ET_j', LT_j']$, and the acceptable delivery TW to avoid penalty costs is $[eT_j, lT_j]$. However, as a result of epidemic prevention and control measures, distribution centers are susceptible to shortages and insufficient capacity. Therefore, the majority of customers are willing to accept a slightly earlier or later delivery time than their preferred delivery window. Assuming $S = 1$, it indicates a lack of goods and insufficient capacity. In this particular scenario, the acceptable delivery window for customers is represented as $[eT_j, lT_j]$, where the x-axis denotes the delivery time t_j and the y-axis represents the CS function $V(t_j)$. Figure 1.1 depicts the relationship between delivery time and CS. As can be seen from Figure 1.1, under special circumstances, when the deliveryman delivers the goods within the $[ET_j', LT_j']$ and the customer is served within the time interval, their satisfaction is rated as 1. If the deliveryman delivers the goods outside the $[eT_j, lT_j]$, CS is reduced to 0. If the deliv-

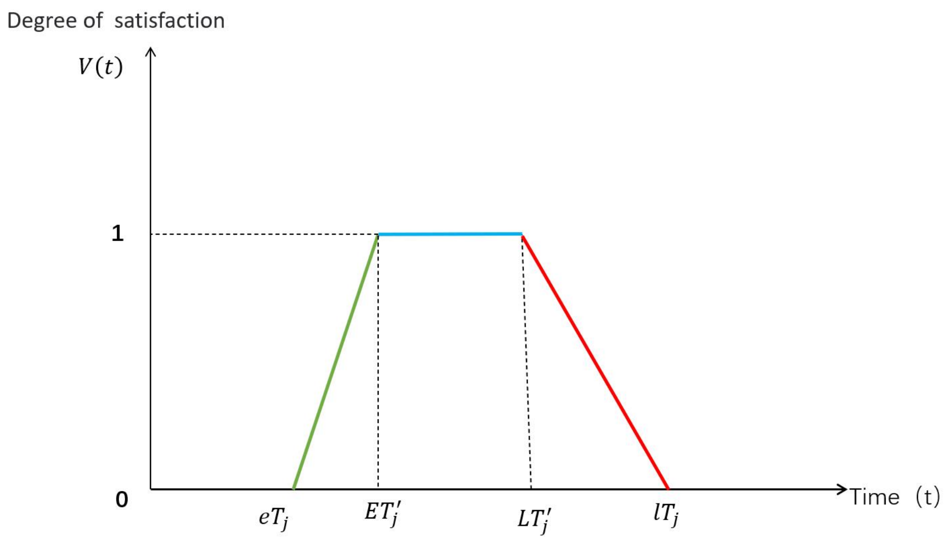

Figure 1.1: Graph of CS with TW.

eryman delivers the goods within the $[eT_j, ET_j']$, CS will increase as the time difference between the delivery time and the earliest delivery time expected by the customer decreases. If the deliveryman delivers the goods within the $[LT_j', lT_j]$, CS will decrease as the time difference between the delivery time and the latest expected delivery time increases.

$$V\left(t_j\right) = \begin{cases} 0, & t_j < eT_j \\ \frac{t_j - ET_j'}{eT_j - ET_j'}, & eT_j \leq t_j < ET_j' \\ 1, & ET_j' \leq t_j \leq LT_j' \\ \frac{LT_j' - t_j}{LT_j' - lT_j}, & LT_j' < t_j < lT_j \\ 0, & lT_j < t_j \end{cases} . \tag{1.17}$$

Case 2: Distance-based CS function..

CS is determined by the proximity of the DC to its location.

$$f(d_{ij}) = \begin{cases} 1, & [0, R_{min}] \\ 1 - (\frac{d_{ij} - R_{min}}{R_{max} - R_{min}})^{\beta}, & [R_{min}, R_{max}] \\ 0, & [R_{max}, \infty] \end{cases} , \tag{1.18}$$

where R_{min} represents the acceptable transportation distance when the customer is very satisfied; R_{max} denotes the delivery distance when the customer is very dissatisfied; d_{ij} is the actual distance between customer i and distribution center j; through the customer i to the distribution center j coordinate measurement; β is the distance sensitivity coefficient, and different values of β represent the customer's sensitivity to distance. When $\beta < 1$, the customer distance satisfaction curve is concave. When $\beta > 1$, the customer distance satisfaction curve is convex. When $\beta = 1$, the customer distance satisfaction curve is a straight line.

1.2.4 Fuzzy Variables and Operations

The inception of fuzzy sets is credited to Zadeh (1965), which represents a noteworthy achievement in the advancement of fuzzy set theory and its practical problem-solving applications. In 1978, the concept of possibility measure was introduced by Zadeh (1978) as a method to quantify fuzzy events. However, despite its extensive acceptance, this measure does not possess self-duality. Nonetheless, both theoretical and practical factors require the presence of a self-dual measure. To meet this urgent need, the concept of confidence measure was introduced by Liu and Liu (2002). Additionally, Li and Liu (2006) proposed a condition that is both necessary and sufficient for assessing reliability. Credibility theory, which was initially established by Liu and Liu (2003) and further developed in subsequent work by Liu and Liu (2009), has become a well-established field in mathematics. In this thesis, the definition of the discrete fuzzy variable provided in Liu's seminal publication from Liu and Liu (2009) is adopted .

Definition 1.1 *(Liu and Liu, 2002) A set function Cr is called a confidence measure if it satisfies normality, monotonicity, self-duality, and maximality.*

Definition 1.2 *(Liu and Liu, 2009) Let Θ be a nonempty set, P be a power set of Θ, Cr be a confidence measure, and let the triple (Θ, P, Cr) be called a confidence space.*

Definition 1.3 *(Liu and Liu, 2009) The fuzzy variable is defined as a (measurable) function from the confidence space (Θ, P, Cr) to the set of real numbers.*

Definition 1.4 *(Liu and Liu, 2009) Let $f : R^n \to R$ be a function, $\xi_1, \xi_2, \ldots, \xi_n$ fuzzy variables over the credibility space (Θ, P, Cr). Then $\xi = f(\xi_1, \xi_2, \ldots, \xi_n)$ is a fuzzy variable, for any $\theta \in \Theta$ has $\xi(\theta) = f(\xi_1(\theta), \xi_2(\theta), \ldots, \xi_n(\theta))$.*

Different methods can be used to define the expected value operator of fuzzy variables. Nevertheless, Liu and Liu (2002) introduced a comprehensive definition for this operator that applies to both continuous and discrete fuzzy variables.

Definition 1.5 *(Liu and Liu, 2002) Let ξ be a fuzzy variable, then its expected value is defined as*

$$E[\xi] = \int_0^{+\infty} Cr\{\xi \geq r\}dr - \int_{-\infty}^{0} Cr\{\xi \leq r\}dr.$$

The premise is that at least one of the two integrals is finite.

Let the triple $(\Theta, P(\Theta), Pos)$ be the possibility space, where Θ denotes the nonempty set,$P(\Theta)$ denotes the power set of Θ, and Pos denotes the possibility measure. Each element in $P(\Theta)$ is called A fuzzy event, and for each event A, $Pos(A)$ denotes the likelihood that A occurs.

Definition 1.6 *(Nahmias, 1978) Suppose ξ is a fuzzy variable on the possibility space $(\Theta, P(\Theta), Pos)$ whose membership function can be derived from the possibility measure Pos, i.e*

$$\mu_\xi(x) = Pos(\{\theta \in \Theta \mid \xi(\theta)\} = x), \forall x \in R.$$

Definition 1.7 *(Liu and Liu, 2009) If $Pos(\{\xi < 0\}) = 0$ or $Pos(\{\xi \leq 0\}) = 0$, then the fuzzy variable ξ is said to be nonnegative (or positive).*

Definition 1.8 *(Liu and Liu, 2009) Suppose ξ is a fuzzy variable on the possibility space $(\Theta, P(\Theta), Pos)$ and $\alpha \in (0, 1]$.*

$$\xi_\alpha^L = inf\{r \mid Pos(\{\xi \leq r\}) \geq \alpha\} \;\; and \;\; \xi_\alpha^U = sup\{r \mid Pos(\{\xi \leq r\}) \geq \alpha\}$$

They are called the α pessimistic and α optimistic values of the fuzzy variable ξ, respectively. The pessimistic value of α is the smallest of the values obtained by the fuzzy *variable ξ with the confidence level α. The α optimistic value is the largest among the values achieved by the fuzzy variable ξ with the confidence level α.*

Definition 1.9 *(Liu and Liu, 2009) By a triangular fuzzy variable we mean the fuzzy variable fully determined by the triplet (a_1, a_2, a_3) of crisp numbers with $a_1 < a_2 < a_3$, whose membership function is given by*

$$\mu(x) = \begin{cases} \frac{x-a_1}{a_2-a_1}, \text{ if } a_1 \leq x \leq a_2 \\ \frac{x-a_3}{a_2-a_3}, \text{ if } a_2 \leq x \leq a_3 \\ 0, \quad \text{otherwise.} \end{cases}$$

Definition 1.10 *(Liu and Liu, 2009) Suppose that the triangular fuzzy variable $\xi = (a_1, a_2, a_3)$, and its α pessimistic value and α optimistic value are expressed as follows. $\xi_\alpha^L = a_2\alpha + a_1(1-\alpha)$ and $\xi_\alpha^U = a_2\alpha + a_3(1-\alpha)$, and its expected value is $E[\xi] = \frac{1}{4}(a_1 + 2a_2 + a_3)$.*

Theorem 1.1 *(Liu and Liu, 2009) Suppose that ξ and ρ are mutually independent fuzzy variables with finite expected values, then for any real numbers a and b, there is $E[a\xi + b\rho] = aE[\xi] + bE[\rho]$.*

Lemma 1.1 *(Liu and Liu, 2009) Let the triangular fuzzy number $\tilde{r} = (r_1, r_2, r_3)$, whose membership function is represented by $\mu_r(x)$, have $Pos\{\tilde{r} \leq z\} \geq \alpha$ for any given confidence level α $(0 \leq \alpha \leq 1)$ if and only if $z \geq (1-\alpha)r_1 + \alpha r_2$.*

Definition 1.11 *(Liu and Iwamura, 1998) If the decision maker wishes to minimize the pessimistic value of the objective function on the premise that the constraint conditions are established at a certain confidence level, the following fuzzy chance-constrained programming model can be developed:*

$$\min \bar{f}$$
$$s.t. \begin{cases} \mathrm{Pos}\{f(x,\xi) \leq \bar{f}\} \geq \beta \\ \mathrm{Pos}\left\{g_j(x,\xi) \leq 0, j = 1, 2, \cdots, p\right\} \geq \alpha \end{cases}$$

where α and β respectively are the confidence levels predetermined by decision-makers, $f(x,\xi)$ is the objective function, and $g_j(x,\xi)$ is the constraint function.

Definition 1.12 *(Carlsson and Fullér, 2001) For a given fuzzy number ξ, its fuzzy possibility mean interval is denoted as $[M_*(\xi_i), M^*(\xi_i)]$, where $M_*(\xi_i)$ and $M^*(\xi_i)$ are the minimum and maximum possible mean values of ξ, respectively, and are defined as :*

$$M_*(\xi_i) = \frac{\int_0^1 \alpha\xi_{i\alpha}^- d\alpha}{\int_0^1 \alpha d\alpha}, M^*(\xi_i) = \frac{\int_0^1 \alpha\xi_{i\alpha}^+ d\alpha}{\int_0^1 \alpha d\alpha}.$$

Then the fuzzy possible mean of the fuzzy number ξ is

$$\overline{M}(\xi_i) = \frac{M_*(\xi_i) + M^*(\xi_i)}{2} = \int_0^1 \alpha\left(\xi_{i\alpha}^- + \xi_{i\alpha}^+\right) d\alpha. \tag{1.19}$$

If ξ is a standard triangular fuzzy number $(\underline{a}_i, a_i, \bar{a}_i)$ and its α level set $\xi_i = [\xi_{i\alpha}^-, \xi_{i\alpha}^+]$, $\alpha \in [0,1]$, where $\xi_{i\alpha}^- = \underline{a}_i + \alpha(a_i - \underline{a}_i)$, $\xi_{i\alpha}^+ = \bar{a}_i - \alpha(\bar{a}_i - a_i)$, then has

$$\overline{M}(\xi_i) = \int_0^1 \alpha\left(\xi_{i\alpha}^- + \xi_{i\alpha}^+\right) d\alpha = \frac{\underline{a}_i + 4a_i + \bar{a}_i}{6}. \tag{1.20}$$

Definition 1.13 *(Cheng, 1998) If fuzzy demand ξ_i is represented by standard triangular fuzzy number, then $\xi_i = (\underline{a}_i, a_i, \bar{a}_i)$ represents customer demand, and the membership function of ξ_i is as follows:*

$$\mu(x) = \begin{cases} L(x), \underline{a}_i \leq x \leq a_i \\ R(x), a_i \leq x \leq \bar{a}_i \\ 0,\ others \end{cases}, \tag{1.21}$$

where $\underline{a}_i$, a_i, and $\bar{a}_i$ are real numbers, $L(x) = \frac{x-\underline{a}_i}{a_i-\underline{a}_i}$ and $R(x) = \frac{\bar{a}_i-x}{\bar{a}_i-a_i}$ are left-right type functions, respectively.

1.2.5 The NSGA-II Algorithm

NSGA-II excels in solving multi-objective optimization problems by efficiently exploring the PF and delivering a well-balanced set of solutions. NSGA-II is an extension of NSGA, as proposed by Srinivas and Deb (1994), which incorporates non-dominated sorting, crowding degree calculation, crowding degree comparison operator, and elitism strategy. The complexity of one generation of the algorithm can be evaluated based on its basic operations and their worst-case time complexities: (i) the time complexity of non-dominated sorting is $O(M(2N)^2)$; (ii) the time complexity of crowding distance assignment is $O(M(2N)log(2N))$; (iii) base on $\prec_n$, the time complexity is $O(2Nlog(2N))$. Therefore, the overall complexity of the algorithm is $O(MN^2)$, which is determined by the non-dominated sorting part of the algorithm (Deb et al., 2002).

Non-dominated sorting uses the concept of Pareto optimal solution to rank the individuals in the population. The higher the non-dominated state, the higher the level of the individual, to select the excellent individuals, so that they have a greater chance to enter the next generation. The pseudocode is as follows:

fast-non-dominate-sort(P) Deb et al. (2000)

for each $p \in P$

$S_p = \phi$

$n_p = 0$ for each $q \in P$

if p dominates q then

Add q to the set of solutions dominated by p

else if $(q \prec p)$ then

$n_p = n_p + 1$

if $n_p = 0$ then

$p_{rank} = 1$

$F_1 = F_1 \cup \{p\}$

Initialize the front counter $i = 1$

while $F_i =/ \phi$

$Q = \phi$

for each $p \in F_i$

for each $q \in S_p$

$n_q = n_q - 1$

$n_q = 0$ then

$q_{rank} = i + 1$

$Q = Q \cup \{q\}$

$i = i + 1$

$F_i = Q$

The crowding degree is only applicable to the comparison between individuals of the same dominance level. The crowding degree of each individual is calculated by each objective function of each individual, and then the crowding degree of each individual is obtained, and the excellent degree of individuals is compared by the crowding degree. The pseudocode is as follows:

crowding-distance-assignment(I) Deb et al. (2000)
Number of solutions in I $l = \|I\|$
for each i, set $I[i]_{distance} = 0$
for each objective m
sort using each objective value $I = sort(I, m)$
so that boundary points are always selected
for $i = 2$ to $l - 1$
$I[i]_{distance} = I[i]_{distance} + (I[i+1]m - I[i-1]m)/(f_m^{\max} - f_m^{\min})$

The pseudocode for the main loop program is as follows:

Non-dominated sorting Genetic Algorithm II (NSGA-II) Deb et al. (2000)
$R_t = P_t \cup Q_t$
F=fast-non-dominated-sort(R_t)
$P_{t+1} = \phi$ and $i = 1$
until $\|P_{t+1}\| + \|F_i\| \leq N$
crowding-distance-assignment(F_i)
$P_{t+1} = P_{t+1} \cup F_i$
$i = i + 1$
Sort(F_i,$\prec_n$)
$P_{t+1} = P_{t+1} \cup F_i[1 : (N - \|P_{t+1}\|)]$
Q_{t+1}=make-new-pop(P_{t+1})
$t = t + 1$

1.3 Problem Statement

Significant logistics and network development advancements have led to a growing emphasis on logistics distribution. Traditionally, the focal point of logistics management has encompassed strategic, tactical, and operational facets, which entail the meticulous selection of DCs' location, inventory control measures, as well as vehicle routing arrangement. Consequently, modern logistics enterprises are faced with critical decision-making processes, including the selection of DCs' locations, optimal inventory management for these DCs, and efficient routing for goods delivery to customers. Figure 1.2 illustrates a common configuration of a supply chain network.

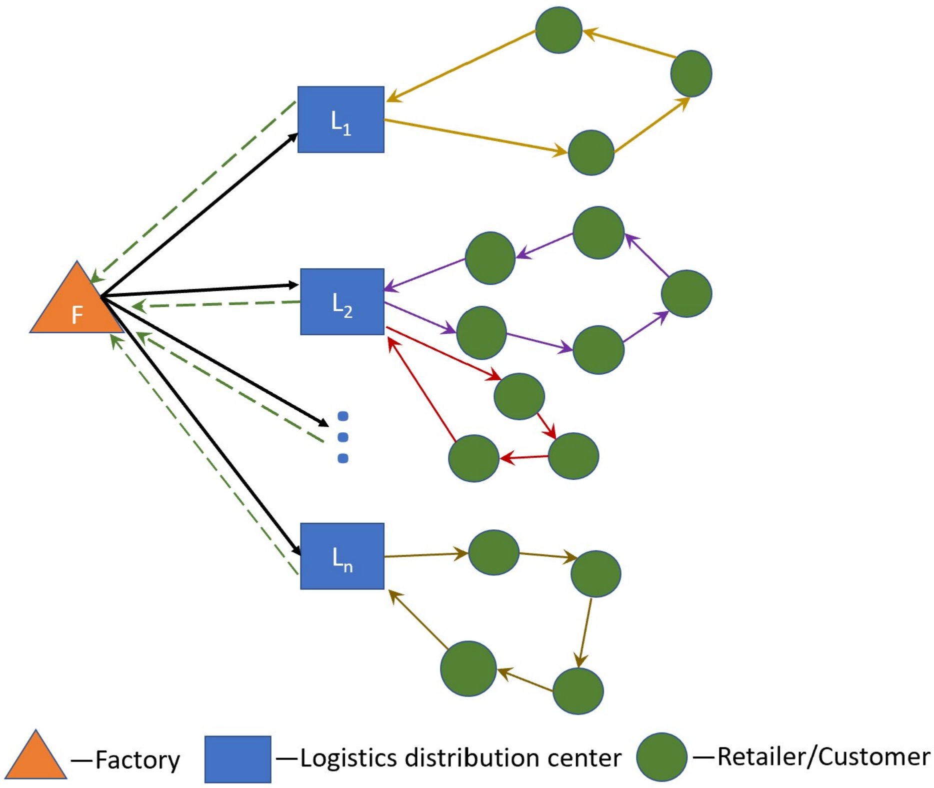

Figure 1.2: A Standard Supply Chain Network Structure.

The supply chain network design and optimization problem (objective) is constructed as a mathematical model problem (modeling). Based on the support of data (input), mathematical optimization technology is used to solve and analyze (method), and the better decision scheme is found (output). This is the kind of thinking we need to have in the study of supply chain network design.

Firstly, the primary focus in supply chain design and optimization lies in the development of a rigorous mathematical model. LIRP embodies an integrated optimization problem that encompasses location, inventory, and routing within supply chain logistics. It necessitates the determination of the DCs' location, the establishment of efficient transportation routes for delivering goods to customers, and the calculation of the optimal inventory level or period at the DCs.

Secondly, it is also crucial to consider the issue of low-carbon emissions in the LIRP model. Research shows that over 70% of carbon emissions from road vehicles come from the global transportation sector (`https://m.huanqiu.com/article/42Q8BXIhAVV`). Therefore, it is important to strategically plan delivery routes in order to minimize the release of carbon emissions.

Thirdly, consideration of uncertainties is paramount in the assessment of decision factors within the LIRP model. The assumption of a static and unchanging customer demand over time is impractical, necessitating the consideration of stochastic or fuzzy demand. Unpredictability within the supply chain and a lack of foresight into DC's capacity introduce uncertainty that can lead to inventory shortages. Uncertain delivery times ultimately impact CS.

Therefore, this study aims to propose a methodology for harmonizing carbon emissions with CS in the field of logistics management. Given the current environmental and market challenges, it is imperative to prioritize the reduction of carbon emissions while ensuring customer contentment. The incorporation of various factors such as carbon trading, uncertainty customer demand, shortage and STW makes the LIRP model more comprehensive. The accuracy of the intricate mathematical model is validated through the utilization of advanced optimization heuristic algorithms. Furthermore, application of the mathematical model to an actual logistics case enhances its practical value and demonstrates its applicability in real-world scenarios.

1.4 Research Questions

Solving LIRP requires making the following decisions:

1. How to choose the location? In the case of comprehensive consideration of various factors, the location and number of DCs are decided, and the transportation costs and operating costs of the facilities are reduced as much as possible.

2. How to calculate the delivery period? If the cycle length is known, it is necessary

to decide when to deliver the product to which DC. If the cycle length is unknown, a decision needs to be made on the frequency of delivery throughout the planning cycle.

3. How to calculate the number of allocations? The distribution volume encompasses both the order volume from the factory to the DC and the subsequent delivery volume from the DC to individual customers. Considering the uncertain demand information, which may be random or fuzzy, it becomes imperative to determine optimal inventory levels at DCs and establish appropriate delivery frequencies for each customer during each shipment.

4. How can one acquire a transportation strategy? When employing less-than-truckload transportation, how can the optimal driving routes for each vehicle be determined? Among these considerations, the initial two choices primarily tackle inventory management concerns, while the latter decision relates to organizing the transportation plan and falls within the realm of solving optimization problems in transportation. The selection of routes plays a crucial role in logistics operations as it requires choosing an appropriate path for timely delivery to specified destinations based on customer requirements and within acceptable cost parameters.

5. How to take low carbon into account in the LIRP model? Is it directly taken into account in the economic cost objective function or set up as a separate objective function?

6. How to express CS in the mathematical formula? How can CS be taken into account in the LIRP model?

7. What uncertainties are being considered? How is it expressed mathematically in the LIRP model?

8. How to change the fuzzy programming model of LIRP into a deterministic model?

9. How to design the algorithm to solve the low carbon LIRP model with uncertain factors? When heterogeneous vehicles are selected, how do select vehicles minimize carbon emissions?

1.5 Research Objectives

The main objective of the research is to propose mathematical models and optimization algorithms for solving the low-carbon LIRP with uncertainty. To achieve this, the specific objectives are:

1. to construct a fuzzy chance-constrained programming model for LIRP, considering cost factors, inventory stockouts, carbon trading mechanism, and customer demand as fuzzy variables.

2. to propose a novel multi-objective LIRP model with soft time window (STW) constraint requirements, accommodating the random normal distribution of customer stochastic demand.

3. to propose a novel multi-objective fuzzy demand LIRP model, taking into account carbon emission and CS.

4. to propose a modified Particle Swarm Optimization-Bacterial Foraging Algorithm (PSO-BFA) and an Improved Non-dominated Sorting Genetic Algorithm with Elitist Strategy (IMNSGA-II) algorithms for solving the proposed LIRP models.

5. to verify and validate the proposed models and algorithms using the simulated and real-world dataset. Since the three models proposed in this thesis are all NP-Hard problems, the model validation process involved the use of benchmark instances and the examination of three real cases to illustrate the problem, followed by the application of the proposed algorithms to solve the model.

1.6 Scopes and Limitations

LIRP is a complex combinatorial optimization problem involving facility location, inventory management, and path planning. Models and optimization algorithms for low-carbon LIRP with uncertainty are used to model and solve the LIRP problem while considering the reduction of carbon emissions and facing demand uncertainty.

The research scopes are as follows:

1. Uncertainty demand modeling: study how to effectively model the uncertainty of demand, which can be used by fuzzy mathematics, stochastic programming, and other methods.
2. Low-carbon goal setting: Study how to set low-carbon goals and incorporate them into the optimization objectives of the LIRP problem under the premise of meeting demand.
3. Decision-making: study how to make reasonable decisions on facility location, inventory management, and path planning in the case of uncertain demand, to balance costs and service levels.
4. Multi-objective optimization: Study how to optimize multi-objectives between uncertain demand and low-carbon goals, balancing carbon emissions, costs, and service levels.
5. Algorithm design: design efficient algorithms suitable for LIRP with uncertainty demand, such as heuristic algorithm, meta-heuristic algorithm, and so on.
6. Decision support system: develop computing tools and software that can assist decision-making, helping managers in practical applications solve LIRP with uncertainty demand.

The research limitations are as follows:

1. Data acquisition: modeling of uncertainty demand requires a large amount of historical data and market information, and the acquisition and accuracy of data may affect the effectiveness of the model. The calculation of carbon emission data will affect the accuracy and reliability of the model, and the challenges brought by uncertainty need to be addressed.

2. Multi-objective conflict: there may be conflicts between low-carbon goals and costs, service levels, and other goals, and how to effectively balance these goals is a challenge.

3. Computational complexity: LIRP problems with uncertain demand and low-carbon targets often have higher computational complexity, requiring the design of efficient algorithms to solve them.

4. Practical application: the assumptions and parameter settings in the model may have certain deviations from the actual situation, leading to the unsatisfactory effect of the model in practical application.

5. Decision risk: in the case of uncertain demand and low-carbon targets, developing appropriate decision strategies may require considering more factors, increasing the complexity of decision-making.

Therefore, the study of low-carbon LIRP problems with uncertain demand needs to comprehensively consider the challenges and limitations of carbon emission modeling, low-carbon target setting, multi-objective optimization, data uncertainty, STW, shortage etc., to provide more effective decision support for low-carbon logistics and supply chain management in practical applications.

1.7 Research Methodology

- Literature analysis method: The definition of LIRP and its current research status is understood by consulting relevant materials and literature, and the literature is systematically reviewed by the PRISMA.

- Mathematical modeling method: Fuzzy chance-constrained programming and multi-objective programming modeling are used.

- Computer simulation method: the established model is analyzed, and the Matlab software is used for simulation tests. The heuristic algorithms the modified PSO-BFA and the IMNSGA-II are proposed to solve the problem, and then cases are proposed to study and analyze them to verify the model and algorithm.

- Comparative analysis method: modified PSO-BFA is compared and analyzed with the standard PSO and Bacterial Foraging Algorithm (BFA). IMNSGA-II is compared with the algorithms Pareto Envelope-Based Selection Algorithm II(PESA-II) and NSGA-II.

The Figure 1.3 presents a methodological framework describe the generalized steps to covering chapters 2-6 of of the main chapters in this thesis.

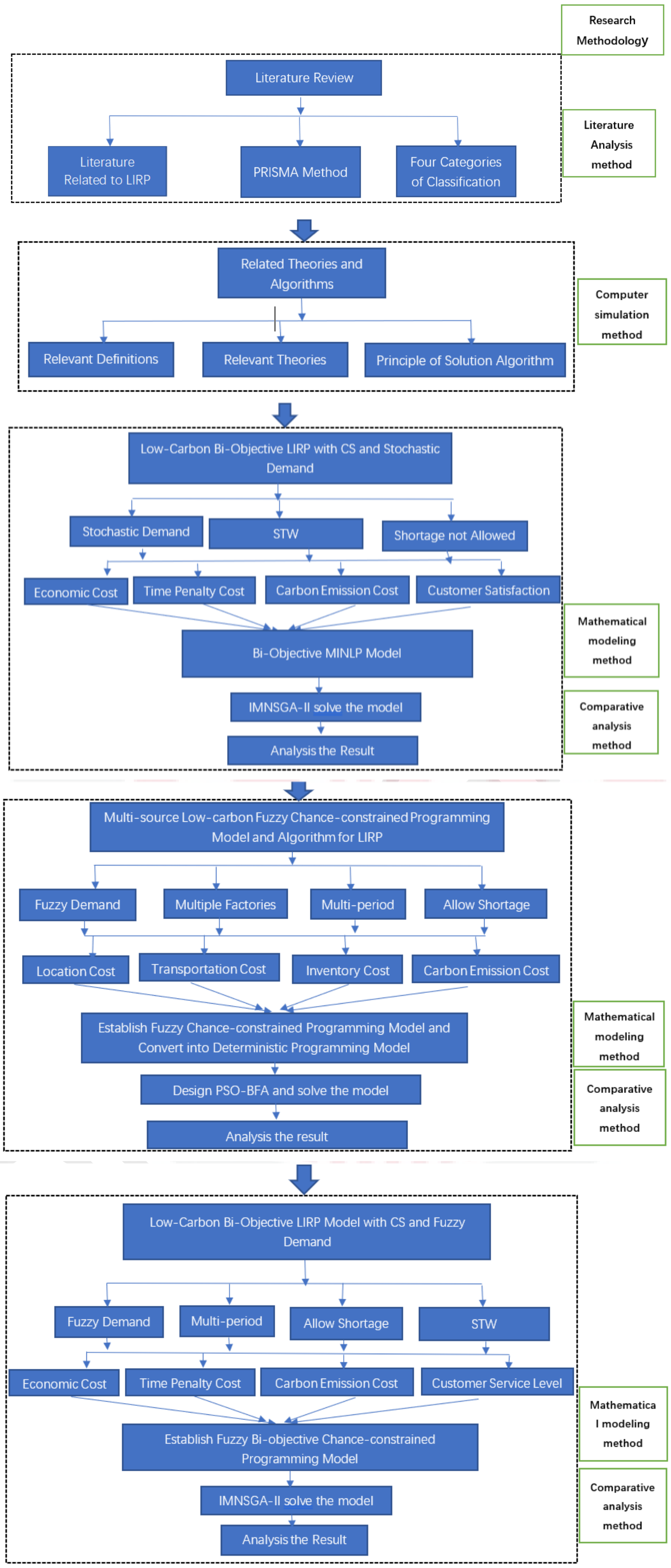

Figure 1.3: Research Methodology Framework.

1.8 Significance of Study

In practical scenarios, the LIRP finds extensive applications. It encompasses a wide range of industries, including the production of goods such as airplanes, cars, food, and clothing in factories, as well as the selection of DCs in different regions to cater to customer demands. The continuous supply of products from factories to distribution centers and their subsequent distribution to customers necessitates careful consideration of inventory replenishment strategies, path lengths, and distribution methods. This becomes particularly critical in the context of today's booming electronic product industry, where logistics activities are intricately linked to people's daily lives. Hence, providing accurate decisions regarding location, inventory, and routes holds significant importance for managers.

The significance of this thesis can be attributed to the following four aspects:

1. The significance of theoretical research.

   Numerous scholars have researched optimizing integrated logistics, focusing on the integration of two out of the three key elements: location, inventory, and routing. Additionally, there have been efforts to achieve comprehensive integration by considering all three elements simultaneously. The research on the fusion of the two has a long history and has achieved fruitful results. For the LIRP problem with demand determination, scholars have used different algorithms to solve it under certain constraints and obtained good decision results. Some scholars have also studied the case of random and uncertain customer demand, but most of them have established a single objective mathematical model, that is, the total cost is the lowest. In this thesis, firstly, the single-objective LIRP model under uncertain demand is established in Chapter 5, and it is analyzed and transformed into a deterministic model by using the uncertain programming theory. Then, based on the model, a bi-objective programming model considering stochastic demand, STW, and low-carbon is established in Chapter 4, and the Pareto efficient solution is solved to maximize CS and minimize TSCC under the condition of satisfying customer time windows. The Entropy-TOPSIS method is used to sort and give the optimal decision. Finally, in the case of uncertain and fuzzy demand, the bi-objective programming model in Chapter 6 considering customer service level and low-carbon is added, and the theoretical knowledge of the first chapter is used to analyze the model. These chapters promote the application of optimization theory and techniques in low-cost production planning models through the study of integrated optimization of LIRP under uncertain demand and the use of uncertain programming theory to transform uncertain models into certain models. Therefore, the LIRP aligns better with the inherent attributes of the present intricate logistics system, thereby holding significant theoretical guidance for investigating this issue.

2. An in-depth study of LIRP algorithm.
   This study provides an in-depth analysis of the NP-Hard problem. The LIRP is a challenging optimization problem that combines elements from the vehicle routing problem (VRP), location problem, and inventory problem. It has been proven to be NP-Hard, making it a subject of significant research interest and difficulty within the academic community. This study examines the impact of environmental protection requirements and uncertain customer demand on the LIRP. Intelligent metaheuristic algorithms, namely PSO-BFA and IMNSGA-II, are developed as potential solution methods. The findings of this study hold significant reference value for further research on NP-Hard problems.

3. The significance of practical guidance.
   In this research, two algorithms are proposed to solve the model, and an example is utilized to analyze the effectiveness of the algorithm and the model in determining suitable decisions for real-world cases. The example data are collected from three Chinese logistics companies: Jiamei Food Cold Chain Logistics in Fujian province, a small logistics distribution company in Jinan, Shandong province, China, and ZB, a prominent food retail enterprise headquartered in Wuhan. These companies specialize in distributing frozen food, juice, bever-

ages, and other grocery items. This analysis can guide enterprises in systematic optimization, resulting in decreased expenses related to location, inventory, and transportation. Additionally, it enables the reduction of product delivery time, improvement in operational efficiency, and enhancement of CS. Consequently, it promotes the overall development of enterprises.

Furthermore, as research on this problem deepens, the application scope can be expanded to address challenges and obstacles in other industries. Moreover, as enterprises evolve, their logistics activities are increasingly becoming intelligent. The integrated optimization of location, inventory, and routing can serve as a guiding framework for enterprise logistics activities, enabling them to adapt to the evolving organizational structures and management methods of the modern era. This, in turn, facilitates enterprise innovation and the creation of additional value.

4. Improve the development of green supply chain

This research introduces the integration of low-carbon emissions into the logistics distribution network planning problem. The analysis begins by examining the existing data on carbon dioxide emissions during vehicle driving and proposes a suitable measurement method. Subsequently, a quantitative method for estimating carbon dioxide emissions during transportation is developed, providing theoretical guidance for accurate estimation of carbon emissions.

The study carefully analyzes the carbon emission factors involved in the LIRP. The main factors are selected and combined with the LIRP, going beyond the consideration of economic costs. Instead, the goal is to achieve emission reduction within the economic cost framework.

This thesis presents research on the location-inventory-routing low-carbon logistics system. It is based on low-carbon economic theory and utilizes integrated logistics theory and methods. The research reveals tactics for reducing carbon emissions in the administration and improvement of integrated logistics and supply chain systems, thereby promoting the development of sustainable supply chains.

1.9 Outline of Thesis

The thesis is composed of seven chapters, with each chapter dedicated to exploring distinct facets as specified below:

Chapter 1 provides an overview of the research background, problem statement, research questions, objectives, scope, and limitations, as well as the significance of the research. This chapter primarily focuses on exploring fuzzy mathematical theory as it forms the fundamental basis for this thesis while also delving into the extensive field of LIRP and its solution algorithms.

Chapter 2 provides a comprehensive analysis of the existing literature on LIRP, focusing specifically on the research scope outlined in Chapter 1.

Chapter 3 presents a study on the bi-objective programming algorithm for optimizing inventory location and distribution routing under low carbon emissions and CS. In this chapter, we proposed a novel improved non-dominated sorting genetic algorithm with an elite strategy II (IMNSGA-II) approach to obtain Pareto solutions, which are then ranked using the TOPSIS-Entropy method to provide optimal choices for decision-makers. Additionally, benchmark data is provided for conducting simulation experiments, followed by an in-depth analysis of the algorithm's performance.

In Chapter 4, a bi-objective programming approach is proposed to optimize the LIRP in a low-carbon environment, considering CS with stochastic demand. This approach comprehensively incorporates various cost factors, such as fixed costs, transportation expenses, inventory holding costs, penalty charges, and carbon tax trading fees. Furthermore, it integrates the disallowed stockout constraint and the carbon trading mechanism while also accounting for stochastic demand following a random normal distribution associated with customer demand. A fresh products logistics and distribution company in Jinan is taken as the case study and IMNSGA-II from Chapter 3 is used to solve this model. Finally, the influence of carbon price on carbon emission and CS is analyzed according to the sensitivity.

In Chapter 5, a multi-source low-carbon fuzzy chance-constrained programming model is presented to optimize the location, inventory, and routing of logistics centers by solving a mixed integer nonlinear programming (MINLP) problem. This model takes into consideration uncertain variables such as cost, inventory shortages, carbon emission trading mechanisms, and customer demand in the development of a LIRP model using fuzzy chance-constrained programming. Subsequently, the problem of fuzzy chance-constrained programming is transformed into a deterministic programming problem utilizing uncertain programming theory. Finally, the optimal location and vehicle routing considering inventory constraints are obtained using the hybrid intelligent particle swarm optimization bacterial foraging algorithm (PSO-BFA).

Chapter 6 integrates fuzzy demand, STW for different vehicles, and customer service level into the framework of the low-carbon bi-objective LIRP model. This chapter contributes to existing research in this field by optimizing the LIRP with fuzzy variables and developing a fuzzy planning model for logistics center location inventory paths considering customer demand as triangular fuzzy numbers, multi-periods, stockouts, and STW. By employing the fuzzy expected value theory and the fuzzy possibility mean method, the fuzzy planning problem is transformed into a deterministic planning problem. Furthermore, formulas are derived for determining the optimal target inventory level and ordering cycle of logistics distribution centers based on the storage strategy of fuzzy demand. To verify the effectiveness of the model, three sets of real-world data from logistics companies in China are solved by IMNSGA-II from Chapter 3. Additionally, the actual data of a clothing distribution logistics company in China is used to test the model and compared with the results obtained from Supply Chain Guru X (SCGX).

Finally, Chapter 7 focuses on summarizing the findings and discussing potential future directions. This chapter presents a comprehensive overview of the primary contributions made in this thesis, acknowledges its limitations, and envisions potential advancements for future research endeavors.

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