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Two-Echelon Location-Routing Problem with Fuzzy Demand of Rural E-Commerce Logistics

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ABSTRACT

To promote the green and high-quality development of rural e-commerce logistics, we propose the Two-Echelon Location-Routing Problem with Fuzzy Demand (2E-LRP-FD) of the rural e-commerce logistics network. Considering fuzzy demand, government subsidies and simultaneous delivery, the objective function aims to maximise the profit of enterprises considering government subsidies. The fuzzy chance-constrained programming method is used to deal with the triangular fuzzy variables of pickup demands. Additionally, we present a two-stage Improved Non-Dominated Sorting Genetic Algorithm II (INSGA-II) that integrates stochastic simulation and a K-means clustering algorithm to effectively solve the problem. In the end, the numerical experiments of algorithm and model design are verified. The experimental results demonstrate that the proposed INSGA-II is significantly efficient and effective. Furthermore, we discuss the relationship between subsidy strategies and logistics enterprise profits. This research contributes valuable insights for the establishment of rural e-commerce logistics systems.

KEYWORDS

two-echelon location-routing problem; fuzzy demand; k-means clustering; improved NSGA-II; rural e-commerce logistics.

1. INTRODUCTION

With the advent of the "Internet +" era and the widespread adoption of smartphones, major e-commerce and logistics enterprises have entered the rural market one after another, and actively constructed rural logistics networks. Consequently, rural e-commerce has experienced rapid growth. In 2021, China's rural network retail sales reached CNY 2.05 trillion, accounting for 15.66% of the country's total online retail sales, marking an impressive year-on-year growth of 11.3% [1]. However, it is difficult for rural e-commerce logistics to form scale effect, high price sensitivity of residents and limited traffic conditions. As a result, its logistics costs significantly higher than those of urban e-commerce logistics.

Current research on rural e-commerce logistics mainly focuses on theoretical studies related to the development status, existing issues and distribution modes. The relevant research results can be elaborated from both macro and micro aspects. Macroscopically, the research mainly focuses on the current status of rural e-commerce logistics development, existing issues, conceptual models and policy recommendations. In recent years, there has been increased participation in e-commerce activities among rural communities. E-commerce can bring opportunities to people living in rural and remote areas [2]. However, there still existed challenges and risks, for example, the rural-urban divide was a common phenomenon and the logistic costs in rural areas were five times higher than in urban areas [3].

Thus, the adoption of adaptable models tailored to the unique circumstances of rural villages becomes imperative to leverage the benefits of e-commerce. Moreover, a model for the coordinated coupling of rural e-commerce logistics and agricultural modernisation was established [4]. On a microscopic scale, the research on rural e-commerce logistics mainly focuses on the last-mile delivery issues. Markowska et al. [5] studied the preferences of rural e-customers for last mile delivery. Seghezzi et al. [6] analysed e-commerce last-mile delivery options–parcel lockers (PLs) and traditional home delivery (HD). Liu [7] constructed a route optimisation model for rural e-commerce logistics (RECL). Yang et al. [8] proposed a cooperative rich VRP in the last-mile logistics industry in rural areas.

The optimisation of logistics networks has consistently been a focal point in research topic. Originating from the foundational travelling Salesman Problem (TSP), it has progressed through iterations to the Vehicle Routing Problem (VRP) and eventually to the Location Routing Problem (LRP). The integration of location and routing aspects traces back to the 1960s, and Watson-Gandy and Dohrn [9] first studied the combination of facility location and transportation network. However, due to the complexity of the problem and environmental constraints, model optimisation could not be achieved through computers. In the late 1980s, Salhi and Rand [10] conducted the first integrated quantitative study of the VRP and the Facility Location Problem (FLP), marking the true beginning of the LRP research.

Routes are expanded from the initial facilities to the depots and from the depots to the customers to hand over goods to the customers. In this type of LRP, routes from the initial facilities to the depots are called the first echelon routes, and routes from the depots to the customers are called second the echelon routes [11]. In 1980, Jacobsen and Madsen [12] were the first researchers who defined the newspaper delivery system in Denmark as Two-Echelon Location-Routing Problem (2E-LRP) and proposed three constructive heuristics to solve the problem. Since then, 2E-LRP has garnered scholarly attention, leading to numerous advancements in this domain. A two-echelon multi-depot multi-period location-routing problem with pickup and delivery (2E-MDMPLRPPD) was proposed and a hybrid multi-objective particle swarm optimisation (HMOPSO) algorithm was developed [13]. Tian and Hu [14] proposed a Two-Echelon Location-Routing Problem with Recommended Satellites (2E-LRPRS). Yıldız et al. [15] proposed a Two-Echelon Location-Routing Problem with Simultaneous Pickup and Delivery (2E-LRPSPD).

Uncertainty presents another dimension to the LRP. In real-world applications, obtaining precise data such as customer demands and travel times proves challenging. Consequently, various modelling approaches, including Stochastic LRP (SLRP) and Fuzzy LRP (FLRP), are employed to address such uncertainties. The concept of fuzzy sets, introduced by Zadeh [16] through membership functions, has been extensively applied to real-world problems. Kaufmann [17] introduced the term “fuzzy variable” to quantify fuzzy events. A modification to possibility theory which is called credibility theory was founded by Liu and Gao [18] and has recently been studied by many scholars all over the world. Most of the existing studies are based on the fuzzy credibility theory, and the uncertain variables are represented by triangular fuzzy variables or trapezoidal fuzzy variables. Fuzzy variables encompass factors such as travel time, time window, transportation costs and the number of affected people, demand, etc. Fuzzy expected value programming and fuzzy chance-constrained programming are the main methods at present, and the summary of the related papers is shown in *Table 1*.

Table 1 – Summary of modelling methods for fuzzy LRP-related papers

Literature	Problem abbreviation	Objective function	Uncertain parameters	Solution algorithm
[19]	MDCLRP	Minimise cost	Trapezoidal fuzzy variable	SA
[20]	LRP	(1) Minimise cost (2) Minimise risks	Trapezoidal fuzzy variable	GA
[21]	MOLRP	(1) Minimise cost (2) Minimise risks	Triangular fuzzy variable	Lingo software
[22]	FCLRP-SPD	Minimise total costs	Triangular fuzzy variable	GCM
[23]	CLRP-FD	(1) Minimise total costs (2) Minimise the total additional distances	Triangular fuzzy variable	HPSO

[24]	MTLRP-TW	(1) Minimise the total travelling time of vehicles (2) Minimise the total violation from time windows defined by demand nodes (3) Minimise the disposal sites risk	Triangular fuzzy variable	CPLEX /GAMS
[25]	LRP	Minimise total costs	Triangular fuzzy variable	GA+TS
[26]	LRPTW	Minimise total costs	Triangular fuzzy variable	GA
Our paper	2E-LRP-FD	Minimise the profit of logistics enterprises considering government subsidies	Triangular fuzzy variable	Two-stage algorithm

Note: *MDCLRP: Multi-Depot Capacitated LRP; SA: Simulated Annealing; MOLRP: Multi-Objective Location-Routing Problem; GA: Genetic Algorithm; FCLRP: Fuzzy Capacitated Location Routing Problem; VNS: Variable Neighbourhood Search; ELS: Evolutionary Local Search; FCLRP-SPD: Fuzzy Capacitated Location-routing Problem with Simultaneous Pickup and Delivery Demands; GCM: Greedy Clustering Method; CLRP-FD: Capacitated Location-Routing Problem with Fuzzy Demands; HPSO: Hybrid Particle Swarm Optimisation; MTLRP-TW: Multi-Trip Location-Routing Problem with Time Windows; TS: Tabu Search; LRPTW: LRP with Time Windows.*

Since both facility location and vehicle routing belong to the class of NP-hard problems, the LRP is also a NP-hard problem [27]. Attaining exact solutions for the LRP within a reasonable time frame is often computationally infeasible, especially for large-scale instances. Consequently, heuristic algorithms have garnered considerable attention and application from scholars both domestically and internationally, such as the Adaptive Large Neighbourhood Decomposition Search Algorithm [28], Fuzzy Correlation Arc Based Adaptive Variable Neighbourhood Search (FCA-AVNS) algorithm [29], Hybrid Lagrangian Relaxation and Alternating Direction Method of Multipliers (LR-ADMM) solution framework [30], and Greedy Randomised Adaptive Search Procedure (GRASP) [31], etc.

There have been many papers about rural e-commerce logistics and LRP in recent years. However, there are still some gaps in the rural e-commerce logistics LRP, mainly as follows:

1) Limited quantitative research on the LRP in rural e-commerce logistics, especially concerning the two-echelon network of rural e-commerce logistics.
2) Moreover, when considering the LRP with fuzzy demand, most objective functions only aim to minimise the total cost, lacking consideration of the role of government in the development of rural logistics.
3) The need to design heuristic algorithms tailored to address the LRP with fuzzy demand, leveraging the characteristics of the existing algorithms.

To address these gaps comprehensively, we consider the characteristics of simultaneous pickup and delivery and fuzzy demand in the two-echelon logistics network of rural e-commerce logistics. The study aims to maximise the profit of logistics enterprises with government subsidies and the Two-Echelon Location-Routing with Fuzzy Demand (2E-LRP-FD) model is constructed. A two-stage INSGA-II algorithm based on stochastic simulation is designed by combining the K-means clustering algorithm, stochastic simulation method and improved non-dominated sorting genetic algorithm. We propose a two-stage INSGA-II algorithm, integrating the K-means clustering algorithm, stochastic simulation method and the improved non-dominated sorting genetic algorithm, to effectively solve the problem.

2. PROBLEM DESCRIPTION AND MATHEMATICAL MODEL

The two-echelon e-commerce logistics network includes the County Distribution Centre (CDC), Township Distribution Station (TDS) and Village Service Point (VSP) (*Figure 1*).

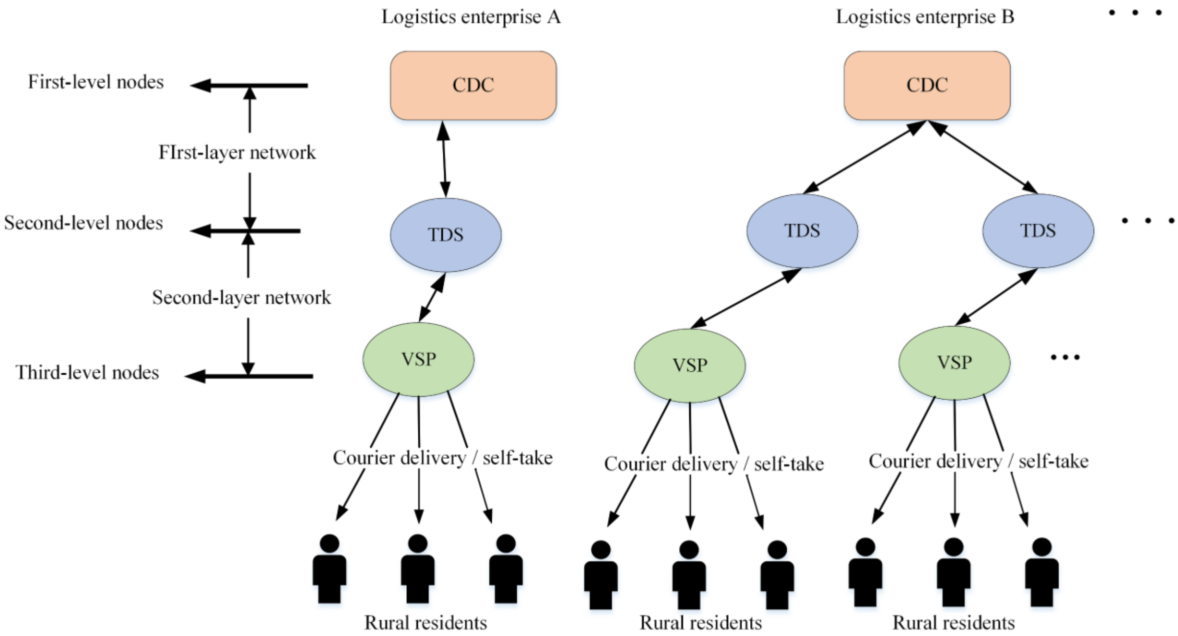


Figure 1 – Two-echelon distribution network

2.1 Problem description

The 2E-LRP-FD is structured into two layers and can be defined as follows: $G = (N, E)$ is a directed network where $N = N_A \cup N_B \cup N_C$ is a set of nodes in which N_A is a set of CDCs; N_B is a set of candidate TDSs; and N_C is a set of VSPs. The set of nodes in the first layer and second layer are denoted by two additional subsets of nodes N_1 ($N_1 = N_A \cup N_B$) and N_2 ($N_2 = N_B \cup N_C$), respectively. The arc set E contains arc $e = (i, j)$, $i, j \in N, i \neq j$. Our decisions include the following: (a) TDS location decision. The TDS is selected from the candidate TDSs; (b) Allocation decision. The node distribution relationship between the two layers is determined; (c) Vehicle routing decision. The vehicle routing of two layers is planned. In practice, only the delivery demand of each VSP can be determined, and the pickup demand of each VSP obviously has great uncertainty. The triangular fuzzy variable $\widetilde{p_i} = (p_{1i}, p_{2i}, p_{3i})$ is used to represent the pickup demand of the VSP, where p_{1i}, p_{2i} and p_{3i} represent the minimum, middle and maximum pickup demand respectively.

2.2 Assumptions

The following assumptions are proposed to simplify the model:

- Vehicles return to their original departure points after delivering freight.
- Upper-level nodes serve lower-level nodes, and transportation services cannot cross levels. Each VSP is visited by only one vehicle.
- The first layer vehicles are large logistics freight vehicles, while the second layer vehicles are medium or small logistics freight vehicles. The vehicles operate at a fixed speed and no uncertain factors, such as sudden incidents or roadblocks, are considered during transportation.
- Each VSP has both pickup and delivery demands, and the method of simultaneous pickup and delivery is selected.
- The location of the CDC is known, with no service capacity constraints. The candidate locations and their service capacities for TDSs are known.
- The differentiation of freight attributes is not considered, and freight can be mixed on the vehicles, but the total weight of freight must not exceed the vehicle's capacity.
- Government subsidies are available for both pickup and delivery activities at each layer. The subsidies are measured in a unified unit.

2.3 Notations

To formulate the MILP mathematical model for the problem, the following notations are introduced (*Table 2*).

Table 2 – Notations

Notations	Definition
N_A	Set of CDCs, $a \in N_A = \{1,2,\cdots,n_a\}$
N_B	Set of candidate TDSs, $b \in N_B = \{n_a+1, n_a+2,\cdots,n_a+n_b\}$
N_C	Set of VSPs, $N_C = \{n_a+n_b+1, n_a+n_b+2,\cdots,n_a+n_b+n_c\}$
N	Set of nodes, $N = \{N_A \cup N_B \cup N_C\}$
N_1	Set of first-layer nodes, $N_1 = N_A \cup N_B$
N_2	Set of second-layer nodes, $N_2 = N_B \cup N_C$
K_1	Set of first-layer vehicles
K_2	Set of second-layer vehicles
K	Set of vehicles, $K = \{K_1 \cup K_2\}$
F_1	Total rent cost of TDS
F_2	Cost of the vehicle
F_3	Punishment cost of VSP
d_{ij}	Travel distance from i to j
V_1	The average speed of the first-layer vehicle
V_2	The average speed of the second-layer vehicle
Q_1	The capacity of the first-layer vehicle
Q_2	The capacity of the second-layer vehicle
H_1	The travel distance of the first-layer vehicle
H_2	The travel distance of the second-layer vehicle
fc_1	The fixed cost of the first-layer vehicle
fc_2	The fixed cost of the second-layer vehicle
vc_1	The variable cost of the first-layer vehicle
vc_2	The variable cost of the second-layer vehicle
C_b	The rent cost of each TDS
q_i	The delivery demand of VSP
p_i	The pickup demand of VSP
ET_i	The earliest expected service time of $i \in N_C$
LT_i	The latest service time expected by $i \in N_C$
m	Penalty coefficient of the vehicle's early arrival at $i \in N_C$
n	Penalty coefficient of the vehicle late arrival at $i \in N_C$
D_{ij}^{1a}	The total amount of freight to be delivered to the TDS by the vehicle when travelling from $i \in N_1$to$j \in N_1$
P_{ij}^{1a}	The total amount of freight pickup from the TDS when the vehicles of the CDC are heading from $i \in N_1$to $j \in N_1$
${}^{-1}P_b^a$	In the previous cycle, the TDS pick up the total amount of freight belonging to the CDC from the VSP
D_{ij}^2	The total amount of freight to be delivered by the vehicle when travelling from $i \in N_2$ to $j \in N_2$
P_{ij}^2	The total amount of freight that has been picked up by the vehicle when travelling from $i \in N_2$ to $j \in N_2$
L_b	The service capacity limitation of TDS
T_b	The start time distribution of the TDS vehicles in the second layer

T_i^a	The time when the CDC vehicle arrives at $i \in N_1$
ft_1	The time required for the TDS to process the unit freight
t_{middle}	The stipulated latest time for first-layer of delivery freight to reach the TDS
s_{ai}	The relationship between CDC and VSP, it is when the VSP belongs to the CDC, otherwise it is 0
α_{ab}	The pickup and delivery income of unit freight between CDC and TDS
α'_{ab}	The government's subsidies for unit freight between CDC and TDS
β_{bc}	The pickup and delivery income of unit freight between TDS and VSP
β'_{bc}	The government's subsidies for unit freight between TDS and VSP
D_b^a	The total amount of freight delivered by CDC to TDS
P_b^a	The total amount of freight collected by the TDS from the VSP
φ_{ijk}	The load capacity of the first-layer vehicle $k \in K_1$ when travelling from $i \in N_1$ to $j \in N_1$
ψ_{ijk}	The load capacity of the second-layer vehicle $k \in K_2$ when travelling from $i \in N_2$ to $j \in N_2$
x_{ijk}	$x_{ijk} = \begin{cases} 1\ If\ vehicle\ k \in K_1\ travels\ from\ node\ i \in N_1\ to\ node\ j \in N_1 \\ 0\ otherwise \end{cases}$
y_{ijk}	$y_{ijk} = \begin{cases} 1\ If\ vehicle\ k \in K_2\ travels\ from\ node\ i \in N_2\ to\ node\ j \in N_2 \\ 0\ otherwise \end{cases}$
Z_b	$Z_b = \begin{cases} 1\ If\ node\ b \in N_B\ is\ selected\ as\ TDS \\ 0\ otherwise \end{cases}$
f_{bi}	$f_{bi} = \begin{cases} 1\ If\ node\ i \in N_C\ is\ serviced\ by\ node\ b \in N_B \\ 0\ otherwise \end{cases}$

2.4 Model formulation

The objective function aims to maximise the profit of logistics enterprises factoring in government subsidies. The profit of enterprises is derived from the difference between income and total cost. Income comprises two components: revenue from pickup and delivery operations and government subsidies for rural area pickup and delivery. The model formulation is as follows:

$$max\,Z = max(T - F) \tag{1}$$

where *Equation 1* represents the objective function of maximising the profit of logistics enterprises considering government subsidies.

The total income consists of two parts: revenue generated from actual operations and subsidies for pickup and delivery in rural areas to incentivise e-commerce logistics enterprises to penetrate rural markets. This is expressed in *Equation 2*.

$$T = (\alpha_{ab} + \alpha'_{ab}) \cdot \left(\sum_{k \in K_1} \sum_{i \in N_B} D_i^a \cdot x_{aik} + \sum_{k \in K_1} \sum_{i \in N_B} P_i^a \cdot x_{aik} \right) + (\beta_{bc} + \beta'_{bc}) \cdot \left(\sum_{k \in K_2} \sum_{i \in N_C} \cdot \widetilde{p_i} \cdot y_{ibk} + \sum_{k \in K_2} \sum_{i \in N_C} q_i \cdot y_{bik} \right) \tag{2}$$

where if vehicle $k \in K_1$ travels from node $a \in N_A$ to node $i \in N_B$

The total cost of rural e-commerce logistics mainly includes the rent cost of the TDS, the cost of vehicles, the penalty cost of the VSP.

1) Total rent cost of the TDS is as shown in *Equation 3*.

$$F_1 = \sum_{b \in N_B} C_b \cdot Z_b \tag{3}$$

where $Z_b = 1$ if node $b \in N_B$ is selected as TDS; otherwise $Z_b = 0$.

2) The cost of the vehicle is composed of the fixed cost and variable cost, as shown in *Equation 4*:

$$F_2 = \sum_{i\in N_1}\sum_{j\in N_2}\sum_{k\in K_1} fc_1 \cdot x_{ijk} + \sum_{i\in N_1}\sum_{j\in N_2}\sum_{k\in K_2} fc_2 \cdot y_{ijk} + \sum_{i\in N_1}\sum_{j\in N_1}\sum_{k\in K_1} vc_1 \cdot d_{ij} \cdot x_{ijk} + \sum_{i\in N_2}\sum_{j\in N_2}\sum_{k\in K_2} vc_2 \cdot d_{ij} \cdot y_{ijk} \tag{4}$$

where if vehicle $k \in K_1$ travels from node $i \in N_1$ to node $j \in N_1$,

3) The penalty cost of the VSP is defined as *Equation 5*:

$$F_3 = m \cdot \sum_{i\in N_C} max(ET_i - T_i, 0) + n \cdot \sum_{i\in N_C} max(T_i - LT_i, 0) \tag{5}$$

Then the total cost can be expressed as *Equation 6*:

$$\begin{aligned} F = F_1 + F_2 + F_3 = &\sum_{b\in N_B} C_b \cdot Z_b + \sum_{i\in N_1}\sum_{j\in N_2}\sum_{k\in K_1} fc_1 \cdot x_{ijk} + \sum_{i\in N_1}\sum_{j\in N_2}\sum_{k\in K_2} fc_2 \cdot y_{ijk} + \sum_{i\in N_1}\sum_{j\in N_1}\sum_{k\in K_1} vc_1 \cdot d_{ij} \cdot x_{ijk} \\ &+ \sum_{i\in N_2}\sum_{j\in N_2}\sum_{k\in K_2} vc_2 \cdot d_{ij} \cdot y_{ijk} + m \cdot \sum_{i\in N_C} max(ET_i - T_i, 0) + n \cdot \sum_{i\in N_C} max(T_i - LT_i, 0) \end{aligned} \tag{6}$$

Constraint (7) indicates that each vehicle of the CDC starts and stops at the same CDC and each vehicle is only assigned to one route.

$$\sum_{j\in N_B} x_{ijk} = \sum_{j\in N_B} x_{jik} \leq 1, \forall i \in N_A, k \in K_1 \tag{7}$$

Constraint (8) restricts the travel distance of the first layer vehicle.

$$\sum_{i\in N_1}\sum_{j\in N_1} d_{ij} \cdot x_{ijk} \leq H_1, \forall k \in K_1 \tag{8}$$

Constraint (9) calculates the load of the vehicle when it departs from the CDC.

$$\sum_{i\in N_B} \varphi_{aik} = \sum_{i\in N_B} D_{ai}^{1a} = \sum_{b\in N_B}\sum_{j\in N_1} D_b^a \cdot x_{bjk} \leq Q_1, \forall a \in N_A, k \in K_1, i \neq j \tag{9}$$

Constraint (10) represents the capacity constraint of the first layer vehicle.

$$D_{ij}^{1a} + P_{ij}^{1a} \leq Q_1 \cdot \sum_{k\in K_1} x_{ijk}, \forall i \in N_B, j \in N_1, a \in N_A, i \neq j \tag{10}$$

Constraint (11) represents the load of the vehicle when it returns to the CDC.

$$\sum_{i\in N_B} \varphi_{iak} = \sum_{i\in N_B} P_{ia}^{1a} = \sum_{b\in N_B}\sum_{j\in N_1} {}^{-1}P_b^a \cdot x_{jbk} \leq Q_1, \forall a \in N_A, k \in K_1, i \neq j \tag{11}$$

Constraint (12) calculates the delivery amount volume from the CDC to the TDS. If node $i \in N_C$ is serviced by node $b \in N_B$, $f_{bi} = 1$; otherwise $f_{bi} = 0$.

$$D_b^a = \sum_{i\in N_C} q_i \cdot f_{bi} \cdot s_{ai} \cdot Z_b, \forall b \in N_B, a \in N_A \tag{12}$$

Constraint (13) limits the total amount of freight collected by the TDSs.

$$P_b^a = \sum_{i\in N_C} p_i \cdot f_{bi} \cdot s_{ai} \cdot Z_b, \forall b \in N_B, a \in N_A \tag{13}$$

Constraint (14) means that each vehicle of TDS starts and stops at the same TDS and is called at most once.

$$\sum_{j\in N_2} y_{ijk} = \sum_{j\in N_2} y_{jik} \le 1, \forall i \in N_B, k \in K_2 \tag{14}$$

Constraint (15) ensures the departure time of vehicles for the second layer distribution from the TDS.

$$T_b = \max_{a\in N_A}\{T_b^a + ft_1 \cdot D_b^a, t_{middle} + ft_1 \cdot D_b^a\}, \forall b \in N_B \tag{15}$$

Constraint (16) ensures the flow balance at the TDSs.

$$\sum_{j\in N_1}\sum_{k\in K_1}\sum_{a\in N_A} \varphi_{jbk} + \sum_{a\in N_A}\left(-D_b^a + {}^{-1}P_b^a\right) = \sum_{j\in N_1}\sum_{k\in K_1}\sum_{a\in N_A} \varphi_{bjk}, \forall b \in N_B \tag{16}$$

Constraint (17) represents the service capacity limitation of the TDS.

$$\sum_{a\in N_A} D_b^a + \sum_{a\in N_A} {}^{-1}P_b^a \le L_b \cdot Z_b, \forall b \in N_B \tag{17}$$

Constraint (18) limits the travel distance of the second-layer vehicle.

$$\sum_{i\in N_2}\sum_{j\in N_2} d_{ij} \cdot y_{ijk} \le H_2, \forall k \in K_2 \tag{18}$$

Constraint (19) states that the load capacity should be less than the load limit.

$$\sum_{j\in N_C} \psi_{jbk} = \sum_{j\in N_C} P_{jb}^2 = \sum_{i\in N_2}\sum_{j\in N_B} p_i \cdot y_{ijk} \le Q_2 \cdot Z_b, \forall b \in N_B, k \in K_2, j \ne i \tag{19}$$

Constraint (20) ensures the flow balance at any VSP.

$$\sum_{j\in N_2}\sum_{k\in K_2}\sum_{b\in N_B} \psi_{jbk} - q_i + p_i = \sum_{j\in N_2}\sum_{k\in K_2}\sum_{b\in N_B} \psi_{bjk}, \forall i \in N_C \tag{20}$$

Constraint (21) describes the relationship between the change in the load capacity of the second layer vehicle.

$$\sum_{j\in N_2} P_{ij}^2 - \sum_{j\in N_2} P_{ji}^2 = P_i, \forall i \in N_c \tag{21}$$

Constraints (22)–(26) constrain the values of binary variables to zero and one.

$$x_{ijk} \in \{0,1\}, \forall i \in N_1, j \in N_1, k \in K_1 \tag{22}$$

$$y_{ijk} \in \{0,1\}, \forall i \in N_2, j \in N_2, k \in K_2 \tag{23}$$

$$Z_b \in \{0,1\}, \forall b \in N_B \tag{24}$$

$$f_{bi} \in \{0,1\}, \forall b \in N_B, i \in N_C \tag{25}$$

$$s_{ai} \in \{0,1\}, \forall a \in N_A, i \in N_C \tag{26}$$

3. FUZZY CHANCE-CONSTRAINED PROGRAMMING AND ALGORITHM DESIGN

The fuzzy chance-constrained programming method is used to deal with the triangular fuzzy variables of pickup demands. Additionally, we present a two-stage INSGA-II that integrates stochastic simulation and a K-means clustering algorithm to effectively solve the problem.

3.1 Fuzzy chance-constrained programming

Liu [18] introduced the fuzzy credibility theory to the solution of the fuzzy demand problem, using fuzzy functions to represent customer demands. Given this framework, the 2E-LRP-FD with the concept of fuzzy credibility theory will be modelled in this paper. Its fuzzy chance constrained programming model is *Equation 27*, where the given confidence level can be understood as the degree of requirement of the decision maker for the establishment of the constraint condition.

$$\begin{cases} min f(x,\tilde{\xi}) \\ s.t. Pos\{\xi | f(x,\xi) \geq f\} \geq \alpha \\ \ Pos\{\xi | g_j(x,\xi) \leq 0\} \geq \alpha, j = 1,2,\cdots,p \end{cases} \tag{27}$$

where x is the decision vector; ξ is the fuzzy parameter vector; the set function Pos represents the possibility; $f(x,\tilde{\xi})$ is the objective function; $g_j(x,\xi)$ is the j^th^ constraint condition; α is a given confidence level, which can be understood as the degree of requirement of decision makers for the establishment of constraint conditions.

Suppose that the triangular fuzzy variable is $\bar{\xi} = (\xi_1, \xi_2, \xi_3)$, at the confidence level $\alpha(0 \leq \alpha \leq 1)$, if $pos\{\xi = z\}$, then $(1-\alpha)\xi_1 + \alpha\xi_2 \leq z$ and $(1-\alpha)\xi_3 + \alpha\xi_2 \geq z$. Since the pickup demand of each VSP $p_i = (p_i^1, p_i^2, p_i^3)$ is a triangular fuzzy variable, the Constraints (19)–(21) can be transformed into Constraints (28)–(33):

$$\sum_{j\in N_C} \psi_{jbk} = \sum_{j\in N_C} P_{jb}^2 \leq \sum_{i\in N_C}\sum_{j\in N_2} \{(1-\alpha)\cdot p_i^3 + \alpha \cdot p_i^2\} \cdot y_{ijk} \leq Q_2 \cdot Z_b, \forall b \in N_B, k \in K_2, i \neq j \tag{28}$$

$$\sum_{j\in N_C} \psi_{jbk} = \sum_{j\in N_C} P_{jb}^2 \geq \sum_{i\in N_C}\sum_{j\in N_2} \{(1-\alpha)\cdot p_i^2 + \alpha \cdot p_i^1\} \cdot y_{ijk} \leq Q_2 \cdot Z_b, \forall b \in N_B, k \in K_2, i \neq j \tag{29}$$

Constraints (28) and (29) are the load capacity and should be less than the load limit.

$$\sum_{j\in N_2}\sum_{k\in K_2}\sum_{b\in N_B} \psi_{jbk} - q_i + (1-\alpha)\cdot p_i^2 + \alpha\cdot p_i^1 \leq \sum_{j\in N_2}\sum_{k\in K_2}\sum_{b\in N_B} \psi_{bjk}, \forall i \in N_C \tag{30}$$

$$\sum_{j\in N_2}\sum_{k\in K_2}\sum_{b\in N_B} \psi_{jbk} - q_i + (1-\alpha)\cdot p_i^3 + \alpha\cdot p_i^2 \geq \sum_{j\in N_2}\sum_{k\in K_2}\sum_{b\in N_B} \psi_{bjk}, \forall i \in N_C \tag{31}$$

Constraints (30) and (31) are the flow balance at any VSP.

$$\sum_{j\in N_2} P_{ij}^2 - \sum_{j\in N_2} P_{ji}^2 \leq (1-\alpha)\cdot p_i^2 + \alpha\cdot p_i^1, \forall i \in N_c \tag{32}$$

$$\sum_{j\in N_2} P_{ij}^2 - \sum_{j\in N_2} P_{ji}^2 \geq (1-\alpha)\cdot p_i^3 + \alpha\cdot p_i^2, \forall i \in N_c \tag{33}$$

Constraints (32) and (33) represent the relationship between the change in the load capacity of the second layer vehicle.

3.2 Two-stage algorithm design

We propose a two-stage algorithm, including the first stage TDS location and the second stage two-layer routing planning.

First stage: K-means clustering

Given a set of VSPs $N_C = \{1,2,\cdots,i\}$, each VSP is a two-dimensional vector composed of longitude and latitude. The K-means clustering algorithm is used to divide the VSPs into K clusters, namely $A = \{A_1, A_2, \cdots, A_K\}$. Based on the Euclidean distance from each VSP to the corresponding centre, the objective function, denoted as B is to minimise the total distance between the VSP and its corresponding cluster center.

The calculation is as *Equation 34*:

$$B = min \sum_{a=1}^{K} \left[\sum_{i=1}^{N_C} z_{ai} \cdot d^2(i, A_a) \right] \tag{34}$$

where $z_{ai} = 1$ if $i \in A_a$, otherwise $z_{ai} = 0$. $d^2(i, A_a)$ represents the Euclidean distance between the VSP and the cluster center.

The key of K-means clustering is the determination of K. The sum of squared errors (SSE) within clusters, also known as the intra-cluster sum of squares, is a common method to measure the clustering effectiveness. *Equation 35* is shown below to plot the curve of the SSE with different values of K in the k-means clustering and find the position on the curve where a 'bend' occurs, which indicates a significant decrease in SSE, indicating an optimal value of K.

$$SSE = \sum_{k=1}^{K} \sum_{p \in N_C} |p - c_k|^2 \tag{35}$$

where K is the number of clusters; c_k is the centroid of the cluster k, p is the sample.

The steps of K-means clustering algorithm are as follows:

— Step 1: Randomly select K VSPs from N_C, initialise K centers and construct an initial membership matrix.
— Step 2: Traverse each VSP and calculate the distance between each cluster centre and the VSPs.
— Step 3: According to the distance between the VSPs and each cluster centre, allocate the VSPs to the nearest cluster centre;
— Step 4: Repeat the above steps until each centre remains unchanged.
— Step 5: Calculate the sum of distances from the VSPs in each category to the TDSs.
— Step 6: Compare the shortest distance and obtain the TDS for the Kth type of VSPs.
— Step 7: Update the collection of TDSs until each category is assigned a corresponding TDS.
— Step 8: Output the location selection results of the TDS.

Second stage: INSGA-II algorithm based on stochastic simulation

The algorithm flow for solving the vehicle routing optimisation problem using the stochastic simulation-based INSGA-II algorithm is illustrated in *Figure 2*.

This paper adopts an improved insertion method to generate a high-quality initial population, aiming to overcome the inherent limitations of NSGA-II's strong reliance on initial solutions. The traditional elite retention strategy is simple and efficient. However, it tends to cause a concentration effect of dominant solutions on the Pareto front, which hinders population diversity and may lead to premature convergence and local optimum. Based on Cordeau's [32] insertion heuristic for solving the vehicle routing problems with a time windows (VRPTW), we propose an improved insertion construction method for generating initial feasible solutions for the two layers routing. The steps are as follows:

— Step 1: Randomly select point $i \in N_C = \{1,2,\cdots,n_c\}$ as the starting point.
— Step 2: Let k be the routing index and initialise the first routing $k = 1$.
— Step 3: Choose a sequence of VSPs, denoted as $[i, i+1, \cdots n, 1,2, \cdots, i-1]$, perform the following operations:

- Step 3.1: Check the current routing k to see if inserting point i into it would violate the vehicle's loading capacity constraint. If it does not violate the constraint, select this routing. If it does violate the constraint, set $k = k + 1$ to the next routing.
- Step 3.2: In the selected routing k find an insertion position for point i such that the insertion does not violate the time window constraint. Among all possible insertion positions, choose the one that minimises the increase in the total distance travelled by the vehicle after the insertion.

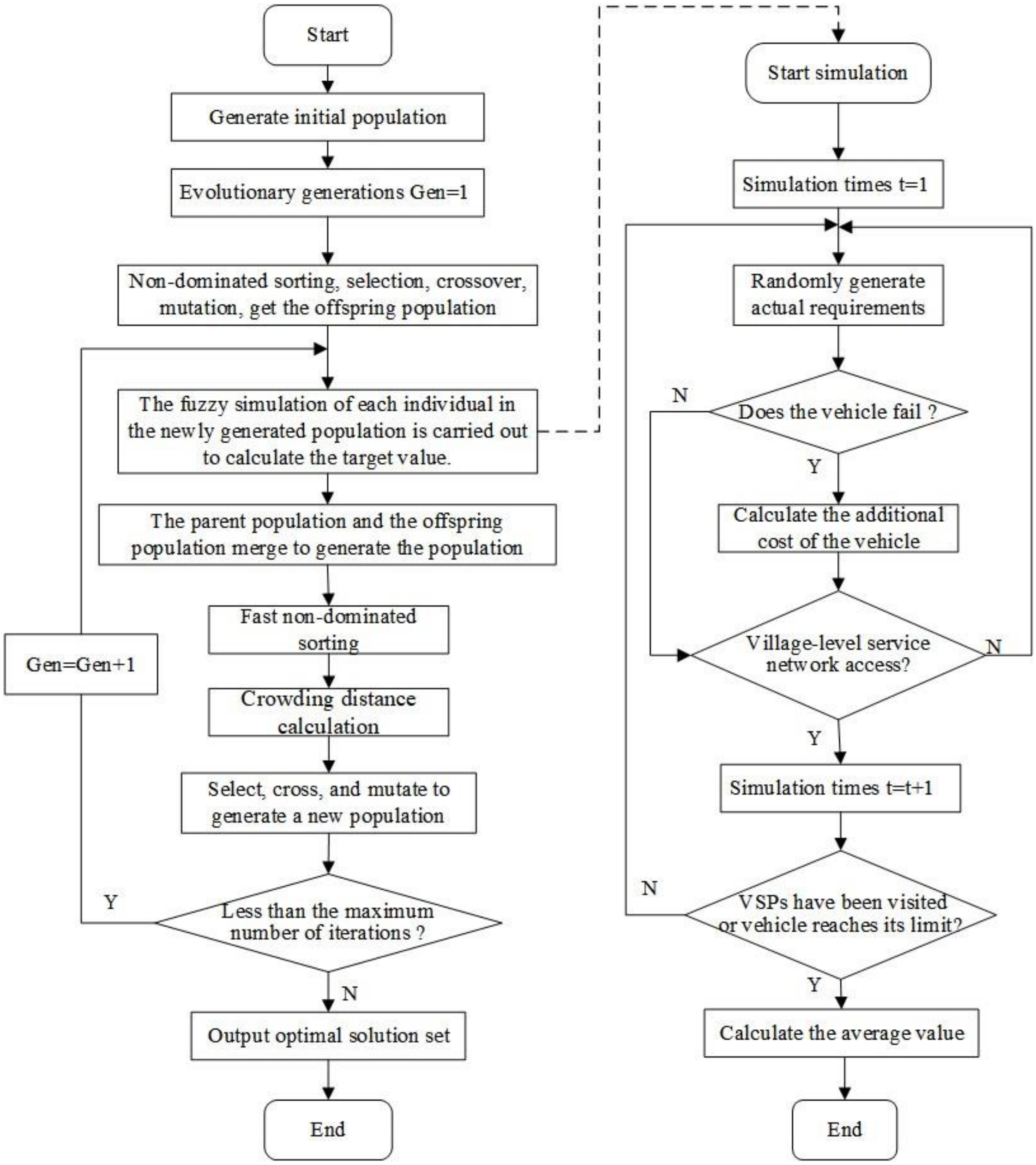


Figure 2 – INSGA-II algorithm based on the stochastic simulation

4. NUMERICAL EXAMPLE

4.1 Data

The model and algorithm are verified by Nguyen instances set [33], which contain a total of 24 instances. The name can be expressed as $n - m - N(MN)[b]$: $n \in \{25,50,100,200\}$ represents the number of VSPs; $m \in \{5,10\}$ represents the number of TDSs; $Q \in \{750,850\}$ represents the capacity of first layer vehicles; $R \in$

$\{100,150\}$ represents the capacity of second layer vehicles; N indicates that the location of the VSP obeys the univariate normal distribution; MN indicates that the location of the VSP obeys the multivariate normal distribution and the demand of the VSP obeys the normal distribution of mean $\mu = 15$ and variance $\sigma^2 = 25$. The suffix 'b' denotes an instance with car capacity is $Q = 850$. However, the dataset does not include settings for fuzzy demand. Therefore, based on the original demand, it is modified to triangular fuzzy demand in the following way. The most likely demand value p_i, lower bound $p_{1i} = p_i + U(-4,-1)$ and upper bound $p_{3i} = p_i + U(1,4)$ of fuzzy demand are recorded, where $U(-4,-1)$ and $U(1,4)$ are the uniform distribution random parameters of $[-4,-1]$ and $[1,4]$ respectively. We take the 25-5MN dataset as an example to verify the effectiveness of the proposed model and algorithm.

4.2 Parameters value

The relevant parameters in the model are assigned as shown in *Table 3*.

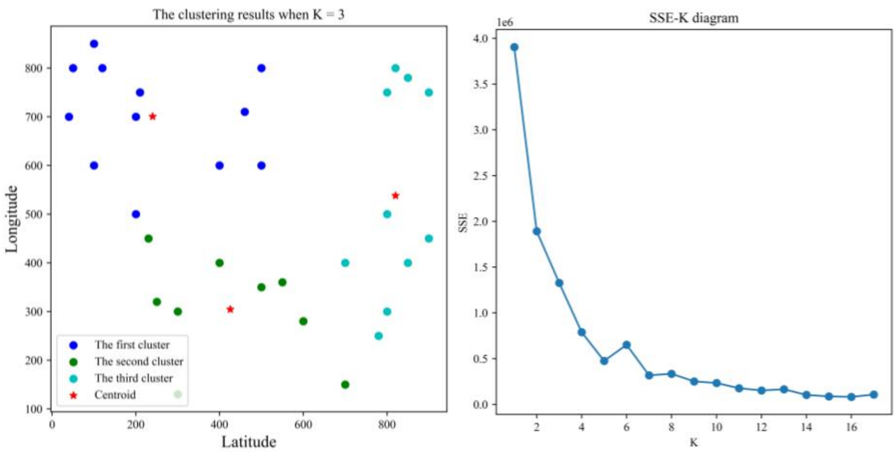
Table 3 – Model parameter value

Notations		Values
V_1	The average speed of the first-layer vehicle [km/h]	45
V_2	The average speed of the second-layer vehicle [km/h]	25
Q_1	The capacity of the first layer vehicle [kg]	7500
Q_2	The capacity of the second vehicle [kg]	4000
H_1	The travel distance of the first layer vehicle [km]	500
H_2	The travel distance of the second layer vehicle [km]	400
fc_1	The fixed cost of the first layer vehicle [CNY/vehicle]	350
fc_2	The fixed cost of the second layer vehicle [CNY/vehicle]	200
vc_1	The variable cost of the first layer vehicle [CNY/km]	1.5
vc_2	The variable cost of the second layer vehicle [CNY/km]	1.0
m	Penalty coefficient of the vehicle's early arrival at $i \in N_C$	0.4
n	Penalty coefficient of the vehicle's late arrival at $i \in N_C$	0.8
T_b	The start time distribution of the TDS vehicles in the second layer	0
ft_1	The time required for the TDS to process the unit freight	0.15
t_{middle}	The stipulated latest time for the first layer of delivery freight to reach the TDS	2
α_{ab}	The pickup and delivery income of unit freight between CDC and TDS [CNY/kg]	3
α'_{ab}	The government's pickup and delivery subsidies for unit freight between CDC and TDS [CNY/kg]	1
β_{bc}	The pickup and delivery income of unit freight between TDS and VSP [CNY/kg]	2
β'_{bc}	The government's pickup and delivery subsidies for unit freight between TDS and VSP [CNY/kg]	1.5
α	Confidence level	0.5

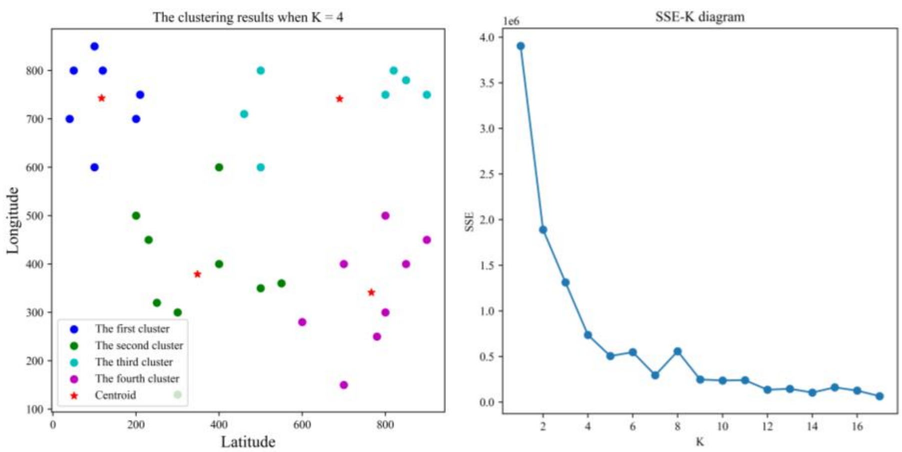
The general population size range is 20 ~ 100, and the value of this paper is 100. The general value range of crossover probability is 0.4 ~ 0.99, and the value of this paper is 0.9. The mutation probability is 0.4 in this paper, which is a high level. The scale of the problem studied in this paper is small, so the number of iterations is set to 200. A computer with the Windows 10 (64-bit) operating system and Intel (R) Core (TM) i7-1065G7 processor was used, and the algorithm was implemented on the MATLAB R2017b platform.

4.3 Analysis of the result

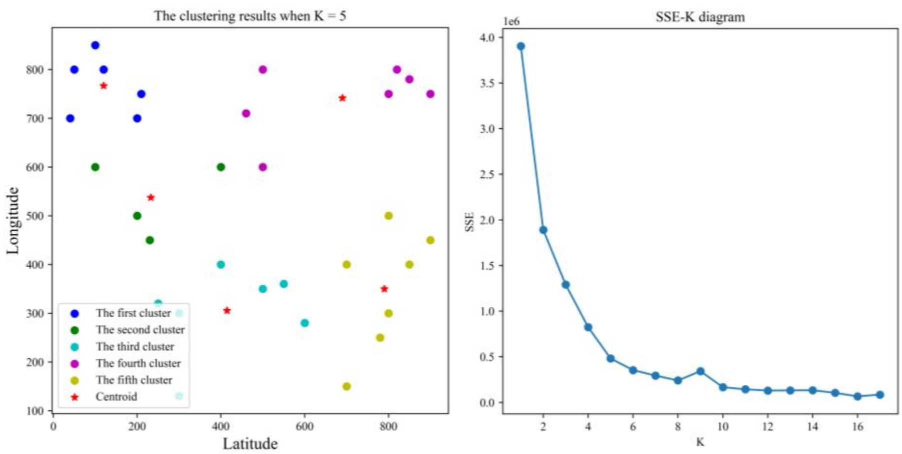
Based on possible values of K, *Figure 3* displays the clustering results and SSE values for the 25-5MN case study for $K = \{3,4,5\}$. The final selected clustering result is for $K = 4$.



(a)



(b)



(c)

Figure 3 – K-means clustering results: a) K=3; b) K=4; c) K=5

According to the results of 2E-LRP-FD in rural e-commerce logistics (*Figure 4*), the selected TDSs are 2, 3, 4 and 5. Among the 25 VSPs, there are two vehicles for the first layer distribution and seven vehicles for the second layer distribution. The total travel distance is 439.04 km, with a total cost of 3,339.49 CNY. In the objective function, the profit of logistics enterprises is 1,085.44 CNY (*Table 4*).

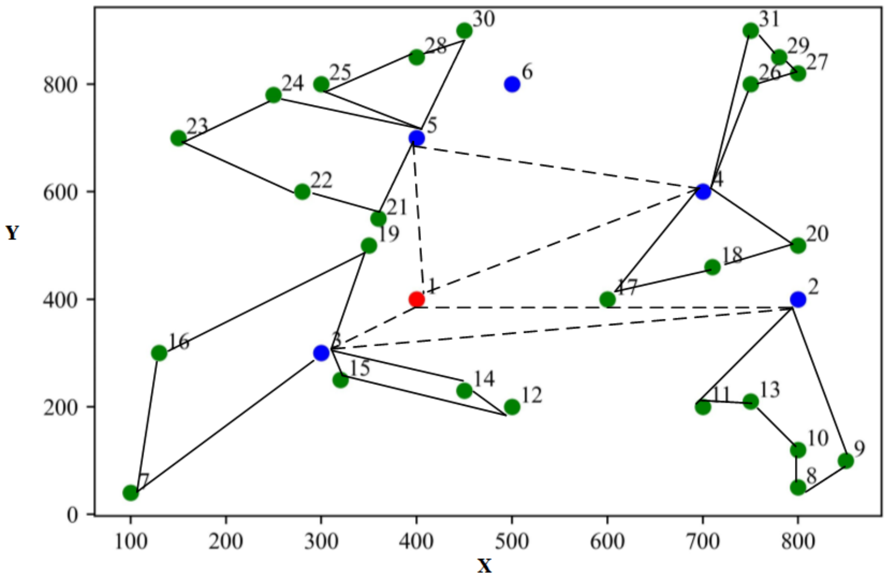


Figure 4 – 25-5MN LRP solution results

Table 4 – Rural e-commerce logistics location-routing

Layers	Routing	Travel distance [km]	Total cost [CNY]	Profit [CNY]
First layer	1-2-3-1	68.09	524.04	135.37
	1-4-5-1	71.01	515.50	144.49
Second layer	2-11-13-10-8-9-2	54.11	334.05	124.05
	3-19-16-7-3	29.80	297.90	114.92
	3-14-12-15-3	42.95	305.68	104.52
	4-17-18-20-4	35.26	327.63	115.63
	4-26-27-29-31-4	51.17	336.58	124.58
	5-30-28-15-5	36.23	369.32	96.32
	5-24-23-22-21-5	50.42	328.79	125.56
Total		439.04	3,339.49	1,085.44

5. DISCUSSION AND CONCLUSION

We compare and analyse the performance and speed of different algorithms. The role of government subsidies in the development of rural logistics is further discussed. At the same time, we discuss the relationship between enterprises profits and demand growth.

5.1 Discussion

To demonstrate the effectiveness of the two-stage INSGA-II algorithm, a comparative analysis with the Greedy Randomised Adaptive Search Procedure (GRASP) algorithm in [34] and the Multi-start Iterated Local Search (MS-ILS) algorithm in [35] is conducted.

As shown in *Table 5*, best known solution (BKS) of the three methods is represented by roughening, and GAP is the error between the optimal result obtained by this method and BKS, i.e. $GAP = (COST - BKS)/BKS \cdot 100$. The last row is the average of each column. The INSGA-II proposed in this paper can obtain the optimal solution of 22 examples, which is higher than the optimal solution of 20 obtained by the MS-ILS. The average GAP of INSGA-II is 0.006, which is less than the average GAP of MS-ILS 0.050. For small to medium-sized instances with third-level nodes less than 200, the INSGA-II algorithm can always find the optimal solution, indicating that the algorithm has good performance.

Table 5 – Results for 2E-LRP instances set Nguyen

Instances	BKS	GRASP	GAP	MS-ILS	GAP	INSGA-II	GAP
25-5N	80,370	81,152	0.97	80,370	0.00	80,370	0.00
25-5Nb	64,562	64,572	0.02	64,562	0.00	64,562	0.00
25-5MN	78,947	80,412	1.86	79,593	0.82	78,947	0.00
25-5MNb	64,438	64,438	0.00	64,438	0.00	64,438	0.00
50-5N	138,126	145,942	5.66	138,126	0.00	138,126	0.00
50-5Nb	111,290	113,234	1.75	111,290	0.00	111,290	0.00
50-5MN	123,484	126,313	2.29	123,484	0.00	123,484	0.00
50-5MNb	105,401	106,033	0.60	105,401	0.00	105,401	0.00
50-10N	116,032	116,709	0.58	116,132	0.09	116,032	0.00
50-10Nb	87,315	90,559	3.72	87,315	0.00	87,315	0.00
50-10MN	136,053	137,321	0.93	136,123	0.05	136,053	0.00
50-10MNb	110,613	110,703	0.08	110,613	0.00	110,613	0.00
100-5N	196,910	200,974	2.06	196,910	0.00	196,910	0.00
100-5Nb	159,989	160,488	0.31	159,989	0.00	159,989	0.00
100-5MN	207,672	210,381	1.30	208,177	0.24	207,672	0.00
100-5MNb	166,640	170,513	2.32	166,640	0.00	166,640	0.00
100-10N	218,040	229,246	5.14	218,040	0.00	218,040	0.00
100-10Nb	157,267	162,308	3.21	157,267	0.00	157,267	0.00
100-10MN	206,450	210,496	1.96	206,450	0.00	206,450	0.00
100-10MNb	170,706	172,276	0.92	170,706	0.00	170,706	0.00
200-10N	355,185	361,971	1.91	355,185	0.00	355,185	0.00
200-10Nb	263,157	267,733	1.74	263,157	0.00	263,157	0.00
200-10MN	336,097	348,866	3.80	336,097	0.00	336,250	0.08
200-10MNb	292,523	302,500	3.41	292,523	0.00	292,600	0.07
Average	164,469.5	168,130.8	1.939	164,524.5	0.050	164,487.9	0.006

In order to test the performance of INSGA-II, standard NSGA-II and Particle Swarm Optimisation (PSO) are used to calculate the above examples. The reason why this paper chose PSO for comparison is its strong local search capability. In addition, the selection of NSGA-II will help analyse the efficiency of the INSGA-II improvement. Therefore, through the comparison of the optimisation results, it can be judged whether the INSGA-II can quickly obtain the optimal solution.

The basic parameters of the three algorithms are the same, running 10 times respectively. The average results are shown in *Table 6*. 'Average Time' represents the average running time of each algorithm over 10 times. 'GAP1' represents the time difference between neighbouring algorithms, and 'GAP2' represents the time difference between each algorithm and the proposed INSGA-II algorithm. It can be observed that NSGA-II has the longest running time, taking 268 seconds. PSO's running time is 8.58% lower than NSGA-II, and INSGA-II is 3.67% lower than PSO. Among these three algorithms, INSGA-II, which is the proposed algorithm in this study, has the shortest running time, being 13.56% faster than the basic genetic algorithm. Therefore, the algorithm proposed in this paper can obtain the optimal solution the fastest.

Table 6 – Comparison Results of Objective Function Values of Each Algorithm

Algorithm	**Average time [s]**	**GAP1 [%]**	**GAP2 [%]**
INSGA-II	236	3.67	/
PSO	245	8.58	3.67
NSGA-II	268	/	13.56

The relationship between subsidy strategies and the profit of logistics enterprises

This section further studies the relationship between subsidy strategies and the profit of logistics enterprises by using numerical data (*Figure 5*).

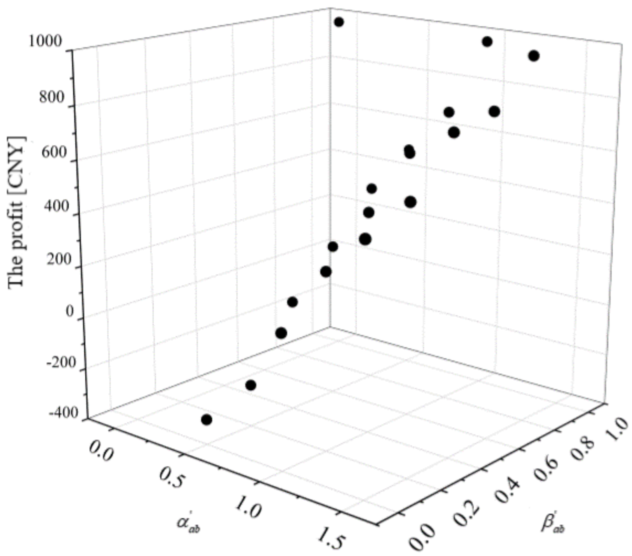


Figure 5 – The impact of government subsidies on the profit of logistics enterprise

— When the government does not implement any subsidy policy ($\alpha'_{ab} = 0, \beta'_{bc} = 0$), the logistics enterprise incurs the maximum loss, which can demonstrate the significance of the government subsidy policy.

— When the government provides a subsidy of more than 1 CNY per unit in the two layers logistics network ($\alpha'_{ab} \geq 1$ or $\beta'_{bc} \geq 1$), the logistics enterprise operates in a profitable state. Moreover, higher government subsidies correlate with increased profits for logistics enterprise.

— From the government's perspective, it is essential to strike a balance between ensuring the profit of logistics enterprises and promoting the development of rural logistics. When the government subsidy is $\alpha'_{ab} = 0.4, \beta'_{bc} = 0.5$, the profit value reaches 27.53 CNY.

The preceding discussion highlighted the relationship between government subsidies and the profits of logistics enterprises. However, government policy support cannot be sustained indefinitely. The purpose of formulating such policies is to foster the healthy development of rural e-commerce logistics, achieve economies of scale and guide production through market forces. Therefore, we investigate how long the policy should be sustained to achieve a virtuous cycle, enabling logistics companies to autonomously expand their operations in the rural market.

The relationship between the profits of logistics enterprises and demands

It is to be assumed that the pickup and delivery demands at VSPs show a growing trend within each subsidy cycle. At the same time, vehicle capacity restrictions mentioned in previous sections are removed. We will study the relationship between the profits of logistics enterprises and the volume of pickup and delivery without government subsidies.

As pickup and delivery demands continue to rise, the profitability of logistics enterprises also increases, and the profit of logistics enterprise also shows an upward trend (*Figure 6*). When the pickup and delivery demands increase to 1.6 times, a certain scale of agglomeration effect is formed in rural e-commerce logistics, and logistics enterprise can achieve profitability on their own. At this point, without government intervention, the market can efficiently allocate resources, creating a virtuous cycle that elevates the level of rural e-commerce logistics.

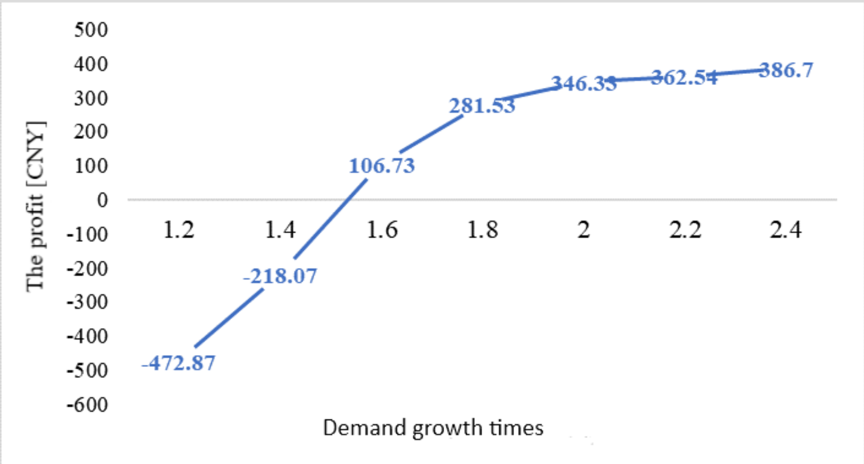


Figure 6 – Relationship between demand and profit

5.2 Conclusions and future works

To further promote the development of rural logistics, this study focuses on the rural e-commerce logistics network. The two-Echelon Location-Routing Problem with fuzzy demand is presented and fuzzy chance-constrained programming is applied to the problem. To solve the problem, we proposed a two-stage INSGA-II. We take the Nguyen instances set as an example to verify the effectiveness of the proposed model and algorithm, drawing the following conclusions:

— The selected TDSs are 2, 3, 4 and 5, respectively. Among the VSPs, there are two first-layer vehicles and seven second-layer vehicles. The driving distance of the two-layer network is 439.04 km, the total cost is 3,339.49 CNY, the profit is 1,085.44 CNY.
— Compared with the GRASP algorithm and the MS-ILS, the two-stage INSGA-II proposed in this paper can obtain the largest number of optimal solutions. Compared with the NSGA-II algorithm and the PSO algorithm, the average solution time of the proposed algorithm is the shortest, which shows the effectiveness of the proposed algorithm.
— The optimal subsidy strategy for the government is $\alpha'_{ab} = 0.4, \beta'_{bc} = 0.5$, where the government provides relatively minimal subsidies while ensuring that the enterprises remain profitable. When the pickup and delivery demand increase to 1.6 times the original level, the local e-commerce logistics form a certain scale of agglomeration effect, allowing the enterprises to achieve profitability on their own.

Additionally, the paper has several potential future works:

— The transportation of freight is limited to general freight, while in rural logistics, there are many special products such as large household appliances, agricultural by-products, cold chain products, and so on.
— The sharing of vehicles among facilities can also be encouraged by relaxing constraints requiring vehicles to return to the origin CDC or TDS, thereby solving open location-routing problems.
— In addition to demand uncertainty, customer time windows and vehicle travel time uncertainty can also be assumed to increase the model's practicability.

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带模糊需求的农村电商物流两级选址—路径问题

摘要:
为促进农村电商物流绿色高质量发展，提出农村电商物流网络模糊需求的两级选址-路径问题(Two-Echelon Location-Routing Problem with Fuzzy Demand, 2E-LRP-FD)。考虑模糊需求、政府补贴和同时交货，以考虑政府补贴的企业利润最大化为目标函数。采用模糊机会约束规划方法处理取货需求的三角模糊变量。此外，本文还提出了一种融合随机模拟和 K-means 聚类算法的两阶段改进非支配排序遗传算法(Improved Non-Dominated Sorting Genetic Algorithm II, INSGA-II)来求解该问题。最后，通过数值实验进行算法和模型验证。结果表明，本文提出的 INSGA-II 算法具有明显的高效性和有效性。进一步，讨论了补贴策略与物流企业利润之间的关系。本研究为农村电商物流体系的构建提供了参考。

关键词:
两级选址-路径问题；模糊需求；K-means 聚类；INSGA-II；农村电商物流