An Improved Genetic Algorithm for the Multi-temperature Food Distribution with Multi-Station

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***Abstract*—This paper studies on the food distribution route planning problem for improving the customer satisfaction and the operator cost of food providers. In the first, the problem is formulated to a combinatorial optimization which is hard to be solved. Thus, a polynomial time algorithm is proposed to solve the problem, combining genetic algorithm and neighbourhood search, to increase the total amount of distributed food and reduce the distribution cost. The proposed algorithm employs the genetic algorithm with integer coding to decide the assignment of customers to distribution vehicles, and integrates the neighbourhood search strategy into the genetic algorithm to improve its performance. Experiment results show that the proposed method improved the distribution performance up-to 111.09%, 73.10% and 70.21%, respectively, in the distributed food amount, the cost efficiency, and the customer satisfaction.**

***Keywords*—Logistics; genetic algorithm; neighbourhood search; food distribution**

I. Introduction

As the development of economy and society in the global, the requirement for the food quality is increasing continuously in most countries. In 2021, the cumulative retail value of grain, oil and food commodities reaches 1675.91 billion yuan, with an increase of 10.8% from 2020, in China [1]. Modern logistics and e-commerce promote the demand growth of food logistics. The main mode of food shopping is becoming from going to retailer to on-line ordering on Internet. Recently, the scale of e-commerce market for fresh food products is increasingly growth. For example, Chinese e-commerce market for fresh food products is increased with a compound annual growth rate at 25%, from 2016 to 2019, and its growth rate has greatly increased during the COVID-19 pandemic [2].

For food suppliers, especially for fresh food suppliers, an unreasonable distribution route strategy can decrease the user satisfaction [3] and increase the distribution cost [4]. Food logistics distribution planning method is an efficient way to address this issue [5]. Unfortunately, the distribution route problem is NP-hard [6], and thus cannot be solved exactly when it is large in the scale. Two kinds of approximate methods can be applied for solving large-scale route problems, heuristics and meta-heuristics. In general, heuristic-based methods can provide a local optimization solution fast. But they usually have a limited performance in problem solving due to their local search strategies. Meta-heuristics can achieve a better performance than heuristics, benefiting from their global search abilities inspired by natural phenomena and laws [7].

Therefore, several existing works exploited various meta-heuristic algorithms to solve the food distribution route problem, for improving the distribution cost or time. But these existing works have some issues which restrict their practices. Some works focused on the single-station distribution problem. A part of works concerned food distribution in only one temperature range. Few works considered to exploit multiple temperature zone refrigerated vehicle for simultaneously distributing foods with different temperature requirements by one vehicle, to improve the usage efficiency of distribution vehicles. Therefore, in this paper, to improve the efficiency of multi-temperature food distribution, a router algorithm is proposed by integrating the neighbourhood search strategy into the genetic algorithm, with objectives of optimizing the amount of distributed foods and the cost for the food distribution. And extensive experiment results verify the performance superiority of our proposed algorithm.

The rest of this paper is organized as follows. Section II illustrates published works aiming at solving food distribution route problems. Section III routes the route problem concerned in this paper. Section IV presents our proposed distribution planning method. Section V evaluates our proposed method by simulated experiments. And finally, Section VI concludes the paper.

II. Related Work

Wang et al. [8] proposed a parthenogenetic algorithm-based method to address the route problem for flesh foods with a same temperature requirement, to optimize the customer value and satisfaction. Zhu and Wang [9] exploited ant colony algorithm to solve the distribution route problem for pharmaceutical cold chain logistics, aiming at completing a distribution task with minimal cost. Based on ant colony algorithm, Fang et al. [10] presented a distribution planning method to improve the operating cost and the green cost. Their method used A* algorithm to improve the slow convergence speed problem due to the insufficient pheromone in the initial stage of ant colony algorithm. For optimizing the total cost of food distribution, Ren et al, [11] designed a knowledge based ant colony algorithm by integrating the elitist tabu search and the knowledge model of dynamic probability selection into ant colony algorithm. By integrating the mutation operator of simulated annealing into genetic algorithm, Li et al. [12] designed a distribution planning method for green fresh foods. These above works focused on the food distribution route problem for single-station, which limits their application scopes.

To address the multi-station problem, Prajapati et al. [13] proposed a heuristic method based on clustering algorithm, to optimize the transport distance and utilization of distribution vehicles. The proposed method first clustered customers, and then iteratively serviced a class of customers with minimal traveller's distance. This work didn't concern the temperature requirements of foods. Wang et al. [14] presented a hybrid heuristic method to optimize the distribution cost and the number of used refrigerator vehicles for fresh foods. This hybrid heuristic method first clustered customers according to their locations and requirements, and then, combine Tabu search and NSGA-II to solve the route problem, with the heuristic idea of using a vehicle to service customers with similar locations and requirements. Tsang et al. [15] exploited multi-objective genetic algorithm based on linear weighting method to improve the number of used refrigerator vehicles, customers' satisfactions and the transport time. These methods assumed there are sufficient refrigerator vehicles for satisfying all customer requirements by only one trip. These assumptions narrow down their application ranges.

Liu et al. [16] employed simulated annealing algorithm for optimizing the transport cost of cold-chain product distributions. This work assumed vehicles didn't return after finishing their distribution tasks, which results in an underestimation of the transport cost. Stellingwerf et al. [17] studied on the cold-chain distribution router problem to optimize the transport cost and the food quality. They modelled the problem into a mixed integer linear programming, and proposed to solve it by existing solvers for small-scale problems. This isn't applicable for solving large-scale problems. Ding [18] used the linear weighting method to transform three optimization objectives into one, for minimizing the distribution cost, the distribution time and the distribution risk, and applied ant colony algorithm with quantum bits to solve the distribution problem. All of these above works assumed each vehicle can transport only one kind of fresh foods. And thus they didn't consider to exploited the multiple temperature zone refrigerated vehicle [19], [20], which can distribute frozen, refrigerated and ambient foods by one vehicle at once. This can lead to a low usage efficiency of distribution vehicles by increasing the number of used vehicles, and thus increase the distribution cost.

Different from existing works, this paper focuses on the distribution router problem in multiple temperature ranges for the scenario of multi-station. This paper try to optimize the distribution efficiency by increasing the total amount of distributed foods and decreasing the total distribution cost, with limited distribution vehicles.

III. Problem Statement

This paper focuses on the router problem for multi-temperature foods distributed by multi-station. Each distribution station is equipped with several distribution vehicles for its food distribution. There are three kinds of foods to be distributed, ambient, refrigerated, and frozen foods. Each vehicle has ability for distributing one or more kinds of foods, considering the refrigerated vehicle with multiple temperature zones. The food supplier need to decide a router strategy to distribute foods to customers of various places from its food distribution stations. The aim of this paper is to provide a router strategy, which is deciding which vehicle is used to distribute foods for each customer, and deciding the distribution router of each vehicle, for optimizing the distributed food amount and the distribution cost. In this paper, each vehicle is assumed to be used once at most for the food distribution. When some customers' requirements cannot satisfied, the food supplier executes our method more times to distribute foods ordered by these customers. Each vehicle is return its original station for subsequent distribution tasks.

Assuming there are S distribution stations, $s_k, 1 \leq k \leq S$. The location of station s_k is (x_k^s, y_k^s), where these two dimensions can represent respectively the latitude and longitude. There are V vehicles, $v_i, 1 \leq i \leq V$. The loading capacities of vehicle v_i for distributing ambient, refrigerated, and frozen foods are respectively q_i^a, q_i^r, and q_i^f. If v_i cannot distribute refrigerated (frozen) foods, q_i^r (q_i^f) is 0. Binary constants $a_{i,k}$ are used to represent whether v_i is equipped in s_k. If v_i is equipped in s_k, $a_{i,k}$ is 1, and otherwise, $a_{i,k} = 0$. There are U customers, $u_j, 1 \leq j \leq U$, ordering various foods needed to be distributed. The amount of ambient, refrigerated, and frozen foods ordered by customer u_j are respectively qa_i, qr_i, and qf_i. The location of u_j is (x_k^u, y_k^u). The distances between a station and a customer and between two customers can be calculated according to their locations, respectively.

Binary variables $z_{i,j}$, $1 \leq i \leq V$, $1 \leq j \leq U$, are used to represent whether the foods required by a customer is distributed by a vehicle. If u_j's required foods are distributed by v_i, then $z_{i,j} = 1$, and otherwise, $z_{i,j} = 0$. To reduce the time of inspecting and tallying foods for customers for avoiding the decreasing of the customer satisfaction, all foods required by a customer are assumed to be distributed by only one vehicle, i.e.,

$$\sum_{i=1}^{V} z_{i,j} \leq 1, 1 \leq j \leq U. \tag{1}$$

A complete router strategy includes not only deciding the vehicle that distributes foods for each customer, but also deciding the distribution order for each vehicle when it serves multiple customers. Integer variables $o_j \in [1, U], j = 1, 2, ..., U$, are used to represent the decision of the distribution order. For a vehicle serving multiple customers, foods required by u_{j1} are distributed before u_{j2} if and only if $o_{j1} < o_{j2}$. As the distribution orders for any two customers are not identical when they are served by one vehicle,

$$\sum_{\substack{1 \leq i \leq V \wedge \\ j1 \neq j2 \wedge \\ z_{i,j1} \cdot z_{i,j2} = 1}} (o_{j1} - o_{j2}) \leq 0, 1 \leq j1, j2 \leq U. \tag{2}$$

For each vehicle, the accumulated amount of foods distributed is not exceeding its capacity, then the following inequation hold.

$$\sum_{j=1}^{U} z_{i,j} \cdot qa_j \leq q_j^a, 1 \leq i \leq V, \quad (3)$$

$$\sum_{j=1}^{U} z_{i,j} \cdot qr_j \leq q_j^r, 1 \leq i \leq V, \quad (4)$$

$$\sum_{j=1}^{U} z_{i,j} \cdot qf_j \leq q_j^f, 1 \leq i \leq V. \quad (5)$$

For a vehicle, there is a cost to use it for food distribution, which is constituted of the startup and transport costs. The commonly linear model is used for evaluating the cost of a vehicle usage,

$$C_i = e_i + \int_l (c_i^{idle} + (c_i^{full} - c_i^{idle}) \cdot \frac{w_i}{q_i^a + q_i^r + q_i^f}) dl. \quad (6)$$

Where e_i is the startup cost of v_i, which includes the driver wage, etc., and is usually considered as a constant. l represents the transport route of the vehicle. c_i^{full} and c_i^{idle} are the costs per unit of transport distance respectively when v_i is empty and full loaded. w_i is the load varied with the transport route, for v_i. $\frac{w_i}{q_i^a+q_i^r+q_i^f}$ represents the utilization of v_i.

The food distribution can be see as three stages for each vehicle, food distribution from the station to the first customer, food distributions from a customer to another customer repeatedly, and return station from the last customer. In the first stage, their is an increased cost ($P1_i$) for distributing foods to the first customer, and the load of v_i is the accumulated amount of foods required by all customers that the vehicle serves, $\sum_{j=1}^{U}(z_{i,j} \cdot (qa_j + qr_j + qf_j))$. $d_{i,j}^{su}$ is used to represent the distance between u_j and the station equipped with v_i, which can be easily calculated by the locations of the user and the station. Then,

$$P1_i = \sum_{\substack{1 \leq j \leq U \wedge \\ z_{i,j} \cdot o_j = 1}} (d_{i,j}^{su} \cdot \quad (c_i^{idle} + (c_i^{full} - c_i^{idle}) \cdot \frac{\sum_{j=1}^{U}(z_{i,j} \cdot (qa_j + qr_j + qf_j))}{q_i^a + q_i^r + q_i^f})). \quad (7)$$

In the second stage, their is a distribution cost for each transport from one customer to another customer, where the transport distance is the distance between these two customers, and the load is the accumulated amount of foods needed to be distributed to customers that have not been served. $d_{jj,j}^{uu}$ is used to represent the distance between customer u_{jj} and customer u_j. Then the cost in the second stage can be calculated by

$$P2_i = \sum_{\substack{1 \leq j \leq U \wedge \\ z_{i,j} \cdot o_j > 1}} ((\sum_{\substack{1 \leq jj \leq U \wedge \\ z_{i,jj} \cdot o_{jj} = o_j - 1}} d_{j,jj}^{uu}) \cdot (c_i^{idle} + (c_i^{full} - c_i^{idle}) \cdot \frac{\sum_{\substack{1 \leq jj \leq U \wedge \\ z_{i,jj} \cdot o_{jj} > o_j}} (z_{i,jj} \cdot (qa_{jj} + qr_{jj} + qf_{jj}))}{q_i^a + q_i^r + q_i^f})), \quad (8)$$

where $\sum_{\substack{1 \leq jj \leq U \wedge \\ z_{i,jj} \cdot o_{jj} = o_j - 1}} d_{j,jj}^{uu}$ is the transport distance from customer u_j to its next customer u_{jj} ($o_{jj} = o_j - 1$). $\sum_{\substack{1 \leq jj \leq U \wedge \\ z_{i,jj} \cdot o_{jj} > o_j}} (z_{i,jj} \cdot (qa_{jj} + qr_{jj} + qf_{jj}))$ is the accumulated amount of foods required by customers with service orders after u_j.

After all customers have been served, in the last stage, the vehicle will return the station that is equipped with it, with idle load. The transport distance is the distance between the station and the last customer served, which is $\sum_{\text{argmax}_j \{z_{i,j} \cdot o_j\}} (z_{i,j} \cdot d_{i,j}^{su})$ for v_i. Therefore, the cost in the third stage for v_i is

$$P3_i = c_i^{idle} \cdot \sum_{\text{argmax}_j \{z_{i,j} \cdot o_j\}} (z_{i,j} \cdot d_{i,j}^{su}). \quad (9)$$

Combining all of above costs, the total distribution cost for each vehicle can be calculated by Eq. (10).

$$C_i = e_i + P1_i + P2_i + P3_i, 1 \leq i \leq V. \quad (10)$$

Then, the multi-temperature food distribution router problem can be formulated by the following optimization problem:

$$\text{Maximizing}\{\sum_{i=1}^{V} \sum_{j=1}^{U} (z_{i,j} \cdot (qa_j + qr_j + qf_j)) - \sum_{i=1}^{V} C_i\} \quad (11)$$

Subjective to:

$$Eq.\ (1)–Eq.\ (10), \quad (12)$$
$$z_{i,j} \in \{0, 1\}, 1 \leq i \leq V, 1 \leq j \leq U, \quad (13)$$
$$o_j \in [1, U], 1 \leq j \leq U. \quad (14)$$

The optimization objective is maximizing the accumulated amount of distributed foods and minimizing the total distribution cost. In practice, the maximization of the distributed food amount is considered as the major optimization objective, as it directly affects the customer satisfaction, and the cost minimization as the minor one. This can be implemented by weighting foods in kilograms (kg) and counting the cost in hundred-dollar units, because a vehicle has thousands of kilograms in loading capacity and it costs hundreds of dollars to distributed foods by the vehicle at a time, in real world. Eq. (refeq:z) and (14) define the value ranges of discrete decision variables. This problem is a combinatory optimization problem, which can be solved by some existing tools, e.g., Gurobi Optimizer [21] and lpsolve [22]. But the time exhausted by these tools are exponentially increased with the problem scale in general, which makes them not suitable for solving large scale problems. Therefore, in the next section, a food distribution router planning method is proposed based on genetic algorithm to provide a router solution in polynomial time.

IV. Improved Genetic Algorithm-based Food Distribution

This section proposes a food distribution router planning method based on genetic algorithm (GA). To improve the performance of GA, the neighbourhood search (NS) strategy is integrated into GA, which helps to increase the diversity of populations. The proposed method, GANS, is outlined in Algorithm 1. As shown in the algorithm, at first, GANS initializes chromosomes by randomly setting the value of

Algorithm 1 GANS: The improved GA with NS for Food Distribution

Input: The information of distribution stations, vehicles, customers and their requirements;
Output: A food distribution router strategy;
```
1: Initializing chromosomes randomly;
2: while the terminal condition is not reached do
3:     Calculating fitness value for each chromosome by Algorithm 2;
4:     Updating the best fitness and the best chromosome;
5:     Executing crossover operator for randomly selected two chromosomes with a certain probability;
6:     Conducting mutation operator on each chromosome with a certain probability;
7:     For each chromosome, swapping two genes randomly, to produce a new chromosome;
8:     Using tournament selection operator to select chromosomes for the next evolution;
9: end while
10: return the distribution router strategy decoded from the best chromosome by Algorithm 2;
```

Algorithm 2 Calculating the Fitness Value for a Chromosome

Input: A chromosome;
Output: The fitness value of the chromosome;
```
1: Decoding the chromosome into the customer assignment to vehicles;
2: for Each vehicle do
3:     for Each customer assigned to the vehicle do
4:         if The vehicle satisfy the customer's requirements then
5:             Loading foods required by the customer to the vehicle;
6:             Updating the residual capacity of the vehicle;
7:             Accumulating the amount of distributed foods (W);
8:         end if
9:         Calculating the distribution cost of the vehicle by Eq. (10), and accumulating it (C).
10:    end for
11: end for
12: return W − C;
```

each gene (line 1 in Algorithm 1), where each chromosome represents an assignment of customers to vehicles. In each chromosome, There is a corresponding relationship between genes and customers, and thus its length is the number of customers. The value of a gene represent the vehicle allocated to the corresponding customer for its food distribution. After the chromosome initialization, GANS repeats the chromosome evolution by crossover and mutation crossovers as well as NS strategy (lines 2–9 in Algorithm 1).

In the stage of the chromosome evolution, a fitness function must be designed for evaluating the quality of each chromosome. In this paper, the fitness function is defined as the optimization objective (11), i.e.,

$$fitness = W - C, \tag{15}$$

where W is the total amount of distributed foods, which is $\sum_{i=1}^{V}\sum_{j=1}^{U}(z_{i,j} \cdot (qa_j + qr_j + qf_j))$. C is the total cost for food distribution, which is $\sum_{i=1}^{V} C_i$.

Given a chromosome, its fitness value can be calculated as following, shown in Algorithm 2. First, the chromosome is decoded into the assignment of customers to vehicles (line 1 in Algorithm 2). Then for each vehicle (line 2 in Algorithm 2), first fit heuristic method is applied for loading foods of customers assigned to the vehicle (line 3–11 in Algorithm 2). When foods required by a customer are loaded, their weights are accumulated to W (line 7 in Algorithm 2). After food loading for a vehicle, its cost can be calculated by Eq. (10), and the cost is accumulated to C (line 9 in Algorithm 2). In the end of Algorithm 2, the fitness value is achieved by $W - C$ (line 12 in Algorithm 2).

In each chromosome evolution, GANS first evaluates the fitness for every chromosome using Algorithm 2 (line 3 in Algorithm 1), and find the best fitness (new one). Then, if the best fitness is better than the current one achieved in preceding evolutions, GANS updates the current best fitness and the current best chromosome to the new best fitness and its corresponding chromosome, respectively (line 4 in Algorithm 1). After this, GANS evolves chromosomes by crossover, mutation, and NS to generate offspring, and the selection operator to produce a new generation (lines 5–8 in Algorithm 1), as detailed following:

Crossover: For the crossover operation, each chromosome is picked with a certain probability, and the one-point crossover operator is performed for every two picked chromosomes to create two new chromosomes (offspring) (line 5 in Algorithm 1).

Mutation: For each chromosome, it has a certain probability to be mutated to produce a new offspring (line 6 in Algorithm 1). In this paper, the uniform mutation is chose due to its effectiveness for large-scale problems.

Neighbourhood Search (NS): To increase the diversity of chromosomes for improving the global search ability of GA, we propose to integrate NS strategy into GA (line 7 in Algorithm 1). Specifically, for each chromosome, GANS randomly generates two points, and swaps genes in these two points, which generates a new offspring.

Selection: To realize the evolution, a selection operator must be performed for the population consisted of chromosomes in the current generation and new offspring produced by above operators, to produce a new generation (line 8 in Algorithm 1). GANS employs the tournament selection which retain the best chromosomes to the next generation.

After the generation evolution, GANS has the best chromosome with the best fitness. Then, by Algorithm 2, a distribution router strategy is provided from the best chromosome.

V. Performance Evaluation

To evaluate the performance of our proposed method, a simulated experiment environment is generated. In the simulated environment, as shown in Fig. 1, the distribution coverage is a square area from (-100, -100) to (100, 100) in km. Four distribution stations are respectively deployed on the points of (50, 50), (-50, 50), (-50, -50), and (50, -50). There are total 10 delivery vehicles. The probabilities of every vehicle having the abilities of distributing refrigerate foods and frozen foods are both 50%. The loading capacity of each vehicle is randomly set in the range [100, 1000] kg for each kind of foods. The startup cost is set as [1, 10] thousand dollars, randomly. The

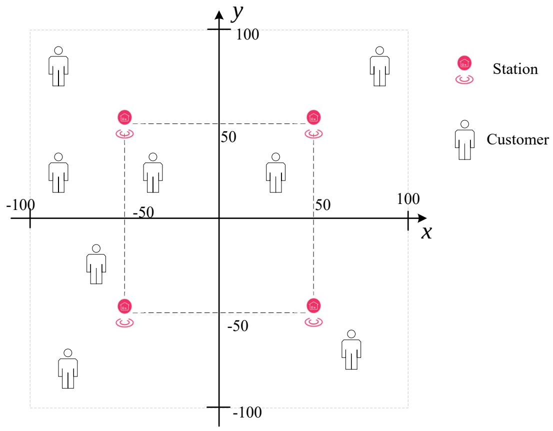

Fig. 1. The Simulated Food Distribution Environment

transport costs of every vehicle are 0.5–1 and 5–10 dollars per kilometre respectively when the vehicle is empty and full-load. There are 100 customers randomly distributed in the service area. The probabilities of each customer requiring refrigerate and frozen foods are both 50%. The amount of foods required by every customer is randomly set in the range of [10, 100] kg.

GANS is compared with the following food distribution router planning methods:

- *Random method* randomly generates a customer assignment solution to vehicles, and uses Algorithm 2 to provide a router solution.
- *Greedy method* assigned every customer to the vehicle that can satisfy its requirements and is closest to it.
- *Particle Swarm Optimization-based method (PSO)* exploits PSO algorithm using Algorithm 2 for evaluating the fitness of particle positions.
- *Genetic algorithm-based method (GA)* is same to GANS except that GA doesn't use NS for its evolution.

The performance of each method is evaluated from the following three aspects. The amount of distributed foods, the cost efficiency, and the customer satisfaction. The first one metric is the major optimization objectives this paper focused on. The second one is the distributed food amount per dollar, which is the ratio of the distributed food amount to the total cost for the food distribution. For the customer satisfaction, the ratio between numbers of served customers and all customers is used to quantify it. The experiment is repeated 20 times, and the results are given in Table I, II, and III. For each time, the environment is identical for all methods' evaluation.

As shown in these results, GANS achieves 15.82%–46.70% more distributed food amount, 17.23%–71.53% higher cost efficiency, and 9.90%–47.18% better customer satisfaction, on average, compared with other methods. This indicates that GANS performs good in all of three aspects. This is benefited from the global search ability of GA and the improvement of NS strategy.

TABLE I. THE DISTRIBUTED FOOD WEIGHTS ACHIEVED BY VARIOUS ROUTER PLANNING METHODS.

	Number	Random	Greedy	PSO	GA	GANS
Original experiment data	1	5365.95	6386.47	6462.48	6572.11	**8120.50**
	2	4716.03	6296.85	6719.02	6323.99	**7905.31**
	3	3778.02	4910.95	6112.24	6050.47	**7120.83**
	4	4219.83	4524.88	5855.58	5316.13	**6725.65**
	5	4507.84	5434.98	6443.13	5975.87	**7054.76**
	6	1852.15	2915.05	3146.72	3211.99	**3604.26**
	7	2981.32	4569.87	4287.65	4600.00	**5694.37**
	8	4602.64	7642.32	7797.57	7526.78	**8663.24**
	9	5137.87	6687.71	6014.42	6285.05	**7677.78**
	10	4974.85	5978.76	6971.77	6690.13	**7758.95**
	11	3411.31	4049.31	4098.26	4109.53	**5053.88**
	12	3227.71	3750.55	4643.57	4748.73	**5504.71**
	13	3321.59	4302.72	5025.42	4520.84	**5692.75**
	14	3105.22	4183.98	4341.57	3834.90	**4871.31**
	15	4084.14	5416.45	6112.63	5759.28	**6949.34**
	16	3351.64	5971.50	6164.76	5626.11	**7074.99**
	17	3912.65	5844.40	6086.42	5802.96	**7167.40**
	18	5033.22	6635.64	6930.95	6995.47	**8079.62**
	19	5157.40	7005.69	7326.74	7018.82	**8696.81**
	20	3506.32	5653.80	5759.91	5153.69	**6577.58**
Statistics of improved performance of GANS	Maximum	111.09%	48.64%	32.81%	27.63%	
	Average	71.53%	26.71%	17.23%	21.44%	
	Minimum	48.15%	13.36%	9.49%	12.21%	

TABLE II. THE COST EFFICIENCY ACHIEVED BY VARIOUS ROUTER PLANNING METHODS.

	Number	Random	Greedy	PSO	GA	GANS
Original experiment data	1	88.37	100.54	98.05	103.02	**115.94**
	2	75.40	98.10	98.80	89.24	**103.41**
	3	63.63	79.75	87.83	91.14	**98.38**
	4	55.25	60.84	73.02	68.35	**78.90**
	5	70.90	87.39	94.74	89.68	**98.81**
	6	28.39	46.11	46.19	44.83	**49.05**
	7	43.46	63.06	58.16	61.41	**70.19**
	8	66.56	105.76	99.13	96.69	**108.18**
	9	64.81	79.85	73.24	75.82	**85.20**
	10	72.63	88.33	91.34	87.45	**98.78**
	11	65.97	80.35	78.22	73.18	**89.18**
	12	59.40	69.72	79.26	78.16	**88.53**
	13	58.23	74.46	80.53	73.94	**85.39**
	14	53.52	72.41	71.62	62.26	**75.25**
	15	59.01	76.63	82.89	78.40	**88.73**
	16	54.50	88.39	86.06	80.93	**94.34**
	17	64.89	88.22	85.49	83.19	**95.64**
	18	84.97	102.74	106.33	104.36	**112.65**
	19	77.97	102.28	98.68	95.77	**112.41**
	20	63.36	92.57	93.54	86.72	**98.29**
Statistics of improved performance of GANS	Maximum	73.10%	29.68%	20.68%	21.87%	
	Average	47.18%	11.93%	9.90%	13.89%	
	Minimum	31.21%	2.29%	4.29%	7.95%	

Compared with GA, GANS achieves 11.29%–30.61% more distributed food amount, 12.21%–27.63% higher cost efficiency, and 7.95%–21.87% better customer satisfaction. This verifies the effectiveness of integrating NS strategy into GA for the performance improvement.

VI. CONCLUSION

This paper studies on the router planning problem for food product suppliers to efficiently distribute multi-temperature foods with several stations. First, the problem is formulated into a combinatory optimization problem. Then, a router planning method is designed based on genetic algorithm, and its performance is improved by integrating a neighbourhood

TABLE III. THE CUSTOMER SATISFACTIONS ACHIEVED BY VARIOUS ROUTER PLANNING METHODS.

	Number	Random	Greedy	PSO	GA	GANS
Original experiment data	1	55	67	61	64	**77**
	2	53	70	67	67	**78**
	3	44	53	60	58	**68**
	4	47	50	61	52	**66**
	5	49	55	55	56	**66**
	6	30	42	39	41	**46**
	7	41	55	50	57	**65**
	8	55	77	70	73	**82**
	9	49	66	55	59	**72**
	10	55	63	71	69	**78**
	11	43	50	43	48	**55**
	12	41	39	46	48	**54**
	13	44	54	54	51	**64**
	14	44	50	51	47	**58**
	15	37	57	51	54	**63**
	16	44	64	58	58	**71**
	17	45	62	60	62	**69**
	18	58	72	69	69	**77**
	19	54	70	68	68	**78**
	20	38	59	55	49	**64**
Statistics of improved performance of GANS	Maximum	70.27%	38.46%	30.91%	30.61%	
	Average	46.70%	15.82%	18.56%	17.78%	
	Minimum	27.91%	6.49%	8.20%	11.29%	

search strategy into the genetic algorithm. Experiment results prove that our method can obtain good performance in various aspects.

There are numerous crossover, mutation, NS, and selection operators that can be applied for GANS. The influences of these operators on the performance of GANS should be studied to implement algorithm instances with better performance for various food distribution scenarios. This is one of our future works.

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