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A Comparative Application Regarding the Effects of Traveling Salesman Problem on Logistics Costs

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Abstract: The necessity of transporting goods from production facilities to buyers requires every company to manage logistics. While the quantity of products ordered has been decreasing in recent years, the number of orders has been increasing. This situation leads to higher logistics costs and more attempts to control logistics costs by business managers. One way to decrease logistics costs is the optimization of traveled distances. The Traveling Salesman Problem (TSP) attempts to optimize travel distances by changing the order of the locations to be visited. By doing so, it reduces the logistics costs associated with travel distances. However, there are also some parameters of logistics costs that are not related to travel distances. This paper examines the effects of optimization results by TSP on logistics costs, using seven different methods to consider a real logistics problem, and comparing the results. Then it discusses the variation in logistics costs due to TSP.

Keywords: *Traveling Salesman Problem, Logistics Costs, Vehicle Operating Costs, Heuristic Algorithms*

1. Introduction

The development of technology and changes in the business and industry environment due to globalization put more pressure on companies and require them to update their competition strategies. In this context, companies should analyze their cost parameters correctly so that they can develop new methods that are superior to those of their rivals. Speed can be interpreted as the quick production and delivery of products to satisfy customer needs, and costs can be defined as the expenditures to fulfill requirements to perform business operations. Logistics is another function that enables firms to utilize costs and speed as advantages in competition.

Companies have been trying to attain the goal of zero-inventory since it was realized that keeping extra inventory increases costs. This situation results in reduced product quantities on orders, while it increases number of orders. As the number of logistics operations gradually increases, companies are pushed to take precautions to control and reduce logistics costs which constitute a major portion of total costs [1]. Transportation is dependent on land roads, especially in countries like Turkey where sea and rail transportation are not sufficiently developed. However, road transportation involves many factors that negatively affect companies in competition, such as high fuel prices and environmental protection measures. Thus transportation costs, which are responsible for 45% of logistics costs, are important [2]. Reducing the vehicle operating costs of product distribution is an optimization problem. TSP, a kind of vehicle routing problem, is about minimizing the distances traveled to meet the demands of customers. TSP aims to achieve a goal that is subject to well-defined constraints. Thus companies that wish to reduce logistics costs due to vehicle operating costs attempt to reduce total travel distance using TSP. More information about TSP is presented in the next section of this paper. In the literature, TSP research focuses on the optimization of distances, time or costs. Nevertheless, there are no studies that considering the effects of these improvements on total logistics costs about distribution.

The aim of this study is to analyze the effects of reduced distances on logistics costs. It discusses the real life distribution problem of a private enterprise in Konya. The routes followed by its distribution vehicles are optimized using seven different methods. The paper identifies the logistics costs of product distribution, subjects them to a TSP analysis and discusses the influence of improvements on logistics costs.

The remainder of this paper is organized as follows: Section 2 describes travelling salesman problem; Section 3 presents a brief literature of TSP; Section 4 describes the heuristic algorithms used in study; Section 5 provides the methodology of study and section 6 summarizes computational results of the study.

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2. The traveling salesman problem

Companies use fleets of one or more vehicles to transport their goods. Some problems must be solved in order to effectively distribution of goods. Problems concerning the order of locations to be visited are known as routing problems [3]. One of these problems is TSP. TSP is a NP-hard (non-deterministic polynomial-time hard) problem, so it requires long time to find an optimum solution [4] by exact methods which are deterministic and guarantee optimum solutions. TSP is the foundation of many problems that require efficient flow or storage of goods, energy, information or humans from sources to markets or end users [5].

A TSP problem can be defined as follows: there exists a traveling salesman; he wants to sell his goods in n cities; however, he wants a route that will enable him to visit each city only once while traveling the shortest distance possible (Figure 1).

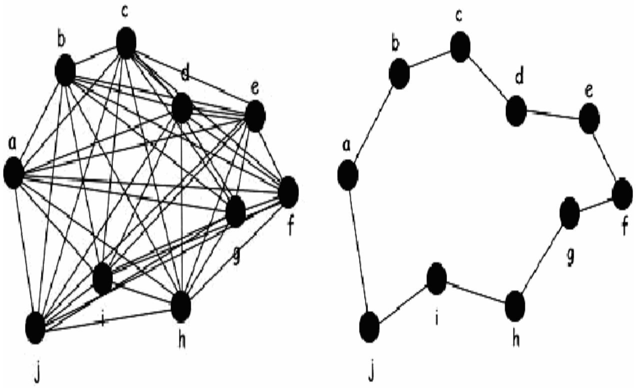

Figure 1. The Traveling Salesman Problem (TSP)

The objective of this problem is to find the shortest path for the salesman. Basically:

- In the first city, the salesman has n-1 possible choices among other cities. In the second city, the salesman has n-2 possible choices among other cities, and the same strategy continues until n-(n-1) city.
- There are (n-1)! different solutions.

As a result, it is enough for the salesman to choose a route among (n-1)!/2 other route since the opposite route will result in the same path, as Hamilton has shown. For a tour that includes 25 cities, this means that there are $24!/2=3.1*10^{23}$ possible routes. If it is supposed that finding a route takes 9 or 10 seconds, then the calculation of all the routes would take ten million years.

TSP can be solved by two solution methods: exact and heuristic solutions. Exact solutions are usually derived from a linear integer programming formulation of TSP. On the other hand, these algorithms are computationally inefficient [4]. The "Branch & Bound" algorithm is an example of the exact solution approach. Intuitively, the method which comes first to mind is to try each possibility. Other methods include linear programming and dynamic programming [6, 7]. Examples of heuristic methods include the greedy algorithm, the insertion heuristic and Christofides algorithm, the tabu search, genetic algorithms, simulated annealing and ant colony algorithm and the iterated Lin-Kernighan algorithm [8, 9].

The integer programming model of TSP can be defined as follows:

$$\min \sum_{i=1}^{n}\sum_{j=1}^{n} c_{ij}x_{ij} \tag{1}$$

$$\sum_{j=1}^{n} x_{ij} = 1,\ i = 1,\dots,n$$

$$\sum_{i=1}^{n} x_{ij} = 1,\ i = 1,\dots,n \tag{2}$$

$$y_i - y_j + nx_{ij} \le n-1,\ \forall\, i \ne j$$

$$x_{ij} = 0 \text{ or } 1\ ,\ i, j = 1,\dots,n$$

where, n is the number of the cities and the arcs in the tour are represented by the variable x_{ij}. Distance of the ith city to jth is c_{ij} ($c_{ij}=\alpha$ for $i=j$). If the salesman visits the city i to j, x_{ij} will be 1 otherwise 0. The variables y_i are arbitrary real numbers which satisfy the constraint.

Logistics companies are not the only ones looking for solutions using TSP. Public institutions and private companies use TSP for things like municipal garbage collection[10], routing school buses [11], military shuttle transportation [12]. The important point in these logistics problems is to reduce logistics costs or operation times by reducing travel distances.

The benefits of reducing travel distances fall into two groups: economical benefits and external social benefits. Economic benefits include vehicle operating costs (VOC), accident costs and travel time costs [13]. In the literature, various authors have calculated vehicle operating costs using the following parameters: a) fuel, b) engine oil consumption, c) tire wear cost d) depreciation cost, e) maintenance and repairing cost, f) insurance cost, g) labor cost[14, 15].

In this study, logistics costs are based on vehicle operating costs related to travel distances and travel time as labor cost. Depreciation and insurance costs vary by nation and by law, while freight load sizes, maintenance and repair costs depend on geographic and structural road conditions. Both are excluded from vehicle operating costs. On the other hand, the cost of time spent visiting customers while distributing goods is included in vehicle operating cost, although it cannot be improved by TSP (since vehicles do not move during a visit).

The next section examines the methods various researchers have developed to solve TSP.

3. Brief Literature Review

In their study, Zhou et al. were developed a new and effective meta-heuristic algorithm with greedy behavior for solving the spherical traveling salesman problem. They were developed an algorithm was based on the discrete flower pollination algorithm, which was the abio-inspired meta-heuristic algorithm, used by pollen discarding and partial behavior and order -based crossover. They were compared the developed algorithm with the genetic algorithm, two genetic algorithms and two types of taboo research. According to the obtained results, they were reported that the developed algorithm was superior to the other algorithms[16].

In their study, Li and Alidaee have developed several taboo search algorithms for the well-known black and white traveling salesman problem, which has applications in aircraft routing, telecommunication, network design and logistics. The authors reported that the developed algorithm reached optimum and near optimum solutions in small size problems in seconds and found feasable solutions for big size problems that could not be solved with the existing methods[17].

In their study, Ezugwu et al. developed a hybrid method for the solution of TSP by using the Simbiotic Organisms Search algorithm and Simulated Annealing. The proposed method was evaluated on different types of TSP problems in the TSPLIB library. They reported that the convergence rate of the proposed method was better than the best known TSP comparative results[18].

In their study, Mahi et al. proposed an ant colony algorithm to improve optimization parameters that affect the performance of the PSO algorithm used for the traveling salesman problem. They have added a 3-OPT algorithm to their proposed method to improve local solutions. The proposed hybrid method has been investigated on 10 different TSP problems from the literature and compared well known algorithms[19].

Ha et al. have studied TSP-D, a version of TSP using drones. Drones are used with trucks for final shaft delivery to improve service quality and reduce transport costs. The model they developed aims to minimize operational costs, including total transport costs and waste time from waiting. They used the Greedy Random Adapted Search Procedure (GRASP) and TSP-LS proposed by Murray and Chu for the solution of the model. They reported that GRASP produced better results than TSP-LS [20].

In their study, Veenstra et al. introduced the pickup and delivery traveling salesman problem with handling costs (PDTSPH) which is a new version of TSP. In the PDTSPH, last-in-first-out (LIFO) approach was used for loading and unloading. They reported that PDTSPH model has provided great reductions in handling costs while caused small increases in traveling distances[21].

Roberti and Wen reported an increase in the use of electric vehicles to reduce greenhouse gas emissions in the field of logistics, and they addressed a problem called Electric Traveling Salesman Problem with Time Windows. They proposed a mixed integer linear formulation and used a Three-Phase Heuristic algorithm based on General Variable Neighborhood Search and Dynamic Programming[22].

In his study Laport has gave an overview of the exact algorithms and heuristic algorithms developed for symmetric and asymmetric versions of TSP [23].

Wang et al. considered multiple objectives and uncertainty in traveling salesman problem first time in their study. They presented an Artificial Bee Colony algorithm for solving uncertain multi objective TSP. The proposed model gave better results than GA, PSO and ACO on the benchmark TSPs[24].

Chen and Chien presented a new method for solving TSP which is called genetic simulated annealing ant colony system with particle swarm optimization techniques. The authors made experiments for 25 data sets obtained from the TSPLIB and compared the results with the different methods in the literature[25].

4. Methods

This paper includes seven different methods to show effects of the studied TSP on logistics costs. The problem is solved using four different methods in WinQSB Version 2.0 Network Modeling Version 1.00 program: the nearest neighbor heuristic, the cheapest insertion heuristic, the two-way exchange improvement heuristic and the branch and bound method. More information about these methods can be found in the WinQSB help file.

The other three methods used the MATLAB program. They are ant colony algorithm, the discrete particle swarm optimization and the discrete artificial bee colony algorithm.

The ant colony algorithm was developed in 1992 by Marco Dorigo. It was later adapted to TSP, and it has been used by various researchers to solve a variety of optimization problems [26].

Particle swarm optimization(PSO) was developed by Eberhart and Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling, and it is based on swarm intelligence [27]. Then it was modified by Fan to solve discrete problems, and it was adapted to TSP [28].

The artificial bee colony(ABC) algorithm was first developed by Karaboğa, who was influenced by nectar gathering and dance movements of real honey bee colonies [29]. Later this method was modified with nine neighborhood operators by Kıran et al. to solve TSP [30]. The details of the algorithms are given in the following subsections.

4.1. Ant Colony Algorithm

Ants produce a scented chemical that is called pheromone in order to find the shortest way to reach the way between nest and food. Ant colony algorithm, proposed by Dorigo, is the population-based heuristic optimization algorithm that is inspired by methods of the shortest path finding of ants. ACO was used for NP-Hard problems such as TSP, Quadratic assignment problem and etc[26].

Pheromone values are updated by all ant m at each iteration. For pheromone updating, the equation given follows is used.

$$\tau(\mathrm{r,s}) \leftarrow (1-\mathrm{p}) \cdot \tau(\mathrm{r,s}) + \sum_{k=1}^{m} \Delta\tau_k(\mathrm{r,s}) \tag{4}$$

$$\Delta\tau_k(\mathrm{r,s}) = \begin{cases} \mathrm{Q}/L_k\,, & if\ (\mathrm{r,s}) \in \text{tour done by ant k} \\ 0\,, & \text{otherwise} \end{cases} \tag{5}$$

Where, τ(r,s) is pheromone value associated with rth and sth cities, 0 < p < 1 is the evanescence rate, m is the number of ants, L_k is the performed tour of kth ant and Q is the constant.

Ants are used the stochastic selection mechanism to find the next city to be visited and utilized the following equation.

$$p_k(\mathrm{r,s}) = \begin{cases} \dfrac{[\tau(\mathrm{r,s})]\cdot[\eta(\mathrm{r,s})]^{\beta}}{\sum_{u\in J_k(\mathrm{r})}[\tau(\mathrm{r,u})]\cdot[\eta(\mathrm{r,u})]^{\beta}}, & if\ s \in J_k(\mathrm{r}) \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

Where τ is the pheromone, η=1/δ is the inverse of the distance δ(r,s), j_k (r) is the set of remain city can be visited. β is the constant which provides for determining the importance between distance and pheromone (β>0).

4.2. Discrete PSO

Particle swarm optimization, population-based heuristic algorithm, is proposed for continuous optimization problems to solve by Eberhart [27]. PSO is modified so as to solve discrete optimization problems via using operators and discrete variables by Fan [28]. Proposed these strategies are called as heuristic factor, crossover, inject or reverse and noise factor.

Conventional PSO use velocity and update equations to find next location of the particle for continuous problems. Fun proposed new velocity equations as crossover operation for discrete problems as follows:

$$X_i(\mathrm{t+1}) = \mathrm{X(t)} \oplus ((\mathrm{c1xr1})\ \mathrm{P}_i(\mathrm{t})) \oplus ((\mathrm{c2xr2})\ \mathrm{P}_g(\mathrm{t})) \tag{7}$$

Where, *t* is the iteration number, $X_i(t)$ is travelling circle of the *ith* particle in iteration *t*, c1 and c2 are social and cognitive constants respectively, r1 and r2 are random number in the range of [0,1]. $P_i(t)$ is the best solution of *ith* particle at the *t* iteration so far, $P_g(t)$is the global best solution at the *t* iteration, ⊕ is the crossover operation. In n-ordered sequence $X_i(t) = \{x_{i1}(t), x_{i2}(t), \dots, x_{in}(t)\}$ and $P_i(t) = \{p_{i1}(t), p_{i2}(t), \dots, p_{in}(t)\}$ crossover operator updates on them $X_i(t) \oplus P_i(t) = \{x_{i(k+1)}(t), x_{i(k+2)}(t), \dots, x_{i(k+m)}(t), \dots, x_{il}(t), x_{i(l+1)}(t), \dots\}$. K is the random number in the range of [1,n-1] and $m = c1xr1$.

Discrete PSO approach uses either inject or reverse operators with %50 probability.

$$X_i(\mathrm{t+1}) = inject(\mathrm{X(t)}, v_c)\,\|\,\mathrm{reverse}\,inject(\mathrm{X(t)}, s, e) \tag{8}$$

where v_c represents the set of near neighbor cities for the injection operation, *s* and *e* (*s*<*e*) represent starting and ending points for the reverse operation. In injection operation, selected city from the set of cities is accepted the starting point to inject nearest cities in the v_c after deleting repetitive cities. In reverse operation, cities between *s* and *e* are reversed in the *X(t)*.

$$X_i(\mathrm{t+1}) = \eta.disturn(\mathrm{X}_i(\mathrm{t+1}), \mathrm{k}) \tag{9}$$

Disturb operation in noise factor works similarly mutation operation in genetic algorithm. In this operation, if the diversity rate is greater than or equal to 0.4, the *kth* city is changed with nearest to *kth* city otherwise sequence is taken without change. Diversity represents the change rate of the traveling circle for each particle.

4.3. Discrete Artificial Bee Colony Algorithm

The artificial bee colony algorithm is inspired by clever behaviors of the real honey bee colonies for solving numerical optimization problems. Basic ABC algorithm is proposed for solving problems which explores the optimum in a continuous solution space [26]. Kıran proposed new neighbor operators to solve discrete problems by modifying ABC algorithm [30]. There are two type foragers which are called employed and unemployed in the honey bee colony. Employed bees use the equation given as follows to update their solutions.

$$v_{i,j} = x_{i,j} + \Phi(x_{i,j} + x_{k,j}) \quad j \in \{1,2,\dots,D\},\ k \neq i \text{ and } k \in \{1,2,\dots,n\} \tag{10}$$

where, $v_{i,j}$ is the candidate solution, $x_{i,j}$ is the employed bee and $x_{k,j}$ is the neighbor employed bee of *ith* employed bee. K is selected randomly and ϕ is the random number it the range of [-1,1].
Unemployed bees have two type as onlooker bee or scout bee. Onlooker bees hold one of the employed bee solution and when the onlooker bees will update own solution, the employed bee are selected through the roulette wheel.

$$p_i = \frac{fit_i}{\sum_{j=1}^{n} fit_j} \text{ and } fit_i = \begin{cases} 1/1+f_i & if\ (f_i \geq 0) \\ 1+abs(f_i) & if\ (f_i < 0) \end{cases} \tag{11}$$

where p_i is to be selected probability, f_i is the objective function value and fit_i is the fitness value of *ith* employed bee.
Basic ABC is modified via three changing in order to solve discrete optimization problems as follows;

- Random permutation is used to generate initial solution and finding new scout bee phase,
- Updating equation is changed to neighborhood operators,
- When the scout bee returns to employed bee, phase of the employed bee starts from the beginning.

Kıran proposed seven neighborhood operator (Random swap (RS), Random insertion (RI), Random swap of subsequences (RSS), Random insertion of subsequence (RIS), Random reversing of subsequence (RRS), Random reversing swap of subsequences (RRSS), Random reversing insertion of subsequence (RRIS)) and two combinations of seven neighborhood operator((RS, RSS, RRSS) and (RI, RIS, RRIS)) . In this study, RRS neighborhood operator was used due to success in the TSP benchmark problems that have more than two hundred cities.

5. Application

5.1. Defining the Problem

This paper examines the logistics problem of Serhun Gida San. Tic. Ltd. Sti., the distributor in Konya of an ice-cream brand, well known in Turkey. The company has a hot sales strategy and a distribution network of 100 locations in Konya. The current distribution route is 152,993 kilometers long according to data from the company. The aim of this study is to improve the route followed by these vehicles and to determine the effect of product distribution on total logistics costs.

5.2. Data Collection

All of the company's distribution locations are indicated by handheld GPS using UTS geographical coordinates. Handheld GPS is commonly utilized to find points with known coordinates, to indicate current position on a map, to prepare reconnaissance surveys and canvases, to create small scale maps and to digitize them. It can also be used to immediately convert coordinates into Gauss–Kruger coordinate system. The locations determined by handheld GPS were loaded into the Netcad program and then transferred from Netcad program to Google Earth (Figure 2).

Figure 2. The transfer of data to Google Earth

Distribution locations were identified on the map of Konya using Google Earth. Later the real distances between each location were determined. The distances used were real route lengths, rather than Euclidean distances in coordinate system. A 100x100 distance matrix was obtained after all distances were determined.

5.3. Defining The Objective Function

The objective function and the constraints for this logistics problem are presented below.

Table 1. Variables and Explanations

Variables	Explanation
CTT	Cost of travel time
CCVD	Wage cost per employee in one cycle
FCC	Fuel cost of the vehicle per 1 km
OCC	Oil cost of the vehicle per 1 km
TWDC	Tire wear and depreciation cost of the vehicle per 1 km
voc	Vehicle operation costs *(CTT + FCC + OCC + TWDC)*
NCS	Number of cycles in a season
AU	Monthly wage of an employee
CS	Monthly working duration of an employee
ZS	Duration of client visit
MS	Number of clients
SD	Demonstration of an hour in minutes
SH	Distance covered by the vehicle per hour
YD	Oil change period of the vehicle
YF	Price of the Castrol 10 / 40 diesel engine oil (9.5 lt)
LDS	Tire change period of the vehicle
LS	Number of tires in the vehicle
LF	Market price of the tire with features 195/75R 16C
TL	Turkish Liras (1 USD = 5.60 TL)

[15] identified the cost of travel duration as traffic congestion cost and fuel consumption cost, oil consumption cost, tire wear and depreciation cost and environmental costs, as well as vehicle operating costs. As mentioned in the second section, the costs associated with distribution include labor cost as the cost of travel time (CTT) and the cost of customer visiting duration (CCVD). Fuel consumption cost (FCC), oil consumption cost (OCC) and tire wear and depreciation cost (TWDC) are related to vehicle operating costs. The mathematical expressions and calculations of costs are given below;

5.3.1. Labor costs:

Cost of Travel Time (CTT): The monthly salary of a distribution employee in the company is 2,500 TL. The weekly work hours total 53 hours. Assuming that a month has four weeks, the total work hours in a month are 212 hours. The driving speed is assumed to be 60 km/h. The cost of travel time for each kilometer is calculated below.

$$CTT = \frac{AU / CS}{SH} \quad CTT = \frac{2500 / 212}{60} = 0.1965\, Tl / km \tag{12}$$

ii. Cost of Customer Visiting Duration (CCVD): The company states that each customer visit takes 15 minutes on the average. The company has totally 100 customers. It is already known that an employee monthly works for 212 hours and its salary is 2,500 TL. The labor cost of an employee per one cycle corresponding to the time spent for customer visits is calculated below.

$$\begin{aligned} CCVD &= \frac{MS\ x\ ZS}{SD}\ x\ \frac{AU}{CS} \\ CCVD &= \frac{100\, x\, 15}{60}\ x\ \frac{2500}{212} = 294.8113\, TL / cycle \end{aligned} \tag{13}$$

5.3.2. Vehicle Operating Costs (VOC):

i.Fuel Consumption Cost (FCC): The vehicle used in product distribution has a fuel consumption rate of 1.10 TL/km. The city fuel consumption rate of the vehicle is presented below:

$$FCC = 1.10\, TL / km \tag{14}$$

ii. Oil Consumption Cost (OCC): Vehicle maintenance personnel indicated that oil changes are needed every 10,000 kilometers. Every change uses 9.5 liters of 10/40 engine oil for diesel engines, costing 260 TL. The oil consumption cost per kilometer is shown below:

$$OCC = \frac{YF}{YD} \quad OCC = \frac{260}{10000} = 0.026\, TL / km \tag{15}$$

iii.Tire Wear and Depreciation Cost (TWDC): Tire replacement was determined to be necessary every 50,000 kilometers, although this depends on the weight of the freight. The vehicle uses six 195/75R16C type tires. The market price for each of these tires is 475 TL. The tire wear and depreciation cost per kilometer is shown below:

$$TWDC = \frac{LF\ x\ LS}{LDS} \quad TWDC = \frac{475\, x\, 6}{50000} = 0.57\, TL / km \tag{16}$$

5.3.3. Number of Cycles in a Season (NCS)

The distribution of ice-cream is seasonal. The season begins on April 30 and ends on September 30. Thus, the season's duration is six months. The company completes two cycles per week. Assuming four weeks in each month, here is the number of cycles in a season:

$$NCS = 2\, x\, 4\, x\, 6 = 48\, cycle / season \tag{17}$$

Considering these cost parameters, **the objective function** is the minimization of logistics costs per season. It is expressed below:

$$Z_{\min} = NCS * \left[\sum_{i=1}^{n} \sum_{j=1}^{n} x_{ij}\, d_{ij}\, voc + CCVD \right] \tag{18}$$

The current distribution route of the company and other routes were obtained by solving the objective function with the four different network modelling methods in WinQSB, along with the ant colony algorithm, the discrete particle swarm algorithm and the discrete artificial bee colony algorithm. They are evaluated in the next section.

6. Conclusion and Evaluation

In this study, three different population-based heuristic algorithm was used for solving a real-life problem. In this real-life TSP, a hundred locations were utilized. In ACO algorithm, evanescence rate (p), β and Q were selected respectively as 0.65, 5,10. In discrete ABC algorithm, scout bee limit bound was selected as population* dimensionality *10000. In discrete PSO algorithm, learning factors c1 and c2 were selected respectively as 1,1. These algorithms were run ten times and best results were evaluated.

A cycle is completed in 152.993 km with the current distribution route of the company. The comparison of the current route and other routes obtained by 7 different methods are given in Table 2. The best WinQSB result was obtained by the two-way exchange improvement heuristic. The length of the distribution route was reduced by 22.51%. Here are the percentages of distribution route reduction calculated by other methods: 28.29% using the ant colony algorithm, 29.33% using the discrete particle swarm optimization algorithm and 30.08% using the discrete artificial bee colony algorithm.

Table 2. Comparison of TSP solutions

Methods	**Cycle Distance (km)**	**Improvement Rate**
(A) Current Route	152.993	---
(B) Nearest Neighbor Heuristic	133.860	12.51%
(C) Cheapest Insertion Heuristic	128.535	15.98%
(D) Branch and Bound Method	128.535	15.98%
(E) Two-way Exchange Improvement Heuristic	118.560	22.51%
(F) Ant Colony Algorithm	109.700	28.29%
(G) Discrete PSO Algorithm	108.120	29.33%
(H) Discrete ABC Algorithm	106.980	30.08%

The current distribution route is shown in Figure 3. The best solution found by WinQSB is shown in Figure 4. Other routes found by algorithms based on swarm intelligence are shown in Figure 5, Figure 6 and Figure 7, respectively.

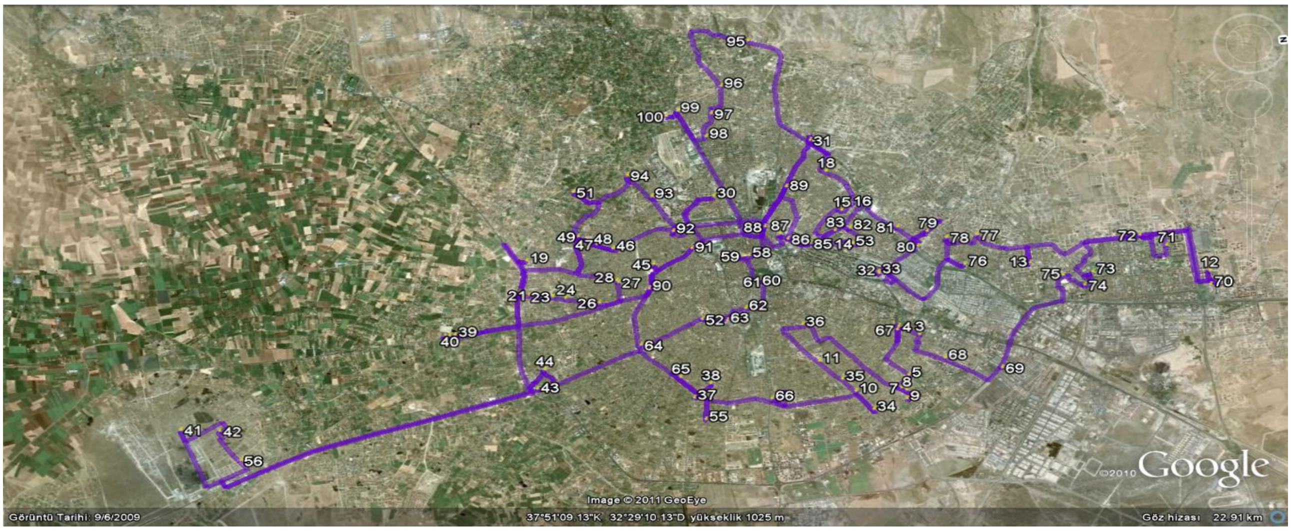

Figure 3. The current distribution route (A)

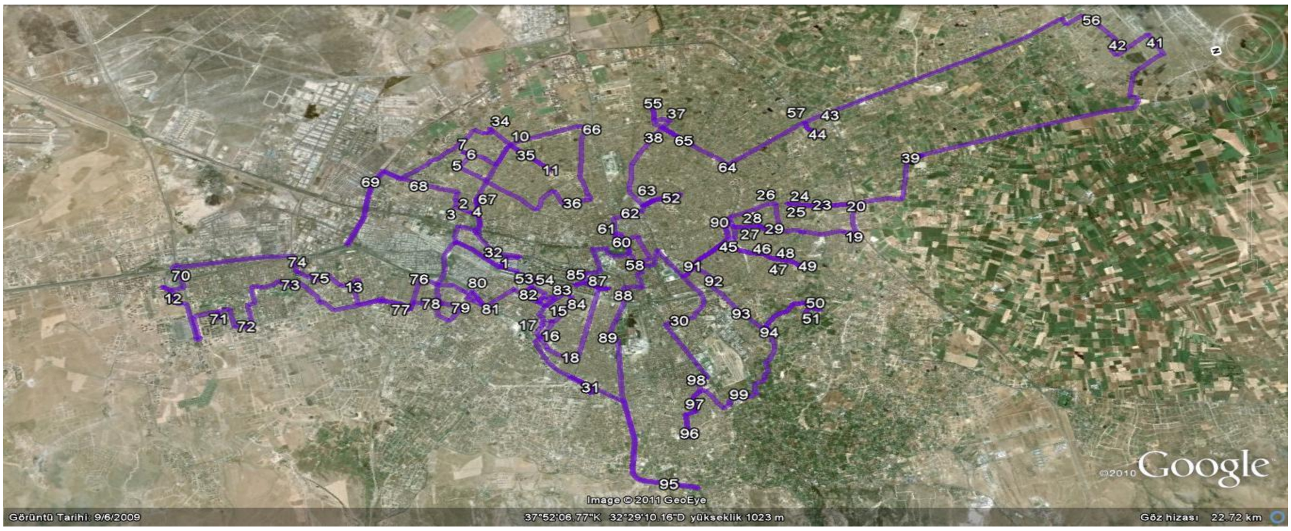

Figure 4. Distribution Route found by Two-Way Exchange Improvement Heuristic (E)

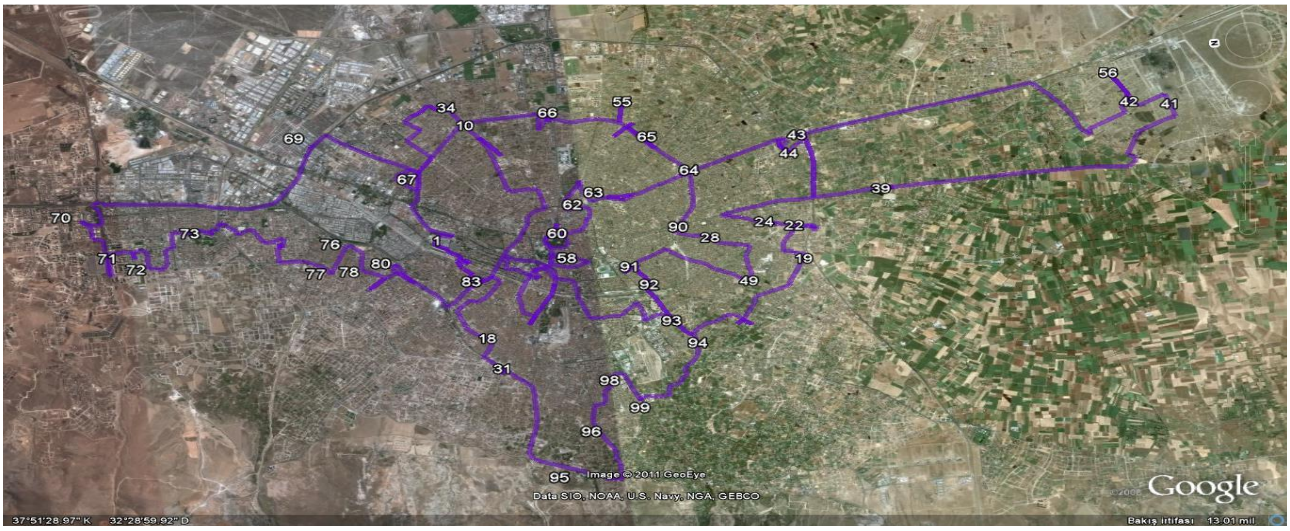

Figure 5. Distribution Route found by Ant Colony Algorithm (F)

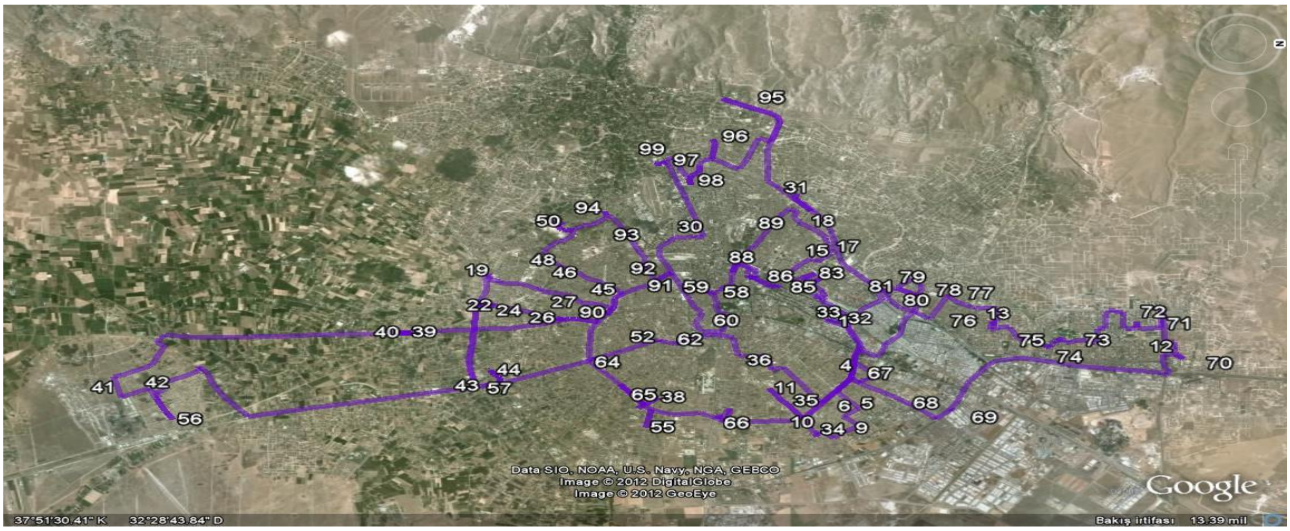

Figure 6. Distribution Route found by Discrete PSO Algorithm (G)

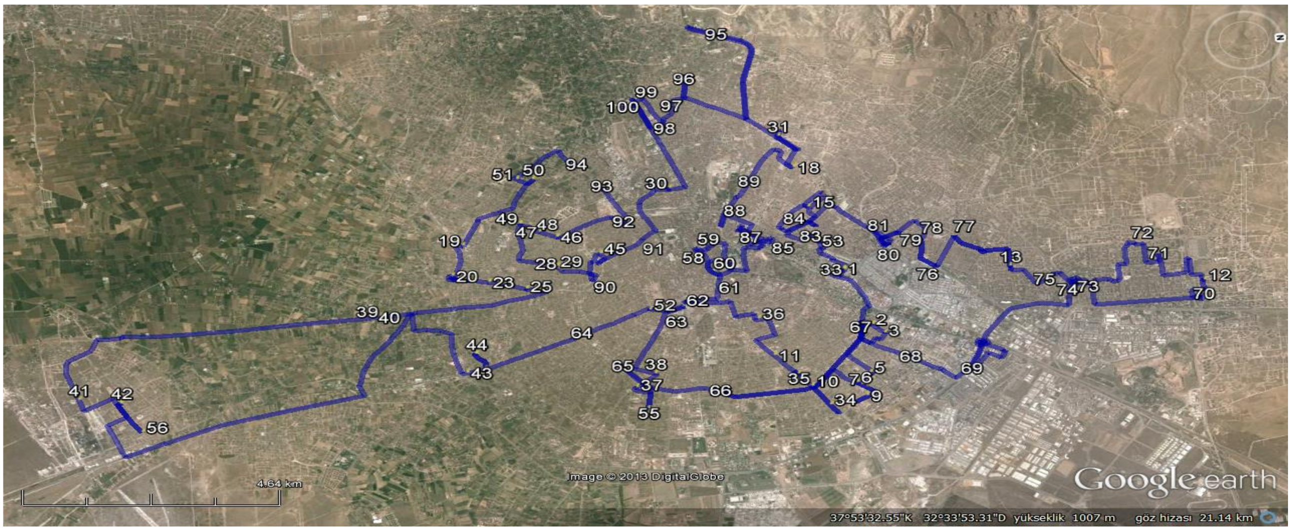

Figure 7. Distribution Route found by Discrete ABC Algorithm(H)

The total distribution costs per season (6 months) based on the cost parameters in section 4.3 are presented in Table 3 for each method.

Table 3. Logistics Costs for Each Distribution Route (Turkish Liras)

Methods	CTT (TL)	FCC (TL)	OCC (TL)	TWDC (TL)	CCVD (TL)	Total Costs	Imp. Rates
(A)	1.443	8.078	190	418	14.150	24.281	---
(B)	1.262	7.067	167	366	14.150	23.014	5.22%
(C)	1.212	6.786	160	351	14.150	22.662	6.67%
(D)	1.212	6.786	160	351	14.150	22.662	6.67%
(E)	1.118	6.259	147	324	14.150	22.001	9.39%
(F)	1.034	5.792	136	300	14.150	21.414	11.81%
(G)	1.019	5.708	134	295	14.150	21.310	12.24%
(H)	1.009	5.648	133	292	14.150	21.234	12.55%

The distribution problem is formulated as TSP, and the distances are reduced using the different methods.

Nevertheless, the reduction rates in distances are not the same as the reduction rates in distribution costs.

The improvement rate in distribution costs is only 14.57%, although the improvement rate of the best solution by discrete artificial bee colony algorithm is 30.08%. This is shown in Table 4 and Figure 8.

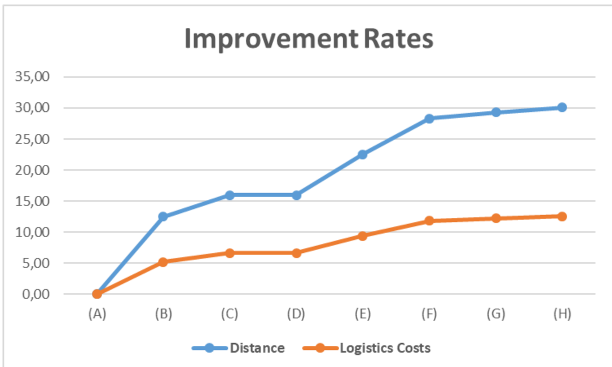

Figure 8. Comparison Improvement Rates Between Distance and Logistics Costs

As Table 4 shows, the reason reduction rates of distances and reduction rates of logistics costs are not the same is that the distribution vehicle does not move during customer visits despite the labor costs that are nevertheless incurred during these visits.

Table 4. The Improvement Rates of Distance and Logistics Costs

Methods	(A)	(B) %	(C) %	(D) %	(E) %	(F) %	(G) %	(H) %
Distance	0	12.51	15.98	15.98	22.51	28.29	29.33	30.08
Logistics Costs	0	5.22	6.67	6.67	9.39	11.81	12.24	12.55

On the other hand, we see that there is an excellent linear relation between distance and cost improvement rates, and $R^2=1$ when the correlation between distance and cost reduction rates is calculated. There will be still a strong correlation between distance reduction rates and cost reduction rates despite increases or decreases in the cost of customer visits (Figure 9).

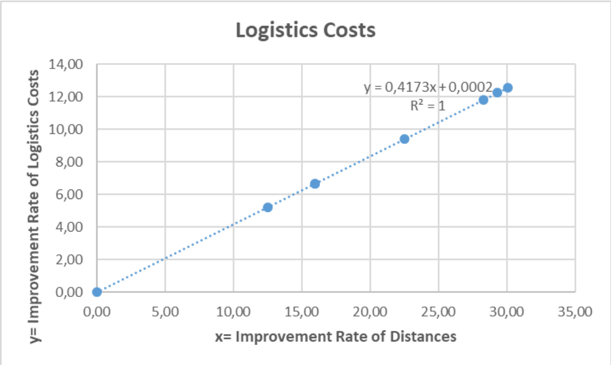

Figure 9. The Relationship Between Distance and Logistics Cost Improvement Rate

The distance reduction rate and total logistics costs reduction rate can be calculated easily using a regression model (y = 0.4173 x - 0.0002) for regression analysis. However, this model is only valid for the corresponding problem. This model will vary according to the proportion of the cost of customer visiting time and total logistics costs. Thus, the model must be redesigned for these particular problems.

TSP reduces total travel distance by changing the current order of customers. When the problem is considered as a whole, we see that TSP reduces costs related to distances. However, costs that are not related to distances are not reduced. As the cycle distance increases or the number of customers increases, logistics costs will be reduced proportionately, and it will be seen that improvement rates in logistics costs approaches to improvement rates in distances.

The reduction of logistics costs will increase proportionally as labor costs or customer visiting times decrease as a function of the cost of customer visiting. On the other hand, reducing labor costs may lead to the employment of less qualified employees, and reducing customer visit durations may lead to lower levels of customer service.

The costs in the problem discussed here are calculated for a period of six months. The maximum labor cost is expected to be 15,000 TL since the monthly labor cost is 2,500 TL. However, Table 3 shows that all methods result in a greater labor cost (CTT + CCVD) than 15,000 TL., and overtime costs are also incurred. On the other hand, the labor capacity is not completely utilized in cases where labor costs are lower than 15,000 TL. The number of customers to be visited should be increased to eliminate idle capacity.

A broader perspective will be attained by future studies as excluded variables and other factors that affect these variables are integrated into the model.

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