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ABSTRACT
Nowadays, the Traveling Salesman Problem (TSP) is one of the most studied combinational optimization problems that researchers study. Although it is easy to define, its solution is hard. Therefore, it is one of the NP-hard problems in the research literature. It can be used to solve real-life problems such as route planning and scheduling, and transportation and logistics applications. In this study, for TSP, an interface that can run on mobile devices using Android and IOS operating systems is developed. Real-world data are used online by the interface. Locations, and the distance between them, are obtained instantly by Google Maps APIs. Genetic (GA) and ant colony optimization (ACO) algorithms are used to solve the TSP. Furthermore, users have also been allowed to conduct trials for different parameter values. The application developed has been tested on two different datasets. The test results show that for the determination of the optimum route, the ACO algorithm is better than the GA. However, when considering the run times, GA works much faster than ACO.

Introduction

The Traveling Salesman Problem (TSP), first proposed by Eular in 1759, is quite an old problem. It was first defined mathematically by Menger (1932) in the early 1930s. Nowadays, this problem is one of the most studied combinational optimization problems that researchers study. Although it is easy to define, its solution is hard. Therefore, it is one of the NP-hard problems in the research literature (Garey and Johnson 1979). It can be used to solve real-life problems such as route planning and scheduling, and transportation and logistics applications. Consequently, it provides an ideal test environment, especially for researchers conducting studies on optimization techniques (Johnson 1990).

The specific solution algorithms (dynamic programing, branch and bound, branch and cut, etc.) proposed for TSP give successful results to some extent

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(Applegate et al. 2011; Ascheuer, Fischetti, and Grötschel 2001; Arora, 1998; Held and Karp 1962; Johnson and McGeoch 1997; Miller and Pekny 1991). However, the problem size and execution times increase as the number of points increases, and as a result, obtaining the optimum results becomes impossible. For that reason, researchers who are studying this issue have concentrated more on heuristic and metaheuristic methods. Although they do not guarantee the optimum result, these methods can produce satisfying results because of the short running times.

A set of studies has been conducted by the researchers using different heuristic and metaheuristic algorithms for TSP. In the first group of studies, various benchmark data were used, and the experiments were performed by computers (Hingrajiya, Gupta, and Chandel 2012; Hlaing and Khine 2011; Király and Abonyi 2015; Li, Wang, and Song 2008; Mohammed 2013; Osaba et al. 2016; Silva and Runkler 2004). In the second group of studies, real-world data have been used and the applications have been developed for use on mobile devices (Aydin and Telceken 2015; Fajardo and Oppus 2010; Helshani 2015; Jana and Chattopadhyay 2015). The first of these applications was MyDisasterDroid, which can operate on devices using the Android operating system (Fajardo and Oppus 2010). This system was designed as a disaster management system for the Philippines. In case of a natural disaster, it was used to determine the optimum route so that rescue and help assistance can reach to the affected regions as effectively as possible. The distances between geographic locations were calculated by Euclidean distance, and a genetic algorithm (GA) was used to determine the optimum route. In the second application, a client–server system was developed (Helshani 2015). An Android application is built on the client side. The location data to be visited are determined by the Android application and sent to the server. There is GA code developed in Java on the server. The location data are processed by this code, and the optimum route is calculated using Google APIs. The route obtained is sent to the Android application built on the client side. In another study, a mobile trip planner for the city of Eskişehir was developed (Aydin and Telceken 2015). First, 30 points and 150 subpoints in this city were determined as the locations to be visited, and then the location data were saved to the application. The application was tested separately for two different scenarios by choosing five and 10 locations to be visited. During the test, both A* and ant colony optimization (ACO) algorithms were used to find the optimum route. The results obtained have shown that both algorithms can determine the same optimum route. In a later study, a navigation system was developed for the campus of Jadavpur University (Jana and Chattopadhyay 2015). It was aimed at helping students, faculty members, and staff to travel from their current location to their required destination as fast as possible. An Android application for users was developed with this aim. A web interface was also developed to update event and location data. The shortest route from users' current location to the requested destination was calculated and sent to the user interface through the interface used by the map manager.

In this study, an interface that can operate on devices with Android and IOS operating systems has been developed for TSP. Real-world data are used online by the interface. The users can determine the locations they want to visit. The locations and the distance between them are obtained instantly by Google Maps APIs. GA and ACO algorithms are used to solve the TSP. Furthermore, users have also been allowed to conduct trials for different parameter values. The results obtained from trials can be displayed as a table and graphic for each algorithm. Furthermore, the locations, trip order, and the route can be examined on the map. The results obtained can be displayed and examined comparatively at the same time for both algorithms.

TSP

In the TSP, a salesman or a vehicle is asked to visit all the locations in the system only once by starting from a certain location and return to the initial location. In the meantime, the aim is to keep the total tour length to a minimum. In order to solve the problem, distances between all points should be known. If n is the total number of points, then for the first point, there are $n - 1$ alternative points to go to, and for the second point, there are $n - 2$ alternative points to go to. Here, n expresses the size of the problem, and the number of possible tours involved is $(n - 1)!$ As stated previously, reaching the exact solution is possible when there are a fewer number of points. However, as the number of points increases, the number of alternative solutions increases quickly and much more time is needed to find the optimum solution. TSP is expressed mathematically as follows (Dantzig et al. 1954):

$$y = \sum_{i=1}^{n} \sum_{j=1,\, i \neq j}^{n} x(i,j) d(i,j) \tag{1}$$

$$\sum_{j=1,\, j \neq i}^{n} x(i,j) = 1, i = 1, 2, \ldots, n \tag{2}$$

$$\sum_{i=1,\, i \neq j}^{n} x(i,j) = 1, j = 1, 2, \ldots, n \tag{3}$$

$$\sum_{i,\, j \in S,\, i \neq j}^{n} x(i,j) \leq |S| - 1, \forall S \subset \{1, 2, \ldots, n\} \tag{4}$$

$$x(i,j) = \begin{cases} 1, & \text{if the path goes from point i to point } j \\ 0, & \text{Otherwise} \end{cases} \tag{5}$$

The objective function of the TSP is shown in Equation (1). Here, $d(i,\ j)$ shows the distance between points i and j. Term $x(i,\ j)$ shows whether it goes from point i to point j. Equations (2) and (3) are aimed at guaranteeing that each point will be visited only once. According to Equation (2), each point is left only once, and according to Equation (3), each point is visited only once. Equation (4) states a subtour elimination limit to prevent subtours being created. In Equation (5), the fact that $x(i,\ j)$ is equal to 1 shows that there was a tour from i to j; if it is equal to 0, it means there was no tour.

In this study, assuming that a vehicle is going to be used, the distances between points are obtained by using real-world data. For this process, Google Directions and Places APIs are used. Because $d(i, j) \neq d(j, i)$ in asymmetric TSP (due to traveling by vehicle), distances from i to j and from j to i are calculated separately in this study as well (Zhang and Korf 1996). When finding the $d(i, j)$ value, the shortest route is taken into consideration if there are more than one alternative routes from point i to point j.

Algorithms

In order to determine the optimum route between locations, GA and ACO algorithm were used in this study. The details of the GA and ACO algorithm specifically proposed for the development of this application are given in subsections.

GAs

GAs are one of the heuristic optimization algorithms applied by researchers to many problems and were first proposed by Holland (1975). In this study, they have been used with real-world data for the solution of TSP on mobile devices with Android and IOS operating systems. First, the random initial population is created according to the population size determined by the user. Each gene forming the chromosomes corresponds to the points to be visited. For example, assuming that the number of points to be visited is 8, 81275463 represents an example of a chromosome. After creating the initial population, the fitness value for each chromosome is calculated. For this, data for the distance between points are used. The fitness value of each chromosome is calculated by adding distance data.

After calculating the fitness value, natural selection for the chromosomes begins. In this process, different methods are used. Because of its quite common use, a roulette wheel selection method has been chosen for this study. In natural selection, the process of the production of a new generation from the selected chromosomes is defined as "crossover." Crossover is carried out according to the crossover rate given to the algorithm as an input. The one-point crossover method is a commonly used method, so it has been used in this study. However, for TSP, some standardization operations need to be applied after crossover, because the salesman is asked to visit all the cities only once. In the population obtained from crossover, this situation falls into decay. In this study, standardization is applied with the condition that the first repeating city in the chromosome is replaced with the unvisited city having the smallest number (see Table 1).

A mutation process is applied by changing the location of the genes in the randomly selected chromosomes according to the mutation rate given to the algorithm as an input by the user. Which genes will be replaced are determined randomly. After this operation, the fitness value of the population obtained is calculated, and hence the initial population is obtained for the next generation (iteration). The process continues up to the iteration number given to the algorithm as an input by the user.

ACO algorithm

The ACO algorithm was developed by Dorigo (1992) in order to solve combinational optimization problems. This algorithm starts with the determination of the initial pheromone value of the routes between points. In this study, initial pheromone values for each route were taken as 10^{-4}. The ant population should be created according to the size of the population input to the algorithm by the user. To do this, each ant should be placed randomly to the locations first. Then, Equation (6) is used to determine to which location the ant k at i location will go out of u alternative locations.

$$j = \left\{ \begin{array}{cc} \max_{u \in J_k(i)} [\tau(i,u)]^{\alpha} * [\eta(i,u)]^{\beta} & \text{if } q \leq q_0 \\ \text{use Equation}(8) & \text{Otherwise} \end{array} \right\} \tag{6}$$

Here, $\tau(i, u)$ is the pheromone trail on the (i, u) path. The term $\eta(i, u) = 1/\delta(i, u)$ is the reverse of the distance from point i to point u. The term $J_k(i)$ represents the nodes that have not yet been reached by ant k at point i. The α value ($\alpha > 0$) indicates the importance of the pheromone amount of the related path, and the β value ($\beta > 0$) indicates the effect of path lengths in the selection of the next point. This parameter is entered into the algorithm as an input by the user. The term q_0 ($0 \leq q_0 \leq 1$) is the parameter that shows the

Table 1. Crossover and standardization processes.

Before crossover		After crossover		After standardization	
Parent 1	81275**463**	Offspring 1	81275**615**	Offspring 1	81275**634**
Parent 2	32478**615**	Offspring 2	32478**463**	Offspring 2	32478**165**

relative importance of searching the solution space. If $q > q_0$, the second transition rule is operated and the probability of the selection of paths to be followed is calculated according to Equation (7).

$$P_k(\mathrm{i},\mathrm{j}) = \left\{ \begin{array}{cc} \frac{[\tau(i,j)]^{\alpha} * [\eta(i,j)]^{\beta}}{\sum_{u \in J_k(i)} [\tau(i,u)]^{\alpha} * [\eta(i,u)]^{\beta}} & \text{if } j \in J_k(i) \\ 0 & \text{Otherwise} \end{array} \right\} \tag{7}$$

Once all the ants have completed their tour, the local pheromone is updated according to Equations (8) and (9).

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t+1) \tag{8}$$

$$\Delta\tau_{ij}^{k}(t+1) = \left\{ \begin{array}{cc} 1/L^{k}(t+1) & \text{if ant k used the path } ij \\ 0 & \text{Otherwise} \end{array} \right. \tag{9}$$

Here, $\tau_{ij}\,(t)$ is the initial pheromone level, and ρ is the pheromone evaporation parameter determined by the user. The term $L^{k}(t+1)$ is the total tour length for ant k. Once all the ants have completed their tour, the global pheromone is updated. The pheromone amount on the paths followed by the ant using the shortest path is increased according to Equations (10) and (11).

$$\tau_{ij}\,(t+1) = (1-\rho)\,\tau_{ij}\,(t) + \Delta\tau_{ij}^{k}\,(t+1) \tag{10}$$

$$\Delta\tau_{ij}^{k}(t+1) = \left\{ \begin{array}{cc} 1/L_{best}(t+1) & \text{if } ij \text{ belongs to the best tour} \\ 0 & \text{Otherwise} \end{array} \right. \tag{11}$$

$L_{best}(t+1)$ is the best tour length obtained globally. These processes in the ACO algorithm are repeated until the iteration number determined by the user has been reached.

The developed interface

A large majority of the operating system market for smart mobile devices (phones, tablets, etc.) is dominated by Google Android and Apple IOS (Strategy Analytics 2015). Therefore, these two platforms are aimed for the applications developed. Embarcadero Delphi 10 Seattle has been used as the application development interface due to its cross-platform quality. TMS WebGMaps for FireMonkey component compatible with Delphi 10 Seattle was preferred for the use of Google Maps APIs such as Directions and Places. The SQLite database was used to store all the data entered into the application and the results obtained.

Figure 1 shows the main window of the developed interface. In this window, the related data-entering window will be opened if the Data Input

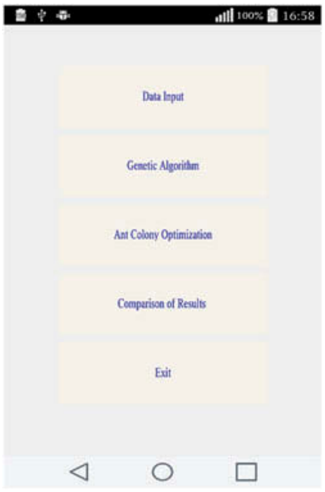
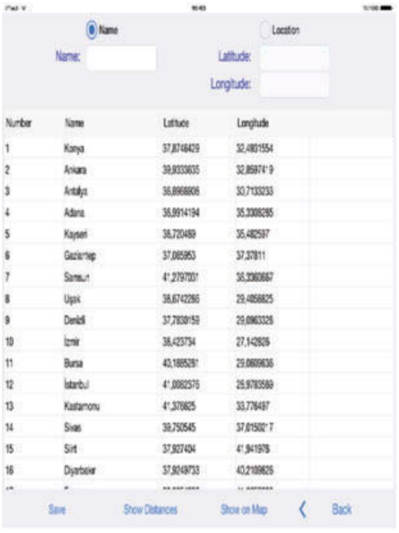


Figure 1. Main window of the interface.

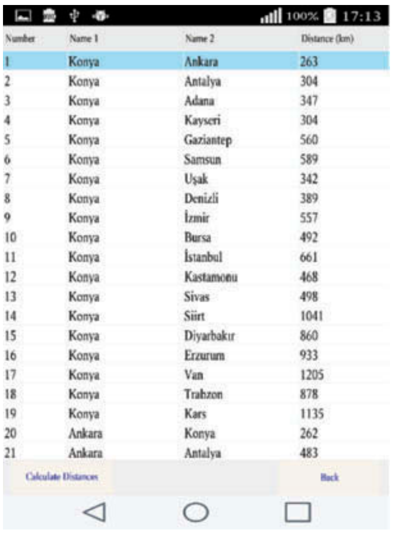
button is clicked (Figure 2). This window is used to enter location information, to show locations on the map, and to calculate the distances between these locations for TSP. As can be seen in Figure 2a, the location information can be entered both as a name and as a latitude–longitude. When it is entered as a name, its correspondence to a latitude–longitude is found and when it is entered as a latitude–longitude, its correspondence to a name is found using Google Places API, and then saved to the database. Moreover, the location information entered can be displayed on the map (Figure 2c). The distances between locations are calculated by using Google Directions API. When more than one routes are found between two locations, the shortest one is taken as the distance between these two locations. Distances between locations are calculated separately as bidirectional, because in asymmetric TSP, the distance from point *i* to point *j* can differ from the distance from point *j* to point *i* (Figure 2b).

Windows providing parameter adjustment for the GA and for the ACO algorithm are shown in Figure 3a and b, respectively. These windows are reached with the help of related buttons from the main window. After entering the parameter values, the algorithms are activated by clicking the Run button. The algorithms use the location and distance information determined by the Data Input window. The details of the algorithms were given in previous sections. The results obtained by the GA and ACO algorithm are recorded along with the parameter values, and are displayed graphically. The window showing the results related to that algorithm as a list is opened by clicking the Results button (Figure 3c). This window shows how much distance has been covered for which route in which iteration. Furthermore, by choosing any iteration, the route of that iteration can be



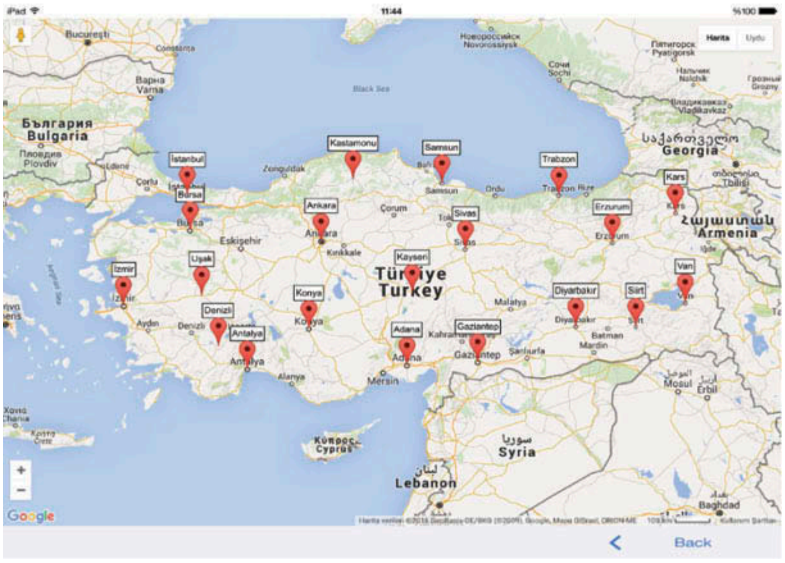
Number	Name	Latitude	Longitude
1	Konya	37,8748429	32,4801554
2	Ankara	39,9333635	32,8597419
3	Antalya	36,8968906	30,7133233
4	Adana	36,9914194	35,3308285
5	Kayseri	38,720489	35,482597
6	Gaziantep	37,065953	37,37811
7	Samsun	41,2797031	36,3360667
8	Uşak	38,6742286	29,4058825
9	Denizli	37,7830159	29,0963326
10	İzmir	38,423734	27,142826
11	Bursa	40,1885281	29,0609636
12	İstanbul	41,0082376	28,9783589
13	Kastamonu	41,376825	33,776497
14	Sivas	39,750545	37,0150217
15	Siirt	37,927404	41,941976
16	Diyarbakır	37,9249733	40,2109825

(a)



Number	Name 1	Name 2	Distance (km)
1	Konya	Ankara	263
2	Konya	Antalya	304
3	Konya	Adana	347
4	Konya	Kayseri	304
5	Konya	Gaziantep	560
6	Konya	Samsun	589
7	Konya	Uşak	342
8	Konya	Denizli	389
9	Konya	İzmir	557
10	Konya	Bursa	492
11	Konya	İstanbul	661
12	Konya	Kastamonu	468
13	Konya	Sivas	498
14	Konya	Siirt	1041
15	Konya	Diyarbakır	860
16	Konya	Erzurum	933
17	Konya	Van	1205
18	Konya	Trabzon	878
19	Konya	Kars	1135
20	Ankara	Konya	262
21	Ankara	Antalya	483

(b)

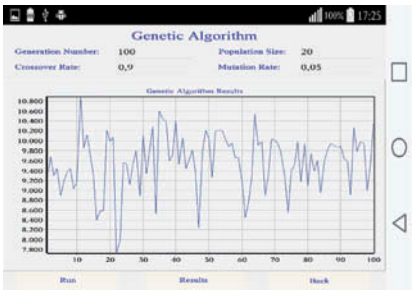


(c)

Figure 2. (a) Entering location information in the IOS operating system. (b) Listing the distance between locations in the Android operating system. (c) Showing the locations on the map in the IOS operating system.

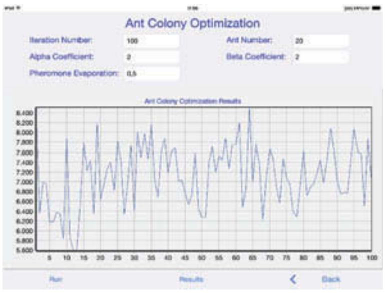
displayed on the map along with the order of the locations visited (Figure 3d).

When the Comparison of Results button is selected on the interface window shown in Figure 1, a window is opened where the results obtained can be compared in different ways. Figure 4a shows the comparison the results obtained for two algorithms in a list. The comparison is made on the basis of the route followed, distance obtained, and elapsed time for each iteration. In Figure 4b, the



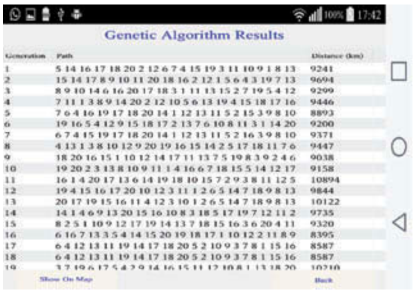
Generation Number: 100
Population Size: 20
Crossover Rate: 0,9
Mutation Rate: 0,05

(a)



Iteration Number: 100
Ant Number: 20
Alpha Coefficient: 2
Beta Coefficient: 2
Pheromone Evaporation: 0,5

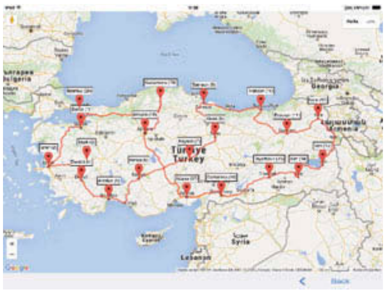
(b)



Genetic Algorithm Results

Generation	Path	Distance (km)
1	5 14 16 17 18 20 2 12 6 7 4 15 19 3 11 10 9 1 8 13	9241
2	15 14 17 8 9 10 11 20 18 16 2 12 1 5 6 4 3 19 7 13	9694
3	8 9 10 14 6 16 20 17 18 3 1 11 13 15 2 7 19 5 4 12	9299
4	7 11 1 3 8 9 14 20 2 12 10 5 6 13 19 4 15 18 17 16	9446
5	7 6 4 16 19 17 18 20 14 1 12 13 11 5 2 15 3 9 8 10	8893
6	19 16 5 4 12 9 15 18 17 2 13 7 6 10 8 11 3 1 14 20	9200
7	6 7 4 15 19 17 18 20 14 1 12 13 11 5 2 16 3 9 8 10	9371
8	4 13 1 3 8 10 12 9 20 19 16 15 14 2 5 17 18 11 7 6	9447
9	18 20 16 15 1 10 12 14 17 11 13 7 5 19 8 3 9 2 4 6	9038
10	19 20 2 3 13 8 10 9 11 1 4 16 6 7 18 15 5 14 12 17	9158
11	16 1 4 20 17 13 6 14 19 18 10 15 7 2 9 3 8 11 12 5	10894
12	19 4 15 16 17 20 10 12 3 11 1 2 6 5 14 7 18 9 8 13	9844
13	20 17 19 15 16 11 4 12 3 10 1 2 6 5 14 7 18 9 8 13	10122
14	14 1 4 6 9 13 20 15 16 10 8 3 18 5 17 19 7 12 11 2	9735
15	8 2 5 1 10 9 12 17 19 14 13 7 18 15 16 3 6 20 4 11	9320
16	6 16 7 13 3 5 4 14 15 20 19 18 17 1 10 12 2 11 8 9	8395
17	6 4 12 13 11 19 14 17 18 20 5 2 10 9 3 7 8 1 15 16	8587
18	6 4 12 13 11 19 14 17 18 20 5 2 10 9 3 7 8 1 15 16	8587
19	3 7 19 6 17 5 4 2 9 14 16 15 11 12 10 8 1 13 18 20	10210

(c)



(d)

Figure 3. (a) GA window in the Android operating system. (b) ACO algorithm window in the IOS operating system. (c) Listing the GA results in the Android operating system. (d) Showing the ACO results on the map in the IOS operating system.

comparison between the results obtained for two algorithms is shown as a graphic. The comparison between the routes followed by two algorithms is given in Figure 4c. The comparison operation shown here can be created by the results obtained from each iteration (by choosing the related iteration from the list).

Results

The developed application was tested for the solution of TSP on two mobile devices with Android and IOS operating systems. The first device is an LG G3 D855 and the other is an IPad Mini 3. The LG G3 D855 has a quad-core 2.5 GHz Krait 400 processor architecture and 3 GB RAM. It has the Android 4.4.2 KitKat operating system. The IPad Mini 3 has an ARMv8 processor architecture and 1 GB RAM and the IOS 8.0 operating system.

The application developed for the smart mobile devices was tested for two different datasets. The first dataset was formed in a way that covered seven different geographic regions of Turkey by selecting 20 different cities. In the second dataset, the districts of Konya were taken into consideration. Twenty districts were selected to be located across the entire city. Table 2 shows the cities and districts in the datasets, with their locations.

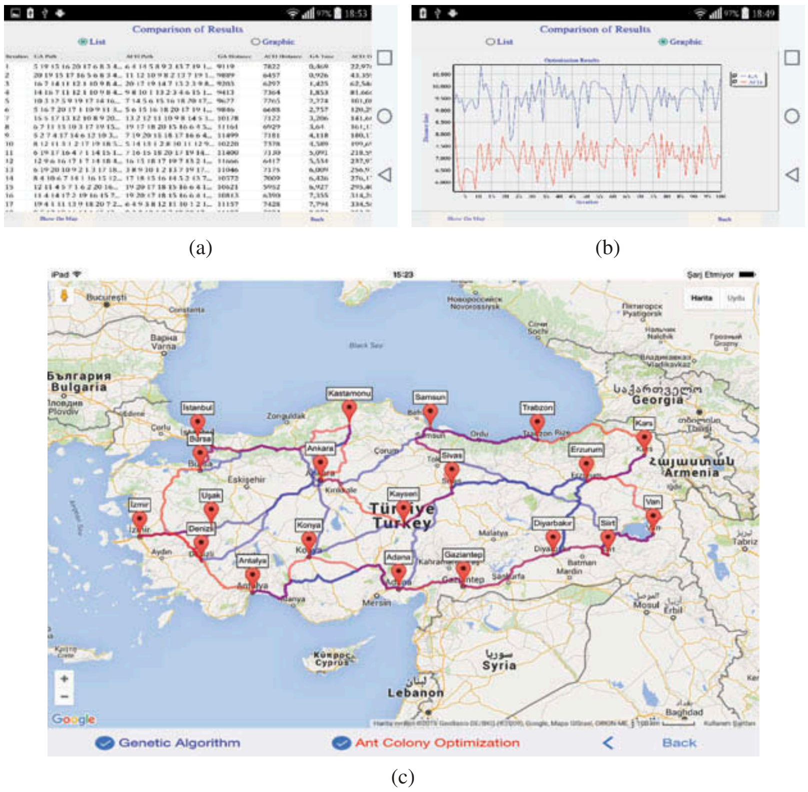


Figure 4. The comparison between the algorithm results obtained from the Android and IOS operating systems. (a) As a list. (b) As a graphic. (c) On the map.

Table 2. The locations of the cities and districts in the datasets.

The first dataset			The second dataset		
City	Latitude	Longitude	District	Latitude	Longitude
Konya	37.8746429	32.4931554	Cihanbeyli	38.656883	32.923303
Ankara	39.9333635	32.8597419	Kulu	39.090245	33.080528
Antalya	36.8968908	30.7133233	Kadınhanı	38.240871	32.207868
Adana	36.9914194	35.3308285	Yunak	38.813456	31.735652
Kayseri	38.7204890	35.4825970	Ilgın	38.281724	31.913950
Gaziantep	37.0659530	37.3781100	Doğanhisar	38.145955	31.676750
Samsun	41.2797031	36.3360667	Beyşehir	37.679796	31.724299
Uşak	38.6742286	29.4058825	Seydişehir	37.419260	31.848216
Denizli	37.7830159	29.0963328	Akören	37.452598	32.371139
İzmir	38.4237340	27.1428260	Bozkır	37.188912	32.245393
Bursa	40.1885281	29.0609636	Çumra	37.573899	32.781038
İstanbul	41.0082376	28.9783589	Karapınar	37.715320	33.546570
Kastamonu	41.3766250	33.7764970	Halkapınar	37.433643	34.186855
Sivas	39.7505450	37.0150217	Akşehir	38.360258	31.417991
Siirt	37.9274040	41.9419780	Hadim	36.986063	32.455875
Diyarbakır	37.9249733	40.2109826	Güneysınır	37.267923	32.727420
Erzurum	39.9054993	41.2658236	Sarayönü	38.264661	32.407075
Van	38.5012085	43.3729793	Altınekin	38.308274	32.868888
Trabzon	41.0026969	39.7167633	Çeltik	39.023429	31.790552
Kars	40.6013378	43.0974525	Hüyük	37.951279	31.599333

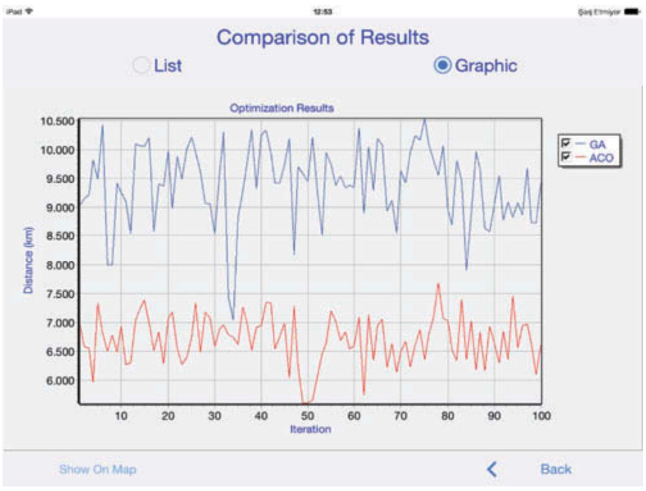
The developed application was tested using the GA and ACO algorithm on each of the two datasets. Test operations was carried out for different iteration and population size values. The crossover rate was taken as 0.9 and the mutation rate as 0.1 for the GA. For the ACO algorithm, α and β parameters were taken as 2 and the pheromone evaporation value as 0.5. Trials were carried out separately on both mobile devices with Android and IOS operating systems. The results obtained are provided with details in Tables 3 and 4. As seen in both tables, ACO produces better results than GA regarding the length of the route. For example, using the dataset of cities for an iteration number of 100 and a population size of 50, while the result was 7588 km for GA, it was 5630 km for ACO, when the Android device was used. Similarly, using the same dataset for the same iteration number and population size, while the result was 7479 km for GA, it was 5637 km for ACO, when the IOS device was used. With regard to their elapsed time, it was observed that GA works much faster than ACO. For example, using the dataset of districts for an iteration number of 100 and a population size of 50, while the result was 198 ms for GA, it was 5074 ms for ACO, when the Android device was used. Similarly, using the same dataset for the same iteration number and population size, while the result was 47 ms for GA, it was 3568 ms for ACO, when the IOS device was used. These results show that ACO works better than GA in determining

Table 3. The results obtained for the dataset of cities.

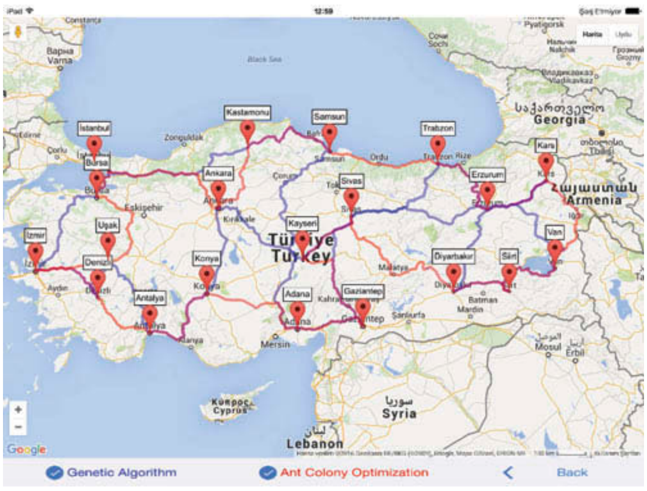
		Android				IOS			
		Distances (km)		Times (ms)		Distances (km)		Times (ms)	
Iteration	Population	GA	ACO	GA	ACO	GA	ACO	GA	ACO
100	20	7588	5891	62	1944	8164	5726	18	1411
100	50	7588	5630	198	4677	7479	5637	47	3517
100	100	6969	5583	292	9742	7049	5596	99	7070
200	50	7436	5475	276	9570	7272	5958	94	7047
200	100	7025	5458	467	39,378	7029	5783	196	14,079
200	200	6698	5458	1281	57,065	6670	5569	427	28,175

Table 4. The results obtained for the dataset of districts.

		Android				IOS			
		Distances (km)		Times (ms)		Distances (km)		Times (ms)	
Iteration	Population	GA	ACO	GA	ACO	GA	ACO	GA	ACO
100	20	1398	1263	67	3267	1464	1212	19	1424
100	50	1398	1245	198	5074	1448	1210	47	3568
100	100	1376	1183	386	10,101	1446	1198	99	7116
200	50	1449	1224	360	10,589	1447	1213	95	7117
200	100	1331	1206	720	39,500	1394	1205	199	14,223
200	200	1329	1198	1052	79,082	1368	1198	432	28,450



(a)



(b)

Figure 5. (a) Graphical comparison of the results. (b) Displaying the best routes obtained on the map.

the optimum route. However, when comparing the elapsed time, the result is reversed with GA working better than ACO.

Figure 5a shows the graphical comparison between the results obtained for GA and ACO with an iteration number and a population size of 100, for the dataset of cities using the IOS device. For each algorithm, the comparisons of the best routes obtained are shown in Figure 5b.

Conclusion

In this study, an interface that can operate on mobile devices with Android and IOS operating systems has been developed. Real-world data have been used online in the developed interface and locations are determined by the user. The locations and the distance between them are obtained instantly by Google Places and Directions APIs. GA and ACO are used to solve TSP. Furthermore, users have also been allowed to conduct trials for different parameter values. The results obtained from the trials can be viewed as a table or a graphic for each algorithm. Moreover, the locations can be analyzed on the map along with the order and route of the travel. The results can also be displayed and analyzed comparatively and simultaneously for both algorithms.

The application developed was tested on two different datasets. The test results show that ACO is better in determining the optimum route, and GA is better in terms of the running times.

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