Using the Genetic Algorithm for the Optimization of Dynamic School Bus Routing Problem

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Abstract

Vehicle routing problems (VRP) are complicated problems, which can be encountered in a variety of different fields and are not possible to solve using conventional methods. Thanks to the technological advancements in areas such as the global positioning system (GPS), geographical information systems (GIS), mobile communication networks, and traffic sensors, it is now possible to solve the VRP in a dynamic and real-time manner. In this study, the school bus routing problem (SBRP), which is a sub-branch of VRPs, was optimized by means of an application developed using Genetic Algorithms(GA), which is one of the heuristic methods. By using the application developed based on mobile communication and GPS, the instantaneous locations of stops and the school bus were determined and the shortest and most convenient route for the vehicle to follow was dynamically identified. The experimental results obtained at the end of this study showed that the existing school bus routes can be optimized using GA and therefore the costs associated with the routing can be reduced.

Keywords: vehicle routing problem, dynamic school bus routing problem, genetic algorithms, optimization

1. Introduction

Transportation and distribution systems are necessary in every field of daily life and concern all sectors. The use of these systems brings along considerable expenses to enterprises. The expenses associated with distribution correspond to 15-20% of the product costs (Rushton, Croucher & Baker, 2006). The growing population, globalizing economy, and increasing demand for consumption make the use of transportation and distribution systems even more important and widespread. This usage density brings along certain problems such as loss of time, traffic jams, additional expenses, and environmental pollution. Traffic jams, road and weather conditions, and unplanned route choices can be listed among the reasons for increasingly longer periods spent in traffic. Longer time-spans allocated to transportation cause significant increases in fuel costs and air pollution, which also raises health concerns. Traffic is a major source of air pollution in urban areas of developing countries that leads to high exposure risk of urban dwellers (Oanh, Kongpran, Hang, Parkpian, Hung, Lee & Bae, 2013). The time loss can be minimized by means of suitable route selection before starting the journey and the routing plans that can be updated against adverse situations such as traffic, road, weather, and accidents. Many countries and many enterprises obtained considerable savings in terms of cost and time via optimization studies on transport and traffic control systems.

School buses are being used more and more frequently due to current socio-economic structures, changing family patterns, earlier age limit to start to school, and increasingly longer distances between school and houses. Route planning is difficult to fully optimize, as the location of bus stops might continuously change due to the discontinuation of the student on a particular day or

address changes. In addition, factors such as multiple routes available between two stops, and changing drivers working on the same route also contribute to the difficulties arising when the route planning is desired to be optimized. Thanks to the advancements in today's information and communication technologies, vehicle fleets can be managed in real-time. When jointly used, devices like GIS, GPS, traffic flow sensors and cellular telephones are able to provide real-time data, such as current vehicle locations, new customer requests, and periodic estimates of road travel times (Khouadjiaa, Sarasolab, Albab, Jourdana & Talbia, 2012). This brings along the opportunity to dynamically redefine the vehicle routes, based on changing conditions. These dynamically defined routes make the saving targets in terms of cost and time in the optimization of VRP even more efficient.

It was seen that more successful solutions were obtained when heuristic techniques instead of conventional methods were used for the solution of complicated problems (NP-Hard) such as VRP. From 1959 onwards, this method and related algorithms have been successfully used for the solution of problems related to VRP and its sub-types that are applied in many sectors including collection/distribution, transportation, military, and emergency services. The VRP is an NP-complete problem, preventing the use of exact algorithms for certain instances of the problem, and thus requiring the use of heuristic approaches (Hsu, Hsu & Lin, 2014). For the optimization of these problems, which always attracted scholarly interest, not only classical heuristic methods such as the classic saving and sweep method, but also meta-heuristics such as tabu search, simulated annealing, ant colony, and (GA) have been widely used. GA is a searching and optimization technique that was introduced by John Holland in 1975 on the basis of Darwin's theory, "only the best survive". In particular, classification optimization problems and multi-dimensional optimization problems that are quite difficult to solve using conventional programming techniques can be easily and rapidly solved using GA. In the relevant literature, there are numerous studies in which GA is applied to solve a VRP. In their study conducted to implement GA to solve SBRP, Sghaier, Guedria, and Mraihi concluded that the number of vehicles in a school bus network can be reduced by bringing down the transportation costs (Sghaier, Guedria & Mraihi, 2013).

In the current study, the visual software that was developed using C#.NET programming language and the GA optimization technique to detect the most suitable and shortest route on the map for school bus services will be discussed. For this software, 10 of the school bus services' routes in the Ankara Province in Turkey were used as case studies to apply the GA method to solve the SBRP. The routes that the school buses follow and the GPS locations of the stops were determined by means of mobile software and were displayed on Google Maps. The present study aims to improve currently available routes, and to update these routes online using the instantaneous GPS locations of the students, tracked down by means of mobile software support. The goal is to avoid the current time, cost, and work-load losses and to reduce air pollution and traffic density by improving the routes.

2. VRP and SBRP

2.1. VRP and literature review

VRP is widely described as the process where the distribution vehicles deliver goods in a depot to the clients found in geographically dispersed locations and then return to the depot on the optimum route. The VRP, first introduced by Dantzig and Ramser in 1959, aims to minimize the total distance to be covered during the routing of the vehicles in a centrally-located depot (Dantzig & Ramser, 1959). The routing process is operated by taking the vehicle capacities into consideration so as to ensure that each client located on the routing plan is visited only once. The depot, vehicle, and goods concepts mentioned in the general description of VRP can be re-adapted as school, student and bus stop, based on different sectors that the problem applies to. Figure 1 shows a scheme indicating the VRP solution applied to a distribution system, where the clientele network is dispersed over three different zones.

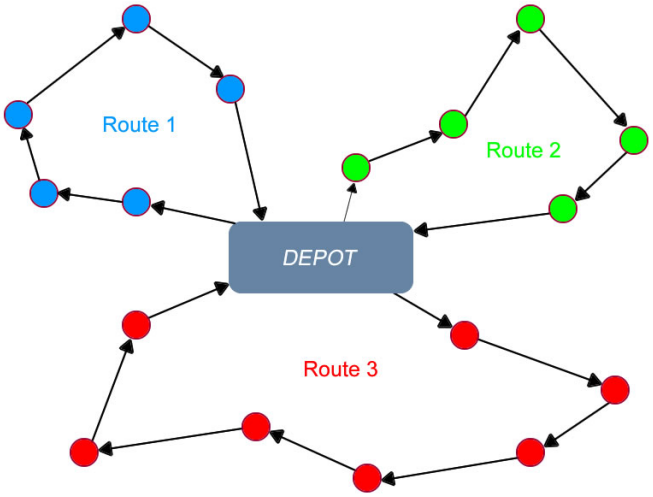


Figure 1. Example of a VRP solution

VRP, which is one of the NP-Hard types of problems, has been studied for more than fifty years, and a number of solution models and algorithms have been developed thus far. For the optimization of this complicated problem, which is not possible to solve using conventional methods, primarily meta-heuristic techniques were preferred for a more efficient and rapid solution. The heuristic methods reported in the literature in relation to VRP are normally examined in two groups: classical methods and meta-heuristic methods. The first known classical heuristic method, applicable to VRP, is the Classic Saving Method developed by Clarke and Wright in 1964. Later, the Sweep Method and Improved Petal Heuristic methods were introduced by Gillet and Miller (Gillet & Miller, 1974), and Foster and Ryan (Foster & Ryan, 1976), respectively. Among the meta-heuristic methods used for the same purpose, one can list tabu search, simulated annealing, ant colony, and GA. In particular, a number of metaheuristic techniques have been successfully applied for the solution of VRP and its variants, such as: simulated annealing (Osman, 1993, Samadi-Dana, Paydar & Jouzdani, 2017), tabu search (Gendreau, Hertz & Laporte, 1994, Taillard, Badeau, Gendreau, Gendreau & Potvin, 1997), granular tabu search (Toth & Vigo, 2003), GA (Van Breedam, 1996), guided local search (Kilby, Prosser & Shaw, 1999), variable neighborhood search (Bräysy, 2003), greedy randomized adaptive search procedure (Resende & Ribeiro, 2003), differential evolution algorithm (Teoh, Ponnambalam & Kanagaraj, 2015) and ant colony optimization (Reimann, Doerner & Hartl, 2004, Yigit & Unsal, 2016).

Today, various studies aim to solve a VRP in many sectors including the distribution of cargo, newspapers, milk, bread, mail and posts, as well as medical and chemical waste collection systems, and personnel and school busses. All of these examples have their own limitations and criteria, such as quality of the transported material, and the last stop to reach, as well as the stop from which the route will begin (for example, in the case of school bus services, the last stop in the morning and the first stop in the evening is the school), necessity to reach a certain stop before the others (cargo sent by a client to another). These limitations should be taken into consideration in the algorithms implemented to create solutions to the problems.

The objective of VRP is to determine a set of conditions such that (Çatay, 2010):

- Each vehicle travels exactly one route.
- Each customer is visited only once by one of the vehicles completely satisfying its demand and supply.
- The load carried by a vehicle between any pair of adjacent customers on the route must not exceed its capacity.
- Total distance given by the sum of the arcs belonging to these routes is minimal.
- Vehicle routes starting and ending point must be the central distribution warehouse.

The mathematical description of general VRP was made by Laporte as given below (Laporte, 1992):

Let G = (V, A) be a graph where V = {0 . . . . , n} is a set of vertices representing cities with the depot located at vertex 0, and A is the set of arcs.

According to this description, the objective function of VRP is as follows:

$$min \sum_{i \neq j} C_{ij} X_{ij} \quad (1)$$

where C_{ij} is the matrix expressing the distance between each arc (i,j) node, while i≠j. Cij represents the time, cost or distance parameter that should be minimized in the objective function (Arias-Rojas, Jiménez & Montoya-Torres, 2012). For a classical VRP, the Euclid equation shown in equation number 2 is used to calculate the distance between i and j nodes having certain x and y coordinates

$$d(i,j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (2)$$

In a classic VRP, d(i,j) is assumed to be the same as d(j, i).

X_{ij}, as shown in equation number 3, stands for a logical variable, whose value varies based on whether arc(i,j) is found in the optimum solution set.

$$X_{ij} = \begin{cases} 1, & If\ (i,j)\ is\ located\ i\ the\ solution\ set \\ 0, & otherwise \end{cases} \quad (3)$$

2.2. Dynamic school bus routing problem(DSBRP)

SBRP, which is a sub-group of VRP, is defined also as a kind of travelling salesman problem. The SBRP includes determining the shortest route for a school bus to pick up all the students from the pre-determined stops and to take them to school, and to pick the students up from school and leave them at the pre-determined stops. The first studies regarding SBRP were carried out by Newton and Thomas in 1969. In later years, numerous studies were carried out regarding SBRP. In the studies conducted by Spada et al. in 2005, meta-heuristic methods were applied to SBRP and a decision-making model was developed (Spada, Bierlaire & Liebling, 2005). Fügenschuh carried out a study in 2009 on school bus route planning in Germany, and concluded that fewer school busses would be needed if schools started their daily schedule at different times (Fügenschuh, 2009). In their study dated 2010, Park and Kim carried out an extensive examination of different types of SBRP and a wide literature review (Park & Kim, 2010). Martinez and Viegas carried out a study in 2011 to examine the specific case of the students in Lisbon using school bus service, and exhibited a two-step approach towards the solution of SBRP. In the first step, they collected information regarding the geographical locations of the students, and assigned these locations to different school busses in the most ideal way. In the second step, the most convenient routes were planned for the identified vehicles (Martínez & Viegas, 2011). In the studies conducted by Samadi-Dana et al. in 2017, a robust optimisation model for SBRP with uncertainty in times associated with moving from one bus stop to another is developed and a solution methodology based on simulated annealing algorithm, is presented for solving the proposed model (Samadi-Dana, Paydar & Jouzdani, 2017). Although a number of studies focusing on SBRP can be found in the relevant literature with a variety of purposes, the following issues appear as the most frequent goals:

- To minimize costs associated with transportation
- To minimize time spent on transportation (Corberán, Fernández, Laguna & Martí, 2002)
- To minimize the total number of vehicles used for transportation
- To identify the stops where the students are taken and dropped off (Thangiah, Bryan, Anthony & William, 2008)

This problem consists of a number of sub-problems. The problem is solved in five steps (Park & Kim, 2010).

- Data preparation

- Selection of stops
- Route development
- Scheduling school bell
- Route planning

In the data preparation step, the addresses of the school and the students as well as the existing roads between these are determined. In the second step, the student addresses are assigned to different stops. In the third step, the route is planned for a single school. If the solution is to be made for more than one school, then the school bells are scheduled for each school, and in the fifth step the route is planned for all schools.

VRP's can also be classified into two categories as dynamic and static routing problems. In the static VRP's, the stops/locations that the vehicle will visit are pre-specified and do not change during the distribution/collection process. In dynamic VRP's, on the other hand, new stops can be added to the planned route during the process or certain stops can be omitted. In similar dynamic problems, some or all of the access points are not known in the beginning. These points are dynamically defined during the route design or planning stages. In the dynamic VRP, using a real-time communication network between the vehicle and decision-making system, the vehicle routes can be re-defined during the operation. This type of problems is defined as online or real-time problems by some scholars (Pillac, Gendreau, Guéret & Medaglia, 2013). Two examples of this can be certain orders getting cancelled or new orders being taken while a water distribution vehicle is on its route, or a school bus being informed on its route that certain students will be absent from school that day. In current conditions, dynamic VRP's are more frequently needed, and are attributed with a more specific importance. The first study dealing with dynamic VRP was carried out by Wilson and Colvin (Pillac, Gendreau, Guéret & Medaglia, 2013). The enhancements in GPS, traffic sensors, and mobile communication systems caused a further acceleration in studies carried out in this field. Within the context of this study, DSBRP will be investigated. DSBRP is graphically explained in Figure 2.

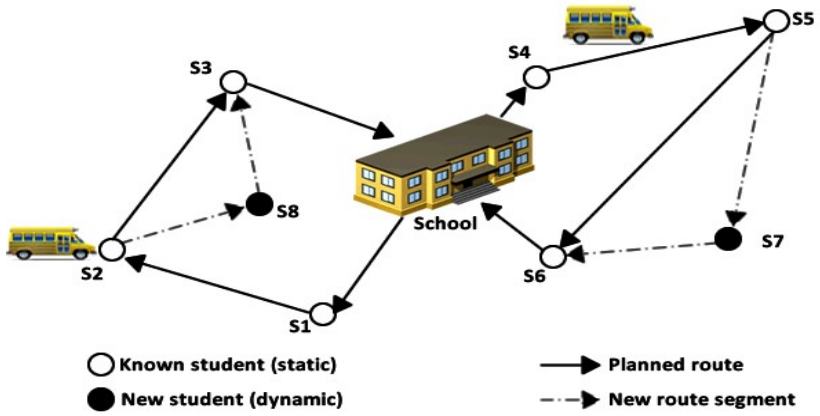


Figure 2. A dynamic school bus routing case

In the previous sections, a number of heuristic methods that are applicable to VRP were mentioned. In this study, school bus route distances (C_{ij}) were optimized for the VRP objective function using GA. In the mathematical formulation of the problem, the vehicles represented as the set V correspond to the school busses, the central distribution depot represented as V_o to the school, the connections represented as set A to the routes between students' houses and the school, and finally the clients to the bus stops.

3. Solving DSBRP with GA

3.1. Genetic algorithms (GAs)

GAs, which are based on the evolutionary approach method in the nature, are a meta-heuristic technique used in the solution of searching and optimization problems. GAs were

recognized as an important technique for optimization after the doctorate dissertation of Goldberg, where the use of a GA was proposed for the purpose of gas pipeline checks, and then the publication of the book entitled "Genetic Algorithms in Search, Optimization, and Machine Learning" in 1989 (Goldberg, 1989). GAs are mostly used for the solution of the problems, where a mathematical model cannot be constructed, the solution domain is too large and there are an extremely high number of factors affecting the problem. Therefore, they are successfully applied to the solution of quite complicated problems such as scheduling, assignment, travelling salesman, network design, logistics, and school service routing.

GAs assess not a single solution, but a multiple number of solutions simultaneously. This characteristic is called the GA's parallel search feature. Since GAs that provide the opportunity to work with a high number of parameters form the solution space through binary coding the variables' values, they do not require theoretical information regarding the problem. GAs work on a population composed of different chromosomes corresponding to different eventual solutions to a given problem (Mohanta, Parhi & Patel, 2011). The costs of GAs associated with problem solving are lower than that of other heuristic methods, and their flowcharts are simpler. They do not scan the whole solution space, but only a specific part of it. Through this more effective way of searching, they reach a solution more rapidly. Another advantage of this method is that they can simultaneously examine the population composed of different solutions, and therefore they can skip local best solutions (Goldberg, 1989).

GA Characteristics:

- They aim to access better points through the random points selected from the solution space by means of operators;
- They use only function values instead of derivative information;
- They use the codes of the variables in the binary system, instead of the variables themselves;
- They use probabilistic rules instead of deterministic ones while producing new solutions (Goldberg, 1989).

A simple GA follows the solution steps given below:

Determine iteration number and population size
Start with a random initial population
For each iteration
Calculate the conformity value for each individual in the population
Apply selection, crossover and mutation operators
Update population
Show best solution

Due to intrinsic features, GA eliminates the bad individuals, i.e. unsuitable solutions, thanks to the operators. GA stops searching for a solution either when the selected conformity value is obtained, or a better solution cannot be produced or the selected number of iterations is performed.

3.2. Implementation of GA to DSBRP

In the previous section, the steps required for DSBRP were listed as data preparation, selection of stops and route planning. In this section, these steps will be enlightened with more details and the manner in which school bus routes are formed using GA will be explained.

For the route that is aimed to be planned, N number of bus stops was selected. Therefore, V= {0,1,…..,N}. The school is denominated as V_0 and V_N during the evening and morning hours, respectively. The roads connecting the school and bus stops are shown as set A, and the problem was defined so that G=(V,A). Distances between the school and bus stops were calculated and C_{ij} matrix was formed. In this study, the actual distances between different points were calculated using the GPS (lat, lng) locations of bus stops.

The distance optimization needed for the formation of the objective function that can be seen in equation number 1 was done using GA operators and parameters. The flowchart that can be seen in Figure 3 shows how the school bus routes are formed using GA.

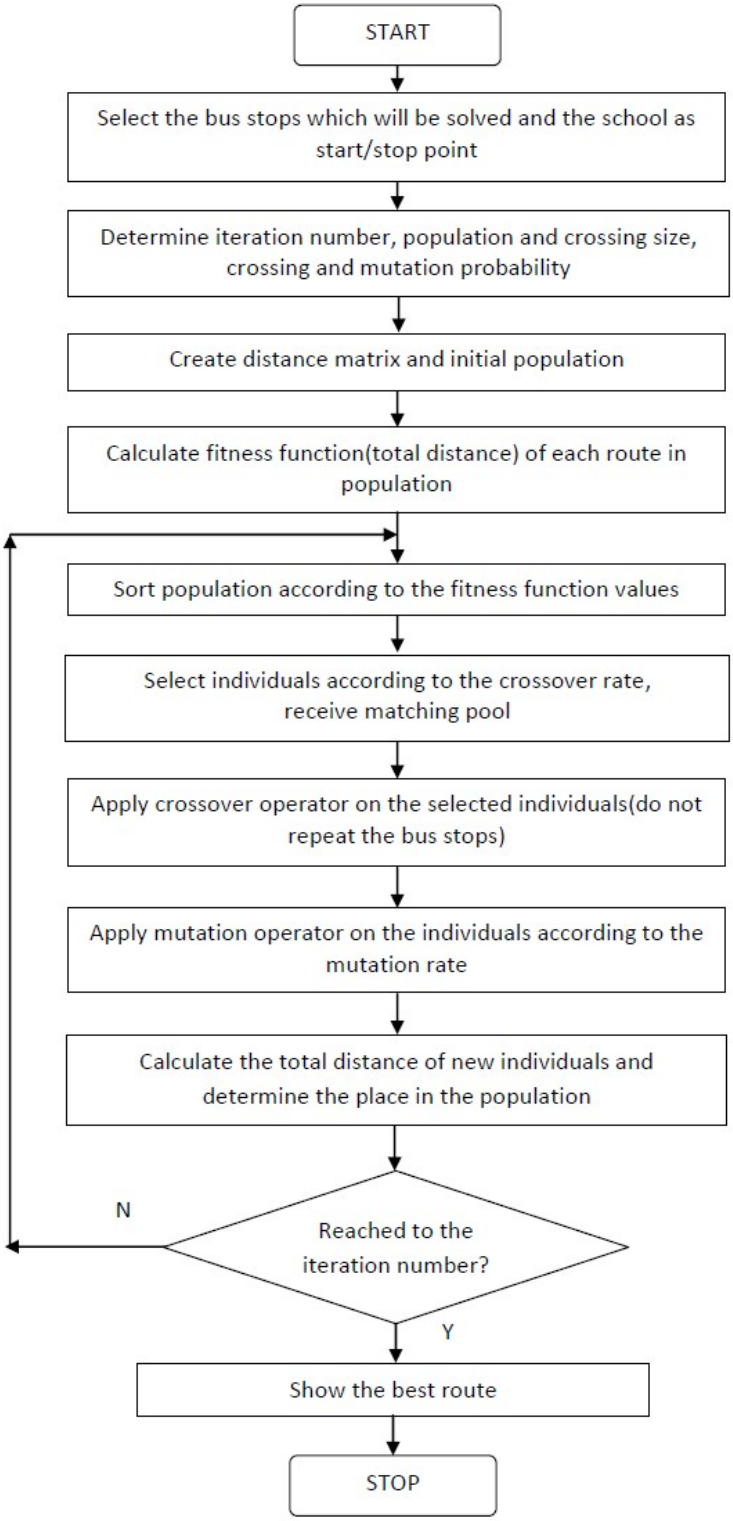


Figure 3. The flow diagram of the SBRP solution by using GA

3.2.1 Data preparation

In this study, the existing school bus routes and the GPS locations (lat, lng) of the related bus stops and the school were collected using mobile software and recorded in a database.

3.2.2 Bus stop selection

In order to ensure a dynamic assessment of the problem, route planning was performed not for all the students using the school bus, but only for selected bus stops. Moreover, the change of the initial and final stops in the morning and in the evening was also taken into consideration.

3.2.3 Forming the route with GA

Parameters

The following parameters were used for the solution of the problem: number of iterations, population size, crossover size, cross-breeding and mutation possibility and whether the school is the initial or final stop of the route.

Coding

Each chromosome found in the population formed in the GA is structurally an equal-length coded series. The chromosomes are made of genes. For coding purposes, binary, permutation, and value coding methods are widely used. In the travelling salesman or other similar VRPs, permutation coding technique is preferred over the other techniques. Using the permutation coding technique, each chromosome found in the population is expressed in terms of the numbers of each stop to be followed in the route, as shown in Figure 4.

8	6	2	5	3	4	9	1	7	0

Figure 4. Example of a chromosome structure with permutation coding

Creating Initial Population

A solution space compatible with a given population size is formed at the beginning of a GA procedure. Each chromosome found in the solution space represents a potential solution. The initial population can be randomly formed, without depending on any rules; however, it can also be formed applying certain rules established based on the nature of the problem. For SBRP, the initial population is formed in a random fashion, paying extra attention to the following two limitations:

- The genes (bus stops) in the chromosomes (route) should not repeat themselves; and
- The initial and final stops of the obtained solution should be constant.

In the randomly produced solutions, it is possible that the genes in the chromosomes are repetitive. However, since in SBRP the school service should call at each bus stop once, the chromosomes were formed accordingly. In the SBRP, the school is the initial point in the mornings, while it is the final point in the evenings. This principle was used to fix the initial and final stops depending on the time of the solution. In the exemplary chromosome given in Figure 4 (route), the stop represented by a 0 is the school and since this route was formed for the morning hours, 0 is the last gene.

Fitness function

For each chromosome in the population, a compatibility function depending on the structure of the problem is calculated. In the solution space, the chromosomes with higher compatibility functions are more likely to be selected and passed down to the next generation. For this problem, the compatibility function for each chromosome found in the population was calculated as the total length of the established route (L), as shown in equation number 4. While calculating this distance, the C_{ij} matrix was used.

$$L = \sum_{i=0}^{n} C_{ij} \quad (4)$$

Selection and crossover

After calculating the compatibility functions of the chromosomes in the population, the crossing over is conducted to produce new individuals. The selection process identifies the families that should participate in the production of new individuals for the following generation (Goldberg,

1989). In the GA, roulette wheel, elitism, tournament, and consecutive selection methods can be used. In the selection mechanism, the individuals passed down from the previous generation occasionally cannot produce a better individual. In that case, the compatibility of the individuals might worsen, while producing the exact opposite is what is expected. To avoid this, the elitism operator is used and it is ensured that the best individual of the previous generation is passed down to the next generation, even though the current population is diminishing on an overall basis as a result of the production operators (Goldberg, 1989). In the current study, the consecutive selection method and elitism selection were preferred. For this aim, after calculating the compatibility function, the population was ranked according to the population function values (total route length). In case the crossover possibility is realized, the number of individuals to select will be determined according to the parameter related to the crossover size. To ensure a high level of variability in the generation, it is suggested that this possibility is taken as 50% and 95% (Goldberg, 1989). The crossover process allows the production of a new individual using the genes taken from two individuals, based on the selected crossover method. In this study, a single point crossover method was selected. During the crossing over, limitations that were previously mentioned regarding the formation of a new initial population were taken into consideration. The identified initial or final point was fixed and kept out of the context of crossing over. An example of crossover can be seen in Figure 5.

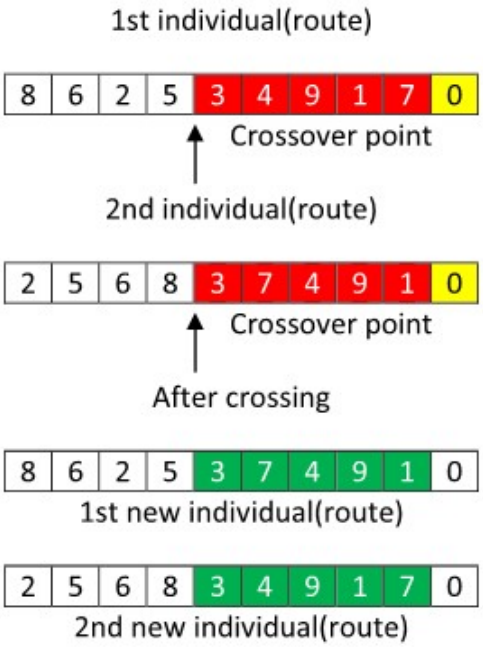


Figure 5. Crossover process

Mutation

The individuals obtained at the end of crossing over might not provide the desired level of variability. In that case, the produced individuals are mutated independently from another individual in such a way that their own gene sequence will change. The mutation process is performed in the event that the mutation possibility that is specified in the beginning comes true. The results obtained from mutation can enhance the outcome or make it worse. It is of utmost importance to specify the most suitable mutation possibility. This possibility should be high enough to prevent the method from becoming stuck at a local point, but at the same time, low enough to allow the best results produced by crossing over and multiplexing. In this study, the mutation possibility was selected as 10%, and the locations of two randomly selected bus stops were changed during the mutation process. As in the crossing over, also during this process, the limitations regarding producing a new individual (route) were adapted. Figure 6 shows an example to mutation process.

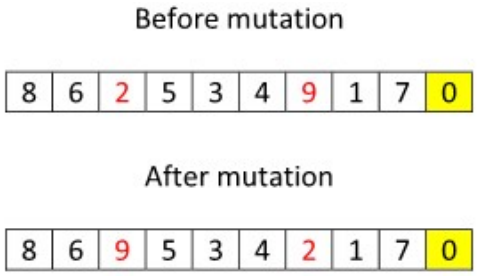


Figure 6. Mutation process

4. Developed software and experimental results

For this study, the school bus routes within the Ankara Province were used as case studies. The school bus routes were recorded by using the Android application and instantaneous GPS monitoring method. The home address of each student was taken as a stopping point. At the end of each route, the distances between the beginning and end points were recorded. After transferring the obtained route data into the database, the ill-adapted points were eliminated.

By means of the developed application, the existing school bus routes are dynamically optimized using GA. It was developed both as a mobile and desktop application. Using Android-based mobile software, the information regarding GPS locations of bus stops and school buses is transferred to the server on a real-time basis. Using the desktop software, where GAs are run, these coordinates are shown on a Google map, and the most suitable route is produced and sent to the school bus via server. This method provides the opportunity to dynamically reflect certain factors such as a different initial point for the school bus, some students being absent from the school on a particular day, and eventual changes on the existing roads on the route production process.

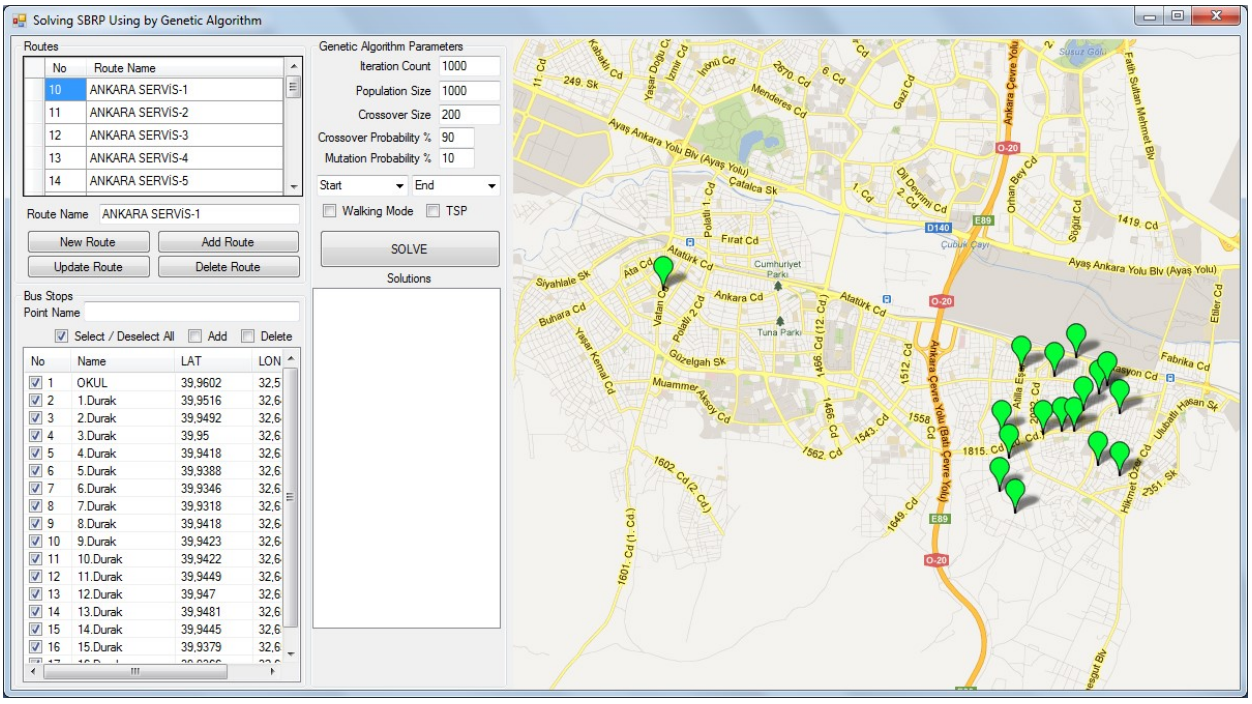


Figure 7. Application main form which includes route, bus stops and GA parameters

The application was developed using C#.NET programming language. In order to store the planned route and points at the route, on the other hand, a SQLite database was used. In this application, GMap.NET was added to locate the routes on Google Maps. The coordinates, as well as latitude and longitude values of each point on the route, were recorded in the database. Figure 7 shows the main form, where the routes are produced; bus stops are added to/deleted from the routes,

the locations of the bus stops belonging to a given route are loaded in the bus stops' list and on a map, and the bus stops for which one desires to produce a solution are selected and GA parameters are defined.

When the main form is loaded for the first time, the route records in the database are uploaded in the routes list, while the locations of the bus stops found in the active route are uploaded in the bus stops' list and on the map together with their names, numbers, and GPS locations. The area that can be seen on the map is adjusted in such a way that the uploaded stops are located in the center. In order to add a bus stop to the selected route, the add bus stop option is clicked, and after the name of the bus stop is typed, the location of the bus stop is clicked twice. When a bus stop existing in the database is desired to be deleted, on the other hand, the location of that particular bus stop is clicked on the map, while the delete bus stop option is on. The bus stops that are desired to be included in the solution should be signed. After making the bus stop selection, number of iterations, population size, crossover size, and crossover and mutation rates are entered using the section where the GA parameters are defined. The parameter values for the developed application are given in Table 1.

Table 1. Application default GA parameters

Parameter	**Default Value**
Iteration number	1000
Population size	1000
Crossover size	200
Crossover probability	90%
Mutation probability	10%

During the route planning, school is the initial point if the students are going home from school, whereas it is the final point if they are going to the school from their homes. The application provides the opportunity to fix not only the school, but also the bus stops as initial or final points. Since the authors hope to develop a routing solution for more than one school in a future study, both the initial and final bus stops were given the opportunity to be selected so that the school bus can complete distribution/collection duties for one school and can go to another school for routing. When these selections are made, the initial and final genes of the chromosomes produced in the population were fixed through these selections. When the TSP option is on, on the other hand, the school bus returning to the initial point after completing the distribution/collection duties is included in the routing process. The information regarding solutions, route distances and the number of iterations produced after all the parameters are defined and the relevant selections are made are listed as shown in Figure 8. Under the solutions list, total crossover, total number of mutations, and algorithm working times are shown.

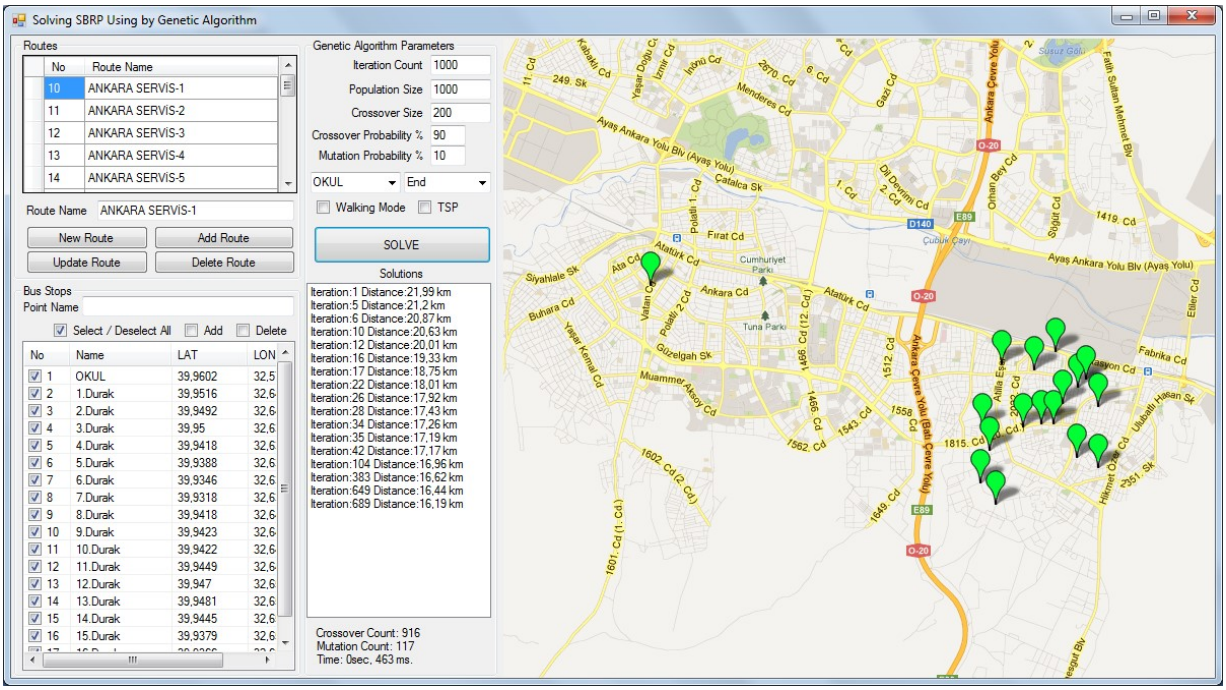


Figure 8. Listing of obtained solutions after running GA on the route

When the solution that is desired to be viewed is double clicked, the connections between bus stops are drawn in turn, and the route is shown as can be seen in Figure 9.

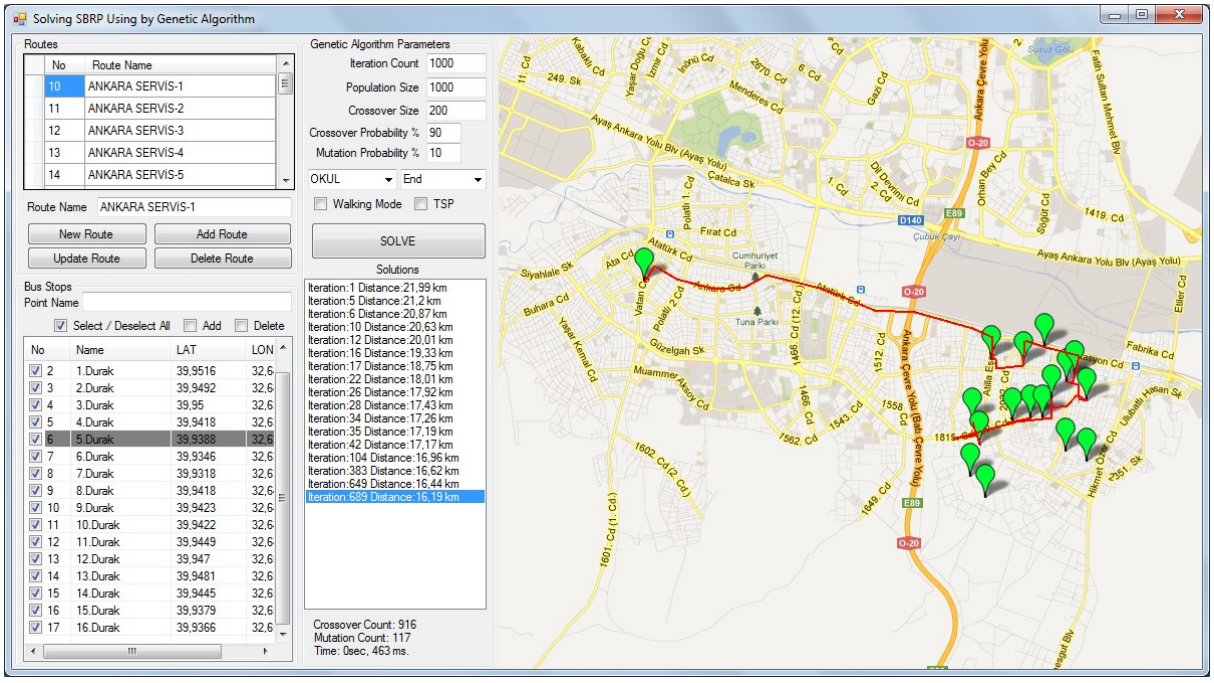


Figure 9. Step by step drawing of the selected route solution

The GA procedure was carried out using the parameter values that can be seen in Table 1, for a total of 10 school bus services' routes identified by means of mobile-based software for a school located in the Ankara Province. The obtained experimental results are shown in Table 2 and Figure 10.

The algorithm working duration also includes the formation of a distances' matrix.

Table 2. Obtained experimental results

Information of the collected routes			**Results of GA**			
No	Number of bus stop	Distance (km)	Best distance obtained (km)	Iteration number	Running time (sec)	Optimization rate (%)
1	16	17.85	15.64	321	0.468	12.38
2	17	18.45	15.90	231	0.496	13.82
3	16	17.11	14.45	701	0.424	15.55
4	12	11.16	10.84	26	0.376	2.87
5	7	7.01	6.98	8	0.294	0.42
6	11	14.47	10.43	248	0.370	27.92
7	10	6.73	4.21	18	0.328	37.44
8	12	16.84	11.79	23	1.227	29.98
9	17	17	14.72	606	7.46	13.41
10	13	15	11.69	167	7.35	22.07

The obtained experimental results showed that the distances can be better optimized with an increasing number of bus stops, and a better solution was obtained for those routes, where the school was fixed as either an initial or a final point. At the end of the optimization studies carried out using GA on the routes of a school bus fleet composed of 10 vehicles, whose total daily route distance is 141.62 km, the total distance to cover was reduced up to 116.65 km, which corresponds to an improvement of approximately 17.63%. According to these results, the 25491.6 km-distance, which is normally covered in one school year (180 day) using the existing routes, can be reduced to 20997 km. Therefore, it is estimated that a cost saving of 4494.6 km can be achieved.

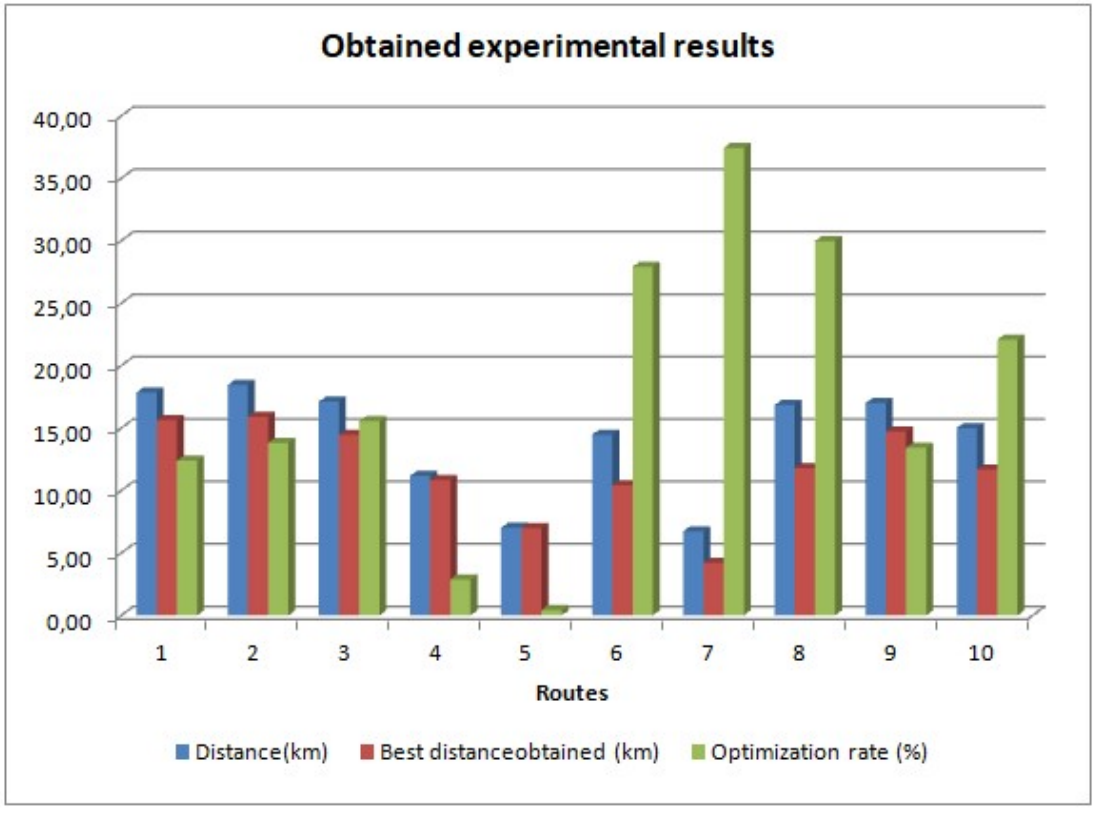


Figure 10. Obtained experimental results

Based on the results obtained from the application, it can be concluded that existing route distances can be successfully optimized using GA. As mentioned also in the previous sections, the traffic density can be reduced by means of shorter route distances. It will, therefore, be possible also to reduce the time spent in traffic, as well as the adverse effects of air pollution due to traffic. In addition to these, the fuel costs can be considerably reduced by means of route optimization studies.

5. Conclusions

Transport and distribution systems are needed in every field of the daily life. When these systems are not managed properly, they can start causing additional costs, environmental pollutions, and time loss. VRPs are complicated problems with a considerable number of sub-branches that become increasingly more important, parallel to the technological advancements. With suitable routing, costs, time, and workload losses and environmental pollution can be significantly reduced. Thanks to today's technological means, the routing studies can be carried out dynamically and more effective solutions can be developed.

In the present study, GA was used for the optimization of DSBRP, which is a sub-branch of VRP. The developed application was tested on existing school bus routes in the Ankara Province. It was clearly seen that the application helped achieve successful results in the optimization of school bus routes. Based on the results obtained for the sample routes, it was concluded that the total distance to cover can be improved by 17.63%. Thanks to the mobile-support feature of the application, real-time solutions can be obtained. A future study is planned to initially distribute the students according to the capacities of school busses, and to carry out the routing process for a school bus network serving more than one school. In addition, to solve the problem, applying different artificial intelligence techniques such as particle swarm optimization are considered.

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