An Evolutionary Solution for Multimodal Shortest Path Problem in Metropolises

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Abstract. This paper addresses the problem of time-dependent shortest multimodal path in complex and large urban areas. This problem is one of the important and practical problems in several fields such as transportation, and recently attracts the research focus due to developments in new application areas. An adapted evolutionary algorithm, in which chromosomes with variable lengths and particularly defined evolutionary stages were used, was employed to solve the problem. The proposed solution was tested over the dataset of city of Tehran. The evaluation consists of computing shortest multimodal path between 250 randomly selected pairs of origins and destination points with different distances. It was assumed that three modes of walking, bus, and subway are used to travel between points. Moreover, some tests were conducted over the dataset to illustrate the robustness of method. The experimental results and related indices such as convergence plot show that the proposed algorithm can find optimum path according to applied constraints.

Keywords: multimodal shortest path, genetic algorithm, metropolis.

1. Introduction

Finding optimum path between two designated points is one of the classic and fundamental problems in the network analysis [6, 13]. According to literature, this problem and its variations have been extensively investigated in different fields. One of the most interesting application domains is transportation in which the problem in various forms including classic, constrained, dynamic, and multi-criteria can be recognized [29]. Moreover, recent developments in intelligent transportation system (ITS), Location-based Services (LBS) and route advisory systems have led many researchers to concentrate further on different aspects of problem [2, 6, 9, 15, 22, 35, 36].

Multimodal transportation systems are public, ordinary networks in urban areas, particularly in metropolises where the citizens may utilize the combinations of several modes of transportation such as personal car, taxi, subway, tram, bus, and walking. Using these networks brings real benefits for

citizens by saving their time and cost, and also greatly assists sustainable development of metropolises with reduction of traffic jams and air pollutions.

Multimodal shortest path problem is concerned with finding a path from a specific origin to a specific destination in a given multimodal network while minimizing total associated cost. The complexity of finding multimodal route is obviously much higher than monomodal one. In the multimodal networks several modes of transportation operate concurrently under the changing conditions. Since using a multimodal network requires information about timetables of vehicles, it is necessary to have some information about departure time of travel to solve the problem. Due to this nature of these networks, they can be considered as dynamic networks in which travel time associated to each arc changes with time [21, 37].

A novel formulation and evolutionary-based solution is proposed in this paper to compute single-objective shortest path on multimodal networks, taking both travel and switching time into account. It is assumed that the multimodal network consists of three modes of walking, bus, and subway and the arcs of network have time-dependent weights. In the remainder of this paper, in section 2, the related researches are reviewed. Section 3 gives a detailed description and formulation of the multimodal shortest path problem, and moreover, states proposed solution to the problem in detail. In Section 4, the solution is examined as a case study, and the results are evaluated to show the proficiency of proposed method. Finally, section 5 concludes with the extensions of the proposed solution.

2.   Review of Related Research

There have been many research on computing multimodal shortest paths. A considerable portion of them is about finding solutions for static multimodal shortest path problem [12, 27, 28, 34]. Most of these algorithms approximate waiting time of transfer according to headway, or using generating of artificial waiting time arcs [11]. But, recent researches have changed the direction towards working on dynamic solutions.

Battista *et al.* [7] introduced a heuristic approach called *path composition approach* for finding reasonable routing rules on bimodal networks based on what a user probably chooses. They used these composition rules to concatenate small number of good sub-paths to create the shortest path.

Modesti and Sciomachen presented an approach based on the classical shortest path problem for finding multi-objective shortest paths in urban multimodal transportation networks with objectives of minimizing the overall cost, time, and users' discommodity associated with the required paths. They used an *ad hoc* utility function to assign the weights to arcs according to their cost and time while simultaneously considered the preferences of the users related to all of the possible transportation modalities [26].

The temporal intermodal optimum path algorithm, which was proposed by Ziliaskopoulos and Wardell according to the principles of dynamic

programming, took the delays at modes, and arc switching points into account. Their Time-Dependent Intermodal Least Time Path (TDILTP) algorithm was based on a general framework in which the routes from all origins, departure time, and modes to a destination node are computed [37]. The TDLITP algorithm operates in a label-correcting manner, assuming that dynamic travel time of arcs and actual schedules of transit lines are known. Chang *et al.* extended the TDILTP algorithm to calculate Time-Dependent Intermodal Minimum Cost Paths (TDIMCP) from all origins and departure time to a destination node, based on time-dependent, fixed travel and transfer costs [11]. Despite the time-invariant problems, this algorithm considered time as an index, which determines the feasibility of a path, while a separate cost function is optimized.

Lozano and Storchi proposed a multimodal shortest path algorithm to find the shortest viable path, in which paths with illogical sequences of used modes were eliminated [23]. They used label correcting techniques and an *ad hoc* modification of the Chronological Algorithm (Chrono-SPT) which was proposed by Pallottino and Scutella [29] to solve the problem. They extended their algorithm to calculate the viable hyperpath [24].

Abdelghany and Mahmassani proposed an algorithm to calculate intermodal paths based on a multi-objective shortest path algorithm, where the set of non-dominated paths was computed and an optimum path is selected among them based on a generalized cost function[1].

Another research was conducted by Sherali *et al.* in the Route Planner Module of Transportation Analysis Simulation System (TRANSIMS) [33]. They proposed a dynamic programming-based approach for the time-dependent, label-constrained shortest path problem by adapting existing partitioned shortest path algorithmic schemes.

Bielli *et al.* proposed a framework to address both algorithmic approaches proposed for solving the multimodal shortest path problem and a transportation network modeling using geographic information systems (GIS) [10]. They developed a modified version of k-shortest path algorithm to define an efficient solution for multimodal shortest path with time constraints.

A new graph structure, namely *transfer graph*, was introduced by Ayed *et al.* to model the multimodal networks [4]. A transfer graph is described by a set of sub-graphs called components. They proposed an algorithm to deal with multi-objective route guidance problem in the time-dependent multimodal network. The advantage of their algorithm was the capabilities to find the multimodal route when all involved networks are kept separated, which imply to be accessed separately.

Qu and Chen proposed a hybrid multi-criteria decision making method combining the fuzzy Analytic Hierarchy Process (AHP) and Artificial Neural Network (ANN) to find the multimodal, multi-criteria paths [31]. They used fuzzy AHP to find the suitable initial input-hidden weights to improve the efficiency of ANN. The improved ANN with error back-propagation is applied to study the relationships between criteria and the alternatives performance. They used this approach to find the best way from a certain origin to a specific

destination through a multimodal transportation network according to six main criteria, which was extracted among 15 criteria.

In addition to these researches, some practical systems have been developed, and most of them are in the form of multimodal route planners, which include modules to find the shortest multimodal path for users. Some of these systems are [8, 16, 20, 25, 30, 32].

The major weakness of these researches is that they were not carried out on real dataset of any metropolises that include complex transportation networks. In these cities, search spaces are too large and highly complex. Thus, the problem will be too complex to be solved by traditional methods, and efficient optimization strategies are required to deal with this difficulty.

3.   Proposed Solution for Time-dependent Shortest Path

An evolutionary-based framework has been developed in this paper to find the optimum solution for the multimodal shortest path problem (Fig. 1). The framework consists of two main parts. One part is the multimodal shortest path module, in which some parameters such as origin and destination, start time, and transportation modes are introduced to the engine. The engine of this module, which works based on an adapted evolutionary algorithm, computes the optimum path according to the input parameters and a geodatabase. It is possible for user to introduce his/her contextual information such as age and health level to engine of this module to have more suitable solutions. The other part of the framework is geodatabase. This part includes all necessary information both in spatial and attribute format, which broadly are divided into two groups of pathways and SST.
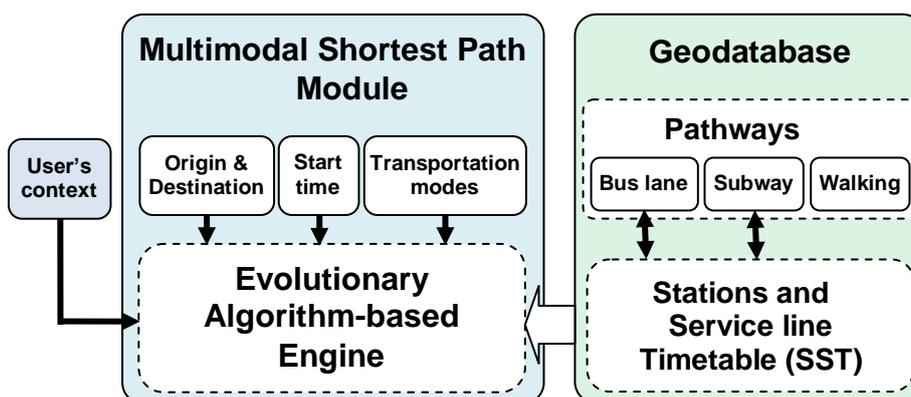

Fig. 1. Proposed framework for multimodal shortest path finder

The remainder of this section consists of three parts to explain the proposed solution in details. An introduction to evolutionary algorithms is described in section 3.1. Then, the basic formulation of the problem is

discussed in section 3.1, and proposed solution for finding shortest paths in multimodal networks are described in sections 3.3.

3.1.   Evolutionary Algorithm

The evolutionary algorithm is a class of optimization methods that simulate the process of natural evolution [17, 18, 19]. Evolutionary computing comprises genetic algorithm (GA), genetic programming, evolutionary programming, evolutionary strategy, and classifier systems [5]. This algorithm is also a member of a group of methods, known as meta-heuristics. This set of techniques includes simulated annealing method, tabu search method, ant colony algorithm, bee algorithm, particle swarm optimization, artificial immune systems, and distributed reinforcement learning, and has been proposed to solve the difficult possible optimization problems [14].

Genetic algorithms (GAs) were invented by John Holland in the 1960s [19] and were developed by Holland, his students, and colleagues at the University of Michigan in the 1960s and the 1970s [17]. The general algorithm of this approach is as follows:

```
Algorithm 1: Evolutionary Algorithm
  initialize population
  evaluate population
  do while (termination-criteria is not satisfied)
    select parents for reproduction
    perform recombination and mutation
    evaluate
  loop
```

GA is different from other heuristic methods in several ways. The most important difference is that GA works on a population of possible solutions, while the other heuristic methods use a single solution in their iterations. The general acceptance is that GA is particularly suited to multidimensional global search problems where the search space potentially contains multiple local minima [18]. The basic GA does not require extensive knowledge of the search space, such as likely solution bounds or functional derivatives. Moreover, GA has a number of other advantages, some of them are (i) the concept is easy to understand, (ii) modular, separate from application, (iii) supports multi-objective optimization, (iv) easy to exploit previous or alternate solutions, (v) there is always an answer, (vi) answer gets better with time, (vii) ability to scan a vast solution set quickly, (viii) bad initial population do not influence the end solution negatively, (ix) are useful and efficient when the search space is large, complex, or poorly understood. According to these considerable advantages of GA, this approach may be the first candidate when someone wishes to solve an optimization problem. Further information on genetic algorithms can be found in [3, 18].

3.2. Basic Formulation of Problem

In contrast with finding monomodal paths, computing the shortest multimodal path may encounter some difficulties. The algorithm should take into account all service lines and transportation modes that pass one station according to their temporal schedules. Furthermore, it is necessary to model the waiting time when the services/modes are changed. The differences between a monomodal and multimodal path are illustrated through an example. As depicted in Fig. 2, it is assumed that there are three service lines and a number of bus stops. Each service line, SL_i, is represented by the sequence of stops. For example, $SL_3= (…, 301, 102, 103, 202, 203, 401,…)$ shows the service line with ID number 3 that passes through the stations mentioned. Each line has a departure timetable and it is possible to build a timetable for each of the stations according to the temporal distance of preceding stations and the line number. If the non-temporal monomodal path from O to D is represented by $Path(O,D) = (O,101,102,103,202,203,204,205,D)$, then this sequence may coincides with different multimodal paths such as the following:

a)   Walking from O to S_{101}, waiting for the bus at S_{101}, going to S_{103} by SL_1, walking from S_{103} to S_{202}, waiting for the bus at S_{202}, going by SL_3 to S_{205}, and finally walking to D.

b)   Walking from O to S_{101}, waiting for the bus at S_{101}, going to S_{102} by SL_1, waiting to change to another bus, going by SL_2 to S_{203}, again waiting for a bus change, then going by SL_3 to S_{205}, and finally walking to D.

c)   Walking from O to S_{102}, waiting for the bus at S_{102}, going to S_{203} by SL_2, waiting to change the bus, going by SL_3 to S_{205}, and finally walking to D.

Obviously, each of these paths may have a different corresponding total cost.
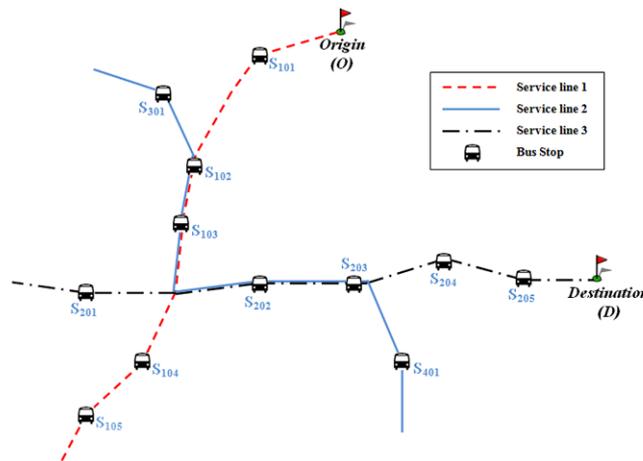
Fig. 2. Sample service lines in a multimodal network

Let the multimodal transportation network be assumed as a directed labeled multigraph of G $(N, A, L_N, L_A, M_N, M_A, \psi, \omega)$. $N = N_B \cup N_S$ is the set of *nodes* consisting of bus stops (N_B) and subway stations (N_S). A is a multiset of *arcs* comprises different passes of service lines and walking paths. L_N is a set of *node labels* showing associated IDs of stops (stations), and L_A is a set of *arc label* showing the service line IDs and departure orders for buses and subways. M_N: $N \rightarrow L_N$ is the *node labeling function* associates a label from L_N with each node. M_A: $A \rightarrow L_A$ is the *arc labeling function* that associates a label from L_A with each arc. ψ: $A \rightarrow N \times N$ is the *incidence function* which associates a pair of nodes from N with each edge in A. ω: $A \times \mathbb{N} \cup \{0\} \rightarrow \mathbb{R}^+$ is the *weight function*, which associates a weight with each arc in A. The weights of arcs represent the time duration required to travel between two nodes with specific departure time.

The cost of each multimodal path consists of two main parts of traveling and waiting time. Traveling time shows the duration of traveling, and waiting time represents the periods when someone changes the service line(s) of transportation. The time it takes to switch between bus and subway mode consists of two parts of walking and waiting. Walking, which is simulated as the connecting arc, is added to travel time. Consequently, as the following formulation demonstrates, the objective function of finding a multimodal shortest path between an origin (O) and a destination (D) consists of two general parts of minimizing the weights of used arcs (first summations) and minimizing the waiting time (second summations) when the modes are changed.

$$\min \quad \sum_{l \in L_A} \sum_{i=O}^{D} \sum_{j=O}^{D} x_{ij}^l \omega_{ij}^l + \sum_{\substack{l,l' \in L_A \\ l \neq l'}} \sum_{\substack{i=O \\ i \neq j,k}}^{D} \sum_{\substack{j=O \\ j \neq i,k}}^{D} \sum_{\substack{k=O \\ k \neq i,j}}^{D} (\tau_{jk}^{l'} - (\tau_{ij}^l + \omega_{ij}^l)) \tag{1}$$

Subject to*:*

$$\sum_{l \in L_A} \sum_{\substack{j=O \\ j \neq i}}^{D} x_{ij}^l - \sum_{l \in L_A} \sum_{\substack{j=O \\ j \neq i}}^{D} x_{ji}^l = \begin{cases} -1 & i = D \\ 0 & i \neq D, O \\ 1 & i = O \end{cases} \tag{2}$$

$$x_{ij}^l \in \{0,1\} \tag{3}$$

In this optimization function, x_{ij}^l is a binary variable associated with each arc (i,j) with label l and equal to 1 if and only if the corresponding arc is used in the solution. ω_{ij}^l and τ_{ij}^l show the travel time (weights) and departure time of arc (i,j) with label l, respectively. Constraint (2) guarantees that the result is a path and there is no loop.

A *stations-service lines timetable* (*SST*) is used to store the essential information about the transportation network. This table is a part of the geodatabase, and its structure is shown in Table 1. The SST consists of four fields of *service line ID*, *from-station ID*, *to-station ID*, and *departure time*. Each row of this table shows the time when the bus/subway with *service line ID* passes *from-station* heading towards *to-station*. *Service line ID* column indicates the mode, order, and ID of a service in the form of a number. Obviously, different service lines may share the same stops/stations. The information in this table is also used to extract adjacency relationships between stations, and to find the neighbors of a specific station. Another advantage of this table is the possibility of modeling all effective factors on temporal distances between two nodes, such as congestion, as time differences.

Table 1. Stations and Service lines Timetable (SST)

Service line ID	From-station ID	To-station ID	Departure time
1001	101	102	06:30
1001	102	103	06:40
1002	102	103	06:42
…	…	…	…
2097	1520	1547	18:45
…	…	…	…

3.3. The Engine of Proposed Multimodal Shortest Path Finder Module

The engine of proposed module, which is based on an adaptive evolutionary algorithm, works in five steps.

Coding of the chromosomes and initialization are the first step. Because the number of nodes for a path is not predefined in this problem, the chromosome with variable length is used to show a path in the network. The values of odd genes show the labels (IDs) of nodes. The values of even genes represent the transportation modes between two successive nodes where number 1 and service line IDs are used for walking and the other modes, respectively. The position of a node represents the order of that node in a path. Fig. 3 shows an example of the encoding. The randomly generated genes (nodes) are appended sequentially to construct a chromosome (path). When the population reached the population size (num_{pop}), the cost of each chromosome is calculated using the SST. Velocity of walking, which actually depends on the context of the user, is assumed approximately an average amount of 4 Km/h. Because large initial population provides the algorithm with a comprehensive sampling of search space; thus, the initial population size is assumed larger than the population size in the other iterations (num_{ipop}).
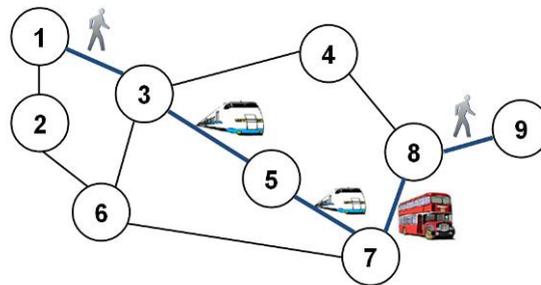
Chromosome (path): | 1 | 1 | 3 | 2 | 5 | 2 | 7 | 5 | 8 | 1 | 9 |

Fig. 3. A path (weighted lines) in a network and its related encoded chromosome

The length of a chromosome depends on the number of intermediate nodes that each path passes. To generate the initial population of the chromosomes, this process is repeated until the predefined size of population is achieved. Algorithm 2 (*Initialization*) shows the procedure.

```
Algorithm 2: Initialization (O, D, G, SST, num_pop)
  // O is the origin and D is the destination point
  // A_i = {adjacent nodes of node i extracted from SST}
  // Scan = {scanned nodes}
  // chrom is a (population-size × n) array where the
     generated chromosomes are stored
  // mode_i,j = {possible transportation modes between
     two successive nodes i and j}
  counter ← 1
  Do While (counter ≤ num_pop)
    previous ← O
    Do While (current ≠ D)
      chrom(counter,1) = O
      current ← Random (A_previous)
      mode ← Random (mode_previous,current)
      add current to Scan
      append mode and current to chrom(counter)
      previous ← current
    Loop
    remove the contents of Scan
    counter ← counter+1
  Loop
  Return (chrom)
```

In the next step, i.e. *natural selection*, the fittest chromosomes survive, and the remaining ones are discarded from the population. The selection rate (C_{rate}) which is usually arbitrary, is used to show the fraction of surviving chromosomes (num_{keep}). It is common to keep half of the population in each

iteration, i.e. C_{rate}=50%. This rate is used in this procedure. The kept chromosomes form the mating pool.

$$num_{keep}=C_{rate}\times num_{pop} \qquad \textbf{(4)}$$

The third step is *selection* in which two chromosomes are selected from the mating pool to produce two new offspring. There are several selection methods, including random pairing, weighted random (roulette wheel) pairing, and tournament selection [18]. The roulette wheel pairing is used in this study. In this method, the probability assigned to a chromosome is inversely proportional to its cost [18].

Mating is the fourth step in which offspring are created from parents selected in the previous step. It is common to produce two offspring from mating two parents using randomly selected crossover point(s) on the parents' chromosomes. In the proposed algorithm, a combined method is used, in which both single-point and two-point crossovers are used. The procedure continues until num_{pop}-num_{keep} offspring are born to replace the discarded chromosomes. Furthermore, an elitism strategy is also adopted. Elitism guarantees that the best individuals in a population survive into the next generation. In our solution, two chromosomes are kept as elite. After this step, the number of chromosomes becomes again equal to population size.

Because a chromosome shows a path as the sequences of stations connecting transportation modes, changing the value of any genes during crossover may cause the chromosome to show invalid paths. To cope with this issue, a rectification procedure was utilized to ensure that newly generated chromosomes have no loops, and show valid paths. This procedure removes some genes, which are inside a loop, to rebuild a valid path.

To avoid locally optimal solutions and prevent the algorithm from converging quickly before sampling the entire cost surface, the random *mutation* is used in the next step. In proposed solution, the mutation is applied only to odd genes. The even genes (transportation modes) are modified according to odd genes. The modification procedure is also applied after mutation. Then, the last check is carried out for avoiding loops along the path. The mutation procedure is illustrated in Fig. 4.

Both crossovers and mutations are applied to chromosomes with predefined probability levels. The probability function has uniform distribution. The costs associated with offspring and mutated chromosomes are again computed and assigned.

The whole process, i.e. step 2 to step 5, is iterated until the temporal differences between twenty best cost paths reach zero in successive iterations. However, if the algorithm does not stop according to specified criterion, the process is set to terminate after 500 iterations.
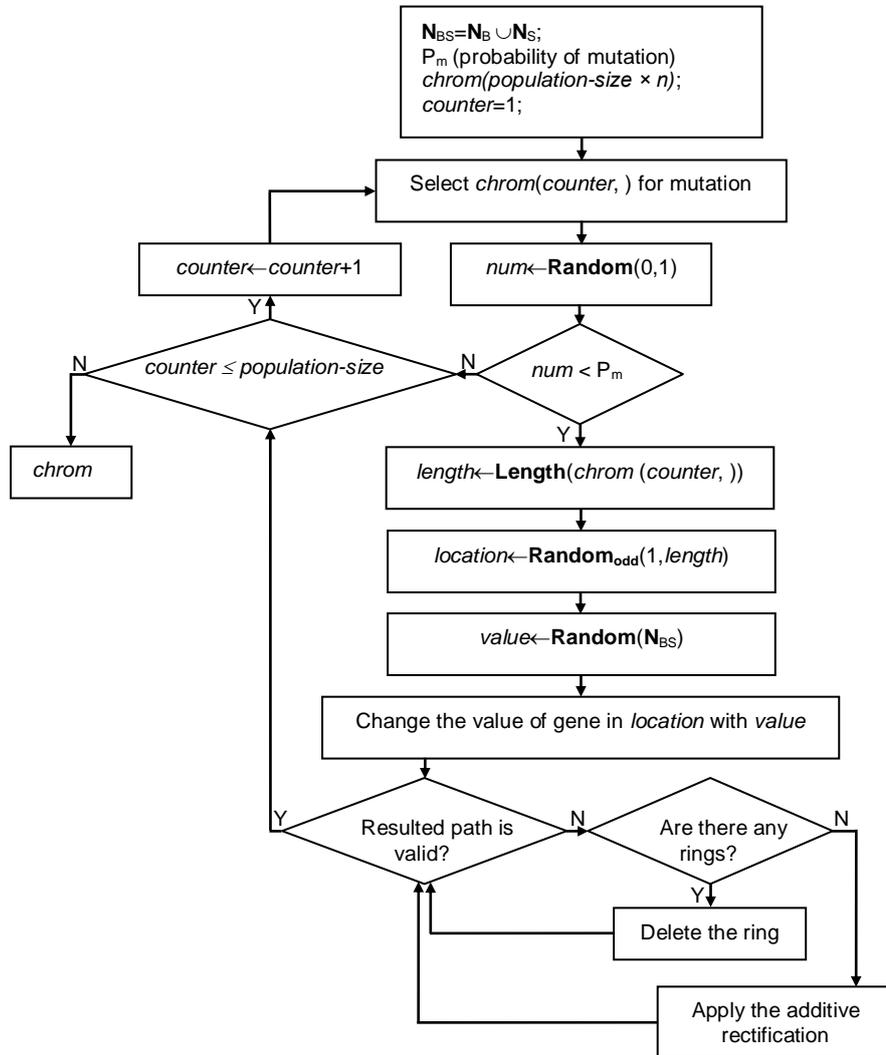
Fig. 4. Flowchart of the mutation procedure

4.   Experimental Results

The proposed framework and formulation is evaluated by conducting some experiments using data from the city of Tehran, which is the capital city of Iran. Tehran is one of the metropolises of Iran with area of about 700 square kilometers and composed of 22 districts. Public transportation in this city

employs five main modes: taxi, van, minibus, bus, and subway. Among these, subway, due to its high speed, and bus, due to its extensive coverage, are of greatest interest for travelers and commuters. Table 2 presents some statistics of these two modes.

Table 2. Information about bus and subway transportation networks in Tehran

Property	Subway	Bus
Number of service lines	4	301
Number of stops (stations)	45	4763
Length of line (Km)	91.6	2761.3

As shown in Fig. 5, the data set, which is the main body of geodatabase, consists of pathways (i.e. streets, avenues, and highways used by buses), subway system (consisting of lines and stations), and bus stops. The dataset is prepared as needed, i.e. the topological structure is rebuilt and the required tables are created.

To evaluate the multimodal shortest path algorithm, 500 points (250 source-destination pairs) with different number of nodes and start time were selected. They were used as the input origin and destination of the algorithm.

The proposed algorithm starts by generating a large population of chromosomes as the initial population. For the initial population it is inferred that $num_{ipop}=250$ is a good choice. Then, the cost of each chromosome is calculated based on the fitness (objective) function, and chromosomes are sorted in descending order according to the assigned cost. In the next step, $num_{ikeep}=num_{pop}=100$ best chromosomes, which had lower costs, are kept for the successive iteration and the others are discarded. It is realized that $num_{pop}=100$ is a suitable value according to our experience. In the next iterations, $C_{rate}=50\%$ is selected. The next steps were natural selection, mutation and checking termination criteria. It was found that the best range for crossover and mutation probabilities are [0.55, 0.85] and [0.07, 0.18] respectively for this dataset. No significant differences in the results were observed within these ranges. Hence, the fixed values of 0.7 for crossover probability and 0.1 for mutation probability are adopted. Four different cases are discussed to illustrate some samples of the results obtained. The first case is a considerably longer path and is shown over the whole extent of the dataset, while the other three cases represent the local paths.
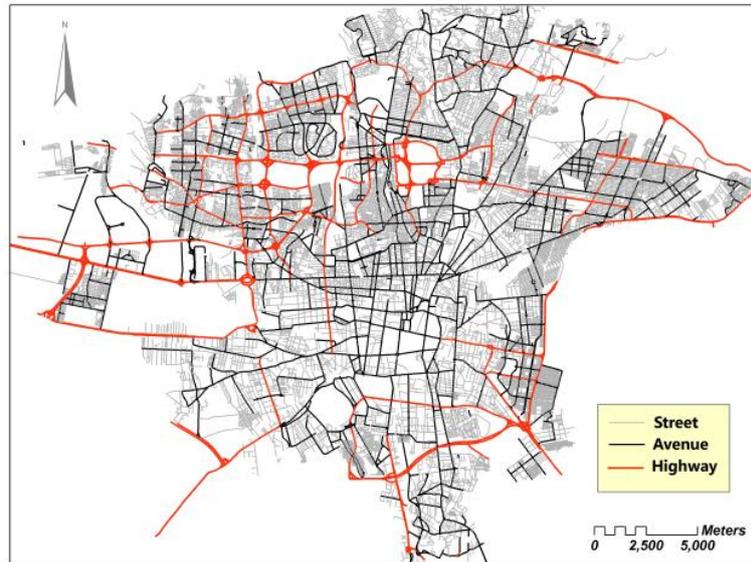
(a)
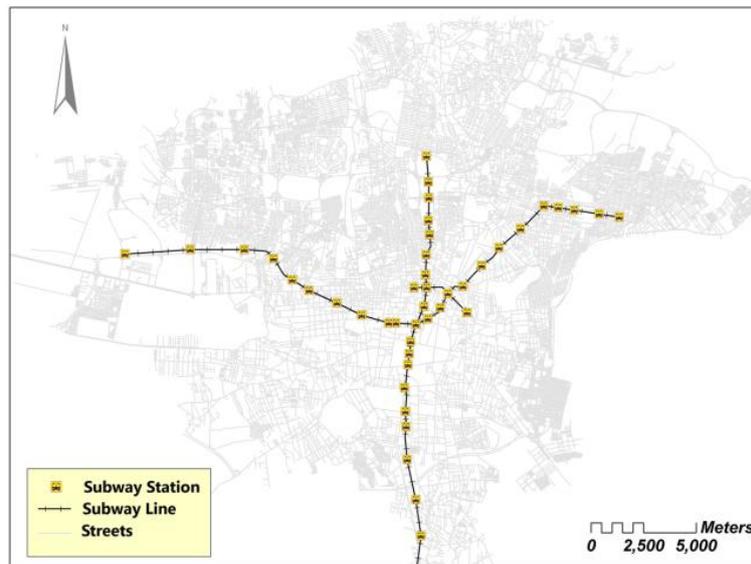
(b)

Fig. 5. Dataset of evaluation of proposed methodology (a) pathways and (b) subway

The first case is representative of those paths that are considerably long. The results show that the paths in this class are generally multimodal. Fig. 6 shows one of the resulted paths on the map. As shown in Fig. 6, the result of finding a shortest path between a source and destination is a multimodal path. It begins by walking from the source to the nearest bus stop, using the bus to reach the subway station, walking from the bus stop to the subway station, using two different lines of the subway (walking to change lines), walking from the subway station to the nearest bus stop, using the bus to stop nearest to the destination, and finally walking to the destination.
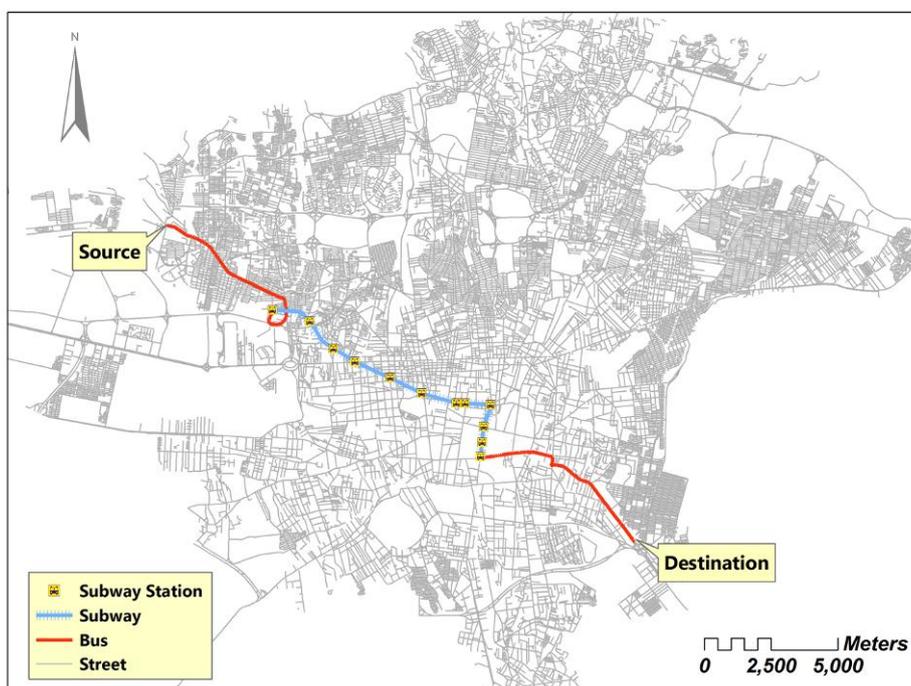

Fig. 6. Result for case 1

The convergence curve plot, which shows the cost of the minimum cost path as a function of iterations, is adopted to represent the results of iterations for this case (Fig. 8.a). As shown by the convergence plot, there is a rapid decrease of the fitness values in the first few generations. The curve also indicates that the process successfully reaches convergence.

In the second case, the result for the multimodal shortest path is also a combination of all three modes (Fig. 7.a). Different compositions of shortest paths are generated using individual modes to compare the results with monomodal transportation. It can be seen that traveling from the selected source to the destination by using only bus or subway is impossible. The result for shortest path by walking between the source and destination is

depicted in Fig. 7.b. Finding the possible shortest path using a combination of two or three modes is also examined. There are no paths composed of a combination of bus and subway modes. For the other two possible situations, i.e. walking-bus and walking-subway, the results are depicted in Fig. 7.c and 7.d, respectively.
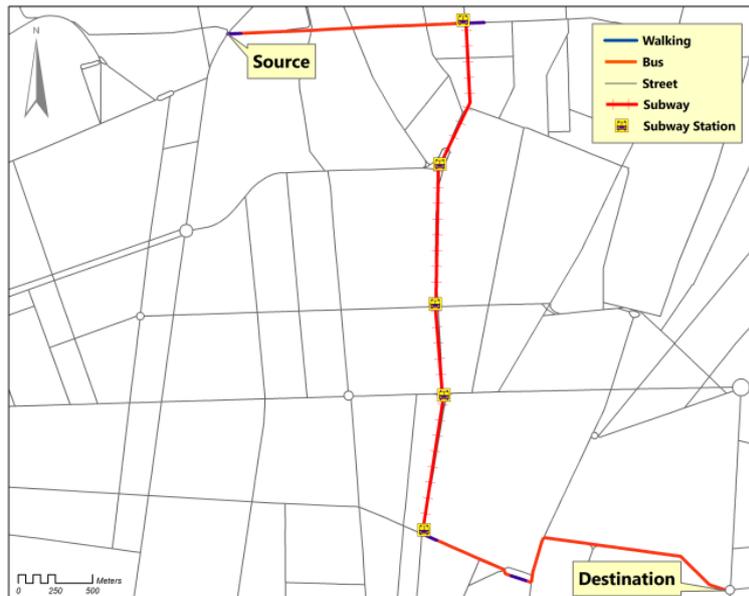

(a)
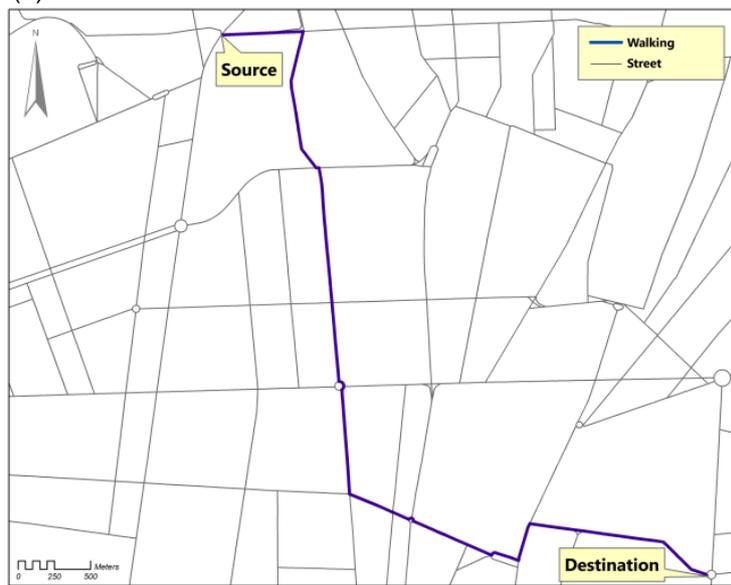
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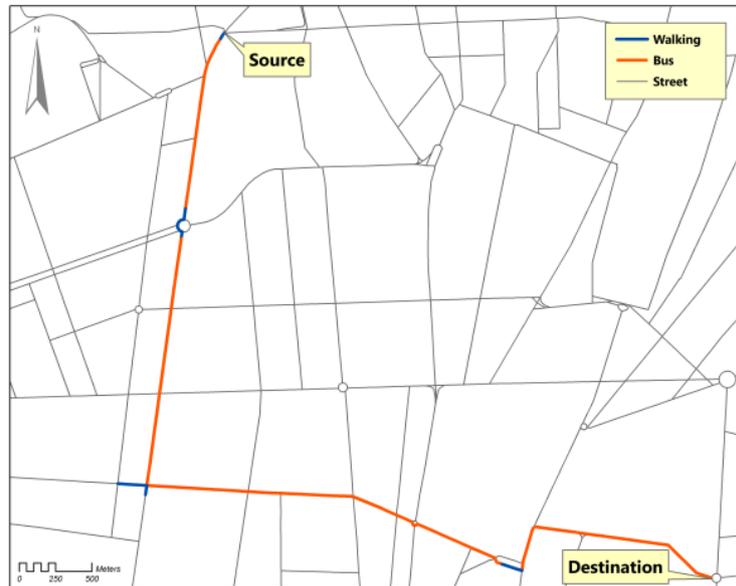
(c)
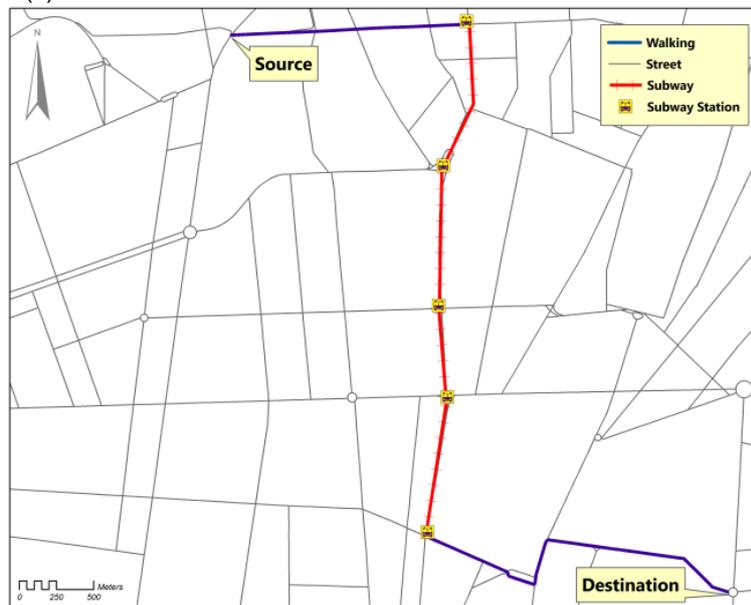
(d)

Fig. 7. Results for case 2

The minimum time of the resulting shortest paths using the different combinations of modes are given in Table 3. According to this table, the minimum cost belongs to multimodal combination.

Table 3. Cost for different combinations of modes for a given source and destination

No. of Mode(s)	Combination	Cost of Shortest Path (Minutes)
Monomodal	Walking	125
	Bus	-
	Subway	-
Dual modal	Walking and Bus	83
	Walking and Subway	69
	Bus and Subway	-
Multimodal	Walking, Bus and Subway	52

The convergence curve plot is also adopted for this case to show the results of iteration, and the convergence of the process (Fig. 8.b). The pattern and general trend of convergence in this case is similar to the first case. This behavior is observed in all cases evaluated.
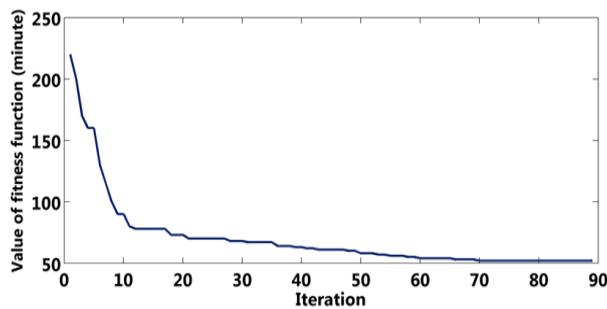

(a)
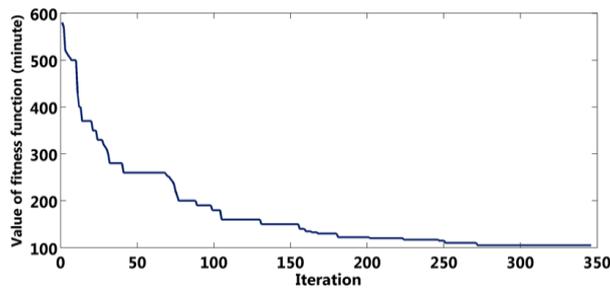
(b)

Fig. 8. Convergence plot of shortest paths of first case (a), and second case (b)

In the third case, the result for multimodal shortest path is a combination of walking and bus modes (Fig. 9.a). It is perceived that this result has the least

cost compared with other combinations. In the fourth case, the result for multimodal shortest path is just walking between the source and destination (Fig. 9.b).
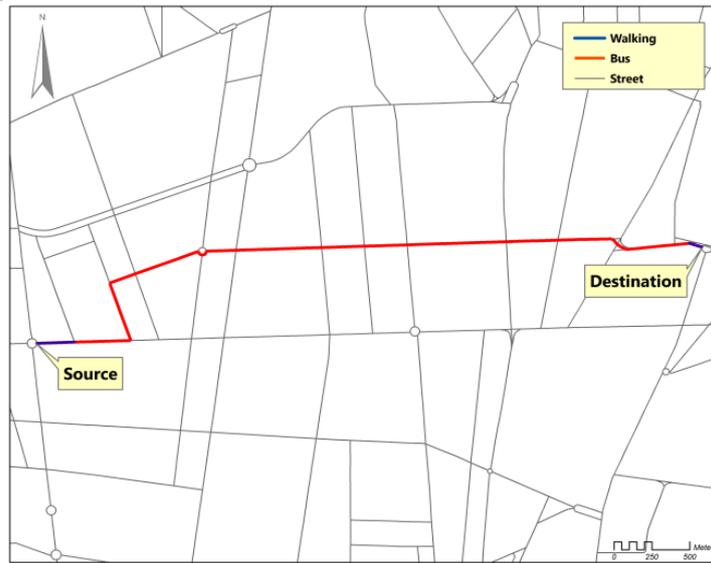
(a)
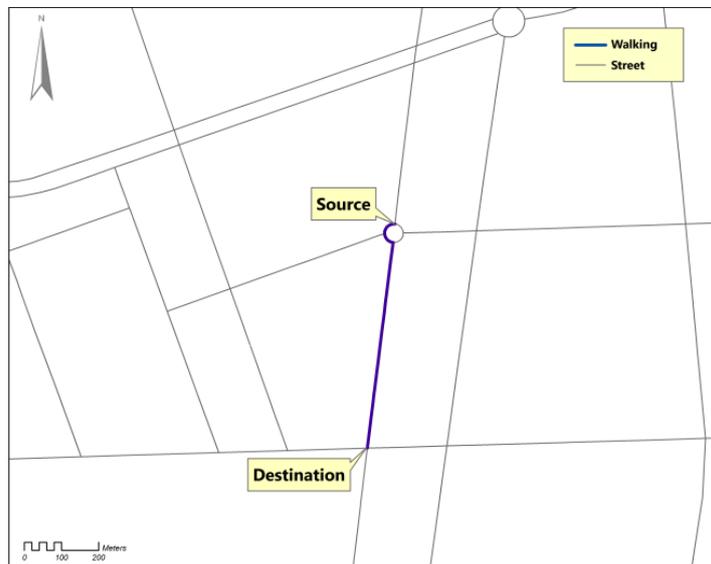
(b)

Fig. 9. Results for case 3 (a) and case 4 (b)

To measure the quality of proposed method, the failure ratio is utilized. This ratio shows the times that an evolutionary algorithm fails to find the global optimum in respect of whole runs. This index was calculated for each of 250 paths, and shows the frequency of paths which fails to be optimum among 30 runs for each of the cases.
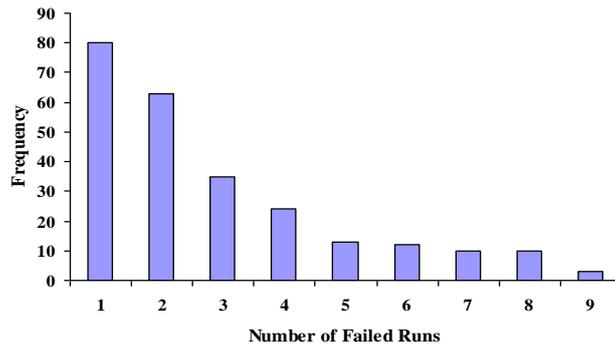

Fig. 10. Failure rates of calculated paths

Fig. 10 shows this index for the evaluated data set. The horizontal axis of this diagram shows the numbers of failed runs among the 30 runs, and vertical axis illustrates the frequency of number of failures among all cases. It was perceived that the average failure rate of proposed path finding algorithm is about 2.77. Therefore, the quality of solution and path optimality is about 90.75%.
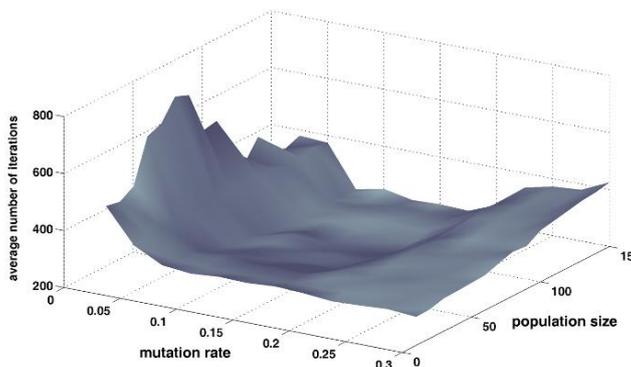

Fig. 11. The correlation between population sizes and mutation rates with average number of iterations

To evaluate the correlation between population size and optimal solution, and to find the suitable population size and mutation rate needed to obtain the acceptable solutions, the algorithm were conducted over 100 different paths for 15 different population sizes and 12 different mutation rates. Each combination was run 20 independent times. Population size varied from 20 to

150 in increments of 10. Mutation rate varied from 0 to 0.3 in increments of 0.025. A three-dimensional plot of the average number of iterations for the different values of population size and mutation rate is depicted in Fig. 11. As shown in this figure, the algorithm works best with population size about 100 and mutation rates interval about 0.1. It was found from this experiment that when the population size increases, the optimal mutation rate decreases.

5.   Conclusion

In this paper, the possibility of using the genetic algorithm to solve the dynamic shortest path problem in urban multimodal transportation networks is investigated. The proposed approach has been tested on a dataset of a part of Tehran. 250 pairs of points, selected randomly as the source and destination to evaluate the algorithm, and to tune some parameters of it. The results were divided into three main groups where path consists of one, two or three modes of transportation. These show that the multimodal path is not essentially the shortest one in all cases. Moreover it is concluded that proposed algorithm has high degree of robustness since it covers monomodal solutions as the special case of multimodal paths. The high average amount of success rate of algorithm shows the high performance of it.

Several topics remain for future research. Since some of the decisions made by citizens to select their ways to transport between two points are not just the function of time; thus, extension of proposed algorithm to address the multi-criteria path finding problem is important. The second activity may be related to consider the real-time implementation of algorithm which in turn needs some modifications to improve the speed and management of on-line input parameters. To develop a useful and practical path finding module for a user, considering his/her contextual information is critical. These parameters modify the selected path to adapt the user situations as much as possible.

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