

A New School Bus Routing Problem Considering Gender Separation, Special Students and Mix Loading: A Genetic Algorithm Approach

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Received 18 January 2020 ; Revised 23 September 2020 ; Accepted 27 September 2020

Abstract

In developing countries, whereas the urban bus network is a major part of public transportation system, it is necessary to try to find the best design and routing for bus network. Optimum design of school bus routes is very important. Non-optimal solutions for this problem may increase traveling time, fuel consumption, and depreciation rate of the fleet. A new bus routing problem is presented in this study. A multi-objective mixed integer model is proposed to handle the associated problem. Minimization of transportation cost as well as traveling time is the main objectives. The main contributions of this paper are considering gender separation as well as mixed-loading properties in the school bus routing problem. Moreover, special and handicapped students are considered in this problem. The proposed model is applied in a real case study including 4 schools in Tehran. The results indicate the efficiency of the proposed model in comparison with the existing system. This comparison shows that the students' travelling time is reduced by 28% for Peyvand middle smart school, 24% for Tehran international school, 13% for Hemmat School and 21% for Nikan High school. A customized Genetic Algorithm (GA) is proposed to solve the model. Penalty functions are used to handle the several constraints of the problem in Genetic Algorithm. The results justify the applicability and efficacy of the both proposed model and solution approach.

Keywords: School bus routing problem; mixed integer mathematical programming; Genetic algorithm; Gender separation; Mix loading

1. Introduction

The school bus routing problem is assumed as a main practical problem in real world. Most of the big cities in the world are involved in this problem (Babaei and Rajabi-Bahaabadi et al. 2019). In Tehran, most schools that provide this service suffer from lacking a plan on how to route and schedule their vehicles (Sahebjamnia et al. 2020). This usually increases traveling time, rate of traffic, fuel consumption, and depreciation rate of the fleet (Ghasemi and Babaeinesami, 2019, Ghasemi and Babaeinesami, 2020, Goodarzian et al, 2020). The problem consists of several sub-problems including how to locate bus stops, how to assign students to the bus stops and how to route and schedule buses. These sub-problems are solved intuitively in real world, which may often result in excessive cost for the transportation. Besides, parents are usually complaining that the traveling time of their children is more than expected (Shirazi et al, 2020).

In School Bus Routing Problem (SBRP), buses should pick up students from their homes (or a bus stop) and transfer them to their schools while satisfying various constraints, such as maximum capacity of the buses (Caceres et al. 2019, Tirkolaee et al. 2020c). If a bus is allocated to a specific school, the problem becomes a vehicle routing problem; but in a SBRP, a bus can serve students from different schools; that is, a bus can visit several schools (Larki, and Yousefikhoshbakht, 2014). There are several classes of SBRP (Park and Kim 2010). The main characteristics of SBRP are: number of schools (single or multiple), problem scope (morning, afternoon or both of them), surroundings of service (urban or rural), mixed load (allowed or no allowed), fleet mix (homogeneous or heterogeneous), special-educations students (considered or not considered), objectives (number of buses used, total bus travelling time, total students riding distance or time, student walking distance, load balancing, maximum route length, and child's time loss), constraints (vehicle capacity, maximum riding time, school time windows, maximum walking time or

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distance, earliest pickup time, minimum student number to create a route) (Niasar et al.2017). The real world school bus problems generally include multiple-schools. However, some studies have concentrated on single-school bus routing problem (Fleszar et al. 2009). The solution approach for SBRP may differ based on the characteristics of the problem. For instance, in urban areas, the school bus transportation system operates as follows. In the morning, the students are picked up at a bus stop near to their residence place (Khalili-Damghani and Ghasemi, 2016). The school bus visits the rest of the bus stops remaining on its route and then goes to the school. In the afternoon, the process is reversed and the students are dropped off at the bus stops where they were picked up in the morning. While in rural areas where the number of the students is small, students may be picked up at their homes. Therefore, bus stop selection is not considered in such types of problems (Yousefikhoshbakht et al. 2015, Tirkolaee et al. 2020b). Mixed-load issue is another characteristic of SBRP. The problem of allowing mixed load was first discussed by Bodin and Berman (1979). In presence of mixed-loading assumptions, students of different schools can be picked up by the same bus. Mixed-load assumption results in increasing flexibility and decreasing total cost. Although real world SBRPs usually allow mixed-load assumption, only a few studies have considered this feature. One of the main features of SBRP is special (handicapped) students. The routing of special students causes several limitations on SBRP. Special student should differently be served depending on the severity of his/her particular disability. Special students usually are picked up and dropped off directly at their homes and not at the bus stops. Due to our best knowledge, only few studies have accomplished considering the routing of special students.

In this paper, a real case study of SBRP considered. The case study is addressed through a customized SBRP considering homogeneous fleet of vehicles, special students and gender separation in an urban environment. Such an integrated problem has not been considered in the literature. The problem is formulated as a new mixed-integer mathematical programming model. The proposed model is applied in a real case study including four schools in Tehran, Iran. The Genetic Algorithm is used to solve the proposed model. The solution approach is coded in MATLAB software. The results of the proposed model are compared with the existing system where in the efficacy of proposed model is declared.

The main contributions of this paper are summarized as follows:

- Considering gender separation in the SBRP.
- Mixed-Loading properties considered in the SBRP.
- Routing of special student.
- Application in a real world case study.
- Improvement of traditional routing plan.

The combination of all aforementioned issues has not been addressed in the previous researches. Moreover, the gender-

separation property is proposed in this paper for the first time. This means that half of the capacity of a bus is allocated to the boys and the rest is allocated to the girls.

The next sections of this paper are organized as follows. A brief review of existing SBRPs and the associated applications are presented in Section 2. The problem of this study and the proposed mixed integer programming model are presented in Sections 3. Section 4 is allocated to present the case study and computational results. Section 5 provides Genetic Algorithm. Also, the results are presented in Sections 6. Finally, Section 7 provides conclusion remarks and future research directions.

2. Literature Review

During the recent years, several studies about school bus routing and location have been published. In this section, a brief review of the literature of past works, based on both the characteristics of the problem and solution methods, is presented. Bodin and Berman (1979) solved the SBRP using a meta-heuristic approach. The proposed SBRP considered the classical constraints on the maximum capacity of buses and maximum allowable travel time for each student. Their solution procedure aimed to minimize the fixed cost for each vehicle, to minimize the total transportation cost, and to minimize the average transportation time for each student. Desrosiers et al. (1981) focused on specific case of rural areas. Desrosiers et al. (1981) also considered constraints on the quantity of bus stops length of the routes as well. The transportation cost, which included both the number of buses and the routing cost, was minimized. Spada et al. (2005) handled the SBRP as a multiple Vehicle Routing Problem (VRP) and developed non-linear mixed-integer programming models for the problem. They proposed a hybrid meta-heuristic approach to solve large scale problems. Schools were considered in increasing order of their opening time and the routes for each school were built by using a Tabu search algorithm. Thereafter, the routes were generated if possible. Finally, the generated routes were improved by Simulated Annealing algorithm. Fügenschuh (2009) also considered a school bus routing problem that permitted the adjustment of school opening time and transshipment of students among trips. Fügenschuh (2009) formulated the problem as a mixed integer programming model based on Vehicle Routing Problem with Time Windows (VRPTW). The proposed model was solved using a branch-and-cut algorithm. However, homogeneous fleet was assumed to be given and even a few small problems could not be optimally solved within the limited solution time (i.e., two hours) due to the complexity of the problem. Daganzo et al. (2012) formulated and solved analytical continuous approximation (CA) models for school bus routing problem. Whereas detailed methods such as mathematical programming require discrete data for each demand point in a particular problem instance, continuous approximation methods employ parsimonious logistics models based on a continuous spatial density of

homogenous, which yielded to same capacity for all buses. Also, a heuristic algorithm based on harmony search was proposed to solve the problem. The results of harmony search algorithm were compared with those achieved by CPLEX software. Marinakis et al. (2013) presented a new method, based on the Particle Swarm Optimization (PSO), for solving the VRP with stochastic demands. This method is a combination of the Particle Swarm Optimization algorithm with the 2-opt and 3-opt local search algorithms and with the path relinking strategy. Also, it was a challenge to find an effective transformation of the solutions of PSO. Finally, they found that the PSO algorithm is suitable for continuous optimization problems. Kontou et al. (2014) presented a model for allocating buses to depots. The proposed model was applied in a real case study in Athens bus system using a hybrid genetic algorithm. Also, a more detailed implementation of the model in the "line" instead of "group of lines" level was considered. The objectives were minimizing the total deadhead kilometer costs and the occupancy imbalance of depots. Results showed that allocating buses to depots would increase the benefits of transportation system. William et al. (2015) provided a general approach using continuous approximation models considering mixed loading in each bus. They also applied the proposed model in a case study for a rural Missouri school region to illustrate the application of the model in practice. Results indicated that mixed load routing was more useful for larger regions, when a large percentage of stops were shared by students of different schools, and when schools were closer together. Kang et al. (2015) proposed a genetic algorithm previously used to apply in vehicle routing problems (VRPs). The VRPs are similar to school bus routing problem. Kang et al. addressed SBRP in two levels. At first, Bus stop selection sub-problem was handled, and then the planning of bus routing and scheduling, based on determined bus stops, was accomplished. Shui et al. (2015) presented a clonal selection algorithm based vehicle scheduling to generate solutions for large-scale bus scheduling problems. A set of vehicles was generated based on the maximal waiting time between any two adjacent trips. Two heuristics adjust the departure times of vehicles to improve the solution. The proposed method was applied to a real-world vehicle scheduling problem. The results showed that the approach was effective and would find satisfactory scheduling solutions in a short time. Chen et al. (2015) presented a mixed integer bi-objective mode for bus scheduling problem. The performance of exact method and meta-heuristic algorithm were compared in detail. They proposed a simulated annealing algorithm to solve the model. They also implemented three algorithms to solve single-school bus routing problem, homogeneous and heterogeneous fleet school bus scheduling problem, respectively. Yao et al. (2016) considered school bus routing problem with virtual stops and interscholastic transportation. The results showed that SBRP considering mixed load planning mode took less time than SBRP with

single load. Also, he proposed that mixed loading with interscholastic transportation was appropriate for large-scale cases. Jonathan et al. (2016) presented the alternative-fuel multiple depot vehicle scheduling problem, a modification of the standard multiple depot vehicle scheduling problem where in each vehicle had a limited fuel capacity and there were limited stations available for the vehicle to refuel. They formulated the problem as an integer programming model and a branch-and-price algorithm was proposed to solve the problem. A heuristic solution was also presented and both were tested on randomly generated data as well as data on the Valley Metro bus network. Azadeh et al. (2017) proposed a mathematical model for close-open mixed vehicle routing problem. Also, in this problem, contractors were used to meet a part of customers' requirements. The objective of the model was to minimize the total service cost and delivering goods to the costumers, according to the constraints of vehicles' capacity and travel distance. The results showed that the solutions achieved by metaheuristic algorithms were more suitable than GAMS solutions for medium-scale problems. Abed Mohammed et al. (2017) presented the capacitated vehicle routing problem (CVRP) model for optimizing UNITEN's shuttle bus services. The bus picked up students from eight locations inside the school in two different routes and returned back to the main location at specific times every day, starting from early morning until the end of official working hours. They found the shortest route for VRP to help UNITEN University reduce student's transportation costs using genetic algorithm. The findings showed that the proportion of reduction the distance for each route was relatively short, but the savings in the distance became greater when calculating the total distances traveled by all buses monthly. Leksakul et al. (2017) considered a real case and compared different methods (Competitive Learning, artificial intelligence, Fuzzy C-means and K-means) to find the routing and bus stop allocation solution. They applied a clustering approach and the Ant Colony algorithm to solve large scale bus routing problems. They provided a significant development in employee bus route management. They concluded that they could more effectively solve large-scale bus routing problems, especially when they took into consideration the current situation. Also, they could apply their proposed technique to some other logistic problems; multi modal logistic system and consolidate truck delivery system. Ren et al. (2019) proposed a mixed integer programming model for the school bus location and routing problem considering walking accessibility. Considering the Mixed Load mode and individual difference of walking accessibilities among students were among the contributions of this research. The main objective of their model was to minimize total commuting time. A two-level solution method was developed to solve their proposed model. In the first level, an iterative clustering method based on k-means was used to locate the stations. In the second level, an

Improved Ant Colony Optimization algorithm (IACO) was used to generate routes. The results indicated the proper performance of the proposed model. Caceres et al. (2019) modeled the school bus routing problem for special education students. Their case study was a suburban school district in Western New York. Considering a higher level of service for special students was one of their contributions. A greedy heuristic coupled with a column generation approach was used to solve their proposed model. Wang and Haghani (2020) presented a mathematical model for school bus scheduling and bell time adjustment. The most important objective of this research was to allocate routes to buses based on a predetermined schedule. Minimizing the number of buses used along with minimizing students' travelling time were other objectives of their research. Chance-constrained model was used to convert the stochastic model to deterministic mode. In order to solve the mathematical model, the column generation approach was used. Regarding the above mentioned literature reveals that there is no unique SBRP in which gender separation, mixed-loading property, and routing of special students have been considered simultaneously in a real world application. So, this paper, which has both theoretical and applied importance, is going to develop such SBRP and to apply it in a real case study.

3. Problem Description and Mathematical Modeling

Tehran is among the rapid growing cities in Asia. Development of the city has posed challenges in terms of city planning, regulation and provision of urban transport services. Some students in Tehran walk to school, although the majority of them use public transportation systems. A considerable group of students use school bus services. The school bus service in Tehran faces many problems including how to locate bus stops, how to assign students to the bus stops, and how to route and schedule buses. The aforementioned problems are experimentally planned in real world. They may result in excessive transportation cost, long routes, high traveling time, high rate of fleet depreciation, higher rate of fuel consumption, higher traffic, and high rate of emissions and pollutions. Many parents are complaining that the traveling time of their children is high. In this study, we are going to develop a customized SBRP for four schools in Tehran. In the proposed model, three main properties should be inserted; i.e., gender separation, mixed-loading, and special students transportation. These properties are considered based on the requirements of a real case study. It is notable that there is no unique model in the past literature of SBRP to be used in this case study. So, a customized model should be developed. The proposed SBRP is modeled through a mixed integer mathematical programming. The objective function of the proposed mathematical model is to minimize the total cost of transportation. The data used in this study is gathered from four schools in Tehran namely; Peyvand middle smart

school, Nikan High school, Hemmat School, and Tehran international school. The research methodology is defined as shown in Figure 1. Related literature will be reviewed first. A review of the literature on the school bus routing and location problem reveals the research gap and research contributions. In the following, a mathematical model for location, allocation and routing will be presented. The purpose of this step is to minimize the cost of providing services to students. After presenting the proposed model, a real case study will be presented to validate the model. Finally, in the last step, the genetic algorithm is used to solve the case study.

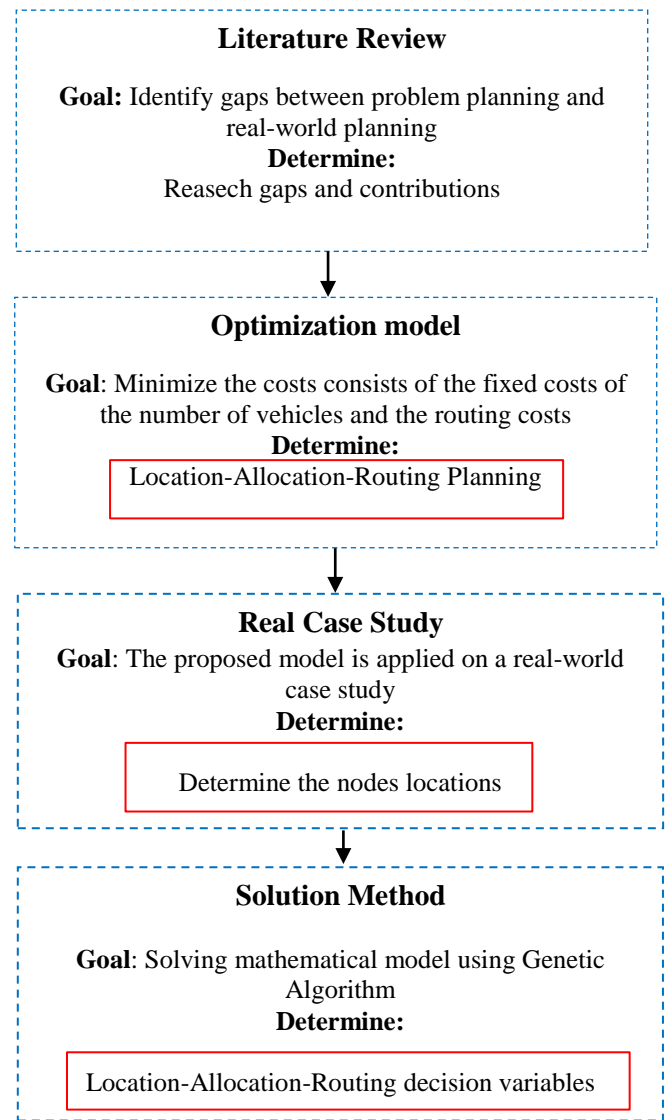


Fig.1. Research Framework

3.1 Mathematical Formulation

In this sub-section, a mixed integer programming model is presented for the SBRP. It is notable that the proposed SBRP of this study contains multiple schools, two types of students (original and special students), and homogenous fleet (i.e., identical buses) with fixed capacity. Gender separation assumption is also considered in this study.

3.1.1 Basic assumptions

- Each route will start from and end at the related depot.
- Transportation cost is deterministic and known in advance.
- Vehicles are homogenous. This means that all vehicles have the same capacity.
- All buses have the potential to serve all stations.
- As a bus completes a trip, it begins the next trip immediately.
- Mixed-loads are allowed in this study.
- The start time of the planning is in the morning time.
- The study is accomplished in urban area.

3.1.2 Sets and indices

The following indices are used in the model formulation.
 L' : Set of boy students (including both original and special students)
 L'' : Set of girl students (including both original and special students)
 L : Set of all students ($L = L' \cup L''$)
 l : Index of student
 S : Set of all schools
 s : Index of school
 J : Set of stops
 T : Set of nodes except depot ($T = S \cup J$)
 t, t' : Index of nodes except depot
 O : Index of depot
 L_t : Students who are associated with the nodes of t (If t is a school, L_t is student of the school, and if t is the station, L_t is student that can be picked up on the station)
 J_l : Set of bus stops that student l can be picked up
 K : Set of school buses
 k : Index of school bus
 P : Set from L_t the total number of nodes in the problem ($|P| = |S| + |J|$)
 p : Counters belonging to the set p

3.1.3 Parameters

The following parameters are used in the proposed model.
 c_{ot} : Transportation cost between node t and depot o
 Q'_k : Capacity of bus k for boy students
 Q''_k : Capacity of bus k for girl students
 $c_{tt'}$: Transportation cost between node t and t'
 F_k : Fixed cost of using bus k

3.1.4 Decision Variables

The decision variables used in the model formulation are as follows.

- x_{tpk} : The Binary variable is equal to 1 if the bus k visits node t at the p -th point of its route; and zero otherwise.
- u_{ttk} : The binary variable is equal to 1 if node t is visited immediately t by bus k ; and zero otherwise.
- w_{tlk} : The binary variable is equal to 1 if student l is picked up by bus k at node t ; and zero otherwise.
- V_k : The binary variable is equal to 1 if the bus k is used; and zero otherwise.
- y_{tk} : The binary variable is equal to 1 if bus k visits node t as the last node of the route; and zero otherwise.
- n_{tlpk} : The non-negative variable used for linearization.

3.1.5 Proposed Model

Using the aforementioned sets, indices, parameters, and decision variables, the mixed-load SBRP considering gender separation and special students' property is formulated as follows.

$$\text{Min } TC = \sum_{t \in T} \sum_{t' \in T} \sum_{k \in K} c_{tt'} u_{tt'k} + \sum_{t \in S} \sum_{k \in K} c_{ot} y_{tk} \quad (1)$$

$$+ \sum_{t \in J} \sum_{k \in K} c_{ot} x_{t1k} + \sum_{k \in K} F_k V_k$$

$$\sum_{t \in T} \sum_{p \in P} x_{tpk} \leq M \cdot V_k \quad \forall k \in K \quad (2)$$

$$x_{tpk} - \sum_{t' \in T} x_{t',p+1,k} \leq y_{tk} \quad \forall t \in S, k \in K, p \in P \quad (3)$$

$$\sum_{t \in T} x_{tpk} \leq 1 \quad \forall k \in K, p \in P \quad (4)$$

$$\sum_{l \in L_t} w_{tlk} \leq M \cdot \sum_{p \in P} x_{tpk} \quad \forall k \in K, t \in J \quad (5)$$

$$\sum_{t \in J} \sum_{l \in L_t} w_{tlk} \leq Q'_k \quad \forall k \in K \quad (6)$$

$$\sum_{t \in J} \sum_{l \in L''_t} w_{tlk} \leq Q''_k \quad \forall k \in K \quad (7)$$

$$\sum_{t \in J_l} \sum_{k \in K} w_{tlk} = 1 \quad \forall l \in L \quad (8)$$

$$x_{tpk} + x_{t',p+1,k} \leq u_{tt'k} + 1 \quad \forall t, t' \in T: t \neq t', k \in K, p \in P \quad (9)$$

$$\sum_{t \in J_l} w_{tlk} x_{tpk} \leq \sum_{p=p+1} x_{tp'k} \quad \forall t' \in S, l \in L_t, k \in K, p \in P \quad (10)$$

$$\sum_{t \in J_l} w_{tlk} + x_{tpk} \geq 2n_{tlpk} \quad \forall t, l, k \in K, p \in P \quad (11)$$

$$\sum_{t \in J_l} w_{tlk} + x_{tpk} \leq n_{tlpk} + 1 \quad \forall t, l, k \in K, p \in P \quad (12)$$

$$\sum_{t \in T} x_{t(p+1)k} \leq \sum_{t \in T} x_{tpk} \quad \forall k \in K, p \in P \quad (13)$$

$$\sum_{p \in P} x_{tpk} \leq \sum_{l \in L_t} w_{tlk} \quad \forall t \in J, k \in K \quad (14)$$

$$w_{tlk} \in \{0,1\} \quad \forall t, l, k \quad (15)$$

$$x_{tpk} \in \{0,1\} \quad \forall t, p, k \quad (16)$$

$$y_{tk} \in \{0,1\} \quad \forall t, k \quad (17)$$

$$V_k \in \{0,1\} \quad \forall k \quad (18)$$

$$u_{tt'k} \in \{0,1\} \quad \forall t, t', k \quad (19)$$

$$n_{tlpk} \in \{0,1\} \quad \forall t, l, p, k \quad (20)$$

The objective function (1) is to minimize the total service cost. The total cost consists of the fixed cost of using vehicles as well as the routing cost.

The first term of the objective function is related to the transportation cost between any two possible nodes. In fact transportation cost between any two stations, two schools or a station and a school will be calculated. The second term of the objective function is related to the transportation cost between the nodes and the central depot. These nodes can be stations or special students' houses, because the buses never go directly from the central depot to the schools. In fact, the buses firstly go to the stations or special students' houses and then travel to school. The third term of the objective function is related to the transportation cost between central depot and the first node that bus visits. The fourth term of the objective function is related to the cost of buying or renting a bus.

Constraint (2) ensures that if bus k is not used, then no station node can be assigned to it. Constraint (3) states that if there is a school that no node including school, station, special student's house exists after it, that school will be the last node of the route. Constraint (4) ensures that each trip is assigned to only one vehicle and no vehicle can simultaneously run two trips. Constraint (5) ensures that student l is not picked up at station t by vehicle k if vehicle k does not visit station t . Constraints (6) and (7) limits the number of boy and girl-students on the bus. Constraint (8) ensures that all students are picked up. Constraint (9) calculates the variable $u_{tt'k}$ and it will be 1 if nodes t and t' will be visited in a row by a bus. Constraint (10) states that bus k can pick up student l at station k on the P -th node of its route only if the student is ready in that station. The proposed model is nonlinear because of left side of constraint (10). Constraints (11) and (12) are applied for linearization. Constraint (13) states that the existing bus stops in locating a bus should be filled upwards. Which means the bus must do the first movement then does the second movement and similarly bus stops should be passed upwards. Constraint (14) ensures that if one student is not assigned to any station, she/he will never be picked up by a bus. Constraints (15) to (20) define decision variables type.

4. Real Case Study of SBRP

As mentioned before, the proposed model has been applied in four schools in Tehran namely; Peyvand middle smart school, Nikan High school, Hemmat School and Tehran international. The schools are located in the core of Tehran, in which the routing, transportation, and travelling time are main issues. The exact locations of the schools are represented in Figure2. Ten nodes, including boy schools, girl schools, stations and special students' houses are considered in this case study. The nodes 1 and 2 are considered for boy schools (i.e., Hemmat school and Tehran international school). The nodes 3 and 4 are considered for girl schools (i.e., Peyvand middle smart school and Nikan High school). The nodes 5 to 8 are considered for the stations. The nodes 9 and 10 are associated with special students' houses. There are 4 buses and 80 students in this case study. The students from number 1 to 40 are boys and from number 41 to 80 are girls. The boy student number 19 and the girl student number 80 are the special ones. In this case, the capacity of all vehicles is assumed to be 10 for boys and girls. Figure 2 represents bus stops for Hemmat school, Tehran international school, Peyvand middle smart school and Nikan High school. The buses run from these points to the schools and will return to the depots after dropping off the students at their related schools.



Fig.2. Map of the schools and their stop locations

Table 2 presents the transportation cost of each student from the house to the stations. The transportation costs have been calculated based on the distance and facilities in the associated area. It is notable that the special students 19 and 80 haven't been included in this table since they don't go to any stations and are picked up at their houses.

Table 2
Transportation cost between students and stations

Stu	Station				Stu	Station			
	5	6	7	8		5	6	7	8
1	58.8	61	30.4	17.4	41	24.5	102	100	33.6
2	68.8	56.7	49.0	22.1	42	64.6	52.8	80.0	24.1
3	59.1	28.8	61.2	44.1	43	92.2	87.0	60.5	27.4
4	20.6	44.2	50.5	68.5	44	43.0	114	90.3	64.4
5	16.4	44.0	45.1	64.4	45	34.2	92.8	76.7	63.9
6	33.8	40.8	11.1	16.7	46	76.0	65.4	39.7	26.5
7	50.4	43.7	31.6	4.1	47	45.0	28.8	82.4	13.9
8	39.9	32.1	27.5	12.0	48	29.2	37.7	40.1	10.1
9	36.4	11.1	56.0	55.3	49	40.0	65.8	17.0	43.6
10	49.3	16.5	61.2	52.1	50	76.0	85.8	75.2	37.0
11	32.5	5.0	43.2	39.1	51	86.0	62.0	34.3	27.7
12	16.7	47.3	42.4	63.6	52	24.8	62.9	20.3	64.6
13	68.7	75.2	38.0	32.5	53	30.4	90.9	11.9	48.8
14	44.2	31.3	33.8	14.8	54	65.0	68.4	65.7	4.0
15	64.6	71.3	34.0	29.1	55	75.0	78.2	86.4	45.6
16	9.8	35.0	40.8	57.3	56	70.0	60.2	75.9	55.5
17	50.8	27.5	46.9	28.3	57	62.7	18.4	59.4	11.6
18	64.7	39.1	59.4	37.0	58	37.7	60.4	56.6	21.9
19	-	-	-	-	59	39.4	50.0	20.0	60.3
20	73.8	34.0	70.1	73.4	60	60.3	72.3	50.0	35.3
21	37.3	60.0	11	90.4	61	43.3	37.3	76.3	85.7
22	14.0	100	27.0	110	62	19.1	72.0	38.9	73.7
23	37.0	28.1	65.0	23.3	63	30.4	29.3	48.0	77.3
24	120	60.0	80.1	48.2	64	80.4	50.0	83.0	25.7
25	90.0	90.0	75.5	92.0	65	39.3	38.3	48.0	56.1
26	40.0	75.0	87.9	75.7	66	38.3	80.0	60.2	74.7
27	70.0	18.0	82.9	77.9	67	93.8	83.7	90.0	11.7
28	51.7	47.9	62.0	90.6	68	38.3	40.2	25.2	63.6
29	19.0	90.9	94.0	65.4	69	38.8	40.2	87.4	73.7
30	68.6	64.4	57.9	30.0	70	111	100	14.1	60.0
31	28.0	64.3	86.7	29.5	71	38.3	40.2	57.7	63.6
32	50.0	78.5	88.7	20.0	72	83.3	20.9	34.5	65.6
33	50.0	45.6	58.0	12.0	73	98.2	38.3	36.3	90.0
34	86.8	70.3	65.5	53.6	74	29.0	60.2	50.1	36.3
35	70.6	30.3	87.5	17.9	75	18.0	60.6	45.2	74
36	69.4	68.1	80.7	32.9	76	113	75.8	45.0	114
37	110	86.6	76.7	68.8	77	39.3	52.0	46.5	100
38	84.7	62.2	65.8	90.0	78	38.8	47.7	113	40.0
39	99.7	39.9	86.5	57.0	79	29.7	55.5	90.3	55.0
40	55.5	83.8	20.1	67.0	80	-	-	-	-

The transportation cost between each school and depot and fixed cost of the buses are illustrated in Table 3.

Table 3
Transportation cost between each school& depot and Fixed Cost of the Buses

School	C_{ot}	Bus Number	F_k
1	51.62	1	51.62
2	35.34	2	35.34
3	66.48	3	66.48
4	32.24	4	32.34
		5	27.45

5. Genetic Algorithm

Metaheuristics are general frameworks to plan heuristic algorithms which are able to run away from local optima (Sangaiah et al. 2020). Genetic algorithm is a Metaheuristic search method based on the evolutionary ideas of natural selection (Ghasemi et al. 2020, Ghasemi, and Khalili-Damghani, 2020). This method considers a population of GA chromosomes that go through a series of changes due to selection, crossover and mutation resulting in a modified set of chromosomes at the end of each GA cycle (Ghasemi et al. 2019, Goodarzian and Hosseini-Nasab, 2019). In this paper, a GA is proposed for the problem. The general structure of the proposed algorithm is as follows:

5.1. Chromosome presentation

Creating a definition of individuals, generally called the representation, is the first step in planning a GA for a problem. In this study there are $l(l = 1, \sim, L)$ students, $s(s = 1, \sim, S)$ buses, and $k(k = 1, \sim, K)$ bus stations. Three parts are considered in the proposed chromosome. The first part of the chromosome in Fig. 3, that includes 4 genes and is filled with, shows that the first bus is assigned to the node 5, the second bus is assigned to the node 10, the third bus is assigned to the node 6, and the fourth bus is also assigned to the node 7. So in the first part, we have determined the buses are assigned to the stations and schools. The second part of chromosome includes 4 genes and shows that the first bus first serves the 27th student, the second bus first serves the 19th student, the third bus first serves the 51th student, and the fourth bus first serves the 63th student. On the other hand, in the second part of the proposed chromosome, the first student which is visited by each bus is introduced. The third section of the chromosome includes L genes which are filled with a random non-repeated integer number between 1 and L . Repeat of numbers is not allowed in the second part as a student cannot be visited more than once. The third section is the sequence of visit of students who are at the same route. The dividers between routes are determined using available capacity of vehicle. According to the second part, the first visiting student in each route has been determined. The first visiting students in all routes are 27, 19, 51, and 63 based on second section. So, considering the capacity of the bus number 1, the 8-15-1-2-9 is the sequence of visiting students in a route.

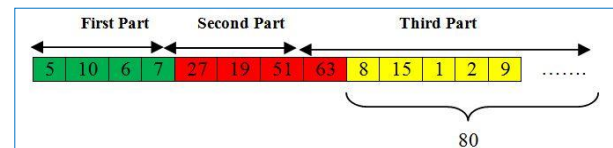


Fig. 3. Chromosome representation

5.2. Crossover operator

To diversify the search, the crossover operator recombines the gene-codes of two parents and produces two offsprings. The conventional one-point crossover operator introduced by Holland refers to replace genes between the parents beginning from a point randomly selected from the chromosomes and the two-point crossover operator refers to the random selection of two points and replace of genes between the parents based on these two points. In this paper, two-point crossover operators were applied. As shown in Fig. 4, both cross points occur in the second part of the chromosome. The first part of the first chromosome (i.e., sequence 5-10-6-7) is placed as the first part of the second offspring. The third section of the first chromosome (i.e., sequence 8-15-1-2-9-...) is replaced as the third section of the second offspring. The first part of the second chromosome (i.e., sequence 6-7-5-3) is placed as the first part of offspring 1. The third part of the second chromosome (i.e., sequence 12-23-9-2-39-...) is replaced as the third part of the first offspring. Then a cross point is done using the second part of the first parent (i.e., sequence 27-19-51-63) and the second part of the second parent (i.e., sequence 20-18-14-4).

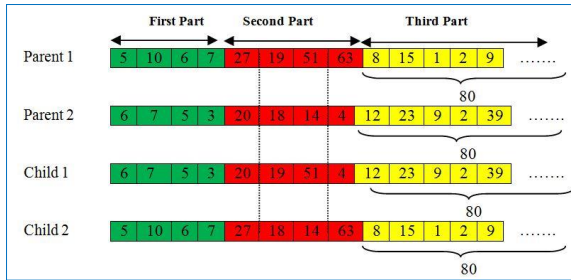


Fig.4. Crossover Operator

5.3. Mutation operator

After the crossover, the mutation is applied to each resulting offspring's chromosome. The goal of this operator is to forbid the algorithm from trapping in local optimum by exploring new solution area. In this study, the mutation operator is accomplished based on a mutation rate that is a parameter of the algorithm. The selected gene is in the second part of the chromosome. In this study, in addition to the selected gene, another gene from the second part of the chromosome is randomly selected. Then, by using swap mutation operator, the alleles of these genes are changed (See Figure 5).

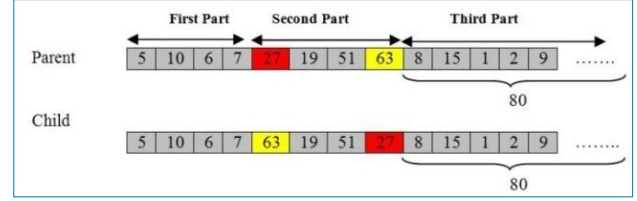


Fig. 5. Mutation (mutation point in the second part of chromosome)

5.4. Selection method and elitism

As a selection process, seed selection was used. Of two parents, the entity corresponding to the father is selected from excellent entities within the defined ranking and the remaining parent, mother, is arbitrary selected. These are used as parents and then returned to the entity group so that they can be used again. The next generation is newly composed using the method of selecting from the genetic operators and the present generation. After creating new entities to the same number as that of the population, elitism is applied to replace bad entities with good entities of the same number. The fitted parameters of GA are shown in Table 4.

Table 4
Fitted parameters of GA

Mutation	Crossover	N Pop	Max Iteration
0.05	0.4	80	200

5.5 Stop Criterion

In this study, two criteria are used as the stop criteria in genetic algorithm. If any of these two following conditions occur, the algorithm will stop:

1. Stop after a fixed number of iterations (maximum of the iterations) occur.
2. Stop when a certain number of iterations occur without improvement in the objective function.

5.6 Constraint handling strategy

Most constraints are satisfied by defining chromosomes, but if a constraint is not satisfied, penalty strategy is used. The penalty strategy penalizes the constraints that have been violated and worsens the objective function. For example, the penalty strategy for Constraints (6) and (7) are as Equations (21) and (22), respectively.

$$A_1 = O_k^6 = \max_{v_k} \{0, \sum_{t \in J} \sum_{L \cap L_t} w_{tlk} - Q'_k\} \quad (21)$$

$$A_2 = O_k^7 = \max_{v_k} \{0, \sum_{t \in J} \sum_{L'' \cap L_t} w_{tlk} - Q''_k\} \quad (22)$$

The total amount of penalties is equal to the sum of the violations, which is defined as Equation (23):

$$Penalty = (A_1 + A_2)$$

6. Results

In this section, the results of the proposed model in the case study are reported and analyzed. As stated earlier, because the problem is Non-deterministic Polynomial-time Hardness (NP-HARD), the genetic algorithm is used as the solution approach. According to Table 5, test problems have been designed in the small and medium scales. After proving the efficiency of the solution approach in the small and medium scale problems, the genetic algorithm will be used to solve the problem in large scale.

Table 5
Dimensions of the instances used to verify the algorithm of the solution

Problem number	Problem Size	school	student	station
1	Small	1	5	1
2	Small	1	10	2
3	Small	2	15	1
4	Small	2	20	2
5	Medium	3	25	2
6	Medium	3	30	3
7	Medium	4	35	3
8	Medium	4	40	4

Table 6 shows the comparison between the solutions of GA and exact method in both small and medium scale problems. Also, CPU time and the gap between GA and exact method are shown in Table 6. Among the eight problems in this table, the first four ones are small-scale and the rest are medium-scale problems.

Table 6
The results of calculation for small and medium size test problems

No	Exact Solution		Genetic Algorithm		Error %
	Objective Function	Time(s)	Objective Function	Time(s)	
1	8150.2	1	8150.2	1	0
2	8342.4	50	8343.5	5	0.01
3	8609.4	88	8701.1	7	1
4	8972.5	112	9036.1	12	0.7
5	9385.0	215	9432.0	13	0.4
6	12321.1	1018	12511.6	27	1.5
7	14159.2	3293	14160.8	30	0
8	16774.9	5963	17023.3	37	1.4
Ave	10839.3	1342.5	10919.8	16.5	0.62

According to Table 6, objective function value increases by increasing the scale of the problem. The mean percentage error is also less than one percent; namely 0.62 percent. According to the percentage error values, efficiency and

reliability of Genetic Algorithm in solving the small and medium-scale problems are proven. In fact, this algorithm has demonstrated acceptable performance in solving such problems. So, according to the solution results of the problems in small and medium scale, the solution results of the problems in large-scale can be trusted and acceptable. A review of the CPU time for Genetic Algorithm and exact solution shows that as the scale of the problem is increased, CPU time of the exact method will dramatically increase, while the increase of CPU time for Genetic Algorithm is approximately slow.

The mean value of error for the proposed Genetic Algorithm is less than 1 % while the CPU time for Genetic Algorithm is very low in comparison with exact method. So, the Genetic Algorithm is reliable to solve and handle large scale test problems. In order to investigate the complexity of the mathematical model, the CPU time is examined in terms of increasing the scale of the problem. As shown in Figure 6, the trend of increasing the CPU time has a much greater slope from sample number 8.

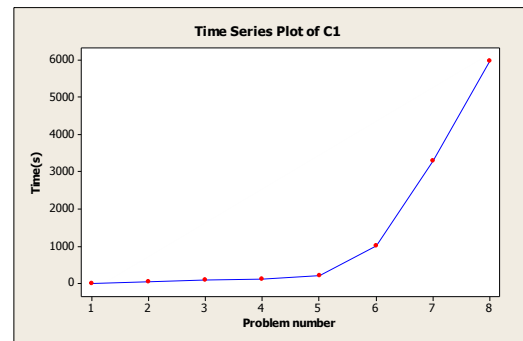


Fig.6. Solution time of the model based on the number of the problem

Figure 7 estimates the distribution function of CPU time of the mathematical model. As it is obvious, the correlation coefficients for normal, 3-parameter lognormal, Exponential and Weibull functions are 0.975, 0.970, 0.990 and 0.950, respectively. Therefore, the CPU time of the mathematical model follows the exponential distribution function with a correlation coefficient of 0.990. Therefore, as the scale of the problem increases, the CPU time increases exponentially.

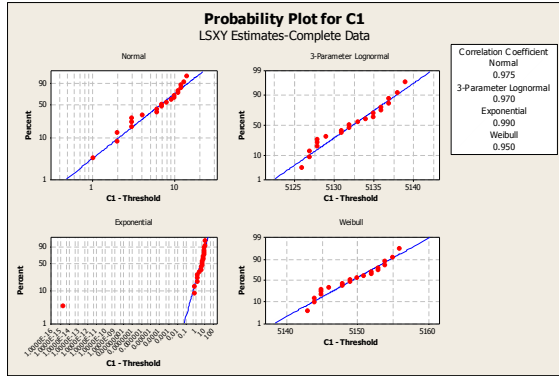


Fig.7. Estimating the distribution function of solution time of the mathematical model

Another reason for increasing the CPU time of the mathematical model is the number of indices, parameters and variables. Therefore, the relationship between them is examined. The proposed model has $(p - \frac{1-s*j*k}{t})$ decision variables and $(l + s + j - pt - k)$ constraints. (Note: Symbols are the model's indices). Therefore, the relationship between the number of variables and constraints in the proposed model is nonlinear. Figure 8 shows the relationship between CPU time and the number of constraints. As can be seen, the CPU time increases exponentially by increasing the number of constraints in the proposed mathematical model.

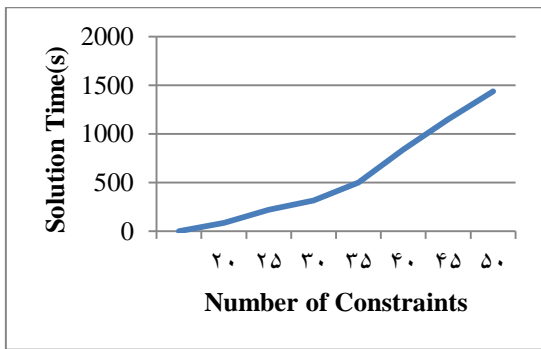


Fig.8. The relationship between problem solution time with number of constraints

Figure 9 shows the convergence of the values of the objective function in the Genetic Algorithm. Convergence graph is one of the approaches to evaluate the performance of the proposed solution method. As can be seen, the convergence of the graph starts from the iteration 40. According to this figure, it can be said that the proposed algorithm has converged with a reasonable and limited number of iterations, and this shows the accuracy of the proposed model.

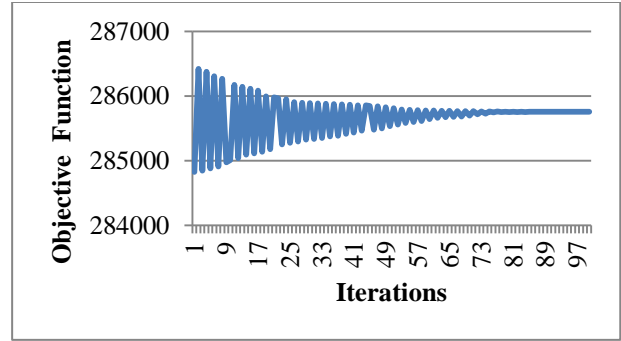


Fig. 9. The convergence of the results obtained from the Genetic algorithm

Figure 10 shows the optimum assignment of students to the stations.

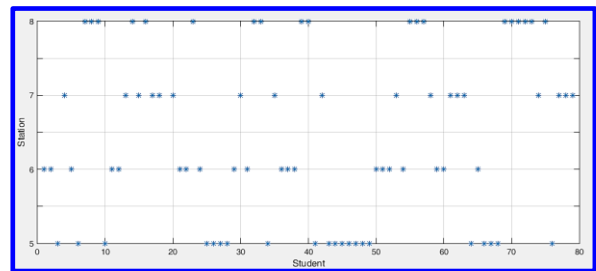


Fig. 10. Assignment of Students to the Stations

It is notable that a student can be assigned to multiple stations along the same route, so the allocation of such students to a particular station is arbitrary. Although, the students that can be assigned to multiple routes need to be distributed in such a way that the capacity of the buses is not violated. After allocation of students to stations, the sequence of visiting the stations through the route of each bus should be determined. The optimum value of x_{tpk} variable helps to analyze the routing sub-problem. The direction and sequence of visiting each node by buses are summarized in Table 7.

Table 7

Direction of each bus (x_{tpk} variable)

K1	K2	K3	K4
Node5.p1	Node10.p1	Node6.p1	Node7.p1
Node9.p2	Node5.p2	Node5.p2	Node3.p2
Node2.p3	Node1.p3	Node7.p3	Node8.p3
Node4.p4	Node8.p4	Node4.p4	Node6.p4
-	Node3.p5	Node2.p5	Node2.p5
-	Node6.p6	Node3.p6	Node4.p6
-	Node2.p7	-	Node1.p7

Table 7 illustrates moving direction of the buses. The first bus starts from the depot and visits station 5 and 9 consequently. It worth noting that node 9 is the house of one of the special students. Then, it goes to schools 2 and 4 and drops off the students. Finally, it comes back to depot. The second bus starts from node 10 in its first route and picks up

student No.10 and then visits station 5. In its second move, the bus will visit station No.5. The third route of the bus No.2 is school No.1. Bus No. 2 visits station 8 in its 4th route and picks up students and then visits school 3. Then the bus visits node6 and node2, respectively. Then the bus visits depot site. Bus No. 3 visits station 6, 5 and7 in its first, second and third route, sequentially and picks up students and then visits school 4. In fact, at the moment, students No.13, 51 and 41 of schools 1 and 6 are on the same bus associating mixed mode loading. Also, bus No.3 visits node 2 and then visits school3. Then, the bus goes towards depot site.

The possible maximum number of the routes of a bus in a routing problem may be equal to the sum of the number of existing nodes. In reality, this number corresponds to the sum of the girl and boy schools, the stations and the special students' houses number. In this case, this number equals to 10 and the maximum of the routes a bus can travel will be 10.

The optimum plans of the proposed model have been compared with those of existing system. Figure 11 shows

this comparison, called current and proposed, for each school of the case study. The results of the proposed model, in term of students' total travel time for all schools, are compared with the existing plan for each bus. In Figure 10, the blue and red bars represent the current and the proposed plan for each bus in each school, respectively. Blank columns in the diagrams of Hemmat School and Peyvand middle smart school indicate that the buses do not go to these schools. By examining the current and the proposed plan for each bus, it is recognized that the total travelling time is often decreased in the optimal solution found by the proposed model. It is notable that the total cost of the proposed plan is reduced for all schools and buses. As mentioned before, the main objective function of the proposed model is minimization of the transportation cost. Based on Figure 11, the model also leads to shorter travelling time.

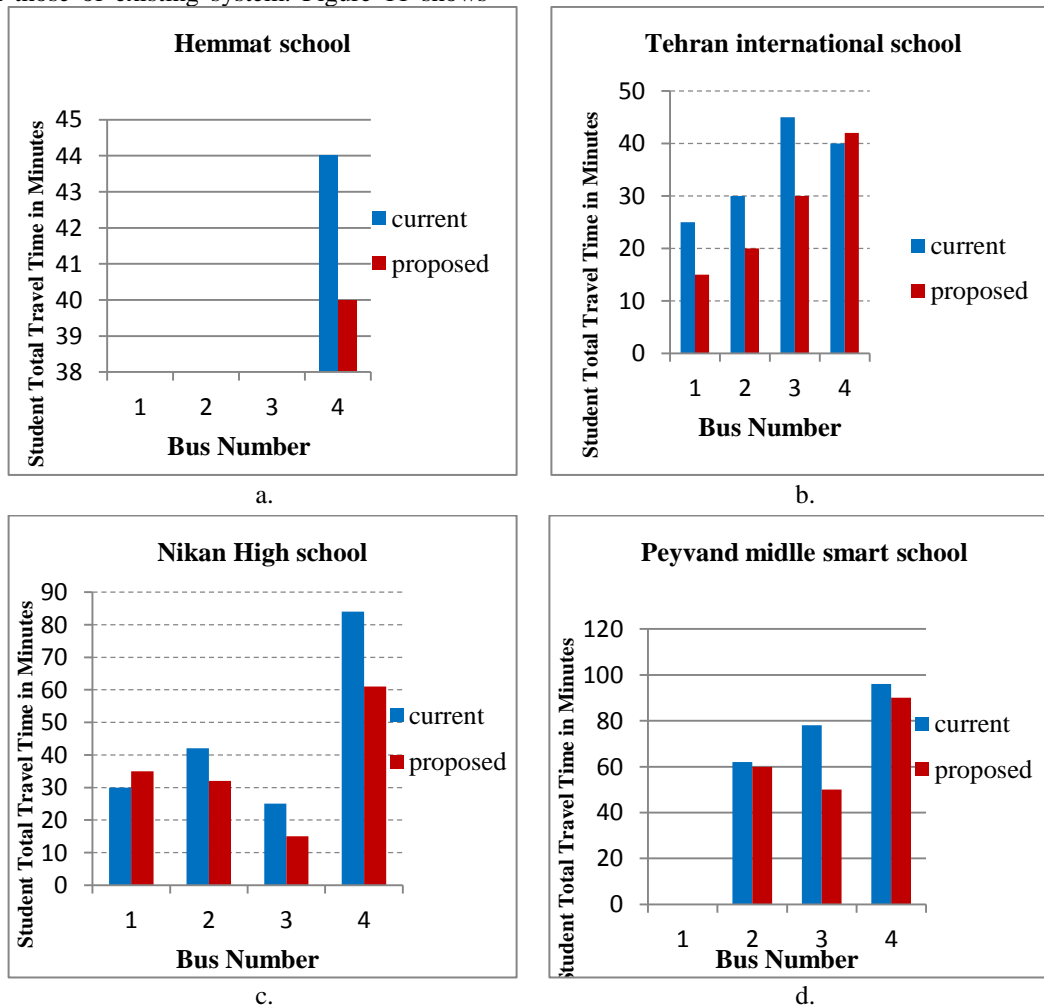


Fig. 11. Comparison in total travel time between current and plan

According to the results, the average students' travelling time are reduced by 28%, 24%, 13% and 21% for Peyvand middle smart school, Tehran international school, Hemmat School and Nikan high school, respectively. The objective function value is 285755.1, which shows 21.5% decrease in total cost of the system in comparison with current system. Total travelling time for the proposed model is 420 minutes while for the current system is 580 minutes. Therefore, the results showed an improvement in the performance of the model by amount of 27 percent. Mixed load on the bus can be seen obviously in the direction of their movement. For example, bus number 3 picks up students of schools' number 2, 3 and 4 on its way. Also, bus number 4 picks up students of schools' number 2, 3 and 4. In fact, students at these schools are in the bus simultaneously and this is the concept of mixed loading. Special students (number 19 and 80) that are shown by nodes 9 and 10 respectively are picked up and dropped off directly at their homes, not at the bus stops. Bus number 1 picks up special student number 19 in node 9. On its way, this bus drops off this student in Tehran international school. Bus number 2 picks up special student number 80 in node 10. On its way, this bus drops off this student in Peyvand middle smart school. The capacity of each bus is 20 students and is dedicated to girls and boys equally. When a bus arrives at the station if boy students' capacity is completed, but the girl students' capacity is not completed and a boy student will be there at the station for a pickup, these students can't use the capacity of girl students. As a result, this student will not be picked up and he should be waiting for the next bus.

Figure 12 depicts the current and proposed path of each bus. As can be seen, the bus number 1 visits Station No. 6 in the current path, while this station will not be visited in proposed path. The bus number 2 visits Nikan School in the current path, while this school will not be visited in proposed path by this bus. The bus number 3 visits Hemmat School in the current path, while this school will not be visited in proposed path by this bus. The bus number 4 visits Station No. 6 in the current path, while this school will not be visited in proposed path by this bus. The Figure 13 shows the relationship between the objective function value and the number of students (boys and girls and special students). As can be seen in the graph, the objective function values are investigated in 5 cases. In these 5 cases, all parameters and data of the problem are assumed to be constant and only the number of students change. The initial data of the problem is exactly the data of the example that was mentioned earlier. In addition, it is important to know that the students added to the problem at every stage are distributed homogeneously between schools and that is why the number of students in every stage increases equally as the number of initial students. Now, the graph is analyzed. When there are 20 students in the problem, the objective function value is equal to 8972.5. Doubling the number of students will change the objective function value to 16774.9. When there are 60 students in the problem, the

cost value will be 20,081.2 and finally, 80 students in the problem will increase in the objective function value up to 28575.1. The reasons of increase in costs are mentioned in the following. The increase in the number of students makes the capacity of each bus to be occupied faster than before. Faster occupation of the capacity of each bus will change the process of moving of the bus. This will be as that a bus should go to a school after completion of its capacity to deliver a number of students and go back to the station and this increase in mobility will result an increase in costs. Moreover, increasing the number of students increases the diversity of students who are waiting for the bus in a station. This diversity means that a station is linked to various schools whereas in cases that the number of students is small, the relationship between the school and the station will be lesser and therefore the costs will be lesser.



Fig.12. Comparing the current and optimal route (red is optimal path and blue is current path)

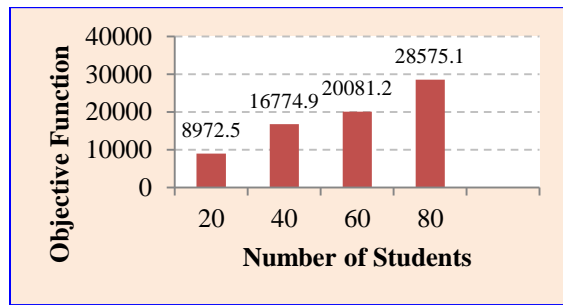


Fig. 13. Relationship between the objective function value and the number of students

The Figure 14 shows the relationship between the number of buses and objective function value. The horizontal and vertical axes show the number of buses and the objective function value, respectively. This problem is exactly the same as mentioned earlier with the difference that the number of buses varies. In addition, the cost of purchasing (renting) of each bus is constant and equals to 60 monetary units. According to the Figure 14, when there is one bus in the problem, the objective function value will be equal to 46701.5. By adding one bus, the objective function value will be 40189. With the purchase of 3 buses, this process continues and the objective function value will decrease to 35184.9. Then, by increasing the number of buses, the objective function value will remain constant in 28575.1. According to the graph, increasing the number of buses will reduce the amount of cost. Maybe this question comes to mind that why increasing the number of buses which leads to the cost of buying the buses, will not increase the costs? The answer is that the cost of buying buses is not much compared to the costs of transportation that are shown in Table 3. In fact, it seems logical that one bus will be purchased and the purchase cost will be paid, but the transportation cost will be reduced.

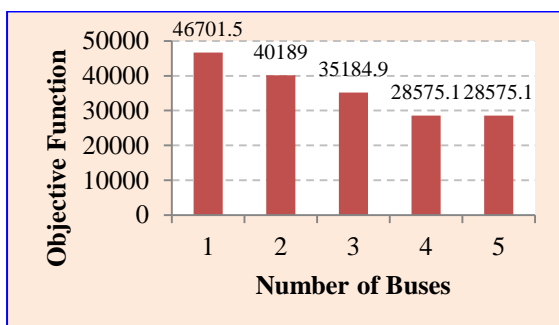


Fig. 14. Relationship between the objective function value and the number of buses

There is another point in Figure 9 and it's the fixation of the chart in points 4 to 7. The reason is that the optimum

number of buses in the model is equal to four. In fact, the number of buses in the model is also potential and when the number of buses in the model increases by decision maker, the optimum number of buses does not change. For this reason, the objective function value remains constant.

7. Conclusion Remarks and Future Research Directions

The development of public transportation as one of the ways to reduce the negative effects of transportation in cities is considered by many countries (both developed and developing). The higher the share of public transportation in citizens' travels is, the greater the economic and environmental benefits will be. The school bus service system, as the oldest and most established public transportation system in cities, has the advantage of being cheap and easy to implement. It can also move a significant number of students in most urban and suburban places and passages and eliminates many extra travels by certain vehicles during traffic peak hours. Undoubtedly, the proper design of the school bus service network (including route, station location and number of fleets) will greatly increase the efficiency of this system. The proposed model obtains the optimal number of stations and services considering cost reduction. Also, the location of stations in the model is done discretely so that several locations will be selected by the decision maker and the model will select the optimal points from the designated ones. Therefore, in addition to reducing costs, the objective function will indirectly reduce fuel cost, urban and suburban traffic, and environmental pollution, save drivers' and students' time.

In this paper a real case study of school bus routing problem was investigated. The case study had real world conditions, including gender separation, mixed-loading, and special students. The case study was handled using homogeneous fleet of vehicles considering special students and gender separation in an urban environment including four schools in Tehran, Iran. Such properties have not been considered simultaneously in a real case study of school bus routing problem. Hence, there was no model in the literature in order to handle this case effectively. The problem of this study was formulated through a new linear mixed-integer mathematical programming model.

The proposed model obtains the optimal number of stations and services considering cost reduction. Also, the location of stations in the model is done discretely so that several locations will be selected by the decision maker and the model will select the optimal points from the designated points. Therefore, in addition to reducing costs, the objective function will indirectly reduce drivers' fuel costs, urban and suburban traffic and environmental pollution and also save drivers' and students' time. According to the results of sensitivity analysis, it can be said that if the number of students increases, increasing the number of buses is the best way to reduce costs. The reason for this is the low cost of bus fares compared to transportation costs.

The proposed model was implemented on a real case study. The results of proposed model were achieved and compared with the existing experimental plans using Genetic Algorithm. The analysis of the results indicated the efficiency of the proposed model in comparison with the existing experimental method. This comparison shows that the students' travelling time is reduced by 28% for Peyvand middle smart school, 24% for Tehran international school, 13% for Hemmat School and 21% for Nikan High school. The proposed model of this study had all of the following properties: 1) mixed-loading assumption; 2) gender separation consideration; 3) special students; 4) multiple-buses planning; 5) homogeneous fleet of vehicles; 6) urban environment planning. The analysis of the results of the case study revealed that the total transportation cost of all buses were decreased for all buses while the travel time was also decreased for most of the buses.

The main bounds and limitations of this study are summarized as follows:

- The number of students in each station was known in advanced and was set as a deterministic value, while this number may vary in real world problems.
- As there was no systematic database for some parts of cost elements, school bus driver's estimations and school transportation officers were asked to help.
- All parameters of the propose model of this study were assumed to be fixed, while in real world problems the cost, travel time, and capacity of the buses may be varied during planning period. The instability of the considered parameters can turn the model into a fuzzy, stochastic, etc. model.
- In this study, due to the lack of access to traffic data, urban traffic has not been considered and the model has been designed in traffic-free conditions.

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http://www.qjie.ir/article_676274.html
DOI: 10.22094/JOIE.2020.1891023.1722

