Public Transport (2018) 10:499–527
https://doi.org/10.1007/s12469-018-0188-0

ORIGINAL PAPER

DRT route design for the first/last mile problem: model and application to Athens, Greece

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Accepted: 30 August 2018 / Published online: 18 September 2018

Abstract
The first/last mile problem in urban transportation services refers to limited connectivity and accessibility to high capacity commuter lines. This is often encountered in low-density residential areas, where low flexibility and resources of traditional public transportation systems lead to reduced service coverage. Demand-responsive transit (DRT) offers an alternative for providing first/last mile feeder services to low density areas, because of its flexibility in adjusting to different demand patterns. This paper presents a mathematical model and a genetic algorithm for efficiently designing DRT type first/last mile routes. The model is applied for the case of a residential area in Athens, Greece and results are discussed.

Keywords Feeder bus · Transit network design · Demand-responsive transport · Genetic algorithms

1 Introduction

As has been widely acknowledged, the use of private vehicles is the major cause of traffic congestion, air and noise pollution, extensive energy consumption and the degradation of living conditions in urban areas (Litman and Burwell 2006; Chapman 2007; Ewing 2008; Zhao 2010). Impacts of motorized vehicle usage can be mitigated by encouraging people to shift to public transport (Litman and Burwell 2006; Banister 2008; Steg and Gifford 2005). However, for this to happen, the latter must be able to provide safe, fast and reliable public transport services. One of

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the main challenges faced by public transportation agencies is to provide adequate connectivity and accessibility for low density areas. Indeed, in such cases connections with commuter lines are usually missing or are inefficient. This fact is widely referred to as the “first/last mile problem”, in the sense that, while high capacity commuter lines (such as metro, light rail or bus rapid transit systems) may present excellent potential for accessing major activity centers within an urban area, absence or limited connection to the final destination of passengers once they get off a commuter line is often noted (Lane 2012). A convenient, yet costly, solution to this problem has recently been the use of dynamic ridesharing services, such as Uber or Lyft, where passengers may instantly book a ride through a mobile phone application (Stiglic et al. 2016). The operation of on-demand dial-a-ride (DAR) systems by local authorities or private agencies has been also widely adopted for overcoming the first/last mile problem. In this case, pre-scheduled departure times are set by the operator and passengers book their trip ahead of time through the internet or phone services. Both system configurations, however, are not optimal neither in terms of operator cost nor passenger loading, underlining a gap in existing practice which calls for more efficient planning and operation of transit feeder services (Li and Quadrifoglio 2011; Chandra and Quadrifoglio 2013; Faroqi and Sadeghi-Niaraki 2016). This problem has attracted the attention of researchers, who have proposed the establishment of demand-responsive transit (DRT) feeder services for connecting residential areas to major high capacity transit corridors, also known as demand-responsive connectors (Chandra and Quadrifoglio 2013).

DRT, often called DAR, essentially refers to more flexible transport systems, compared to traditional public transportation, which is characterized by high inelasticity and predetermined frequencies. The attractiveness of DRT schemes lies in the fact that they respond to the actual transportation demand, whereas regular transit services operate based on pre-defined schedules (Qiu et al. 2015). Flexible transportation is attracting research attention, mostly due to the rapid and significant technological advances in GPS systems and telecommunications. Several studies have been completed in the past decade, mostly focusing on the benefits of incorporating DRT in public transportation systems, in terms of efficiency and profitability in comparison to existing transit network structures. Ambrosino et al. (2004) investigated different aspects of DRT services: the reasons for their popularity, the technologies used for operation and development, implementation strategies, possible benefits arising from their use and the potential that they present for the future. In a study by Li et al. (2007) the efficiency of DRT systems was tested in low demand areas. Results demonstrated that a few modifications in already existing routes could bring about high improvements in terms of level of service, reliability and cost. Brake et al. (2007) offered some insights on sustainability, technologies used and proper marketing needed for DRT services to perform as planned. Laws et al. (2009) studied DRT systems in Wales and the UK, suggesting that more research should be conducted on DRT services, as they appear very promising for the evolution and improvement of public transport. Along these lines, the potential of integrating DRT and fixed route services to satisfy DAR requests was explored in the paper by Häll et al. (2009). In another study by Davison et al. (2014), several DRT services in the UK were examined for detecting those performing at an acceptable level, as well as identify key factors for their successful implementation. Similarly, Häll et al. (2015) investigated the parameters affecting the performance of DAR systems, for providing transit operators with practical design guidelines for operating such services.

All in all, there is a consensus among the research community that DRT systems may prove effective in responding to the needs of low demand density areas, due to their increased flexibility and higher service level, particularly when compared to regular fixed-route services (Chandra and Quadrifoglio 2013). Yet, researchers seem to agree that their integration in public transportation systems has been quite underwhelming due to several operating and practical challenges, mainly related to costs (Qiu et al. 2015). Similarly, research on optimal planning and operation of demand-responsive connector systems remains scarce (Li and Quadrifoglio 2011). In this context, this paper focuses on developing a new model for designing a Demand-Responsive Connector Service. The problem at hand is called the "Demand-Responsive Feeder Bus Network Design Problem" (DR-FBNDP). The term FBNDP refers to a bus network with the specific purpose of collecting passengers from a specific area and transferring them to one or more stations of a high-capacity public transportation corridor. The planning objective is to determine optimal routes in terms of travel time, while satisfying passenger demand. For this purpose, in case of overwhelming demand, additional shuttle buses are deployed. In fact, to the best of our knowledge, existing studies present formulations considering full demand satisfaction, whereas we propose a more realistic formulation allowing for planning extra routes to handle real-world cases such as "overbooking" or limited fleet availability. Passenger demand is assumed to vary daily, thus the concept of DRT systems applies in this context. In line with modern commercial shuttle services, routing requests are assumed be known a few hours in advance, thus the algorithm runs on a fixed demand matrix for the time horizon specified. The problem is formulated as a modified capacitated vehicle routing problem (CVRP) with a many-to-many demand pattern, as there are multiple origins and destinations, whereas most of the studies previously published deal with a many-to-one problem. Extensive reviews on the CVRP and its variants are offered by Golden et al. (2008) and Toth and Vigo (2014). The problem is then solved using a genetic algorithm (GA), which constitutes an effective approach for similar routing problems (Kuan et al. 2006; Deng et al. 2013) even for real-world implementations (Ciaffi et al. 2012; Shrivastava and O'Mahony 2006). An efficient and straightforward implementation is showcased, while the generated tool is intended for planning purposes and is suitable for use by planners/administrative staff or people without technical skills.

The remainder of this paper is structured as follows: first, a brief review of past research on feeder bus network design is presented. Then, the problem at hand and relevant mathematical formulation are presented. Next, the solution method is described in detail. Subsequently, a real- life application of the model is presented, for the case of linking a residential area in Athens, Greece with three of the city's metro stations. The paper concludes with findings and further directions.

2 Background

The feeder bus network design problem belongs to the general class of the transit route network design problem; its objective is to design a service for transporting passengers to/from high capacity metro stations. In the past decades, there have been several studies on the FBNDP, proposing different solution methodologies, design objectives and constraints, as well as applications in real time problems. An early paper on the FBNDP was published by Kuah and Perl (1988) who developed an analytical model to determine optimal routes and frequencies of the feeder bus routes, also considering the spacing of bus stops as a design variable. The authors noted that stop spacing is inextricably linked to the determination of routes and frequencies, thus, specifying the location of stops during the route design process is crucial to improving accessibility. Recent studies used mathematical programming models for finding the optimal solutions to the FBNDP. Martins and Pato (1998) employed heuristic approaches to simultaneously determine optimal routes and frequencies in terms of both passenger and agency cost. First, they built a set of initial solutions through the sequential savings or two-face building method and then, to further improve those solutions, they used a tabu search heuristic. Chien and Yang (2000) developed an algorithm for producing the optimal bus route location and its operating headway in a heterogeneous service area. The aim of this study was to maximize spatial coverage and consequently, ridership. In a study by Jerby and Ceder (2006), a three-step methodology for developing a feeder bus network was proposed: initially, a method for estimating the possible demand of a feeder bus service was created, then a model for automatic design of optimal routes was developed and finally, a heuristic algorithm was applied for generating feeder routes operational constraints specified in previous steps.

Kuan et al. (2006) presented a solution for the FBNDP using a metaheuristic approach. The authors initially employed a heuristic route construction method and subsequently improved their results using Genetic Algorithms and Ant Colony Optimization. Genetic algorithm optimization was also employed in the study by Shrivastava and O'Mahony (2006). Their model simultaneously determined optimal bus routes and operating frequencies, while ensuring that the bus frequencies would correspond to the train frequencies, so that the two modes could operate in a complementary manner. Hu et al. (2012), introduced the term of marginal trip distance, which was defined as the distance that must be exceeded for the combination of rail transit and feeder buses to be superior to a direct bus trip. They introduced a design objective which considered the passenger comfort level as well as the ticket price for both modes. A model proposed by Ciaffi et al. (2012) consisted of two steps: first, a heuristic algorithm creating two supplementary sets of routes was employed, one set using the k-shortest path method and one using a traveling salesman model. Then, a genetic algorithm was applied to find an optimal or close to optimal route network and frequency using those sets as a base. In this case, a penalty was included in the objective function for unsatisfied demand and transfers, in an effort to more realistically represent passenger needs. Finally, Deng et al. (2013) proposed a solution based on genetic algorithms, where a different demand pattern was used. In this case, passenger demand was not limited to requests from many origins to a single destination, train station, but also included every available train station as a possible destination. While previously reported studies mostly focused on regular feeder services, the paper's objective is to offer a straightforward approach for designing an efficient DRT type feeder service. For that purpose, an appropriate concept of DRT operations for that case is set and a straightforward model and solution approach are developed for addressing the associated design problem. A special feature of the proposed GA that makes it particularly attractive for the specific variant of the CVRP, i.e. the M-to-M (many to many) DR-FBNDP, is the ability to concurrently optimize different chromosomes during each run, with each chromosome representing the feeder network for a specific station. The parallel implementation, besides being computationally efficient, is also more straightforward, provides flexibility and ability to more realistically capture real-world conditions, as it allows to shorten/extend the feeder network as desired. In this way, lack of demand/station closures/network expansions can be easily modeled with little modifications to the existing implementation.

3 Problem formulation

3.1 Problem overview

The problem-at-hand is that of designing a DRT service, which offers accessibility between locations of a residential area and stations of a metro line within that area (Fig. 1). Passengers are assumed to be picked up from pre-designated locations (bus stops) and transported to their desired metro station. This implies that, based on demand, fleet availability and traveler preferences, a bus stop may be served by more than a bus route. The service considers routes whose origins are metro stations, with each route originating from and terminating to a single station. In the case of unserved passenger demand, an additional cyclical route originating from the metro station is established, as shown in Fig. 1.

A homogeneous fleet of vehicles is assumed, which operate under the same operational and practical constraints. As DRT operations require earlier booking of service, demand is assumed to be known. In this context, design objectives considered include minimization of travel time, the number of routes and unsatisfied demand. Design outcomes include service routes with minimum fleet requirements while unsatisfied demand is tackled by introducing additional ("repair") routes.

3.2 Mathematical model

The mathematical formulation of the problem is an extension of those proposed by Martins and Pato (1998), Kuah and Perl (1989) and Deng et al. (2013), where we have introduced additional decision variables to handle unsatisfied demand. In the present

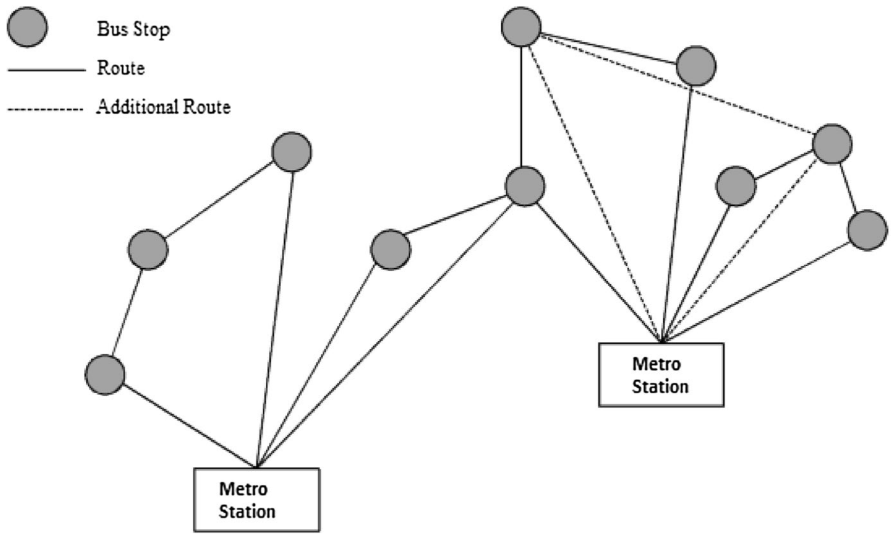

Fig. 1 Design concept

case, each bus stop has been connected to all metro stations, while additional circular routes are introduced, based on unsatisfied demand. With respect to the objective function, a weighted-sum is employed to capture both user and operator cost, similarly to existing studies (Kuah and Perl 1989; Deng et al. 2013; Martins and Pato 1998). The values of the weighting coefficients reflect a policy decision; for instance an operator might want to use the minimum number of buses or minimize distance traveled (thus fuel expenditure) or unsatisfied demand (e.g. publicly subsidized DRT). To address this issue, a sensitivity analysis for different weight combinations will be shown in Sect. 4.5.2.

The mathematical formulation for the problem at hand is as follows. Let:

Sets

I	Set of nodes representing bus stops
$N \subseteq I$	Subset of nodes i with unsatisfied demand
P	Set of metro stations p, $p=1,\ldots,P$
$M=I \cup P$	Set of bus stops and metro stations
$H \subseteq M$	Containing P, any proper subset of M that contains all metro stations
K	Set of routes k, $k=1,\ldots,K$
$B \subseteq K$	Subset of routes k representing extra routes

Parameters

q_k	Bus capacity for route k
a, b, c	Objective function weights (default values $a=b=c=1$)
o_{ip}	Total passenger demand between node i and metro station p
tc_{ijk}	Travel cost (time) to traverse link ij via route k

Decision variables

x_{ijk} 1 if link *ij* is served by route *k*, otherwise 0
u_{ip} Number of unsatisfied passengers between stop *i* and metro station *p*
d_{ipk} Number of passengers traveling between node *i* and metro station *p* on route *k*
l_{ijk} Passenger load on arc *ij* for route *k*

The problem is formulated as follows:

$$\min a \cdot \sum_{i \in C} \sum_{j \in C} \sum_{k \in K} tc_{ijk} \cdot x_{ijk} + b \cdot \sum_{j \in C} \sum_{k \in K} x_{0jk} + c \cdot \sum_{i \in N} \sum_{p \in P} u_{ip}. \tag{1}$$

Subject to:

$$\sum_{i \notin H} \sum_{j \in H} \sum_{k \in K} x_{ijk} \geq 1, \quad \forall H \tag{2}$$

$$\sum_{i \in I} x_{ijk} \leq 1, \quad \forall j \in M, k \in K \tag{3}$$

$$\sum_{j \in M} x_{ijk} \leq 1, \quad \forall i \in I, k \in K \tag{4}$$

$$\sum_{p \in P} \sum_{i \in I} x_{ijk} = 0, \quad \forall k \in K \backslash B \tag{5}$$

$$\sum_{i \in I} \sum_{p \in P} x_{ipk} \geq 1, \quad \forall k \in K \tag{6}$$

$$\sum_{k \in K \backslash B} \sum_{j \in M} x_{ijk} = P, \quad \forall i \in I \tag{7}$$

$$\sum_{j \in M} x_{ijk} - \sum_{m \in I} x_{mik} \geq 0, \quad \forall i \in I, k \in K \backslash B \tag{8}$$

$$\sum_{j \in I} l_{0jk} = 0, \quad \forall k \in K \tag{9}$$

$$l_{ijk} \leq q_k \cdot x_{ijk}, \quad \forall i \in I,\ j \in M,\ \forall k \in K \tag{10}$$

$$d_{ipk} = \min\left(q_k \cdot \sum_{j \in M} x_{ijk} - \sum_{j \in M} l_{jik}, o_{ip} \cdot \sum_{j \in M} x_{jik} \right), \quad \forall i \in I,\ k \in K,\ p \in P \tag{11}$$

$$\sum_{i \in I} l_{ijk} + d_{jpk} = \sum_{i \in I} l_{jik}, \quad \forall j \in M,\ \forall k \in K,\ p \in P \tag{12}$$

$$u_{ip} = o_{ip} - \sum_{k \in K \setminus B} d_{ipk}, \quad \forall i \in N,\ p \in P \tag{13}$$

$$d_{ipk} \geq 0, \quad \forall i \in I,\ p \in P,\ k \in K \tag{14}$$

$$u_{ip} \geq 0, \quad \forall i \in I,\ p \in P \tag{15}$$

$$l_{ijk} \geq 0, \quad \forall i \in I,\ j \in M,\ k \in K \tag{16}$$

$$x_{ijk} = \{0, 1\}, \quad \forall i \in I,\ j \in M,\ k \in K. \tag{17}$$

Objective function (1) seeks to minimize the sum of the total travel time, which includes riding time plus service time at each stop, the required number of routes (thus indirectly the fleet size) and the number of passengers that have not been served by the proposed design of regular (not extra) routes. Constraint (2) suggests that every subset of bus stops must be directly linked to a metro station (connectivity constraint). Constraints (3)–(6) are feeder bus route integrity constraints. Constraints (3), (4) indicate that each node is included at most once on a regular route. Constraint (5) ensures that every regular (not additional) route terminates to a certain metro station. Constraints (6) make sure that every bus route includes at least one bus stop and one metro station (non-empty constraint). Constraint (7) specifies that every bus station is linked to all metro stations via a separate regular route of the main network. Constraint (8) ensures that every regular bus route of the main network is an acyclic route. Constraints (9)–(13) handle vehicle capacity and passenger demand satisfaction. Constraint (9) specifies initial bus load as zero. Constraint (10) is the vehicle capacity constraint. Constraint (11) determines the number of passengers boarding at each stop. Constraint (12) is the flow conservation constraint. Constraint (13) shows that unsatisfied demand at a bus station is calculated as the difference between the total passenger demand at that bus stop and the number of passengers actually served by a regular (not extra) route. Constraints (14)–(16) are non-negativity constraints and constraint (17) states that decision variable x_{ijk} is binary.

3.3 Solution method

As the general feeder bus network design problem has been found to be NP-hard (Martins and Pato 1998), a metaheuristic technique is required for obtaining a good solution in a reasonable time frame. Moreover, we have introduced additional decision variables and constraints related to unsatisfied demand, while we are aiming at simultaneously determining more than one feeder network, thus increasing problem difficulty. Given that researchers have reported satisfactory results and have been able to solve the FBNDP for real-world cases using GAs, the latter constitute a reasonable choice. Indeed, GAs are deemed appropriate for the problem at hand because of:

- The satisfactory performance of GAs in previous FBNDP-related studies (Chien and Yang 2000; Jerby and Ceder 2006; Kuan et al. 2006).
- The applicability of GAs in real life FBNDP networks (Ciaffi et al. 2012; Shrivastava and O'Mahony 2006, 2007).
- The suitability of GAs for NP-hard problems with many variants and constraints, such as the FBNDP (Lenstra and Rinnooy Kan 1981; Haupt and Haupt 2004).
- The suitability of GAs for multi-objective applications (Konak et al. 2006).
- The potential of GAs for hybridization with existing models and systems and implementation in parallel computational environments (Haupt and Haupt 2004).

Genetic algorithms were first introduced by Holland (1975) and simulate the process of natural evolution. The main idea behind GAs comes from the theory of evolution from Darwin, in which an initial population evolves into a new one through the processes of natural selection and genetic operators. A candidate solution is properly represented by one or more chromosomes; each chromosome consists of genes (the solution's individual values). Sets of candidate solutions (the population) are generated and evaluated using a fitness measure and the best among them are chosen to seed the next generation, through a series of transformations performed by genetic operators (crossover, mutation, replacement etc.) (Eiben and Smith 2003). The process is repeated, with new generations of solutions produced, evaluated and transformed, until some termination criterion is met. Often, GAs are hybridized by introducing external procedures, which are used for properly representing the problem at hand, handling constraints and calculating the problem's fitness measure.

In the present case, the GA is applied for generating and evaluating alternative DRT routes so that minimization of design objectives is achieved. The GA is hybridized by an external procedure, which is introduced (a) for determining routes under vehicle capacity constraints, and (b) for efficiently assigning unsatisfied passengers to additional routes.

3.3.1 Representation scheme

A parallel representation scheme is used; every candidate solution of the problem is represented as a set of n chromosomes, where n is the number of metro stations considered in the design. These chromosomes are concurrently evolved by the GA, each one representing the feeder network for a specific metro station. Every chromosome gene represents a bus stop ID; bus stops are assumed to be assigned to an ordered ID. Each of the chromosomes represents a sequence of consecutive bus stops, in the order in which they will be visited by routes starting from a station and returning to that station, under vehicle capacity constraints. For example, the following chromosome represents 15 bus stops which must be connected to a station:

$$[11\ 15\ 7\ 13\ 9\ 2\ 1\ 5\ 12\ 8\ 10\ 14\ 6\ 3\ 4].$$

Depending upon vehicle capacity, alternative route sets may be extracted for this chromosome. An alternative route set, consisting of three routes would be:

1. Station–11–15–7–13–9–Station,
2. Station–2–1–5–12–8–Station,
3. Station–10–14–6–3–4–Station.

Route extraction is based on an external procedure described later on. An example representation of a candidate solution for the case of three stations and 15 nodes is as follows:

$$[11\ 15\ 7\ 13\ 9\ 2\ 1\ 5\ 12\ 8\ 10\ 14\ 6\ 3\ 4]$$
$$[5\ 10\ 2\ 9\ 8\ 12\ 15\ 1\ 6\ 3\ 11\ 14\ 4\ 7\ 13]$$
$$[1\ 8\ 6\ 12\ 3\ 14\ 10\ 2\ 5\ 9\ 11\ 15\ 4\ 7\ 13]$$

3.3.2 Fitness measure

Each group of chromosomes is evaluated based on a common fitness measure. This is calculated as the sum of total travel time, the number of routes needed to fully serve passenger demand and the number of unsatisfied passengers, already depicted in Eq. (1) of the mathematical programming formulation.

3.3.3 Genetic operators

The initial population is randomly generated and the members are evaluated in terms of fitness. Subsequently, parent selection occurs based on a ranking method, where the members of the population are ranked based on their fitness. Crossover and mutation operators are then applied for creating the offspring. An ordered crossover is used (Eiben and Smith 2003), where two random points are selected from the parent chromosome and the genes located between these points are copied to the first offspring. The remaining genes are copied in the second parent. The same procedure is performed for the second offspring, in which the roles of the parents are reversed. In this way, part of the node sequence remains intact and is kept in the chromosome, while a new order is also created. Subsequently, a swapping mutation method is selected, and two genes are randomly selected and interchanged (Jih and

Hsu 2004). A steady state approach is followed for replacement: worst population members are replaced instead of the whole population.

3.3.4 Route extraction

An external procedure is incorporated in the GA for determining routes and unsatisfied demand for each candidate solution. Calculation of unsatisfied demand is essential to the process, as it dictates the need for additional (repair) routes that will originate from a station and collect remaining passengers. The algorithm extracts routes based on passenger demand and calculates the cost of every route as follows:

1. *Initiation* The algorithm starts from the first gene of the chromosome, which represents the first bus stop to be visited.
2. *Route construction* For every gene of the chromosome sequence, the algorithm calculates the sum of passengers whose origin is its corresponding bus stop and destination is the metro station.
3. *Route termination* Two cases are considered:

    a. If capacity constraints are violated, the algorithm returns to step 1 and sets the gene that violates the constraint as the first bus stop in the next route.
    b. If capacity constraints are not violated, the next gene (bus stop) is added to the route. The number of passengers boarding the bus is subtracted from the bus capacity, for calculating spare capacity. If passengers wishing to board are more than the latter, available seats are filled and the rest of the passengers are considered unsatisfied. Furthermore, the number of unserved passengers and the specific gene are stored in memory. Then, the algorithm returns to step 1, moving on to the next gene. If another gene cannot be added to the route, the algorithm sets this gene as the first one in the next route.

4. *Construction of additional routes* The bus stops with unsatisfied passengers are known from the previous step and additional routes originating from each metro station are constructed in the same manner (steps 1–3) to serve these stops. Therefore, with the same capacity constraints as the main routes, some extra routes are created for serving travelers who could not be satisfied by original routes.
5. *External process termination* The process terminates when all stops are included in the network and every stop with unserved passengers has been visited a second time.

3.3.5 Genetic algorithm termination

The termination criterion is set as an improvement of less than 1% in the fitness measure after a specific time duration defined through experimentation and GA calibration, on a case-to-case basis.

4 Application

4.1 Preliminary tests

Before applying the proposed algorithm to the problem at hand, its performance was tested using a popular dataset by Kuah and Perl (1988) consisting of 55 bus stops and 4 rail stations. The authors developed a Savings Heuristic algorithm, while later, Kuan et al. (2004, 2006) developed four algorithms, a simulated annealing, a Tabu search, a genetic algorithm and an ant colony optimization model to solve the FBDNP. In order to evaluate the performance of our model on the specific instance, we suitably adjusted the algorithm to the problem considered in these studies. As our model does not consider frequencies due to the DRT concept, we utilized an average frequency value within the range reported by the authors (thus not necessarily the optimal) to calculate costs. As can be seen in Table 1, our GA manages to produce better results than the other models in short computational times. Furthermore, it is evident from the preliminary tests that our proposed algorithm's results are robust, as the average deviation between the average and the best solutions found are kept in a reasonable level. Indeed, according to Table 1, for the proposed GA, the best and the average of fitness measure values obtained differ by 6.9%, which is better compared to a simple savings algorithm (over 13%), and slightly increased but still comparable to other algorithms found in the literature (1.7–5%). Also, the time shown for our model is very short, given that it refers to a personal laptop of 2.6 GHz and 4 GB RAM. However, with respect to other studies, hardware largely affects computational performance, while there are various factors such as the number of generations and population size that render a straightforward comparison typically infeasible (Talbi 2009).

4.2 Overview

The proposed model is demonstrated for the design of a DRT feeder service in a residential area of Athens Greece (Fig. 2). The area is served by three metro stations (MS) and routes are to be created in such a way that they connect these stations to a set of bus stops. Tables 2 and 3 present the distances between stations and bus stops and hourly demand for service, respectively; an operational speed of 20 km/h and buses with a capacity of 45 passengers are considered.

4.3 GA calibration

For calibration purposes, experiments were undertaken for different combinations of GA parameters. Population sizes were set to 25, 50 and 75 while crossover and mutation rates were assigned values of 0.2, 0.4, 0.6 and 0.05, 0.1, 0.15, respectively. As such, a total of $3 \times 3 \times 3 = 27$ different combinations were considered. Each of the combinations was tested 5 times, leading to a total of $27 \times 5 = 135$ calibration runs. The best fitness value was found for the combination of

Table 1 Comparison between known metaheuristics and proposed algorithm

Solution method	Best total cost	Average total cost	Average running time (s)	% Difference between average and best solution (%)
Savings heuristic[a]	6033	6848		13.5
Simulated annealing[b]	6519	6845	4.6	5.0
Tabu search[b]	6338	6485	13.8	
Genetic algorithm[c]	6412	6519	10.1	1.7
Ant colony[c]	6535	6716	9.0	2.8
Our genetic algorithm	5643	6031	7.8	6.9

[a]Kuah and Perl (1989)

[b]Kuan et al. (2004)

[c]Kuan et al. (2006)

population = 25, crossover = 0.2, mutation = 0.05. The GA was executed in a 2.6 GHz, 4 GB RAM computer. The evaluation procedure was developed in Visual Basic for Applications™ and the GA was implemented using Palisade Evolver 6.0™. Table 4 shows results for different parameter combinations while algorithm convergence for some and the best combination of GA parameters (shown in bold in Table 4) are presented in Figs. 3 and 4. For Fig. 3, four random experiments were chosen, from the population, crossover, mutation combinations: (50, 0.4, 0.05), (50, 0.6, 0.15), (75, 0.2, 0.15), (75, 0.6, 0.05). The results demonstrated the robustness of the algorithm, as the fitness measure converges to the best solution around the same computational time, regardless of the GA's parameters. Consequently, as can be seen from Figs. 3 and 4, the algorithm tends to become parallel to the horizontal axis in about 18–20 min; this implies that solutions may be obtained in a rather short amount of time, which is suitable for practical purposes.

4.4 Results

Figure 5 shows the resulting feeder bus network for the three metro stations, while results are presented in detail in Table 5. Also, satellite images of the residential area considered, incorporating the road geometry and traffic regulations, along with the corresponding feeder networks, are shown in the "Appendix".

It is observed that the proposed design by the model requires an additional route for accommodating unsatisfied demand. This implies that a vehicle will need to perform an additional trip for providing service along that extra route or an additional vehicle should be scheduled for that purpose. Route durations range from 0.15 to 0.41 h, depending on the number of stops in each route. By looking at both Tables 2 and 4, it is easy to note that lower demand stops are included in longer routes, as relatively more stops may be visited in this case until capacity is exhausted. Similarly, higher demand stops, such as 5 or 7, may be exclusively served by a route (for MS 1

Fig. 2 Application area

Table 2 Distances between stops (km)

Stop name	Stop index	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	MS 1	MS 2	MS 3
Gymnastirio	1	0	0.8	1.7	2.6	1.7	2	1	1.4	1.1	0.6	1.1	1.6	1.8	1	1.8	2.2	3.1	2.4
Sixth Aigaiou	2	1.5	0	0.9	1.8	0.9	1.3	0.8	1.3	1	0.5	1	1.4	1.9	1	1.8	2	2.3	2.1
Eighth Artakis	3	1.8	0.5	0	1.7	0.7	1	1.3	1.2	1.4	1	1.4	1.9	2.4	1.4	2.3	2.3	2.2	2.6
Agias Fwteinis	4	2.6	1.1	0.7	0	0.5	0.7	1.5	1	1.4	1.6	2	2.5	2.8	2.1	3	3	2.8	3.2
Loutra	5	2.5	1.5	0.8	1.5	0	0.8	0.4	0.6	0.7	1.2	1.5	1.8	2.3	2	2.9	2.9	3	3.1
Tenth Artakis	6	2.5	1	0.5	1.8	0.3	0	1.1	0.9	1	1.4	1.5	2.1	2.6	1.9	2.8	2.8	2.7	3.1
Dragatsaniou	7	1.7	0.7	1.1	1.8	0.9	1.1	0	0.5	0.1	0.4	0.7	1.2	1.7	1.1	2	2.1	3	2.3
Iaswnos	8	2.2	1.2	1.3	1.6	0.7	0.8	0.5	0	0.4	0.9	1.1	1.5	2	1.6	2.6	2.6	3.4	2.8
Arsakeiou	9	1.9	0.8	1.2	1.7	0.9	1	0.1	0.4	0	0.5	0.8	1.3	1.8	1.3	2.2	2.3	3.1	2.4
Ainou	10	1.3	0.5	1.3	2.2	1.2	1.4	0.4	0.8	0.5	0	0.5	1	1.4	0.8	1.7	1.7	2.7	1.9
Nekrotafeio	11	1.5	1	1.8	2.7	1.7	1.9	0.8	1.3	0.9	0.7	0	0.5	1	0.8	1.6	2	3	2.2
Mouriki	12	1.4	1.2	2.1	2.8	2	2	1.2	1.4	1.1	0.9	0.6	0	1	0.7	1.7	1.9	2.9	2.1
Third Papagou	13	1.2	2	2.9	3.8	2.8	3.3	2.2	2.7	2.3	1.8	1.8	1.6	0	1.3	0.7	1.8	2.8	1.1
Scholeio	14	0.7	0.9	1.8	2.7	1.7	2.1	1.1	1.5	1.2	0.8	0.6	1.1	1.2	0	0.9	1.2	2.2	1.3
Panagitsa	15	0.6	1.4	2.3	3.1	2.3	2.6	1.6	2	1.7	1.2	1.1	1.6	1.4	0.6	0	1.1	2.1	1.1
Metro Dafni	MS 1	0.7	1.5	2.3	2.8	2.4	2.7	1.6	2.1	1.8	1.3	1.4	1.9	1.7	0.9	1.4	0	0	0
Metro Ag. Ioannis	MS 2	1.7	2	2.8	2.5	2.8	3.3	2.6	3.1	2.8	2.3	2.4	2.9	2.4	1.9	2	0		
Metro Ag. Dimitrios	MS 3	1.2	1.8	2.7	3.6	2.7	3	2	2.4	2.1	1.6	1.5	1.2	0.7	1.2	0.7	0		

Table 3 Hourly demand for DRT service

From	Index	To		
Stop name		Dafni Metro Station	Agios Ioannis Metro Station	Agios Dimitrios Metro Station
Gymnastirio	1	12	13	18
Sixth Aigaiou	2	20	27	23
Eighth Artakis	3	26	38	32
Agias Fwteinis	4	17	13	22
Loutra	5	48	32	36
Tenth Artakis	6	32	19	43
Dragatsaniou	7	36	38	32
Iaswnos	8	30	32	25
Arsakeiou	9	6	26	21
Ainou	10	11	6	13
Nekrotafeio	11	8	21	11
Mouriki	12	15	18	18
Third Papagou	13	8	24	9
Scholeio	14	4	5	6
Panagitsa	15	1	6	4

and MS 3, respectively), which means that, on average, the passengers at those stops experience lower travel times, since they are able to travel directly to a metro station. Further, as expected, additional routes are mostly composed by high demand stops, such as 3 and 5, as a small proportion of passengers are required to wait for the next bus to arrive. These observations validate that the algorithm produces reasonable results, which reflect real-world conditions. Results for average travel times for each metro station are shown in Table 6:

Table 6 shows a comparison between two different cases of the average travel time per passenger for the routes of the network towards each metro station. First, the total travel time is measured as the sum of the time the buses travel between each station (riding time- RT) plus the service time (ST) at each bus stop, while in the second case total travel time estimation also takes into account the waiting time (WT) of the extra route passengers at the bus stations. Service time is assumed to be proportional to the demand at each stop, with an average value of 60 s. Average travel time is calculated by multiplying the various time components by the corresponding demand and then averaging over the total number of passengers for that metro station. The passengers which are unable to board at first and are thus, served by the additional routes, are assumed to wait for the first available vehicle to pick them up. Therefore, their waiting time is calculated as the time for a bus to travel from the metro station to the first stop plus the time to travel between preceding stops of the additional route, i.e. the passengers on the last stop of the additional route have to wait the longest. It is clear that, for the routes of the network, the contribution of waiting time at the bus stops is insignificant compared to other travel time components. Since the model is designed under the context of DRT systems, it

Table 4 Results for different GA parameter combinations

Population	Crossover	Mutation	Average fitness	Standard deviation
25	**0.2**	**0.05**	**57.27**	**3.01**
		0.1	61.74	1.51
		0.15	59.33	4.14
	0.4	0.05	61.51	2.66
		0.1	59.22	5.68
		0.15	61.97	2.14
	0.6	0.05	63.88	3.99
		0.1	59.59	6.18
		0.15	59.57	2.88
50	0.2	0.05	59.02	3.80
		0.1	59.38	2.10
		0.15	61.28	4.31
	0.4	0.05	63.88	2.45
		0.1	60.82	4.70
		0.15	62.98	3.31
	0.6	0.05	67.14	1.62
		0.1	60.21	3.97
		0.15	62.31	6.29
75	0.2	0.05	60.38	2.83
		0.1	62.80	3.59
		0.15	58.14	3.87
	0.4	0.05	63.73	5.15
		0.1	64.83	1.82
		0.15	66.01	2.86
	0.6	0.05	62.02	2.24
		0.1	60.76	5.43
		0.15	65.96	2.64

Bold values indicate the best combination of parameters and best solution

is reasonable that waiting time does not affect average travel time, as, in DRT systems, typically, by booking a ride in advance and knowing bus arrival times beforehand, waiting times are eliminated. Finally, test results show that the average travel time is approximately 0.2 h, or 12 min per passenger. This indicates that the model generates routes that offer fast transportation to the metro stations, with travel times comparable to those of taxis or private vehicles.

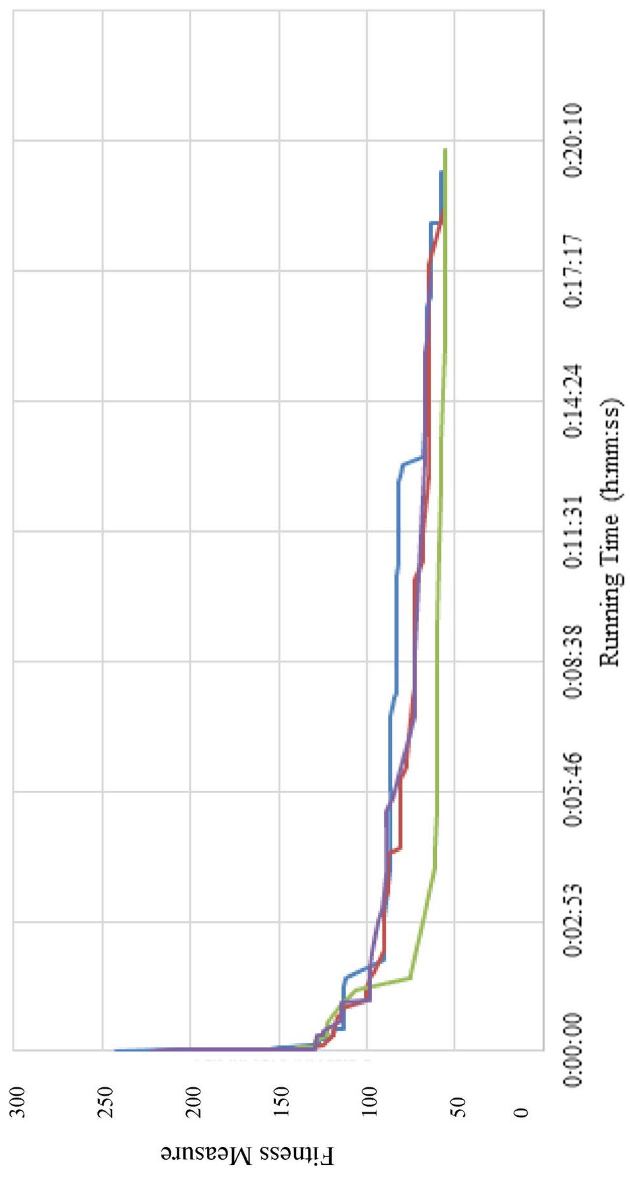

Fig. 3 Time evolution for indicative combinations of GA

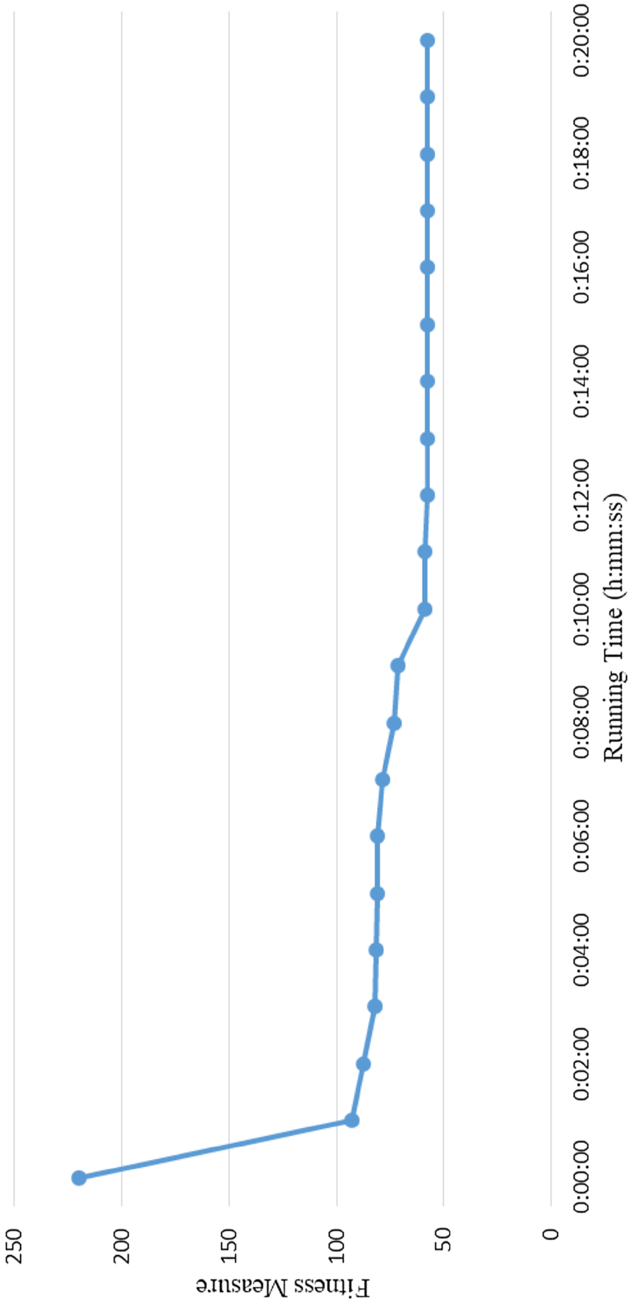

Fig. 4 Time evolution for best combination of GA

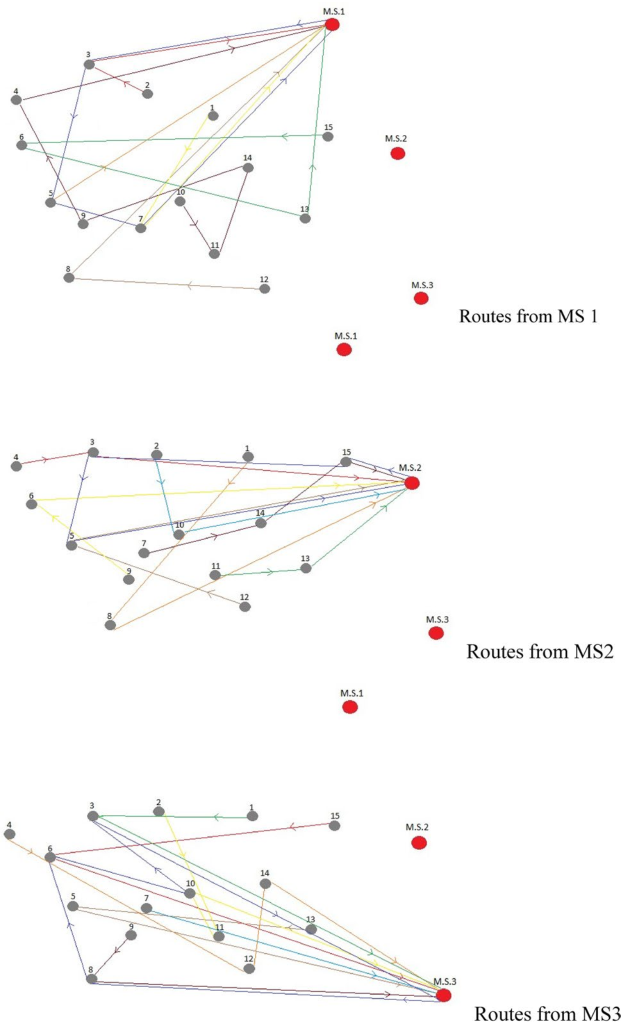

Fig. 5 Design of feeder routes

4.5 Sensitivity analysis

4.5.1 Problem parameters

Sensitivity analysis was carried out for three major problem parameters: operating speed, capacity, and passenger demand. Figure 6 illustrates the impact of changing these variables on the fitness value and the number of required routes. As expected, an increase in vehicle operating speed results in a smaller fitness value, as travel time decreases. Moreover, the number of routes does not vary with changes in the operating speed, as the latter only affects travel time and capacity constraints are binding. For bus

Table 5 Feeder Route Network

Metro station	Route number	Stop sequence	Duration (h)
Dafni (MS 1)	1	10–11–14–9–4–MS 1	0.41
	2	2–3–MS 1	0.21
	3	12–8–MS 1	0.25
	4	5–MS 1	0.20
	5	1–7–MS 1	0.17
	6	15–6–13–MS 1	0.35
	7 (additional)	MS 1–3–5–7–MS 1	0.17
	1	7–14–15–MS 2	0.25
Agios Ioannis (MS 2)	2	4–3–MS 2	0.16
	3	12–5–MS 2	0.27
	4	1–8–MS 2	0.25
	5	9–6–MS 2	0.21
	6	11–13–MS 2	0.21
	7	2–10–MS 2	0.19
	8 (additional)	MS 2–15–3–5–MS 2	0.30
Agios Dimitrios (MS 3)	1	9–8–MS 3	0.18
	2	15–6–MS 3	0.29
	3	13–5–MS 3	0.31
	4	4–12–14–MS 3	0.27
	5	2–11–10–MS 3	0.20
	6	1–3–MS 3	0.24
	7	7–MS 3	0.15
	8 (additional)	MS 3–8–6–10–3–MS 3	0.20

Table 6 Average travel time per passenger (h) for each metro station

	RT + ST	RT + ST + WT
MS 1	0.2	0.2
MS 2	0.2	0.21
MS 3	0.18	0.19

capacity, a rise in the number of available seats leads to smaller fitness values as well as fewer routes required to satisfy passenger demand. On the other hand, a reduction in capacity leads to higher values for the fitness value and the number of routes. The changes in fitness, however, are less significant when capacity exceeds 45 compared to smaller values where the increase in fitness may be more than 100%.

Finally, as can be seen in Fig. 6, decreasing demand results in smaller values for the fitness value and the number of routes, as expected. A 10% increase in demand leads to an increase of almost 75% in fitness, while the effect is similar for a 20% increase in demand. In the case of route number, the overall trend seems linear, with the number of routes consistently increasing as demand increases.

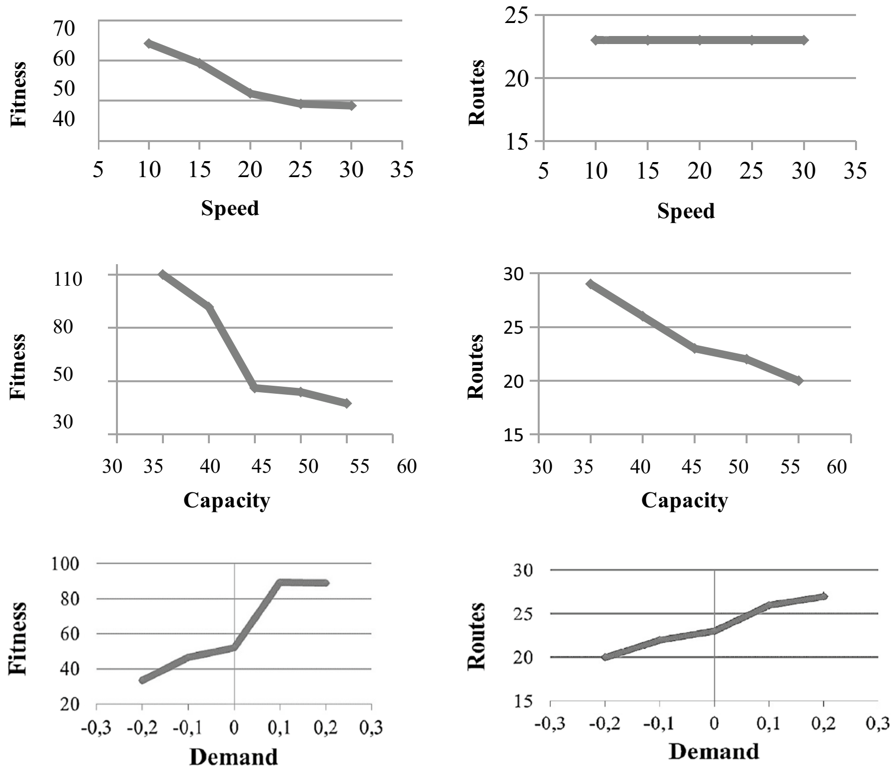

Fig. 6 Sensitivity analysis results for different speed, capacity and demand levels

4.5.2 Objective function weights

Sensitivity analysis was also conducted for the weights of the objective function components. Ten indicative combinations were explored for the weighting used coefficients. In all cases, five 15-min runs were carried out for each parameter combination to obtain the average characteristics of the best route sets for each objective. Results for each combination are shown in Fig. 7.

Figure 7 shows the changes in each of the objective function terms in relation to the weighting coefficients employed; the latter are shown using stacked column charts, while the values of each component are shown using lines. As can be seen in Fig. 7, travel time retains approximately the same value for all weight combinations. Similarly, the number of routes generally remains the same, except for the cases where the value of c (unsatisfied demand coefficient) is raised above 1. In this situation, the number of routes rises to 24 versus 23, as the higher number of routes allows for more passengers served at once. Interestingly, in these cases the travel time value slightly drops as well, as the service network design is more efficient due to allowing a higher number of shorter routes. Overall, it may be observed that determining appropriate weights for each of the three terms is mostly important with

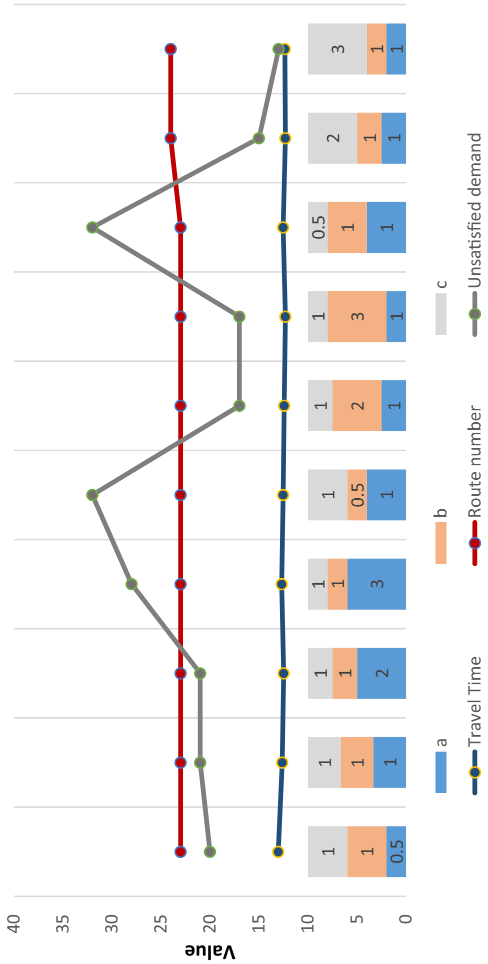

Fig. 7 Sensitivity analysis results for different weight combinations

respect to unsatisfied demand. Indeed, reducing the value of c below 1 as well as placing too much importance on travel time, i.e. increasing a above 1, will create route sets with higher unsatisfied demand values. This is once again considered reasonable, as the fitness value is used throughout the optimization process in parent selection and population replacement, where members are ranked based on fitness. Apparently, overly favoring solutions with lower travel times reduces diversity in the pool of candidate solutions and eliminates solutions which could potentially prove valuable (through evolution) later on in the search process.

5 Conclusions

This paper focused on the design of an efficient demand-responsive feeder network for the first/last mile problem. The proposed model contributes to the integration of DRT systems in public transportation which has so far been hindered by various operating and practical challenges. In order to realistically address the problem, a formulation that can handle cases of overwhelming demand or limited fleet availability was presented. A mathematical programming model was introduced and solved using a genetic algorithm. A parallel representation scheme was employed, enabling the concurrent optimization of more than one chromosome, providing flexibility and ability to easily incorporate changes in demand and network configuration in the model. The latter was demonstrated for the case of a residential area in Athens, Greece. The case study considered 15 bus stations and 3 metro stations, creating simultaneously three different networks, one for each metro station, requiring approximately 15 min to converge to a solution. Test results showed that under the proposed route network structure, passengers at higher demand stops experienced lower waiting times, while passengers on lower demand stops were served by longer routes. The proposed GA was tested against existing methods and was proven to be effective and computationally efficient, while sensitivity analysis demonstrated its robustness.

In general, the relatively short computational times highlight the potential of the model's application in real-world planning and operations of such DRT services. The proposed model is user friendly and is suitable for planners/administrative staff without technical skills as it is straightforward to implement and runs based on an Excel spreadsheet. The flexibility and efficiency of the proposed model provides a base for future research and improvements. These could include the introduction of additional design objectives (for example those related to comfort), the consideration of a concurrent location determination of bus stops with routes and the investigation of other algorithms for solving the problem at hand.

Appendix

See Figs. 8, 9 and 10.

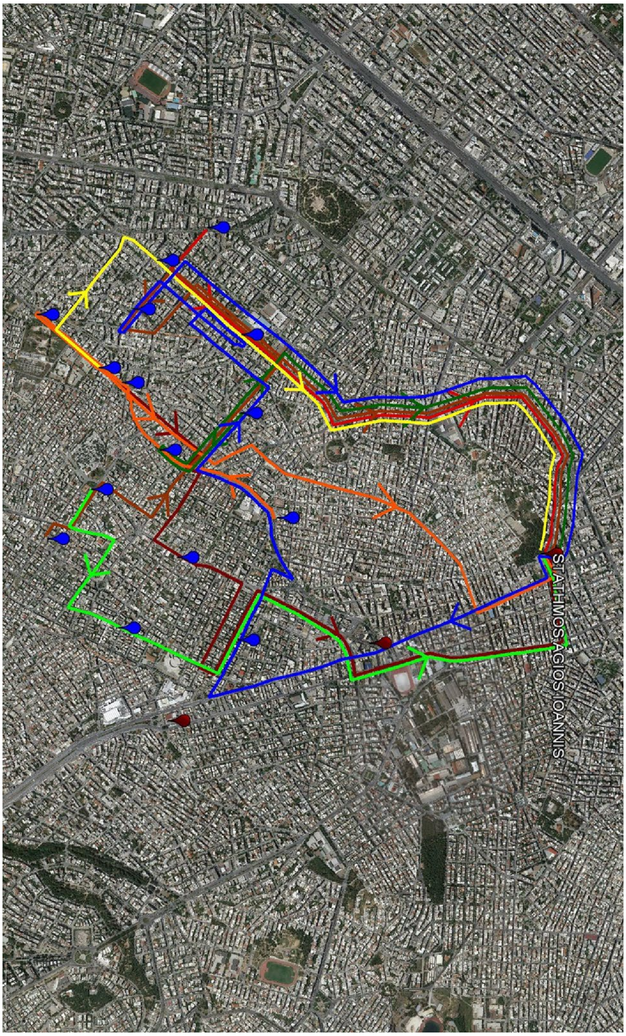

Fig. 8 Network for MS 1

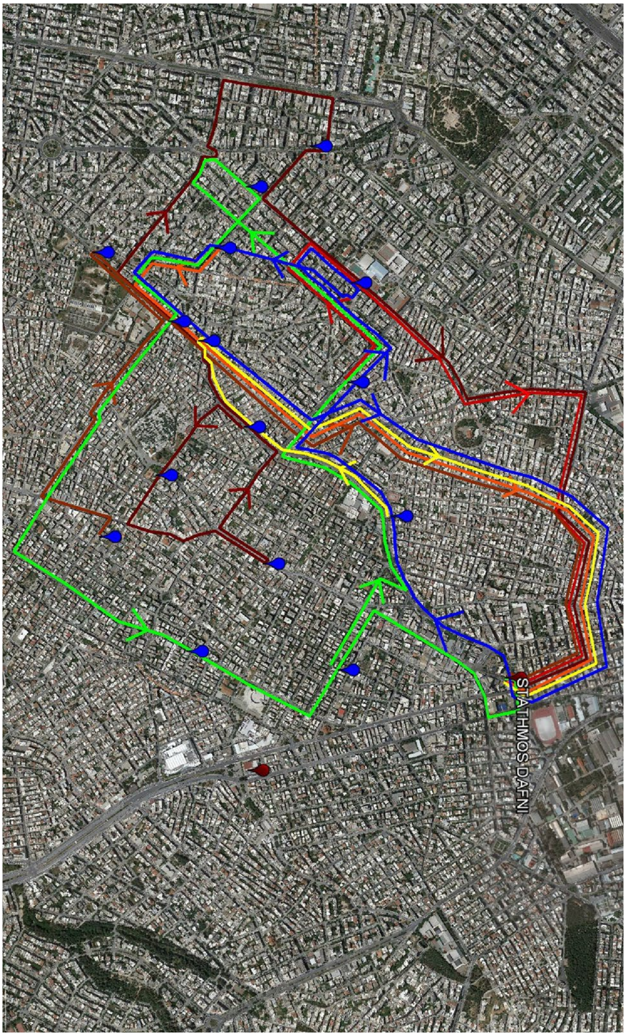

Fig. 9 Network for MS 2

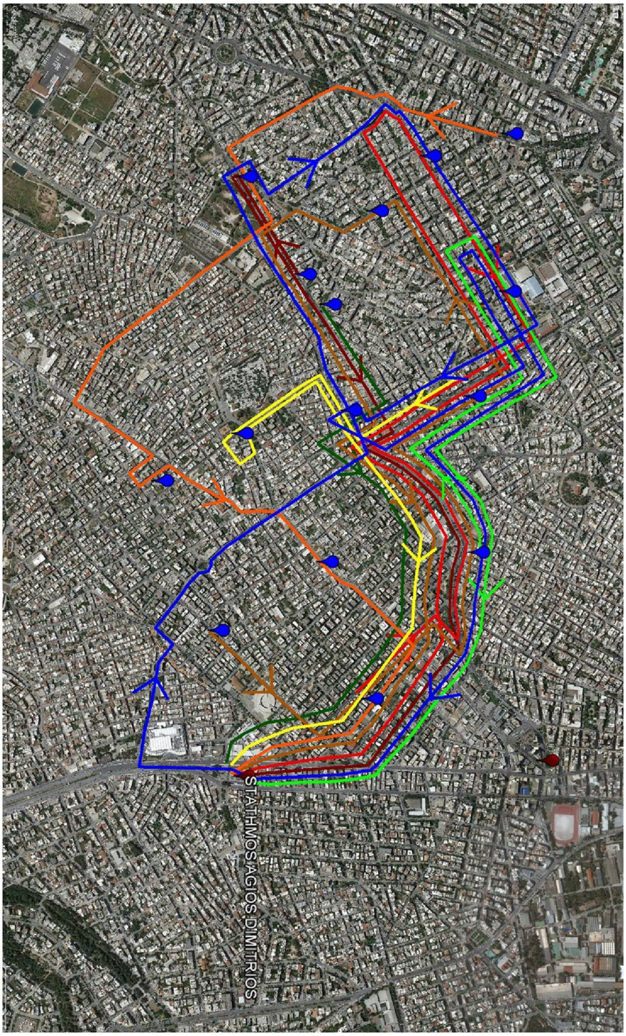

Fig. 10 Network for MS 3

References

Ambrosino G, Nelson JD, Romanazzo M (2004) Demand responsive transport services: towards the flexible mobility agency. ENEA, Italian National Agency for New Technologies, Energy and the Environment, Rome

Banister D (2008) The sustainable mobility paradigm. Transp Policy 15(2):73–80

Brake J, Mulley C, Nelson JD, Wright S (2007) Key lessons learned from recent experience with flexible transport services. Transp Policy 14(6):458–466

Chandra S, Quadrifoglio L (2013) A model for estimating the optimal cycle length of demand responsive feeder transit services. Transp Res Part B Methodol 51:1–16

Chapman L (2007) Transport and climate change: a review. J Transp Geogr 15(5):354–367

Chien S, Yang Z (2000) Optimal feeder bus routes on irregular street networks. J Adv Transp 34(2):213–248
Ciaffi F, Cipriani E, Petrelli M (2012) Feeder bus network design problem: a new metaheuristic procedure and real size applications. Procedia Soc Behav Sci 54:798–807
Davison L, Enoch M, Ryley T, Quddus M, Wang C (2014) A survey of demand responsive transport in Great Britain. Transp Policy 31:47–54
Deng LB, Gao W, Zhou WL, Lai TZ (2013) Optimal design of feeder-bus network related to urban rail line based on transfer system. Procedia Soc Behav Sci 96:2383–2394
Eiben AE, Smith JE (2003) Introduction to evolutionary computing. Springer, Berlin
Ewing RH (2008) Characteristics, causes, and effects of sprawl: a literature review. In: Urban ecology: an international perspective on the interaction between humans and nature. Springer, Boston, MA, pp 519–535
Faroqi H, Sadeghi-Niaraki A (2016) GIS-based ride-sharing and DRT in Tehran city. Public Transp 8(2):243–260
Golden B, Raghavan S, Wasil EA (eds) (2008) The vehicle routing problem: latest advances and new challenges. Springer, Berlin
Häll CH, Andersson H, Lundgren JT, Värbrand P (2009) The integrated dial-a-ride problem. Public Transp 1(1):39–54
Häll CH, Lundgren JT, Voß S (2015) Evaluating the performance of a dial-a-ride service using simulation. Public Transp 7(2):139–157
Haupt RL, Haupt SE (2004) Practical genetic algorithms. Wiley, New York
Holland J (1975) Adaptation in natural and artificial systems. MIT Press, Cambridge
Hu Y, Zhang Q, Wang W (2012) A model layout region optimization for feeder buses of rail transit. Procedia Soc Behav Sci 43:773–780
Jerby S, Ceder A (2006) Optimal routing design for shuttle bus service. Transp Res Rec 1971:14–22
Jih W-R, Hsu Y-J (2004) A family competition genetic algorithm for the pickup and delivery problems with time window. Bull Coll Eng 90:121–130
Konak A, Coit DW, Smith AE (2006) Multi-objective optimization using genetic algorithms: a tutorial. Reliab Eng Syst Saf 91(9):992–1007
Kuah GK, Perl J (1988) Optimization of feeder bus routes and bus-stop spacing. J Transp Eng 114(3):341–354
Kuah GK, Perl J (1989) The feeder-bus network-design problem. J Oper Res Soc 40:751–767
Kuan SN, Ong HL, Ng KM (2004) Applying metaheuristics to feeder bus network design problem. Asia Pac J Oper Res 21(4):543–560
Kuan SN, Ong HL, Ng KM (2006) Solving the feeder bus network design problem by genetic algorithms and ant colony optimization. Adv Eng Softw 37(6):351–359
Lane BW (2012) On the utility and challenges of high-speed rail in the United States. J Transp Geogr 22:282–284
Laws R, Enoch MP, Ison SG, Potter S (2009) Demand responsive transport: a review of schemes in England and Wales. J Public Transp 12(1):19–37
Lenstra JK, Rinnooy Kan AHG (1981) Complexity of vehicle routing and scheduling problems. Networks 11(2):221–227
Li X, Quadrifoglio L (2011) 2-Vehicle zone optimal design for feeder transit services. Public Transp 3(1):89–104
Li Y, Wang J, Chen J, Cassidy MJ (2007) Design of a demand-responsive transit system. California PATH program (No. UCB-ITS-PWP-2007-4). Institute of Transportation Studies, University of California at Berkeley, Berkeley
Litman T, Burwell D (2006) Issues in sustainable transportation. Int J Glob Environ Issues 6(4):331–347
Martins CL, Pato MV (1998) Search strategies for the feeder bus network design problem. Eur J Oper Res 106(2):425–440
Qiu F, Shen J, Zhang X, An C (2015) Demi-flexible operating policies to promote the performance of public transit in low-demand areas. Transp Res Part A Policy Pract 80:215–230
Shrivastava P, O'Mahony M (2006) A model for development of optimized feeder routes and coordinated schedules—a genetic algorithms approach. Transp Policy 13(5):413–425
Shrivastava P, O'Mahony M (2007) Design of feeder route network using combined genetic algorithm and specialized repair heuristic. J Public Transp 10(2):109–133
Steg L, Gifford R (2005) Sustainable transportation and quality of life. J Transp Geogr 13(1):59–69

Stiglic M, Agatz N, Savelsbergh M, Gradišar M (2016) Enhancing urban mobility: integrating ride-sharing and public transit. Comput Oper Res 90:12–21

Talbi EG (2009) Metaheuristics: from design to implementation, vol 74. Wiley, New York

Toth P, Vigo D (eds) (2014) Vehicle routing: problems, methods, and applications. MOS-SIAM Series on Optimization, 2nd edn. SIAM, Philadelphia

Zhao P (2010) Sustainable urban expansion and transportation in a growing megacity: consequences of urban sprawl for mobility on the urban fringe of Beijing. Habitat Int 34(2):236–243