Optimizing urban transit routing problem base on Differential Evolution: A Case Study

Ahmed Tarajo BUBA[a*], Lai Soon LEE[b,]
[a,b]Department of Mathematics, Faculty of Science,
Universiti Putra Malaysia, 43400 UPM Serdang, Selangor, Malaysia.
[b]Laboratory of Computational Statistics and Operations Research, Institute for Mathematical Research,
Universiti Putra Malaysia, 43400 UPM Serdang, Selangor, Malaysia.

Abstract

In this paper, the urban transit routing problem (UTRP) is addressed for a realistic urban transport network. Given the road network infrastructure and the demand, the problem consists in designing routes such that the service level as well as the operator cost are optimized. The optimality of the service level is measured in terms of average journey time and the route set length. A differential evolution (DE) metaheuristic is proposed to solve the UTRP. The proposed algorithm produces a solution that improves closer to the lower bound cost of the passenger and the operator. In addition, the proposed algorithm produces approximate Pareto fronts that enable the transit operator to evaluate the trade-off between operator costs and passenger costs.

Keywords:

Transit network design, Differential evolution, Transit routing problem

1. Introduction

Over the years, public transportation system plays a significant role in daily lives of people in many cities of the world. With the rise in population and urbanization of many cities, especially in developing and emerging countries, have led to the increase in travel demand. As a result, there are significant increase of usage of private vehicles for daily commuting in urban and suburban areas. These issues had contributed to the problems including constant traffic congestion, excessive and unreliable travel times, stress, greenhouse gas (GHG) emissions and noise, more traffic accidents and energy consumption among others. One of the most viable solution to handle these problems is to improve the public transport systems and raise their attractiveness. This can be achieved through proper design of bus transit networks that takes into account the interest of the user and the operator. In practice, improving the efficiency of public transport is an often-stated goal of transportation policy in big cities because only efficient public transport can successfully compete with private vehicles and thus help to reduce the increasing traffic congestion.

One of the most important challenges confronting urban transit planners is to achieve suitable (viable) transportation systems that can accommodate these huge urban travel demands. With regard to the capacities of urban highways in many cities of the world, one can easily conclude that the use of private personal vehicles cannot handle the large numbers of urban travel demands. Rather, the most viable solution to address the demand in such cities is to utilize public transportation systems at different levels of operation. In addition, a number of benefits can be secured through the public transport usage including reduction of energy consumption, congestion, and carbon emissions among others. However, in many cities of the world, public transport has suffered under funding leading to low patronage with many transit users opting for private vehicle usage for comfortable and more convenient journey (John, 2014).

In this paper, the DE metaheuristic, which has been proposed by Storn and Price (1995) to solve global optimization problems over continuous space is adapted to solve the UTRP from multiobjective perspective. Over the years DE has been successfully applied to a wide range of optimization problems (Das and Suganthan, 2011).The key objectives of the problem are minimizing the average travel time of the passengers and the total route set length of the operator. The proposed algorithm is applied to a realistic transit network, whereby an approximate Pareto optimal set is produced that allows the decision maker to select the best suited solution.

2. Literature Review

A comprehensive coverage of the previous work on route generation and improvement algorithms are provided in the review papers (Guihaire and Hao (2008), Farahani et al. (2013), Ibarra-Rojas et al. (2015, Buba and Lee (2016a)). Heuristic and metaheuristic algorithms are dominantly used for the optimization of UTRP in the literature.

Pattnaik et al. (1998) presented a two phase GA in the UTNDP. The design is done in two phases. First, a set of candidate routes competing for the optimum solution is generated. Second, the optimum set is selected using a GA. Two coding schemes are developed, namely, fixed string length coding and variable string length coding. The GA is solved by adopting the two coding schemes proposed in the study. Fixed string length predefines a solution route set size, and attempts to find that best routes from the candidate route set. The route set size is varied iteratively to find the optimum route set. On the other hand, variable string length can handle simultaneously selection of the route set size and the set of routes, but this requires complex coding. The model is applied to a case study network that is a part of a real network. If computation time is not a constraint, the fixed string length model is found to be slightly superior to the variable string length model.

Chakroborty and Wivedi (2002) introduced an optimization algorithm procedure based on the principles of GA, which evolves "optimal" or "efficient" transit route sets for a given road network and transit demand data from an initial set of routes. The procedure is used to determine "optimal" route sets for a real world network used as a benchmark by several authors. The results show that the proposed method performs substantially better than the existing procedures.

Ngamchai and Lovell (2003) proposed a model that uses a GA to optimize the bus transit route design, incorporaing unique service frequency settings for each route. The proposed GA uses seven new genetic operators in integer representation. The model designs the bus routes by the route improvement algorithm using genetic operators, and coordination of headways to improve the efficiency of the network. The proposed model proved to be more efficient than a binary coded GA.

Fan and Mumford (2010) devised a model of the UTRP, in which candidate routes are evaluated. The objective is to minimize the weighted sum of overall passenger travel time and number of transfers. HC and SA are employed to solve the problem using Mandl's Swiss network. The potential for tackling larger problem instances is also explored. Computational results demonstrate that the average solution obtained for SA is slightly better than HC, however the results produced by both HC and SA are competitive with other previous approaches in the literature.

Chew et al. (2013) solved a bi-objective UTRP utilizing GA. Passengers' and operators' costs are optimized, and the quality of route sets are evaluated by a set of parameters. The proposed algorithm employs an adding-node procedure to convert an infeasible solution to a feasible one. A simple yet effective route crossover and identical-point mutation are proposed to perform the genetic operations. The biobjective UTRP is executed by switching the objective function after the first objective has converged. The proposed GA is tested on benchmark Mandl's Swiss network and the results outperform the previous best published results from the literature in most cases.

Nikolić and Teodorović (2013) developed a BCO algorithm for the UTRP. The objectives are to maximize the number of satisfied passengers, to minimize the total number of transfers, and to minimize the total travel time of all served passengers. The methodology includes generating the initial solution using a simple greedy algorithm and subsequently employed the improvement version of the BCO. The numerical experiments are performed on known benchmark problems indicating that the BCO algorithm approach is competitive with other approaches in the literature, and it can generate high quality solutions.

Kechagiopoulos and Beligiannis (2014) designed and presented a PSO for solving the UTRP with emphasis on appropriate representation of candidate solutions, and evaluation procedure. The methodology is aimed to achieve efficient solution of UTRP by considering the quality of service offered to each passenger as well as the operator cost. Results are compared on the basis of Mandl's Swiss network. The obtained results compared with other results published in the literature indicate that the proposed soft computing algorithm is competitive with existing approaches.

Nayeem et al. (2014) developed two versions of GA based model (GA with elitism and GA with increasing population) with inelastic demand to solve the UTRP by considering the following objectives: maximize the number of satisfied passengers, minimize the total number of transfers, and minimize the total travel time of all served passengers. GA with elitism is found to be competitive with Baaj and Mahmassani (1991), Chackroborty and Dwivedi (2002), and Nikolić and Teodorović (2013). In addition, GA with increasing population outperforms all previous results.

Kilić and Gök (2014) proposed a novel route generation algorithm based on travel demand for public transit network design. The initial route sets are generated based on link usage statistics of the transit network. Hill climbing and tabu search algorithms are utilized to test the algorithms calibrated on Mandl's Swiss network and four large networks presented in Mumford (2013). The experiments conducted on the larger networks indicate that the results obtained are better, interms of the average travel time, direct transfer, and passenger cost values as compared to Mumford (2013).

Most recently, Buba and Lee (2016b) proposed a DE with the aim of minimizing the average travel time of all served passengers. Computational experiments performed on the benchmark Mandl's Swiss network show that the proposed DE is competitive to other approaches in the literature.

3. Problem Definition and Formulation

The urban transit routing problem (UTRP) involves the development of transit routes on an existing road network with associated link travel times and predefined demand (stop) points, such that the routes optimally satisfy some user-defined objectives, subject to the constraints.Generally, passengers would prefer to travel to their destination within the shortest time possible, but avoiding the discomfort associated with too many transfers. The passenger cost for a route set, $\mathfrak{R}$ is defined as the average journey time over all passengers, where the journey time consists of in-vehicle travel time plus transfer penalty. On the opposite, operator costs depend on many factors including the fleet size required to maintain the needed service level, the daily distance covered by the vehicles, vehicle operating hours and the cost of employing enough drivers.

The UTRP can be formally defined as in John et al. (2014). Given a road network represented as a graph $G = (V, E)$, where $V = \{v_1, \dots v_n\}$ is a set of vertices representing demand points (bus stops) and $E = \{e_1, \dots, e_m\}$ a set of edges representing street segments. The weight for each edge, W_e, defines the time it takes to traverse edge e_i, and matrix $D_{n\times n}$ such that D_{v_i,v_j} gives the passenger demand between a pair of vertices v_i and v_j are also known.

Let $G_R = (V_R, E_R)$ be the subgraph formed by a route R_i, where a route R_i is defined as a simple path (i.e. no loops/repeated vertices) through the graph G . A solution is defined as a set of overlapping routes $\mathfrak{R} = \{R_1, \dots, R_r\}$ where r, is the size of routes in route set to be prespecified by the service provider due to resource limitation. The length of R_i is measured by the minimum (m_1) and maximum (m_2) number of vertices for service quality. Additionally, Let $\tau_{i,j}(\mathfrak{R})$ denote the shortest journey time from any pair of vertices (v_i, v_j) using route set $\mathfrak{R}$ calculated using Dijkstra's algorithm (Dijkstra, 1959), which consist of in-vehicle travel and transfer penalty. Therefore, for a given origin-destination (O-D) matrix $D_{n\times n}$ that represents demand among these vertices together with a travel time matrix TR, where tr_{ij} is the in-vehicle travel time between vertices i and j. The multiobjective UTRP is to determine a set of transit route networks that minimizes the equations (1) and (2) while meeting all the requirements and constraints of equations (3) – (6).

$$\min \quad C_p(\mathfrak{R}) = \frac{\sum_{i,j=1}^{n} D_{ij}\tau_{ij}(\mathfrak{R})}{\sum_{i,j=1}^{n} D_{i,j=1}}, \tag{1}$$

$$\min \quad C_o(\mathfrak{R}) = \sum_{\forall R_i \in \mathfrak{R}} \sum_{\forall e_{j\in R_i}} W_{e_j}, \tag{2}$$

subject to

$$m_1 \le |V_{R_i}| \le m_2 \quad \forall R_i \in \mathfrak{R}, \tag{3}$$

$$|\mathfrak{R}| = r \tag{4}$$

$$G_R = (\cup_{i=1}^{|\mathfrak{R}|} V_{R_i}, \cup_{i=1}^{|\mathfrak{R}|} E_{R_i}) \text{ is connected} \tag{5}$$

$$\cup_{i=1}^{|\mathfrak{R}|} V_{R_i} = \mathrm{V}. \tag{6}$$

The equation (1) is the passenger cost (C_p) for a route set $\mathfrak{R}$, defined as the average journey time over all passengers and equation (2) is the operator cost (C_p) defined by total route set length. Constraint (3) specifies that each route should contain between m_1 and m_2 vertices. Constraint (4) ensures that the solution contains the correct number of routes. Constraint (5) ensures that all vertices in V are in at least one route in $\mathfrak{R}$. Constraint (6) specifies that a path exists between all pairs of vertices in G_R. If Constraint (6) is satisfied then

$$G_R = \left(V, \bigcup_{i=1}^{|\mathfrak{R}|} E_{R_i}\right).$$

For this problem formulation, the following assumptions are also made:

1. Each route in the route set is free from repeated nodes. Hence, no cycles or backtracks should be allowed in the individual routes.
2. All nodes must be included in the route set to form a complete route set.
3. The demand, travel time, and distance matrices are symmetrical along the same route.
4. The demand level is inelastic throughout the period of the study and passenger choice of routes is based on the shortest travel time.
5. The policy headway is relaxed. It is assumed there are adequate vehicles and capacity, and total travel time consist only of in-vehicle travel time plus transfer penalties at five minutes for each transfer.

For the UTRP, this travel time includes in-vehicle time, and transfer penalty that is equal to 5 minutes per passenger.

4. DE for Multiobjective UTRP

In this study, because of the multiobjective nature of the UTRP, both passenger and operator costs are considered to solve the UTRP.Inspired by Chew et al. (2013), the implementation of the proposed DE algorithm consists of alternating the objective only when the entire population of the first objective (C_p) has converged. Therefore, the algorithm will only switch once and both of the objectives will start with the same initial population that has been recorded earlier.

4.1 DE Framework for the Multiobjective UTRP

The proposed DE for the multiobjective UTRP is carried out analogous to the work of Mumford (2013). Each individual is a route set also known as a vector in DE terminology from the given road network. The construction heuristic proposed in Mumford (2013) is employed to generate the initial population. The improved sub-route reversal (iSRR) repair mechanism is incorporated to deal with infeasible route set. The detailed description of the proposed DE is provided below.

STEP 1: Generate an initial population of N_p solution vectors based on the construction algorithm in Mumford (2013) by incorporating the iSRR repair mechanism to deal with the infeasible vectors.

STEP 2: During the generation G, for a *Target* vector $X_{i,G} = (x_{1,i,G}, x_{2,i,G}, \ldots, x_{d,i,G})$, where i = 1, d represents d-components in the d-dimensional space; a random vector is selected from the population (except the selected *Target* vector) and an identical point mutation proposed in Ngamchai and Lovell (2003) is applied on the random vector to generate a *Noisy Random* vector, $V_{i,G}$. If $V_{i,G}$ is infeasible, the iSRR is invoked to correct the infeasibility.

STEP 3: To increase the diversity of the *Target* and *Noisy Random* vectors, the uniform route crossover (Beasley et al., 1993) is introduced. A pair of *Trial* vectors, $U_{i,G}$ is generated through selecting the vector component values either from the *Target* vector, $X_{i,G}$ or the *Noisy Random* vector, $V_{i,G}$ using a 0/1 crossover mask where each sub-route in the *Trial* vector is constructed by copying the corresponding sub-route either from the *Target* or the *Noisy Random* vector. If$U_{i,G}$ is(are) infeasible, the iSRR is introduced.

STEP 4: After the crossover, the objective function values corresponding to the *Trial* vectors, $U_{i,G}$ are evaluated and compared with that of the *Target* vector, $X_{i,G}$.

STEP 5: An elitism selection strategy is employed, where the best vector with the lowest fitness value between the *Target* vector, $X_{i,G}$ and the *Trial* vectors, $U_{i,G}$ will be selected for the next generation. Repeat **STEP 2** – **STEP 4** for i= 2,…,N_p to complete one generation.

STEP 2 – STEP 5 are repeated until the termination criterion (e.g., maximum generation, execution time, etc.) is met. The framework of the proposed DE for solving the UTRP is shown in Algorithm 1.

Algorithm 1: DE for UTRP

```
Generate N_p candidate route set based on heuristic in Mumford (2013) with iSRR repair mechanism
for i := 1 to N_p
    fitness evaluation
end for
for n := 1 to G
    for i := 1 to N_p
        set Target vector = X_{i,n}
        select randomly a vector (except the selected Target vector, X_{i,n}) in the population
        apply identical point mutation to generate a Noisy Random vector,V_{i,n} (repair if infeasible)
        apply uniform crossover between X_{i,n} and V_{i,n} to generate a pair of Trial vectors, U_{i,n} (repair if infeasible)
        fitness evaluation of U_{i,n}
        elitism selection
        if Trial vector fitness ≤ Target vector fitness
            new_population [i] = Trial vector, U_{i,n}
        else
            new_population [i] = Target vector, X_{i,n}
    end for
    N_p = new_population
end for
return BEST
```

4.2 Route Set Representation

Each individual is a route set also known as a vector in DE terminology from the given road network. A route set is represented as a single integer vector of lists. For instance, the Mandl's Swiss network (Mandl, 1980) with 15 nodes is denoted by integers from 0 to 14. For example, in Figure 1 below, there are four routes in the route set (vector) where the iterinary along the first route is either first visit node 0, follow by node 1, then node 3, and finally node 4 or in reverse order. This can also be represented using the notation 0 – 1 – 3 - 4 for the first route. A sample vector containing 4 routes (separated with "*") is shown in Figure 1.

0 1 3 4*1 3 11 10 9 6 14 8*11 10 12 13*10 11 3 1 2 5 7

Figure 1: A sample route set (vector) with 4 routes

4.3 Initial Population

The construction heuristic proposed by Mumford (2013) is utilized to generate the initial population. The iSRR mechanism is incorporated into the heuristic to correct the infeasible route set. In the UTRP, a complete route set is composed of at least two routes generating from a list of nodes. Thus, to initialize the population, the nodes are listed in the order in which they are visited in integer vector ordered list where each route is separated by an '*' (see Figure 1). In the literature, the length of a typical route is commonly measured by the number of nodes it contains. One of the important assumptions is that a typical route must contain two or three nodes as the minimum number of nodes of a feasible route set and a maximum number of nodes to be predefined by the operator.

4.4 Route Set Evaluation

Each vector or particle is represented using single integer vector ordered list, which constitute a route set. A fitness evaluation is used to evaluate the fitness value of a vector or particle according to the objective function. The fitness value will determine the quality of solutions and enables them to be compared. Recall the components of objective functions (1) and (2). Therefore, in fitness evaluation function, each route set will go through Dijkstra's algorithm (Dijkstra, 1959) to calculate the shortest path of the route set for every O-D pairs. The Dijkstra's algorithm has the capability to search for alternative route(s) with same distance which is important due to the fact that different path might require different number of transfer(s) in a route set of which the transfer penalty will affect the total travel time of the passengers.

The assumption is that every passenger would want to travel through the shortest path. However, in a route set there might be a possibility of having more than one route sharing the same shortest distance. Note that the total travel time includes a five-minute penalty waiting time each time a passenger makes a transfer. Therefore, to calculate the total travel time for each passenger, we assume that the passenger will take into account the transfer waiting times when choosing their travel path. Undoubtedly, passenger will always prefer to avoid transfers and travel in a shorter time period. Finally, the value of average travel time can be obtained by dividing the total travel time with total demand.

4.5 Input data

In this section, the proposed algorithm is implemented on a real size Nigeria network, in order to compare its effectiveness with the performance of the existing transit network. The study network is a small and dense city in Nigeria. The road network is composed of 30 nodes and 44 bidirectional links (see Figure 2). The "Key" associated with Figure 2 describes the bus stop and its corresponding location (abbreviated) within the city. The existing network is comprised of 15 routes with many overlapping routes. In the peak hour, the transit demand is composed by 422,186 units. The highest node pair travel demand is 4800 units. Both travel demand and travel time matrices have a "many-to-many" structure and are provided in Tables 1 and 2.

The specific parameter values used for the considered real case network include:

i. Transfer penalty: 5 min
ii. Minimum number of nodes in each route: 2
iii. Maximum number of nodes in each route: 15

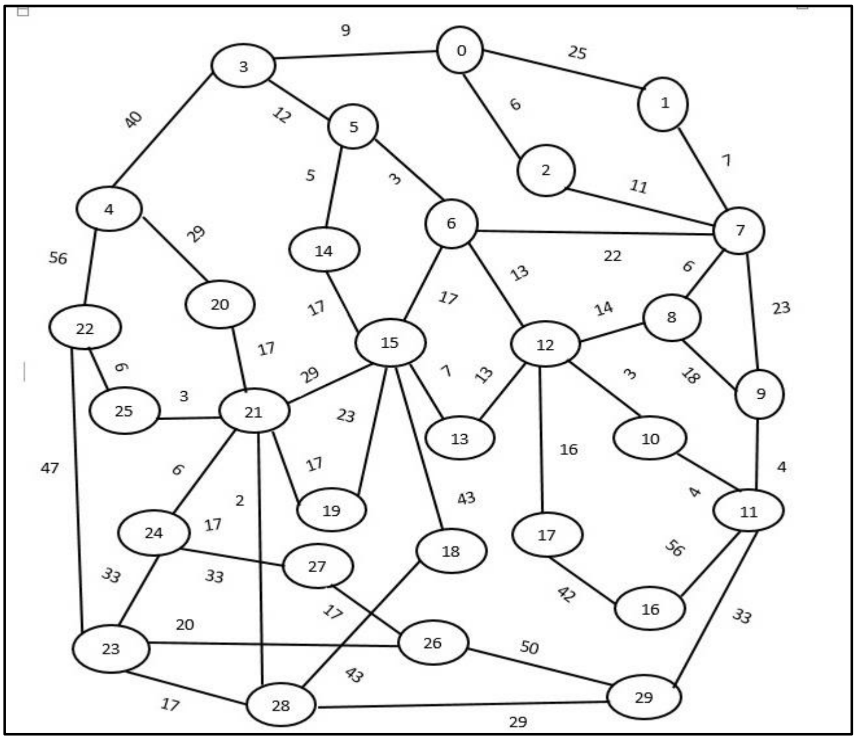

Figure 2: Real transit network

Table 1: Network Travel Time

0	25	6	9	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf
25	0	inf	inf	inf	inf	inf	7	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf
6	inf	0	inf	inf	inf	5	11	8	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf
9	inf	inf	0	40	12	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	14	inf	inf	inf	inf	inf	inf	inf	inf
inf	inf	inf	inf	0	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	29	inf	56	inf	inf	inf	inf	inf	inf	inf
inf	inf	inf	12	inf	0	3	inf	inf	inf	inf	inf	inf	inf	5	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf
inf	inf	5	inf	inf	3	0	22	inf	inf	inf	inf	13	inf	inf	17	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf
inf	7	11	inf	inf	inf	22	0	6	23	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf
inf	inf	8	inf	inf	inf	inf	6	0	18	inf	inf	14	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf
inf	inf	inf	inf	inf	inf	inf	23	18	0	inf	4	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf
inf	inf	inf	inf	inf	inf	inf	18	inf	inf	0	4	3	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf
4	4	inf	inf	inf	inf	inf	inf	inf	4	4	0	inf	inf	inf	inf	56	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	33
inf	inf	inf	inf	inf	inf	13	inf	14	inf	3	inf	0	13	inf	inf	inf	16	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf
inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	13	0	inf	7	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf
inf	inf	inf	inf	inf	5	inf	inf	inf	inf	inf	inf	inf	inf	0	17	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf
inf	inf	inf	inf	inf	inf	17	inf	inf	inf	inf	inf	inf	7	17	0	inf	inf	43	23	inf	29	inf	inf	inf	inf	inf	inf	inf	inf
inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	56	inf	inf	inf	inf	0	42	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf
inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	16	inf	inf	inf	42	0	56	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf
inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	43	inf	56	0	inf	inf	41	inf	inf	inf	inf	inf	inf	43	inf
inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	23	inf	inf	inf	0	inf	17	inf	inf	inf	inf	inf	inf	inf	inf
inf	inf	inf	inf	29	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	0	16	inf	inf	inf	inf	inf	inf	inf	inf
inf	inf	inf	14	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	29	inf	inf	41	17	16	0	9	inf	6	3	inf	34	2	inf
inf	inf	inf	inf	56	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	9	0	47	inf	6	inf	inf	inf	inf
inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	47	0	33	inf	20	inf	17	inf
inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	6	inf	33	0	inf	inf	33	inf	inf
inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	3	6	inf	inf	0	inf	28	inf	inf
inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	20	inf	inf	0	17	inf	50
inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	34	inf	inf	33	28	17	0	inf	inf
inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	43	inf	inf	2	inf	17	inf	inf	inf	inf	0	29
inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	33	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	50	inf	29	0

Table 2: Network Travel Demand

0	120	400	130	420	200	500	1200	850	100	115	550	200	1800	100	1300	2000	750	115	130	1200	115	120	850	135	1400	1250	1315	105	750
120	0	615	820	2000	1250	820	2150	2200	2400	960	715	1352	782	133	1052	132	163	165	136	108	1265	312	162	185	143	165	106	113	102
400	615	0	1143	1555	1078	108	1558	1632	1432	1645	128	423	1135	95	763	1185	85	93	0	1105	1700	0	1500	325	240	86	1420	86	50
130	820	1143	0	1423	1650	1725	1950	1850	136	75	124	108	1165	50	1620	0	50	30	40	320	1253	35	1730	483	425	480	1113	82	20
420	2000	155	1423	0	1735	312	56	50	0	32	24	324	35	23	40	362	43	46	375	286	1825	20	0	362	317	376	0	42	15
200	1250	1078	1650	1735	0	50	2200	2200	465	535	615	635	2850	30	1263	1320	512	685	425	1535	1260	425	1740	235	86	422	1325	30	30
500	820	108	1725	312	50	0	1350	1400	322	386	300	315	1520	50	1435	1263	725	1125	80	410	1320	440	1520	56	50	315	1170	200	40
1200	2150	1558	1950	56	2200	1350	0	1435	1325	215	360	390	1380	70	382	230	185	200	325	300	1700	60	176	40	56	60	615	63	145
850	2200	1632	1850	50	2200	1400	1435	0	735	800	815	786	900	120	985	125	143	156	60	300	1850	86	800	75	90	60	220	65	230
100	2400	1432	136	0	465	322	1325	735	0	65	86	36	1550	135	843	300	346	295	175	73	1600	73	985	85	40	245	845	63	150
115	960	1645	75	32	535	386	215	800	65	0	30	40	1500	150	685	815	421	232	135	85	1925	60	1235	63	72	58	814	43	70
550	715	128	124	24	615	300	360	815	86	30	0	60	1255	76	415	465	390	490	150	70	1750	70	685	45	68	110	615	120	165
200	1352	423	108	324	635	315	390	786	36	40	60	0	1450	60	785	1125	1400	1485	285	75	1850	83	765	146	125	170	915	115	132
1800	782	1135	1165	35	2850	1520	1380	900	1550	1500	1255	1450	0	215	483	213	235	0	250	20	2300	73	0	35	140	85	0	40	50
100	133	95	50	23	30	50	70	120	135	150	76	60	215	0	125	175	132	140	150	0	395	245	165	319	213	58	327	107	238
1300	1052	763	1620	40	1263	1435	382	985	843	685	415	785	483	125	0	50	55	62	43	38	1200	72	0	85	93	73	78	60	50
2000	132	1185	0	362	1320	1263	230	125	300	815	465	1125	213	175	50	0	272	275	200	0	1365	169	620	68	146	0	0	63	582
750	163	85	50	43	512	725	185	143	346	421	390	1400	235	132	55	272	0	483	125	0	982	240	0	152	140	0	0	150	385
115	165	93	30	46	685	1125	200	156	295	232	490	1485	0	140	62	275	483	0	180	0	1400	140	0	72	255	0	0	130	232
130	136	0	40	375	425	80	325	60	175	135	150	285	250	150	43	200	125	180	0	0	800	280	130	232	263	247	355	463	450
1200	108	1105	320	286	1535	410	300	300	73	85	70	75	20	0	38	0	0	0	0	0	722	62	460	165	372	360	420	135	220
115	1265	1700	1253	1825	1260	1320	1700	1850	1600	1925	1750	1850	2300	395	1200	1365	982	1400	800	722	0	585	1200	365	85	800	1110	525	1005
120	312	0	35	20	425	440	60	86	73	60	70	83	73	245	72	169	240	140	280	62	585	0	65	212	325	0	520	430	200
850	162	1500	1730	0	1740	1520	176	800	985	1235	685	765	0	165	0	620	0	0	130	460	1200	65	0	715	700	520	417	145	230
135	185	325	483	362	235	56	40	75	85	63	45	146	35	319	85	68	152	72	232	165	365	212	715	0	68	215	618	78	245
1400	143	240	425	317	86	50	56	90	40	72	68	125	140	213	93	146	140	255	263	372	85	325	700	68	0	420	735	86	235
1250	165	86	480	376	422	315	60	60	245	58	110	170	85	58	73	0	0	0	247	360	800	0	520	215	420	0	316	222	156
1315	106	1420	1113	0	1325	1170	615	220	845	814	615	915	0	327	78	0	0	0	355	420	1110	520	417	618	735	316	0	645	217
105	113	86	82	42	30	200	63	65	63	43	120	115	40	107	60	63	150	130	463	135	525	430	145	78	86	222	645	0	135
750	102	50	20	15	30	40	145	230	150	70	165	132	50	238	50	582	385	232	450	220	1005	200	230	245	235	156	217	135	0

4.6 Algorithm's Parameters and Evaluation Criteria

The arguments for algorithm's parameters are the ones proposed by Fan and Mumford (2010) in order to have a fair comparison between all algorithms' results. The performance or effectiveness of the proposed algorithm is evaluated using the same parameters adopted by several researchers in the literature (Mandl (1980); Baaj and Mahmassani (1991); Chakroborty and Dwivedi (2002); Fan and Mumford (2010); Nikolić and Teodorović (2013); Kechagiopoulos and Belligiannis (2014)):

- d_o - the percentage of demand satisfied without any transfers,
- d_1 - the percentage of demand satisfied with one transfer,
- d_2 – the percentage of demand satisfied with two transfers,
- d_{un} – the percentage of demand unsatisfied,
- ATT – average travel time in minutes per transit user (mpu),

5. Computational Results

5.1 Experimental Design

The algorithms are coded in Python 2.7.6.4 and executed on a 1.60 GHz Intel Core™i5-4200 CPU with 4.00 GB of RAM under Windows 8.1 environment. A population size of 30 vectors and 200 generations is used for the computation. The algorithm terminates when no improvement is observed over 50 consecutive generations.

5.2 Experiments with Real Data

In solving the UTRP, the proposed DE algorithm is applied on the real case network aiming to redesign the existing transit routes. We notice that because reference solution (i.e. the solution operated by the public transportation system of the city) is not available to compare the result obtained by the proposed algorithm. In addition, neither optimum solutions are known, nor any previous published results exist. In such a situation, a lower bound on the passenger's cost and the operator cost for the UTRP is computed as proposed in Fan and Mumford (2010). The lower bound (shown in brackets in Table 3) on the passenger cost is based on an ideal situation for passengers travelling on the transit network; namely, every passenger can travel to their destinations by the fastest (or shortest) path without any transfers. We calculate the ideal travelling path between each pair of nodes using Dijkstra's algorithm on the entire transit network, provided the number of nodes, travel time and travel demand between each pair are known. Thus, "ideal travel paths" between various pairs of nodes may or may not be attainable from a given route set. For the operator cost, the lower bound indicated in bold (Table 3) is found by using minimal spanning tree. It is easy to see in the lower bound situation the total number of shortest routes can be obtained by the following formulation (Fan 2009):

$$Total\ number\ of\ shortest\ routes = N(N-1)/2 \qquad (7)$$

where N is the total number of nodes in the transit network, at the same time, the Total-Transfer-Time is 0.

We conducted experiments using the formulations developed in Section 3 on a real-life network in Nigeria to obtain the best route set, having 15 routes (pre-specified by the transit operator). Table 3 shows the solutions produced by the proposed algorithm. The best route sets constructed by the proposed algorithm are given in Table 4 – 5. The approximate Pareto front achieved by the proposed DE for the real case network is shown in Figure 3 so that the decision maker can evaluate the best suited solution.

Unlike the previous work's in the literature, in which the demand is considered unsatisfied provided the passenger makes more than two transfers to reach his/her destination. We extend the level of the unsatisfied demand to more than five transfers to demonstrate the ability of the proposed algorithm to determine distribution of the transfer demand in a route set. In addition, in real-life situation, passengers will normally make more than two transfers and still consider such travel demand is satisfied.

From Table 3, the percentages of demand satisfied with three, four, and five transfers are denoted as d_3, d_4, and d_5, respectively. On the passenger, all demand are satisfied with at most 3 transfers, while 2.31% required more than 5 transfers on operator. It can be observed that if the percentage of demand with more than 2 transfers is considered unsatisfied, then on the operator it is 33.44% (i.e. 17.67+10.27+3.19+2.31), which is very high. Hence, it is reasonable to consider the percentage demand satisfaction to more than two transfers.

In addition, the results produced by the proposed algorithm for the passenger (C_p = 42.88) is relatively close to the lower bound (=38.90). From the operator perspective, the operator cost is higher by 22.37%. Furthermore, there is significant reduction operator cost from 3891 to 569, and this can be attributed to the higher percentage of demand satisfied. It can be concluded that the proposed DE algorithm is capable of constructing efficient transit routes.

Table 3: Best Results (15 routes) of Real-Life Network

Parameters	Proposed DE algorithm	
	Passenger	Operator
d_o	40.11	17.12
d_1	45.08	26.60
d_2	11.78	22.84
d_3	3.03	17.67
d_4	0.00	10.27
d_5	0.00	3.19
d_{un}	0.00	2.31
C_p	42.88(**38.90**)	60.83
C_o	3891	569 (**465**)

Table 4: Best Route Sets generated (for Passenger) by the proposed DE algorithm

Routes	Sequence of Routes

1	27-26-29-11-10-12-8-7-2-6-5-3-4-20
2	6-2-0-3-21-24-23-28-29-11-9-8-7-1
3	7-6-2-8-12-17-16-11-29-26-23-24-27-25-22
4	19-21-28-18-15-6-7-2-0-3-4-22-25-27-24
5	13-15-14-5-3-21-25-22-23-26-29-11-16-17-12
6	7-1-0-3-21-20-4-22-23-28-29-11-9-8-2
7	16-17-12-8-2-6-15-19-21-20-4-22-25-21
8	17-12-8-9-11-29-26-23-22-25-21-19-15-6-5
9	1-0-2-8-7-6-15-14-5-3-4-20-21-25-22
10	28-21-19-15-14-5-6-2-7-8-12-10-11-29-26
11	2-8-7-1-0-3-5-14-15-13-12-10-11-16-17
12	7-2-6-5-14-15-21-28-29-11-9-8-12-13
13	19-21-20-4-22-25-21-28-29-11-9-8-7-1-0
14	12-8-7-1-0-2-6-15-18-21-28-23-26-29-11
15	12-8-9-11-29-28-21-25-22-4-3-5-14-15-13

Table 5.: Best Route Sets generated (for Operator) by the proposed DE algorithm

Routes	Sequence of Routes
1	21-3-5-14
2	13-12-10
3	5-3
4	18-15-14
5	10-12-8
6	2-0-1
7	20-4-3-5
8	16-17-12-6-5
9	9-11-16
10	29-28-23-26-27-24
11	2-8-7
12	24-21-25-22
13	11-10
14	19-15-13
15	2-8

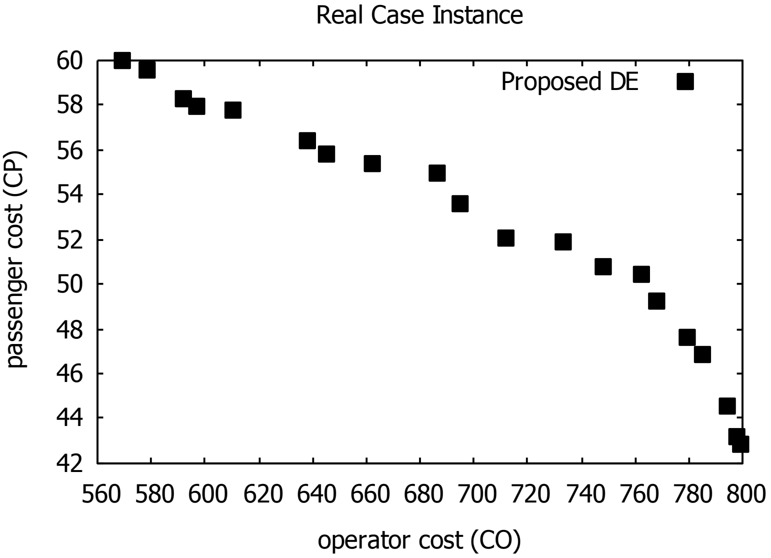

Figure 3: Approximate Pareto Fronts for Multiobjective UTRP

6. Conclusions and future work

This paper presents a differential evolution to solve the UTRP for a realistic urban transport network. The problem is modelled base on existing urban transport models in the literature.The results obtained indicate that the proposed DE give solutions that significantly improves over the service level and the operating cost closer to the lower bound costs established on the existing transit network.The efficiency of transit network depends on the configuration of transit routes and associated service frequency. In the future work, we aim to solve the transit network design and frequency setting problem simultaneously for the real data. In addition,expanding the components of the objective functions and the constraints of the current system to accommodate more complex and realistic transit scenarios will constitute part of our future research.We will also examine the optimal modification of some routes within the transit network at the expense of redesigning the existing transit network.

References

Baaj, M. H., and Mahmassani, H. S. (1991). An AI-based approach for transit route system planning and design. *Journal of advanced transportation,* 25(2): 187-209.

Beasley, D., Bull, D. R., and Martin, R. R. (1993). An overview of genetic algorithms: Part 2, research topics. *University Computing,* 15(4): 170-181.

Buba, T. A., & Lee, L. S. (2016a). Urban transit network design problems: A review of population-based metaheuristics. *Pertanika Journal of Scholarly Research Review*, 2(3), 86-99.

Buba, A. T., and Lee, L. S. (2016b). Differential evolution for urban transit routing problem. *Journal of Computer and Communications*, 4: 11-25.

Chakroborty, P., and Wivedi, T. (2002). Optimal Route Network Design for Transit Systems Using Genetic Algorithms. *Engineering Optimization,* 34(1): 83-100.

Chew, J. S. C., Lee, L. S., and Seow, H. V. (2013). Genetic Algorithm for Biobjective Urban Transit Routing Problem. *Journal of Applied Mathematics,* 2013. Article ID 698645, 15 pages.

Das, S., and Suganthan, P. N. (2011). Differential evolution: a survey of the state-of-the-art. *Evolutionary Computation, IEEE Transactions on,* 15(1), 4-31.

Dijkstra, E.W. (1959) A Note on Two Problems in Connexion with Graphs. *Numerische Mathematik,* **1**(1), 269-271.

Fan, L., Mumford, C. L. and Evans, D. (2009). A simple multi-objective optimization algorithm for the urban transit routing problem. *In IEEE Congress on Evolutionary Computation,* 1–7.

Fan, L., and Mumford, C. L. (2010). A metaheuristic approach to the urban transit routing problem. *Journal of Heuristics,* 16(3): 353-372.

Farahani, R. Z., Miandoabchi, E., Szeto, W. Y., & Rashidi, H. (2013). A review of urban transportation network design problems. *European Journal of Operational Research, 229*(2), 281-302.

Guihaire, V., & Hao, J.-K. (2008). Transit network design and scheduling: A global review. *Transportation Research Part A: Policy and Practice, 42*(10), 1251-1273.

Ibarra-Rojas, O., Delgado, F., Giesen, R., & Muñoz, J. (2015). Planning, operation, and control of bus transport systems: A literature review. *Transportation Research Part B: Methodological, 77*, 38-75.

John, M. P., Mumford, C. L., and Lewis, R. (2014). An improved multi-objective algorithm for the urban transit routing problem. In: Blum, C., Ochoa, G. (eds) *Evolutionary*

Computation in Combinatorial Optimisation. EVOCOP Lecture Notes in Computer Science, vol 8600. Springer, Berlin, Heidelberg.

Kechagiopoulos, P. N., and Beligiannis, G. N. (2014). Solving the urban transit routing problem using a particle swarm optimization based algorithm. *Applied Soft Computing,* 21: 654-676.

Kilić, F., and Gök, M. (2014). A demand based route generation algorithm for public transit network design. *Computers and Operations Research,* 51: 21-29.

Mandl, C. E. (1980) Evaluation and Optimization of Urban Public Transportation Networks. *European Journal of Operational Research*, **5**(6), 396-404.

Mumford, C. L. (2013). New heuristic and evolutionary operators for the multi-objective urban transit routing problem.*2013 IEEE Congress on Evolutionary Computation*, 939-946.

Nayeem, M. A., Rahman, M. K., and Rahman, M. S. (2014). Transit network design by genetic algorithm with elitism. *Transportation Research Part C: Emerging Technologies,* 46, 30-45.

Ngamchai, S., and Lovell, D. J. (2003). Optimal time transfer in bus transit route network design using a genetic algorithm. *Journal of Transportation Engineering,* 129(5): 510-521.

Nikolić, M., and Teodorović, D. (2013). Transit network design by Bee Colony Optimization. *Expert Systems with Applications*, 40(15): 5945-5955.

Pattnaik, S., Mohan, S., and Tom, V. (1998). Urban bus transit route network design using genetic algorithm. *Journal of Transportation Engineering,* 124(4): 368-375.

Storn, R. and Price, K. (1995). Differential Evolution-A Simple and Effective Adaptive Scheme for Global Optimization over Continuous Spaces. International Computer Science Institute, Berkeley, CA, *Technical Report* TR-95-012.