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Araştırma Makalesi Research Article

A BI-LEVEL ALGORITHM PROPOSAL FOR THE INITIAL PLANNING OF FEEDER BUS ROUTES

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Keywords

Feeder Bus Routes Planning, Multiple Traveling Salesman Problem, Genetic Algorithm.

Abstract

A sustainable urban transportation system uses different classes of transportation modes whose services should be well integrated. The Feeder Bus Route Network Problem (FBRNDP) is an important part of this integration. FBRNDP primarily deals with the provision of access to an existing mainline movement through feeder transit system usually to expand it's the service coverage. The multiple traveling salesman problem (MTSP) has similar properties with FBRNDP, thus, making the formulation of MTSP to be adoptable for feeder bus routes. In this study, a bi-level heuristic algorithm is developed to solve this problem by clustering demand nodes around nearest destination and using genetic algorithm (GA) based on fixed start MTSP to optimize the shortest distance the salesmen will have to travel to cover the service area. The algorithm compares well to the results of a case study found in literature and shows a promising way of designing feeder bus routes strictly based on the shortest distance and variation of the number of routes required. The proposed method can be useful in the initial planning of an integrated transit system and it may serve as a seed solution in a multi-objective optimization.

BESLEYİCİ OTOBÜS ROTALARININ ÖN PLANLAMASI İÇİN İKİ DÜZEYLİ BİR ALGORİTMA ÖNERİSİ

Anahtar Kelimeler

Besleyici Otobüs Rota Planlaması, Çoklu Seyahat Satıcısı Sorunu, Genetik Algoritma.

Öz

Sürdürülebilir bir kentsel ulaşım sisteminin, hizmetleri iyi entegre edilmesi gereken farklı ulaşım türlerini kullanması gerekmektedir. Besleyici Otobüs Rotası Ağ Tasarım Problemi (BORATP) bu entegrasyonun önemli bir parçasıdır. BORATP öncelikle hizmet kapsamını genişletmek için besleyici transit sistemi aracılığıyla mevcut bir ana hat hareketine erişim sağlanması ile ilgilenir. Çoklu seyahat eden satıcı problemi (ÇSESP), BORATP'ye benzer özellikler içermektedir ve bu nedenle ÇSESP formülasyonu besleyici otobüs rotalarının optimizasyonu için kullanılmaya uygundur. Bu çalışmada, BORATP'nin çözümü için talep noktalarını en yakın hedef etrafında kümeleyen ve satıcıların hizmeti kapsaması için seyahat etmesi gereken en kısa mesafeyi sabit başlangıçlı ÇSESP'ye dayalı bir genetik algoritma (GA) kullanarak optimize eden iki seviyeli deneysel bir algoritma geliştirilmiştir. Algoritma, literatürde bulunan bir vaka çalışmasının sonuçlarıyla karşılaştırılarak ve iyi bir uyum sağladığı görülmüş ve gerekli olan rota sayısının en kısa mesafesine ve varyasyonuna dayanarak besleyici otobüs güzergahları tasarlamak için cazip bir yöntem olduğu ortaya konmuştur. Önerilen yöntem, entegre bir toplu ulaşım sisteminin ilksel planlamasında yararlı olabilecek ve çok amaçlı bir optimizasyonda bir başlangıç çözümü olarak kullanılabilecektir.

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1. Introduction

Utilizing urban transportation infrastructure in the most efficient way has been the main purpose of sustainable engineering-oriented studies in recent years (Başkan et al. 2019, Yaslı and Güvensan 2019, Erkan 2014). Modern metropolitan areas usually have a high transit demand, which is widely spread, across the entire city. This requires harnessing the advantages of different types of mass transportation systems, which is typical of a modern developed city like Izmir in Turkey. With multiple transportation systems, comes the challenge of integrating the various operations to develop a sustainable transit system that is more cost-effective and efficient. Mainline (rapid transit) often has a considerably larger capacity and relatively higher speeds, thus, it can function as a major transport corridor but may create problems of accessibility especially to residential areas where the demand normally originates. In the same way, a feeder bus system with lower capacity and speed can provide access services closer to the residential demand. Therefore, a simple form of intermodal transit system may consist of an integrated mainline movement which may be a rapid transit line and a lesser transit system called a feeder (bus) connecting the service areas (residential) to the transfer stations where their journey will continue on the mainline. The service coverage of the rail systems is expected to expand and an improvement in the utilization of different public transportation modes overall. Some of the main advantages of an integrated transit system include; reducing costs and increasing revenues, eliminating duplication of services, reduced travel times and access costs, and consequently a better overall quality of service of the system (Kuan et.al. 2004). Therefore, the planning and design of a set of connecting bus routes for the provision of access between residential areas to a train station can be defined as Feeder Bus Route Network Design Problem (FBRNDP), in other words, it is the determination of feeder-bus routes consisting of stations, route structures and the operating frequency (Kuah and Perl, 1989). An example of this scenario is common with rush hour to work trips to the city centers in the mornings. In modeling terms, most passengers can be assumed to go to a common place (central city station or central business district). Therefore, passengers aggregated at bus stops in the service area who wish to connect to CBD will do so by using a lesser mode say a bus to connect to any of the train stations going to the city center. Routing problems are generally concerned with finding the shortest tour amongst locations and consequently making a route network. Tour construction problems as a way of classification fall under two classes: Travel Salesman Problem (TSP), Bus (vehicle) routing as depicted in Figure 1 below (Eldrandy, et.al. 2008). Vehicle routing problem (VRP) is a problem of obtaining the maximum set of possible routes constrained by the number of available vehicles to deliver to a given set of customers to a particular destination, and it is composed of many variants such as capacitated VRP. But, when the vehicle capacity in this problem is assumed to be sufficiently large enough such that the vehicle capacity does not become a constraint, then the problem is the same as the MTSP. Similarly, MTSP is also a general form of the TSP in which multiple salesmen are allowed to visit a set of cities with a minimized cost, constrained by visiting each city once, and by one salesman. Therefore, the mathematical formulations and solution approaches of the above-mentioned problems may be utilized for MTSP (Bektas, 2006). These problems can be used in areas such as; planning of bus routes, in case of emergencies, movement around cities and towns, and tourism.

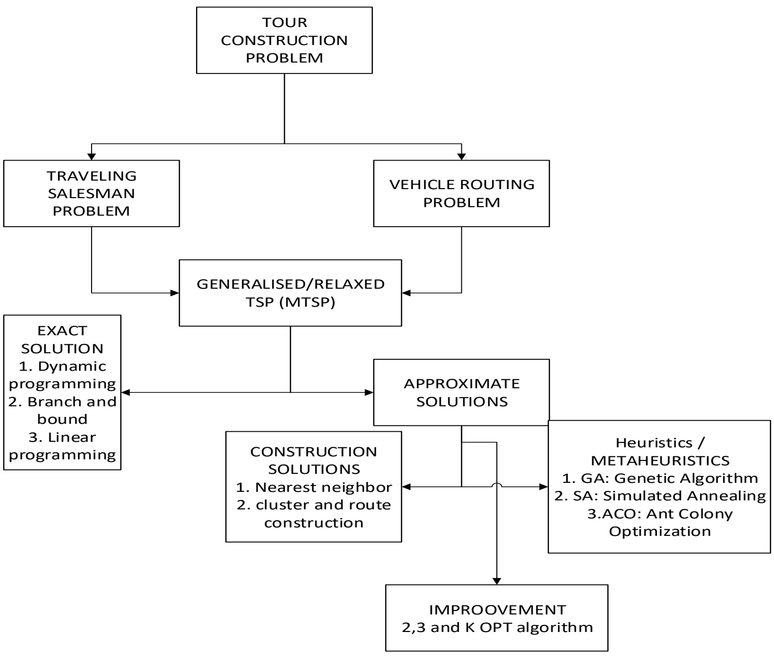

Figure 1. Classification of Tour Construction Problems

2. Literature Review

FBRNDP is a routing kind of problem which may be comparable to other routing problems like multiple traveling salesman problem (MTSP) because they both belong to a group of NP-hard combinatorial optimization which is usually solved using greedy exhaustive search even though a huge amount time is involved. While for small instances of these problems it may be solved exactly, a simple TSP solution with 30 cities can take an unimaginable time to solve for all possible routes to be evaluated. Therefore, a kind of intelligent algorithm which gives a good solution, but not necessarily optimal solution may be required. The FBRNDP falls under large routing formulations that can only be solved satisfactorily by a heuristic, metaheuristic (GA, SA, ACO) and sometimes a combination of solution approaches (Kuah and Perl,1989; Kuan et.al. 2006). FBRNDP and MTSP being similar, allows us to adopt an existing heuristics solution used for the MTSP. Please see Figure 1 for the classification of the techniques. Exact algorithms are successfully used only for relatively small problem sizes and they are known to guarantee an optimum solution. As the size of the problem expands the solution may be stuck in local optima making it inefficient. Examples of exact solutions are dynamic programming, branch and bound, linear programming, etc. Similarly, for larger problems such as TSP with a large number of cities, approximate approaches are used to solve this type of problem in a feasible time. These approaches are mainly concerned with finding a solution near-the optimal tours rather than the optimal tour in a shorter time. For background information on solution methods used in solving large problems refer to the work of Eldrandy et al. 2008.

In this study, we are particularly interested in using GA. They are search algorithms that copy the way populations evolve genetically through natural selection (Goldberg, 1989). This evolution is quite simple as it starts from a randomly generated sample space of strings, each string in the sample space is then evaluated through a fitness function, and consequently acted upon by GA operators which create a better population repeatedly through reproduction, crossovers, and mutation. The iteration of GA may be stopped by using a termination criterion (e.g. number of iteration, crossover, mutation probability) because with a better population a better solution is expected. Some of its advantages are;

1. GA directly searches from the potential solutions and the objective function themselves, not their derivatives which is used by exact approaches which makes it suitable for application in real-life problems like routing problems.
2. Extensive algorithms have been developed using GA, even though they may not guarantee optimal solution but with manipulation of population, iterations, high crossover rate, low mutation rate, the probability of GA solutions will tend towards an optimal solution.
3. Also, GA is very popular especially in academic researches because of its implementation and its rigorous ability in solving practical engineering problems.

These reasons amongst others make GA a competitive algorithm in solving routing and NP-hard problems. As highlighted by Karakatic and Podgorelec, 2015, claimed that, GA used in solving VRP has been on the increase considering publications written on the subject matter from 1993 to 2012. Perhaps the first work to deal with MTSP using GA is by Zhang et. al 1999, who worked on team schedules. Tang et al. (2000) developed a GA for hot rolling scheduling and the algorithm was able to solve both TSP and MTSP. Many research done with regards to GA and MTSP mainly focus on the vehicle scheduling problem using the different variants such as vehicle capacities, time windows and fixed number salesman with no constraints on the length of the routes (Park, 2001). Also in further development by Yu et al., 2002, also implemented the same algorithm in the planning of paths for cooperative mobile robots. Sometimes the solution search space becomes so large with redundant solutions, Carter and Ragsdale 2006, developed an effective approach to cater to these problems using GA. Kiraly and Abonyi, 2011, proposed a novel interpretable representation-based algorithm for MTSP using GA. Similarly, a modified GA was used to solve MTSP as presented by Varunika et al. ,2014. A good review of the solving MTSP using GA can be found in Singh, 2016. The research by authors Aristeguieta et al. 2006 states that GA with limited computer power performs reasonably well when compared to other metaheuristics even though some of them yield better results.

Problems involving designing transit routes (TRNDP) are large problems, therefore, the use of flexible and practical heuristic methods is common in literature. TRNDP is usually partitioned in a sequence of procedures to be manageable. Two major approaches are used; heuristics to generate routes and subsequently improving them and direct route construction and improvement using metaheuristics (Kepaptsoglou, & Karlaftis,2009). In essence, FBRNDP can be solved by applying heuristic algorithms to build initial routes, followed by the improvement of these initial routes using an optimization technique. One of the earliest heuristics is the sequential saving approach used for solving a vehicle routing problem with multi depots (Kuan et.al.,2004). For generating feeder bus routes based on demand matrix a heuristic was proposed by Shrivastav and Dhingra, 2001 which they claimed performs better than algorithms they compared it to. Also, metaheuristics like GA have been used to randomly generate an initial population even though it makes the optimum solution elusive and unstable as suggested by Chien et al.

2001. Therefore, to improve the randomness of the solutions that can be generated, the concept of the delimiter algorithm was used (Kuan et.al., 2006)

The focus of this work is on the preliminary design of bus routes connecting to train stations using a two-level algorithm process. It includes a clustering algorithm which attributes sparsely distributed stops to a particular station and consequently solving the FBRNDP as MTSP using GA. For this algorithm to work the following assumptions were made:

1. Individual bus stops can only be assigned to a feeder bus route.
2. Similarly, feeder-bus routes generated from a cluster of bus stops can only be attached to a train station closest to it.
3. The capacity and speed of the buses are constant.

Subsequent sections discuss the bi-level algorithm for planning feeder bus routes methodology, the discussion of results and finally, conclusion and recommendations

3. Proposed Methodology Bi-level Algorithm for Planning Feeder Bus Routes

We present FBRNDP as a representation of MTSP. The problem is solved in two distinct but related levels. The first problem is a clustering problem which deals with subdividing the list of n cities into k cluster groups. The second problem deals with the optimization of the shortest paths for k cluster. Although, it is possible to generate routes first then and then cluster but this approach performs poorly (Eldrandy,2008). The approach of clustering first and route construction was adopted.

1. Clustering and classifying of bus stops by assigning them to particular train stations.
2. MTSP based genetic algorithm is implemented to find feeder bus routes

3.1. Clustering

With known points, K nearest neighbor (KNN) algorithm predicts the specified K closest neighbors to that point. Therefore, to make predictions with KNN, there are different metrics used for measuring the distance between the query point and the cases from the sample. Some of the most popular choices are; Euclidean, Euclidean squared, City-block, and Chebyshev. In this study, Chebyshev distance metric is used, it is also known as maximum value distance and is computed as the absolute magnitude of the differences between the coordinate of a pair of objects is used. It examines the absolute magnitude of the differences between the coordinates of a pair of objects.

Let B = {b1, b2, b3…….., bn} be the set of bus stop points and C = {c1, c2, c3…., cn} be the set of train station.

1. Select 'c' cluster centers.
2. Calculate the distance between each data point and cluster centers using the distance metric as follows

$$\text{Dist } BC = \max\left(B_{ik} - B_{jk}\right) \tag{1}$$

Where B_{ik} and B_{jk} are coordinates of pair (querry point and other samples). The pseudo flow chart of clustering algorithm is given in Figure 2.

3.2. MTSP based GA

Consider a graph Z= (D, F), where D is the set of n vertices, and F is the set of edges. Associated with each edge (i, j) ∈ F is a cost (or distance) Tij. Assuming the starting point is the first vertex and there are h salesmen at the vertex. The variable Xij (takes the value 1 if edge (i, j) is included in a tour and xij takes the value 0 otherwise) can be defined for each edge (i, j) ∈ F. General formulation of MTSP is presented below (Arostegui Jr, 2006).

OBJECTIVE: $$Minimize \sum_{(i\ j)\in A} T_{ij} X_{ij} \tag{2}$$

CONSTRAINTS:

h salesmen leave vertex 1 $$\sum_{j\in D:(1,j)\in F} X_{1,j} = h \tag{3}$$

h salesmen return back to vertex 1	$\sum_{j \in D:(j,1) \in F} X_{j,1} = h$	(4)
one route enters each vertex	$\sum_{i \in D:(i,j) \in F} X_{1,j} = 1, \forall\, j \in D$	(5)
one route exits each vertex	$\sum_{j \in D:(i,j) \in F} X_{1,j} = 1, \forall\, j \in D$	(6)

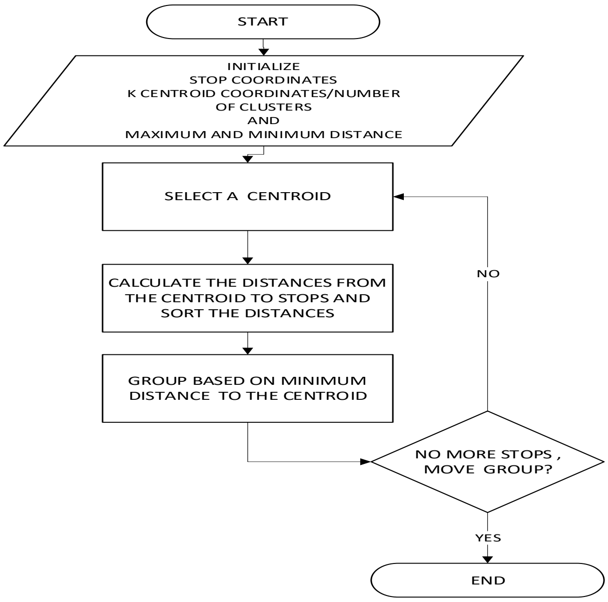

Figure 2. Clustering (KNN) Flowchart

In this study, a modification of Joseph's algorithm (2020), Fixed Start (train station) Open Multiple Traveling Salesmen Problem was used. In summary:

1. The first point is the starting for each salesman who travels to a different group of points(cities) but none of them return to their starting points.
2. Except for the first, each city is visited by exactly one salesman

Pseudo flow chart of genetic algorithm is given in Figure 3.

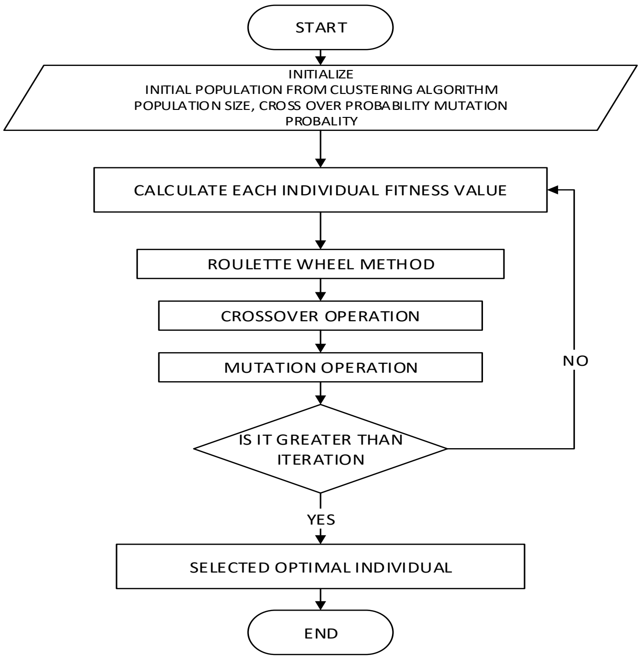

Figure 3. Flow chart for GA

4. Results and Discussion

This methodology was tested on the case study by Kuah and Perl, 1989. This case has a network of 59 vertices, which include 55 bus stops (BS1-BS55), four rail stations (TR56-TR59) with a service area of 2×2.5 mile, and 200 passengers per stop per hour. The inputs of each vertex were extracted and all coordinates are in 100 miles. Figure 4 shows the sample problem representing plotted coordinates of bus stops and train stations.

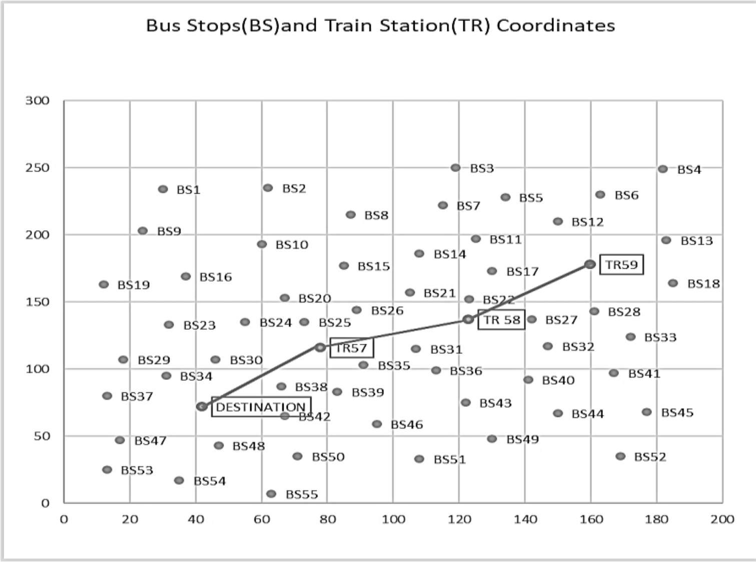

Figure 4. Layout of the Sample Problem

4.1. Clustering of the Sample Problem

For this work, the bus stops and train station coordinates taken and were classified using the KNN search using the Chebyshev distance metric and the results are presented in Table 1 below. TR (56, 57, 58, 59) represents train stations and the BS (1 to 55) represents the bus stops. Therefore, station 57 had the largest number of stops clustered around while the other stations has an equal number of stations.

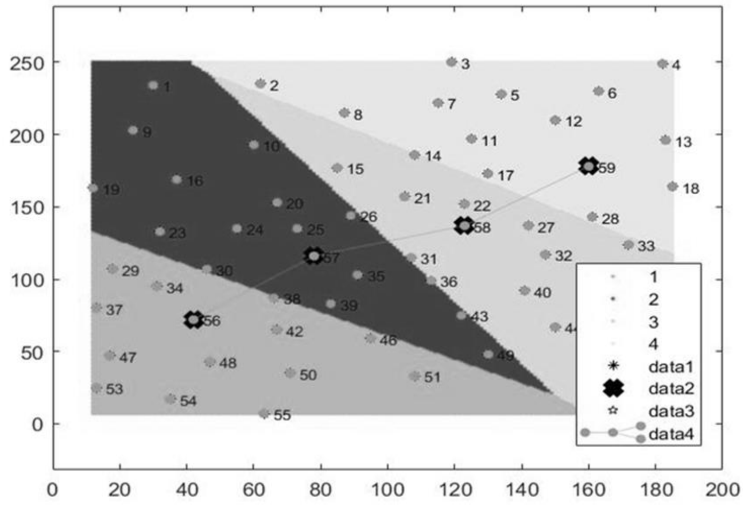

Figure 5. Clustering

4.2. MTSP based GA Optimization for the Sample Problem

The input of the clustered points, MTSP based genetic algorithm was implemented and the number of routes representing salesman was generated for each train station and the best solution was taken and the procedure is repeated by varying the number of the salesman from 2 to 5. The parameters used for genetic algorithms are a number of salesmen, minimum tour, number of iterations. Figure 6 given below shows the route structure for each case of the salesman.

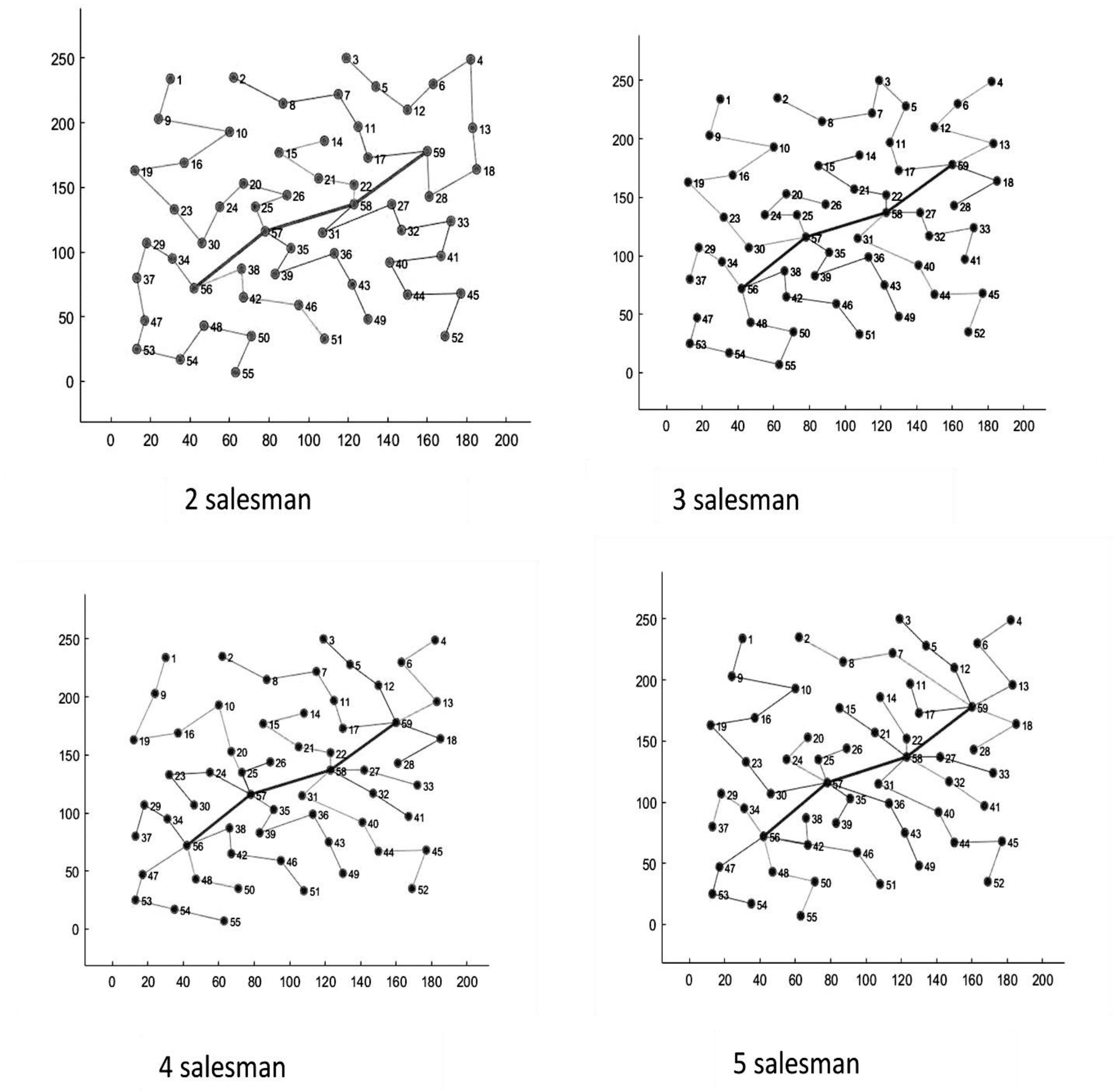

Figure 6. Route Structure

4.3. Evaluation of the Optimized Network

Analysis of transit system borders on the estimation of ridership and direct cost of the system. Also calculation of total cost will require other salient factors like such as various components of time (waiting, riding,), fleet size and other performance measures listed below. Representing system performance requires that one calculate additional parameters. The listed system performance measures are calculated by using the parameters in Table 1(Kuah and Perl, 1989):

- Routes (NR)
- Route Length (TRL)
- Average Frequency (AF)
- Total Vehicle Miles (TVM)
- Total Passenger Miles (TPM)
- Bus operating Cost (BOC)
- Bus User Cost (BUC)
- Bus Riding Cost (BRC)
- Bus Waiting Cost (BWC)

Table 1. Parameters

Descriptions	Units	Value
Operating cost unit (λ_0)	$/veh. mile	3
Riding cost unit (λ_r)	$/pass. hr	4
Waiting time Cost (λ_w)	$/pass. hr	8
Max. allowable route length (RL)	mile	2.5
Bus capacity	seat	50
Average bus operating speed (U)	mile/hr	20
Average demand per hour at bus stop i to station j (q_i)	pass./hr	200
Bus operating frequency (f_{ij})	veh./hr	
Distance from stop i to station j (l_{ij})	miles	

The cost components in a given transit system may consist of waiting cost, operating cost and riding costs:

- Bus operating cost: can be defined based on unit of time or distance cost in connection with the transit service provided.

$$BOC = 2 * \lambda_0 f_{ij}\, l_{ij} \qquad (7)$$

- Bus waiting cost: The waiting cost includes passengers waiting for the buses, which is the product of average wait time, demand, and the value of users 'wait time.

$$BWC = \frac{\lambda_W q_i}{2f_{ij}} \qquad (8)$$

- Bus riding cost: the product of demand, in-vehicle time, and value of time can define the user in-vehicle cost. In some literatures it is regarded as running time

$$BRC = \frac{\lambda_r l_{ij}\, q_i}{U} \qquad (9)$$

- Bus user cost

$$BUC = BWC + BRC \qquad (10)$$

- Frequency: bus operating frequency

$$f_{ij}=0.5(\,((\lambda_W\, q_i)/\,(\lambda o\, l_{ij})\,)\hat{}0.5 \qquad (11)$$

- Total Vehicle Miles: is given by multiplying the vehicle hours by the average speed

$$TVM = Uf_{ij}\,(l_{ij}\,/U) \qquad (12)$$

- Total Passenger Miles: summation of (segment length* average volume)

$$TPM = \sum((l_{ij}\, q_i) \qquad (13)$$

In Figure 7, when the operations measure of MTSP based solutions are compared with Kuah and Perl (1989) solution, similar performance can be obtained by four salesmen, especially for AF. Besides four salesmen solution provides slightly better performance than Kuah and Perl's solution. TRL measure increases from two to four salesmen solutions and then decreases for five salesmen solution, even though the routes increase in number. To provide short and fast feeder bus routes with small vehicle capacities, it is beneficial to keep the number of salesmen high in the solution.

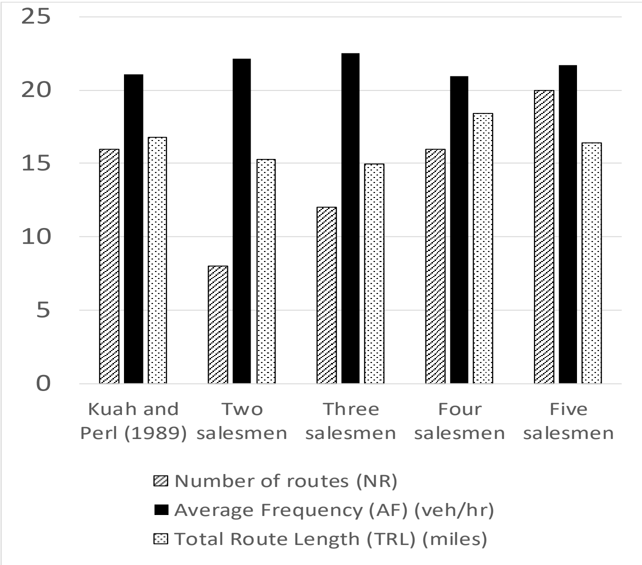

Figure 7. Comparison of Operation Measures NR, AF and TRL

Figure 8 shows the comparison of operation measures and cost components. It is clear from the figure that, although the total vehicle miles (TVM) and bus operating cost (BOC) are nearly unchanged, total passenger miles (TPM) and the bus user cost (BUC) values decreased by increasing the number of salesmen. Therefore, the redundant travel lengths of passengers can be eliminated in this way.

The results of this algorithm may not be favorable from the operator's perspective as one will expect that as the number of routes increases, the fleet size will increase and consequently increase in operating cost but the BOC value highly fluctuates. This may be largely due to the fact that the feeder routes were designed based on the shortest distance which tends to favor the user perspective. The users will prefer a minimized travel time and cost while the transit operators will focus more on the maximization of profit which may be a function of ridership. Like most optimization problems, FBRNDP strives to create optimal routes taking into consideration the cost incurred by the operator, user, and even social and environmental costs. At this stage, multi-objective optimization has become important since different opposing objectives yields different results.

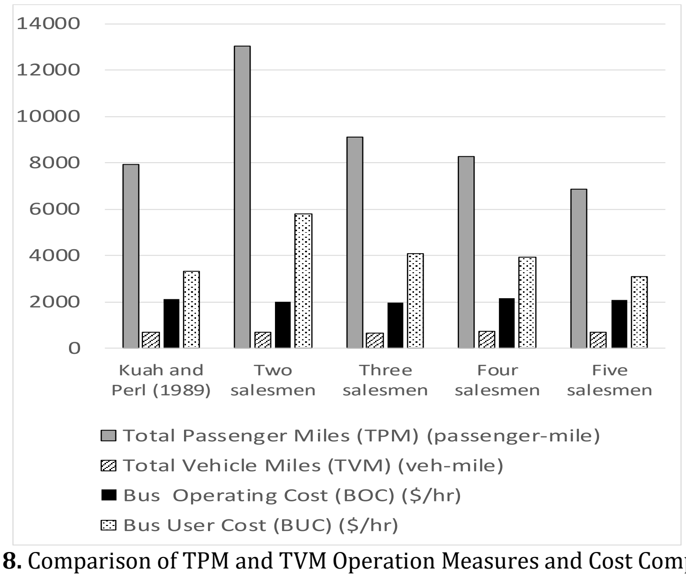

Figure 8. Comparison of TPM and TVM Operation Measures and Cost Components

5. Conclusion

Tour construction problem, which has mainly TSP and VRP as sub problems can be represented by MTSP as a generalization or relaxation respectively. MTSP is quite similar to real-life problem FBRNDP where we have many origins and one destination. This paper proposes a two-level algorithm for defining initial bus routes connecting an existing rapid transit system. A clustering algorithm was introduced to assign bus stops to the nearest station and a fixed multiple salesman genetic algorithm was used to optimize feeder bus routes based on the shortest distance with a constraint of no return journey. According to the need of the designer, the number of the salesperson (number of routes) may be varied to show its sensitivity to other factors such as frequency, route length, and route structure. These parameters can subsequently be used to estimate user and operator's perspectives impacts. As the number of route increases, the total passenger miles decreases even though the total vehicle miles fluctuates and the fleet size increases. The proposed heuristic generates good bus route networks connecting to the fixed train stations especially when compared to a well-utilized result of Kuah and Perl, 1989. The use of variable demand, which may be obtained from a more reliable source like smart card data, may be appropriate rather than using fixed demand. Similarly, practical distance (not a straight-line distance) among locations may be more representative; therefore, usage of geographic information systems is needed in real-life applications. Finally, the results of this bi-level algorithm can be used as initial input or solution in a multi-objective optimization to address the different perspectives often associated with the bus route network design problem and it allows sensitivity analysis be carried easily. The main advantage of this model is that bus stops can be clustered around the nearest train station based on nearest neighbor algorithm and this has a huge potential with increasing numbers of bus stops and railway stations in a given system.

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Conflict of Interest

The authors declare no conflict of interest.

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