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Urban Bus Network of Priority Lanes: a Combined Multi-Objective and Multi-Criteria Approach

Yuval Hadas · Oren E. Nahum

Abstract This work presents a multi-objective approach for selecting an optimal network of public transport (PT) priority lanes. Bus priority schemes and techniques on urban roads and highways have proven effective for increasing reliability, efficiency, and faster travel times. Recently, several papers presented system-wide models and algorithms for optimal PT network coverage, based on priority lanes. This work develops a multi-objective model for optimal selection of a set of PT priority lanes that optimizes three objectives. 1) Maximizes the total travel time saving, 2) Maintains balanced origin and destination terminals, and 3) Minimizes the budget. In contrast to commonly used single objective models, which must be executed numerous times in order to provide to the decision maker a set of feasible solutions, multi-objective models exhibit, with a single execution, a complete set of feasible solutions. The results, based on a case study (revisited) of Petah-Tiqwa, a mid-size city of Israel, provides the decision maker with a set of non-dominated feasible solutions, from which a solution can be selected based on the preferences of the decision maker.

Keywords: Bus Priority Lanes · Multi-Criteria · Multi-Objective Optimization · Public Transport Network Design

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1 Introduction

Bus priority schemes and techniques on urban roads and highways have proven effective for almost a half century. Many bus-priority strategies have been demonstrated worldwide. Traditionally, priority is granted for bus operation at stops, at intersections, and by preferential/exclusive lanes. It is known that bus travel times, reliability of service, and vehicle productivity are improved when buses are able to use higher-speed, uncongested lanes. These improvements make the bus systems more attractive and thus increase the potential to gain new riders (Kittelson & Associates., Transit Cooperative Research Program. et al. 2003). Eight preferential treatments to buses on street lanes are known (Ceder 2007) as follows: exclusive curb lane; semi-exclusive curb lane (shared only with cars about to turn); exclusive median lane (with stop island); exclusive lane in the center of a street; bus malls (limited to pedestrians and buses); exclusive freeway/highway lanes; ramp bypass (for entering a freeway/highway during traffic congestion); and congestion bypass (exclusive lanes to bypass traffic bottlenecks). Some exclusive bus lanes are shared with high-occupancy vehicles (taxis, certain minimum number of people in a car, for encouraging carpools). In Europe, numerous transit-priority projects have been executed; for example, in Athens, Dublin, Munich, Turin, Vienna, and Zurich. Ceder (2004) listed the lessons that can be learned from these six case studies in terms of the benefits gained from the implementation of bus priority schemes in these cities; among the results attained are reduction of travel time, increase of patronage and revenue, and increase of average speed. The first to introduce a system-wide approach for designing priority lanes were Mesbah, Sarvi, and Currie (Mesbah, Sarvi et al. 2008, Mesbah, Sarvi et al. 2010, Mesbah, Sarvi et al. 2011). In their work, they proposed a bi-level model combining priority lanes selection and traffic assignment. Recently, a model was developed for optimal construction of connected network of bus priority lanes (Hadas and Ceder 2014). This model presented an optimization model aims at maximizing the travel time reduction resulted from the use of priority lanes, given a predefined budget. For the policy maker it is required to execute the algorithm multiple times with different budget constraints, to investigate wide range of scenarios. Larger budget leads to more priority lanes being constructed, and increased travel time reduction. However, it is time consuming, and cumbersome.

The aim of this paper is to introduce a multi-objective approach to the problem, which provides, with one execution, a set of solutions for the policy maker to choose from. In order to assist the decision maker, multi-criteria methods are used for the ranking of the solution set. Following the literature review, a multi objective optimal connected urban bus network of priority lanes model is introduced, along with a case study and some conclusions.

2 Literature Review

2.1 Public Transport Network Design

Baaj and Mahmassani (1991, 1992, 1995) developed transit-network-design methods based on artificial intelligence (AI). The methods discussed are developed by a typical formulation of the network-design problem as a programming problem with minimum frequency, load-factor, and fleet-size constrains. Ramirez and Seneviratne (1996), using GIS, propose two methods for route-network design with multiple objectives. Both methods involve ascribing an impedance factor to each possible route and then choosing those routes that have the minimum impedance. In the first method, the impedance factor depends on passenger flow and on the road length travelled. This method requires the use of an assignment model. In the second method, the impedance factor depends on the number of employees who have a reasonable walking distance from the route. Bielli, Caramia et al. (2002) described another method for designing a bus network, using a genetic algorithm. As in other genetic algorithms, each population of solutions goes through reproduction, crossover, and mutation manipulations, whose output is a new generation of solutions. In the proposed model, each iteration involves demand assignment on each network of the current set of solutions and a calculation of performance indicators based on the assignment results. These indicators supply input to a multi-criteria analysis of each network, leading to the calculation of its fitness-function value. Yan and Chen (2002) presented a method for designing routes and timetables that aims at optimizing the correlation between bus-service supply and passenger demand. The method is based on the construction of two time-space networks: a fleet-flow network and a passenger-flow network. Both networks are depicted in bi-dimensional diagrams in which the horizontal dimension represents bus stops and the vertical dimension represents time. While the fleet-flow network shows the potential activities of the bus fleet, the passenger-flow network illustrates trip demand. The objective of the model is to feed buses and passengers at minimum cost in both networks simultaneously. A mixed-integer, multiple-commodity, network-flow problem and a solution algorithm based on Lagrangean relaxation are presented. Tom and Mohan (2003) continued the development of genetic methods for route-network design. In the current model, frequency is the variable; thus, it differs from earlier models in terms of the coding scheme adopted. Whereas fixed-string length coding and variable-string length coding were used in previous models, a combined route and frequency-coding model is proposed here. Bagloee and Ceder (2011) developed a complete heuristic methodology for a complex problem of transit-network design to handle actual-size road networks. The methodology proposed takes into account the major concerns of the transit authorities such as budget constraints, level-of-service standards and the attractiveness of the transit routes. In addition this approach considers other important aspects of the problem including categorization of stops, multiclass of transit vehicles, hierarchy planning, system capacity and the integration between route-design and frequency-setting analyses. Estrada, Roca-Riu et al. (2011) presented and tested a method to design high-performance transit networks, which produces conceptual plans for geometric idealizations of a particular city that are later adapted to the real conditions. The objective function is composed of analytic formulae for a concept's agency cost and user level of service. This method has been applied to design a high performance bus (HPB) network for Barcelona (Spain), and provided sub-optimal spatial coverage (because Barcelona lacks suitable streets) with a high level of service. Simulations suggest that if the proposed system was implemented side-by-side with the current one, it would capture most of the demand.

All those models and approaches neglects to incorporate priority schemes, as integral part of PT network design. Many bus-priority strategies have been demonstrated worldwide. Traditionally, priority is granted for bus operation at stops, at intersections, and by preferential/exclusive lanes. It is known that bus travel times, reliability of service, and vehicle productivity are improved when buses are able to use higher-speed, uncongested lanes. These improvements make the bus systems more attractive and thus increase the potential to gain new riders (Kittelson & Associates., Transit Cooperative Research Program. et al. 2003). Skabardonis (2000) reviewed existing control strategies, which were evaluated on a real-life arterial corridor, identified the major factors affecting transit priority, and formulated both passive and active transit priority strategies. According to the review, both passive and active priority strategies placed major emphasis on the system wide improvements to the transit movements and on minimization of the adverse impacts to the rest of the traffic stream. An evaluation technique, which showed modest improvements, was also developed to assist in the design of the signal priority strategies and to predict the impacts of the transit priority measures. Turnquist and Bowman (1980) used a set of simulation experiments to investigate the effects on service reliability of several characteristics of network structure in urban bus systems. The main focus of these experiments was on the factors which lead to vehicle bunching, and on the effects of network form and route density on transfers. The results of these experiments highlight the importance of controlling link travel time variability, and of scheduling to ensure expeditious transferring, especially in radial networks. Yao, Hu et al. (2014) presented a Tabu search based transit network optimization method, in which travel time reliability on road is considered. The optimization model aims to maximize the efficiency of passenger trips in the optimized transit network. The results show the proposed method can effectively improve the reliability of a transit network and reduce the travel time of passengers in general.

Dynamic priority lanes concepts were investigated by Currie and Lai (2008). They reviewed the performance of a variation on the Intermittent and Dynamic Transit Lanes (IBL) concept, the dynamic fairway (DF) adopted for trams in Melbourne, Australia. The paper documents the world's first practical, ongoing experience with IBL-DF operation. Future plans for a Melbourne bus-based IBL called the "moving bus lane" are also presented. Significantly, both applications found good driver compliance with transit lanes, suggesting the IBL-DF concept has practical performance benefits. Eichler and Daganzo (2006) described strategies for operating buses on signal-controlled arterials using special lanes that are made intermittently available to general traffic. According to the paper, bus lanes with intermittent priority (BLIPs), do not significantly reduce street capacity. Intermittence, however, increases the average traffic density at which the demand is served, and as a result increases traffic delay. The main factors determining whether an intermittent system saves time are: the traffic saturation level; the bus frequency; the improvement in bus travel time achieved by the special lane; and the ratio of bus and car occupant flows. In some cases, where a dedicated bus lane could not be operated, a BLIP can save to bus and car occupants together as much as 20 persons-min of travel per bus-km. Xie, Chiabaut et al. (2012) describes how dynamic bus lanes with intermittent priorities (BLIPs) allocation strategies may improve bus transit. These strategies consist in intermittently opening the bus lane to general traffic when not in use by a bus. Simulated results show a good agreement with analytical results. The first to introduce a system-wide approach for designing priority lanes were Mesbah, Sarvi, and Currie (Mesbah, Sarvi et al. 2008, Mesbah, Sarvi et al. 2010, Mesbah, Sarvi et al. 2011, Mesbah, Sarvi et al. 2011). In their work, they proposed a bi-level model combining priority lanes selection and traffic assignment. The model assesses the impact of exclusive lanes on private cars travel time and optimize the overall weighted travel times and distances. Due to the complexity of the model, heuristics are introduced, such as genetic algorithms. However detailed and innovative, the model has some issues to consider: a) the model handles two alternatives, namely exclusive or mixed, while it is possible to consider other alternatives, i.e. the eight preferential treatments described in (Ceder 2007), which differ in cost, PT flow, travel time reduction, etc.. b) The resulted priority lanes are not necessarily connected (or continuous). It is possible to add explicit constraints, which further increase complexity and model size. c) The priority lanes do not necessarily efficiently cover the network, as the model takes into account travel time reduction alone. Recently, Hadas and Ceder (2014) introduced a new approach and modelling for selecting an optimal network of public transport (PT) priority lanes. The approach used is based on a system-wide concept to result with the optimal PT network coverage. The work develops a model for optimal selection of a set of PT priority lanes that maximizes the total travel time saving and, at the same time, maintains balanced origin and destination terminals given a budget constraint.

In this work, a combined multi objective and multi criteria variation of the model is introduced; hence the next section is dedicated to multi objective optimization and multi criteria decision making.

2.2 Multi objective optimization

Many problems have multiple conflicting objectives, for which there is no single, best solution when measured on all objectives. In that case there exists a Pareto front of solutions, in which all solutions are considered equally good (Coello Coello 2006). Fig. 1 presents an example of a Pareto front (Wikipedia contributors 2014). The boxed points represent feasible choices, and smaller values are preferred to larger ones. Point C is not on the Pareto front because it is dominated by both point

A and point B. Points A and B are not strictly dominated by any other, and hence do lie on the frontier.

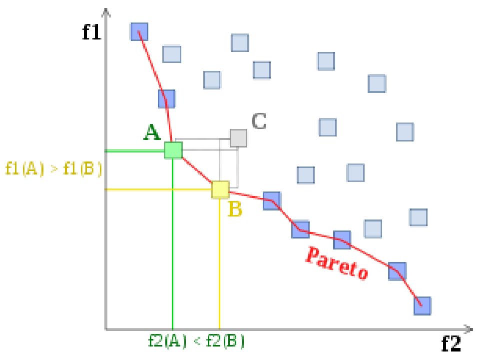

Fig. 1 Example of a Pareto front

Practically speaking, users need only one solution from the set of optimal solutions. Therefore, solving MOPs can be seen as the combination of both searching and decision-making (Horn 1996). In order to support this, there are four main approaches in the literature (Miettinen 1999). 1) **No-preference** - These methods solve a problem and give a solution directly to the decision maker (DM) without using preference information. Global criterion is an example for such method (Zeleny and Cochrane 1982, Miettinen 1999). The global criterion method transforms MOPs into single objective optimization problems by minimizing the distance between some reference points and the feasible objective region. 2) **Decision making after search / Posteriori** – These methods find all possible solutions of the non-dominated set and use the user preference to determine the most suitable one. The weighted-sum (Miettinen 1999, Cohon 2013) and ε-constraint (Haimes, Lasdon et al. 1971) are examples for such method. In the weighted-sum method, all objectives are combined into a single objective by using a normalized weight vector. The Pareto optimal solution is obtained by resolving the problem using different weights. In the ε-constraint method the problem is transformed into a single objective problem, such that only one objective is optimized, while the others are transformed as constraints. The ε vector is determined and uses the boundary (upper bound in the case of minimization) for all objectives. For a given ε vector, this method will find an optimal solution by optimizing objective *j*. By changing ε, we will obtain a set of optimal solutions. 3) **Decision making before search / Priori** – These methods incorporate the use of preference before the optimization process, and thus will result in only one solution at the end. One obvious example for such method is the weighted-sum method, where the weights can be used to represent the DM’s preference. Another example is the lexicographic method (Fishburn 1974), in which, the DM is asked to arrange the objective functions by their importance. The optimization process is performed individually on each objective following the order of importance, when the result of each optimization process is used as constraints for the next process. 4) **Decision making during search / Interactive –** These methods are a hybridization of the second and third methods, in which human DM is periodically used to refine the obtained trade-off solutions and thus to guide the search.

2.3 Multi-Objective Evolutionary Algorithms

Multi-objective evolutionary algorithms (MOEAs) are stochastic optimization techniques. Similar to other optimization algorithms, MOEAs are used to find Pareto optimal solutions for a particular problem, but differ by using a population-based approach. The optimization mechanism of MOEAs is quite similar to that of EAs, except for the use of the dominance relation. At each iteration, the objective values are calculated for every individual and are then used to determine the dominance relationships within the population, in order to select potentially better solutions for the production of the offspring population. In the non-elitism MOEAs, best solutions of current population are not preserved when the next generation is created (Deb 2001) (by selecting individuals from the current generation, and applying crossover and mutation operators on them, as in EAs). The only difference from conventional EAs is that they use the dominance relation when assessing solutions. Instances of this category include VEGA (Schaffer 1985), MOGA (Fonseca and Fleming 1993), NPGA (Horn, Nafpliotis et al. 1994) and NSGA (Deb 2001). Elitism is a mechanism to preserve the best individuals from generation to generation. In this way, the system never loses the best individuals found during the optimization process. Algorithms such as PAES (Knowles and Corne 2000), SPEA2 (Zitzler, Laumanns et al. 2001), PDE (Abbass, Sarker et al. 2001), NSGA-II (Deb, Pratap et al. 2002) and MOPSO (Coello, Pulido et al. 2004) are typical examples of this category.

2.4 Multi-Criteria Decision Making

In most cases, when solving a multi-objective optimization problem, the result is a set of non-dominated solution (a set in which there is no solution that is better in all objectives from another solution in the set), from which the decision maker (DM) has to choose his preferred alternative. Multi-criteria decision making (MCDM) methods are automated methods for selecting a preferred solution; some of them are listed below. The Max-Min method, for example, can be used when the DM wants to maximize the achievement in the weakest criterion. The Min-Max method can be used when the DM wants to minimize the maximum opportunity loss. Compromise Programming identifies the solution whose distance from the ideal solution (an artificial solution consists of the upper bound, for maximization, of the criteria set) is minimum. ELECTRE Method (Roy 1991) compares two alternatives at a time and attempts to eliminate alternatives that are dominated using the outranking relationship. In the first version of this method, the result is a set of alternatives (called the kernel) that can be presented to the DM for the selection of "best solution". The second version of this method is a complete rank ordering of the original set of alternatives. The TOPSIS method (Hwang and Yoon 1981) operates on the principle that the preferred solution should simultaneously be closest to the ideal solution and farthest from the negative-ideal solution (an artificial solution consists of the lower bound, for maximization, of the criteria set). TOPSIS does not require the specification of a value (utility) function, but it assumes the existence of monotonically increasing value (utility) function for each (benefit) criterion. The method uses an index that combines the closeness of an alternative to the positive-ideal solution with its remoteness from the negative-ideal solution. The alternative maximizing this index value is the preferred alternative. Multi-Attribute Utility Theory (MAUT) (Keeney, Raiffa et al. 1979) is based upon the assumption that every DM tries to optimize a utility function, not necessarily known at the beginning of the decision process, which aggregates all their points of view. The utility function is composed of various criteria which enable the assessment of the global utility of an alternative. For each criterion, the DM gives a score, called the marginal utility score. The marginal utility scores of the criteria will be aggregated in a second phase to the global utility score. Each alternative is evaluated on the basis of the utility function, and receives a ‘utility score’. This utility score allows the ranking of all alternatives from best to worst. Many MCDM methods require the use of relative importance weights of criteria. Many of these methods require ratio-scaled weights proportional to the relative value of unit changes in criteria value functions. A simple and common method for ranking criteria is the weights from ranks method. In this method the DM ranks each criteria, r_i, in order of increasing relative importance (the highest ranked criterion gets a rank of 1). Next each the weight of criteria is defined as $\lambda_i=(k+r_i+1)/\sum_{j=i..k}(k+r_j+1)$, when k is the number of criteria. While this method produces an ordinal scale, it not guarantee the correct type of criterion importance because ranking does not capture the strength of preference information (Masud and Ravindran 2008). When a large number of criteria are considered, it may be easier for the DM to provide pairwise ranking instead of complete ranking. As an example of such method consider the analytic hierarchy process (AHP) proposed by Saaty (1977, 2008). With AHP, the decision problem is first structured in levels of a hierarchy. At the top level is the goal of the problem, the subsequent levels represent criteria, sub-criteria, and so on and the last level represents the decision alternatives. Next, value judgments, concerning the alternatives with respect to the next higher level sub-criteria, are calculated based on available measurements or, if not available, from pairwise comparison. After the value judgments of alternatives with respect to sub-criteria and relative importance of the sub-criteria and criteria have been computed, composite values indicating overall relative priorities of the alternative are then determined by finding weighted average values across all levels of the hierarchy. Analytic network process (ANP), a generalization of the AHP method which deals with dependencies, is another example (Saaty 2001). ANP allows for more complex interrelationships among the decision levels and attributes than AHP. Two-way arrows represent interdependencies among attributes and attribute levels. The directions of the arrows signify dependence. Arrows emanate from an attribute to other attributes that may influence it. The relative importance or strength of the impacts on a given element is measured on a ratio scale similar to AHP (using pairwise comparisons and judgment). A priority vector may be determined by asking the decision maker for a numerical weight directly, but there may be less consistency, since part of the process of decomposing the hierarchy is to provide better definitions of higher level attributes. The ANP approach is capable of handling interdependence among elements by obtaining the composite weights through the development of a “supermatrix".

3 Multi Objective Model for Connected Urban Bus Priority Lanes

The model's objective is to select a set of priority lanes that optimize three objectives: 1) maximizes the total travel time saving, 2) maintaining a balanced origin and destination nodes, and 3) minimizing the budget. Each priority lane will have the properties of a path in a graph (Ahuja, Magnanti et al. 1993), and must starts and ends at a pre-selected set of nodes serving as terminals of the PT network. A connected urban bus priority lanes network is a system-wide approach for PT planning. In contrast to micro-level analysis of priority lanes, such an approach increases the PT connectivity level and thus improves the attractiveness of the PT service. That is, the PT connected priority lanes will improve the reliability of transfers made on these lanes with other lines such as feeder buses, BRT, LRT and metro lines. Moreover, efficient transfers can enhance the overall PT network performance, by providing better coverage and connectivity. The network presented in Fig. 2, which was adapted from Hadas and Ceder (2014), illustrates the model. Each arc (between two numbered nodes) is a road section (or intersection priority scheme) which can be constructed as part of a possible priority lane (exclusive or semi-exclusive). Each priority-lane alternative will be examined in terms of its cost and benefits (time saving). All circled nodes are a set of possible origins and destinations for the priority lanes. The goal is to construct a set of priority lanes that connects PT stations, transfer hubs, routes' start/end stops, and link one priority lane to other priority lanes. By doing so, the PT network will be characterized by uninterrupted routes (such as 15-14-32-13-12-11-33), as opposed to the construction of isolated priority lanes, which often experiencing traffic bottlenecks in the form of non-prioritized sections.

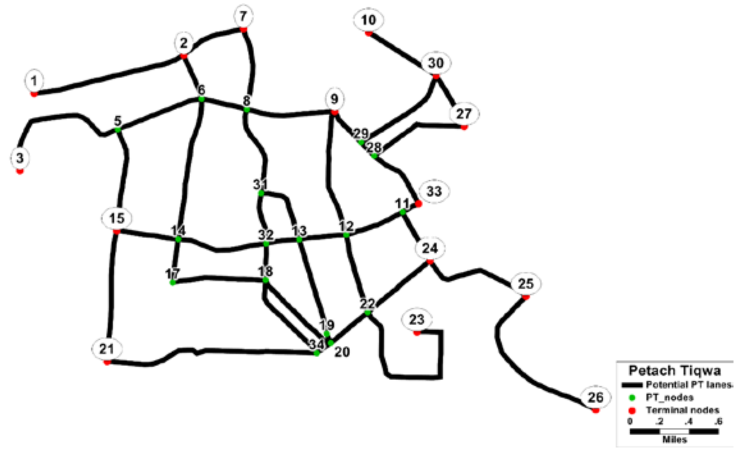

Fig. 2 Potential priority lanes and terminal nodes

3.1 Model Formulation

Let $G(N, A)$ be a directed network comprises all road sections traversed by PT routes. Let $x_{i,j}^{k}$ be a binary decision variable, such as "1" represents the selection of priority lane alternative *k* for road section (i, j), and "0" otherwise. Furthermore, let $c_{i,j}^{k}$ be the construction costs, $v_{i,j}^{k}$ the travel time saving per passenger, and $f_{i,j}$ the total passengers' flow of all routes passing through road section (i, j). Let $I \subseteq N$ be a set of all nodes from which a priority lane starts or ends. For constructing paths, let $p_{i,j}^{m,s,t}$ be an indicator whether road section (i, j) is part of path *m* that start from node $s \in I$ and terminates at node $t \in I$. Matrix P can be easily calculated, as describes in the next sub-section. For clarity the index *m* will be omitted henceforth. Let $px^{m,s,t}$ be a decision variable, such as "1" represents the selection of path *m* that start from node $s \in I$ and terminates at node $t \in I$. Again, for clarity, the index *m* will be omitted. Furthermore let *B* be the budget available, and D_l, D_u be the lower- and upper- bounds for nodes' degree.

$$\max \sum_i \sum_j \sum_k x_{i,j}^{k} \cdot v_{i,j}^{k} \cdot f_{i,j} \tag{1}$$

$$\max \min_{i \in SL} \left\{ \min_j \left(\sum_t px^{j,t}, \sum_s px^{s,j} \right) \right\} \tag{2}$$

$$\min \sum_i \sum_j \sum_k x_{i,j}^{k} \cdot c_{i,j}^{k} \tag{3}$$

s.t.

$$\sum_{k} x_{i,j}^{k} \leq 1 \; \forall i, j \in N \tag{4}$$

$$\sum_{k} x_{i,j}^{k} - \left[\sum_{s} \sum_{t \neq s} \left(p_{i,j}^{s,t} \cdot px^{s,t} \right) \geq 1 \right] = 0 \; \forall i, j \in N \tag{5}$$

$$x_{i,j}^{k} = \{0,1\} \tag{6}$$

$$px^{s,t} = \{0,1\} \tag{7}$$

Equation (1) maximizes total time saving resulted from using the selected PT priority lanes. Equation (2) maintains a balanced connectivity between the selected terminal nodes. This balance is maintained by maximizing the minimal in-degrees and out-degrees (the number of nodes directly connected to/from a given node) of all terminal nodes among all feasible solutions (*SL*). An unbalanced priority lanes set will impact the overall reliability of the PT network and reduce the level of service. Equation (3) minimizes budget allocation and constraint (4) maintains the selection of one alternative. Constraint (5) enforces that if at least one path ($\left[\sum_{s} \sum_{t \neq s} \left(p_{i,j}^{s,t} \cdot px^{s,t} \right) \geq 1 \right]$) from *s* to *t* is selected ($px^{s,t} = 1$), then one alternative ($x_{i,j}^{k}$) for road section (i, j) must be selected given that the road section is part of path from *s* to *t* ($p_{i,j}^{s,t} = 1$). This constraint also maintains the continuity of each selected priority lane.

3.2 Multi Objectives Algorithm

In this work, the Strength Pareto Evolutionary Algorithm 2 (SPEA2) (Zitzler, Laumanns et al. 2001), a technique for finding or approximating the Pareto set for multi-objective optimization problems, was used to find a set of non-dominated solution. The algorithm was tested using the single objective formulation and test cases presented in the original paper (Hadas and Ceder 2014), and found to be very efficient. SPEA2 uses an external set (archive) for storing primarily non-dominated solutions. It is then combined with the current population to form the next archive that is then used to create offspring for the next generation. To avoid the situation that individuals dominated by the same archive members have identical fitness values, each individual *i* in the archive A_t and the population P_t is assigned a strength value *S*(*i*), representing the number of solutions it dominates. For each individual *i*, raw fitness *R*(*i*), determined by the strengths of its dominators in both archive and population, is calculated. For the raw fitness, *R*(*i*)=0 corresponds to a non-dominated individual, while a high *R*(*i*) value means that *i* is dominated by many individuals. The raw fitness may fail when most individuals do not dominate each other. Therefore, additional density information, based on the k^{th} nearest neighbor, is incorporated.

Algorithm – SPEA2

Input: N - Archive size
M - Offspring population size
T - Maximum number of generations
Output: A∗ - Non-dominated set

1. Initialization: Generate an initial population P_0 and create the empty archive (external set) $A_0=\emptyset$. Set t=0.
2. Fitness assignment: Calculate fitness values of individuals in P_t and A_t.
3. Environmental selection: Copy all non-dominated individuals in P_t and A_t to A_{t+1}. If size of A_{t+1} exceeds N then reduce A_{t+1} by means of the truncation operator, otherwise if size of A_{t+1} is less than N then fill A_{t+1} with dominated individuals in P_t and A_t.
4. Termination: If $t \geq T$ or another stopping criterion is satisfied then set $A*$ to the set of decision vectors represented by the non-dominated individuals in A_{t+1}. Stop.
5. Mating selection: Perform binary tournament selection with replacement on A_{t+1} in order to fill the mating pool.
6. Variation: Apply recombination and mutation operators to the mating pool and set P_{t+1} to the resulting population. Increment generation counter (t=t+1 and go to Step 2.

3.3 Representation and Genetic Operations

For the studied problem, a candidate solution must specify the selected paths and the selected alternative for each node belong to the selected paths. A solution can be encoded using an array of integers of size equals to the number of nodes plus number of paths. This array is composed of two parts. This first part contains information about the selected alternative for each node, when 0 represents an unselected node, 1 represent that the first alternative was selected and so on. The second part contains information about the selected paths when 1 represents a selected path a path and 0 otherwise. For the crossover operation, two parent chromosomes are selected using tournament selection. Next, one-site crossover, implemented on the second part of the parent chromosomes, i.e. information of selected paths, is used to create two new chromosomes, which contain a combination of paths from both parents. For each new chromosome, information about the nodes is updated based on the information present in the parent chromosomes. Three types on mutation operations are used in this research: (1) Remove path – this operation removes a path and information about its associated nodes from a given solution; (2) Add path – this operation adds a path and randomly fills information about its associated nodes to a given solution and (3) Change information – this operation randomly change information of a node belonging to a selected path in a given solution.

4 Case Study – Revisited

In this paper, we re-evaluated the work on optimal connected urban bus network of priority lanes model for Petah-Tiqwa municipally originally introduced (as a single objective model) in (Hadas and Ceder 2014). Petah-Tiqwa is the fifth largest city in Israel with 211,000 residents, and area of 36 KM^2. The city is located in Israel's largest metropolitan area (Gush-Dan). As of 2010, the population's compound annual growth rate was 3.3% (as compared to 1.5% of the total population of Israel). Based on the 2008 census (Central Bureau of Statistics), 49% of Petah-Tiqwa's residents worked in the city (~50,000), with additional 84,000 commuters to Petah-Tiqwa from other cities. As of 2008, PT share of the trips was 26%. The city's urban PT network is served by one bus operator. All routes share the road with private and commercial vehicles. A LRT line is being developed, which will connect the city's central station and other municipalities in the metropolitan area as is depicted in Fig. 3 by a Red Line. Some of the major points of interests, such as bus terminals and industrial parks are illustrated as well. In order to select an optimal set of priority lanes, the following steps were carried out: 1) selecting road sections candidates for priority lanes, possible road sections to be used as priority lanes, as well as terminals to serve as start and end points for the priority lanes are illustrated in Fig. 3 (ii) estimating costs and benefits, based on the call for proposal's guidelines (Ministry of Transport and Ministry of Treasury 2011), costs and benefits were calculated as constructions costs per KM, and annual time saving (ATS) for distance travelled, respectively.

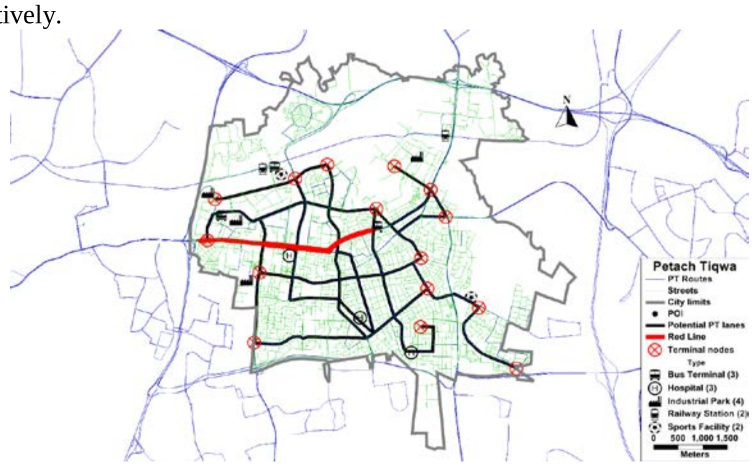

Fig. 3 Petah-Tiqwa's Street and PT network with potential road-sections and terminals

5 Results

The optimal multi-objective model for priority lanes selection was solved. The result is a set of non-dominated solutions, from which the decision maker can select a single solution, based on a set of preferences. A 3D graph of the Pareto-front is given in Fig. 4. As it can be seen from the results, when the budget is low, in the range of 0$ to about 30,000K$, in all solutions the degree is 0 (meaning that not all terminals are connected). This is because when the cost is low, it is not possible to connect all terminals. As the budget increases, more options are available for selection. TABLE 1 summarizes the results of selected scenarios. Each scenario comprises a budget, annual time saving, and balanced origin and destination nodes (degree). The selected scenarios provides the decision maker with three clusters of solutions, in each, one objective is set fixed, while the two others are variable. For example, for a fixed annual time saving (3,932K), and a degree range of 0-7, the required budget is presented. It can be observed that for higher connectivity (degree), larger budget is required, assisting the decision maker selecting the right alternative. The same applies when fixing the degree, or fixing the budget. Thus, the decision maker can set preferences for the objective functions and explore a more fine-tuned solutions.

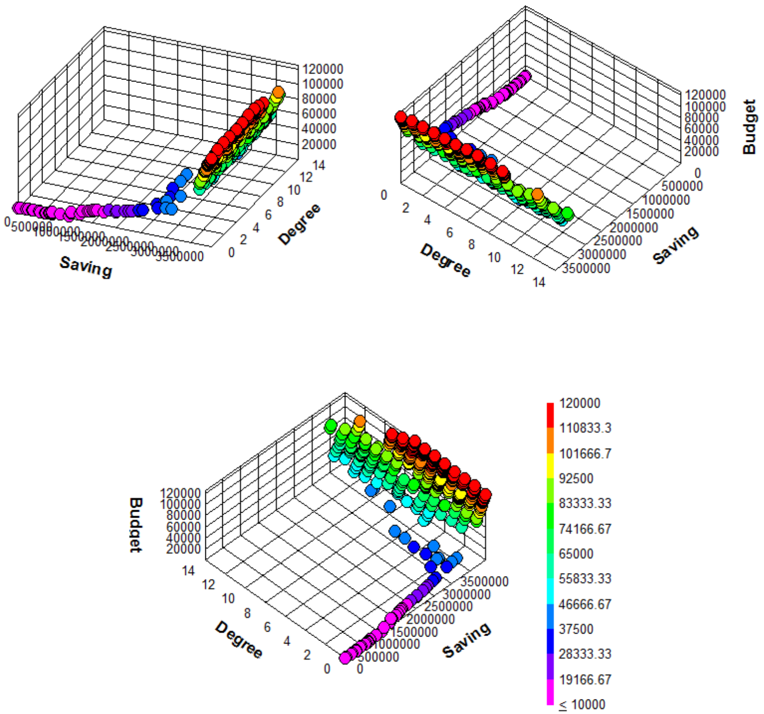

Fig. 4 A 3D graph of the solution Pareto-front

Table 1 optimal results for different scenarios

	Budget	Degree	Annual Time Savings (Pax x KM)
Fixed Saving	118M	0	3,932K
	121M	1	
	122M	2	
	123M	4	
	124M	5	
	126M	7	
Fixed Degree	53M	6	3,421K
	75M		3,631K
	96M		3,759K
	106M		3,817K
	119M		3,889K
Fixed Budget	100M	3	3,791K
		7	3,786K

5.1 Multi-Criteria Decision Making

This section demonstrates the use of multi-criteria decision making method as an aiding tool for the DM for selecting a preferred solution based on the DM preferences. Two such methods are used in this section, AHP and TOPSIS. The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a multi-criteria decision analysis method, based on the principle that the preferred solution should simultaneously be closest to the ideal solution and farthest from the negative-ideal solution. The method uses an index that combines the closeness of an alternative to the positive-ideal solution with its remoteness from the negative-ideal solution. The alternative maximizing this index value is the preferred alternative (Hwang and Yoon 1981). The Analytic Hierarchy Process (AHP) considers a set of evaluation criteria, and a set of alternative options among which the best decision is to be made. Based on the DM's pairwise comparisons, the AHP algorithm generates pairwise comparison matrix between all alternative solutions, with respect to the first criteria. Next, all the elements of the matrix are normalized with respect to the sum of elements in each column, and a new column, which its elements are the normalized values of the sum of the rows, is added. The resulting priority matrix tells us, which alternative solution has the highest priority. In order to obtain a preferred solution, a consistency ratio has to be calculated. For that, a consistency index, which is the max eigenvalue of the comparison matrix, is calculated. Dividing the consistency index by random index (consistency index of the totally random matrix) results with a consistency ratio. To create full AHP model the process should be repeated for all criteria and then in the final step arrive at the synthesis by multiplying preferences for all criteria times choice selections within each criteria (Kniaz , Teknomo , Saaty 1977).

An online questionary was distributed among public transport decision makers (DM) and stakeholders (authorities, operators, and users). The DMs have been asked to assign weights to the three criteria (to be used with TOPSIS), to provide a pairwise comparison of these criteria (to be used with AHP), and to provide criteria's range for feasible solutions. Table 2 summarizes the DM's preferences.

Table 2 decision makers' preferences

DM	Criteria	Weights	Pairwise comparison			Range (M$)
			Cost	Saving	Degree	
1 (authority)	Cost	3	1	***5***	***3***	30-50
	Saving	10	0.2	1	0.5	>0
	Degree	8	0.333	***2***	1	>0
2 (user)	Cost	7	1	***5***	***8***	40-60
	Saving	8	0.2	1	***2***	>0
	Degree	10	0.125	0.5	1	>0

From the 365 solutions only 14 match the first DM preferences, and 31 match the second DM preferences. Both AHP and TOPSIS methods have been used to sort the solutions based on the user preferences. Weights were also calculated from the pairwise comparison matrices and were used with the TOPSIS algorithm, (AHP-TOPSIS). The results are listed in Table 3 and Table 4. As it can be seen from the results, the AHP and TOPSIS recommendations are inconsistent, with similar extreme rankings. The reason stems from the different weighting technique used. The TOPSIS is based on a traditional weighting of all objective functions, whereas the AHP is based on a pair-wise comparison. The later has the benefits of a more focused weighting technique and the consistency analysis. This is evident from the combined TOPSIS-AHP ranking, which incorporates the AHP weighting with the TOPSIS ranking. This method has similar results to the AHP, hence strengthen the advantages of AHP.

Table 3 DM #1 Solutions ranking based on AHP & TOPSIS

No.	Cost	Degree	Saving	AHP	TOPSIS	AHP-TOPSIS
9	47560	13	3281674	1	1	1
5	42479	11	3236502	2	4	2
4	41071	9	3335523	3	9	9
7	45406	11	3268631	4	6	6
11	48880	12	3367782	5	2	3
10	48366	12	3305832	6	3	5
8	47405	11	3349103	7	5	4
6	45242	10	3363844	8	8	7
12	48894	11	3382294	9	7	8
3	39924	5	3263791	10	11	10
2	38224	4	3077972	11	14	13
13	49668	5	3382540	12	10	11
1	37721	1	2784613	13	13	14
14	49817	4	3412336	14	12	12

Table 4 DM #2 Solutions ranking based on AHP & TOPSIS

No.	Cost	Degree	Saving	AHP	TOPSIS	AHP-TOPSIS
2	42479	11	3236502	1	10	1
1	41071	9	3335523	2	21	2
6	47560	13	3281674	3	1	5
4	45406	11	3268631	4	11	3
3	45242	10	3363844	5	18	4
7	48366	12	3305832	6	3	7
5	47405	11	3349103	7	12	6
8	48880	12	3367782	8	4	8
13	51028	13	3324070	9	2	10
9	48894	11	3382294	10	13	9
14	51173	12	3401525	11	6	11
22	54235	13	3357861	12	5	14
16	52164	11	3415455	13	14	13
29	56070	13	3500749	14	7	19
25	55023	12	3407849	15	8	18
20	53788	11	3441195	16	15	16

12	50445	9	3396230	17	22	12
28	55985	12	3413562	18	9	22
23	54397	11	3442082	19	16	20
19	53775	10	3419026	20	19	21
30	58637	11	3508101	21	17	26
10	49668	5	3382540	22	25	15
18	53120	7	3447309	23	23	23
31	59879	10	3539263	24	20	27
11	49817	4	3412336	25	29	17
17	52411	5	3416734	26	26	24
27	55175	6	3466875	27	24	29
15	52134	4	3426225	28	30	25
24	54865	5	3474573	29	28	30
26	55025	5	3494307	30	27	31
21	54134	4	3451799	31	31	28

6 Concluding Remark

This work presents a novel multi-objective approach for selecting an optimal network of public transport (PT) priority lanes. It is based on a system-wide concept to result with the optimal PT network coverage. The model's contribution stems from the multi-objective properties, when compared to the single objective model (Hadas and Ceder 2014). A single objective model must be executed numerous times in order to provide a set of feasible solutions to the decision maker, while multi-objective models exhibit, with a single execution, a complete set of feasible solutions. Moreover, based AHP or TOPSIS it is possible to easily rank the solution set, based on the DM preferences.

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