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Urban bus network of priority lanes: A combined multi-objective, multi-criteria and group decision-making approach

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ABSTRACT

This study 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. This study develops a multi-objective model for selecting an optimal PT priority lanes network that 1) maximizes total travel time savings; 2) maintains balanced origin and destination terminals; and 3) minimizes the construction budget. In contrast to commonly used single objective models, which must be executed numerous times in order to provide the decision-maker with feasible solutions, multi-objective models exhibit a complete set of feasible and optimal solutions with a single execution. Since the major disadvantage of a multi-objective model is the need to select a preferred solution from a set, a multi-criteria approach was developed for: 1) ranking each decision-maker's solutions; and 2) selecting a compromise solution acceptable to a group of decision-makers. This methodology is demonstrated with a case study of Petah Tikva, a medium-sized city in Israel.

1. Introduction

Public transport priority schemes are used to "reduce or eliminate certain types of general traffic interference that can slow down transit service, make it less reliable, or reduce its capacity" (Kittelson & Associates. et al., 2003). This priority can be both spatial (dedicated lanes) and temporal (traffic signal priority). Spatial schemes can be classified as: mixed traffic (no priority to public transport vehicles); semi-exclusive (a lane partially reserved for public transport but also available, based on time or location, to other types of vehicles); exclusive (a fully reserved lane, but interaction with other modes of transport occurs at intersections, turnings, etc.), and grade separated (exclusively dedicated for public transport vehicles).

Ceder (2004), investigated several priority schemes in Europe (Athens, Dublin, Munich, Turin, Vienna, and Zurich) and concluded that they have a positive effect on reducing travel times and increasing average speed, patronage and revenues. Mesbah, Sarvi, and Currie (Mesbah et al., 2008, 2010, 2011b) were the first to introduce a system-wide approach for designing priority lanes based on a bi-level model comprising priority lane selection and traffic assignment. A model was recently developed for optimal construction of a connected network of bus priority lanes (Hadas and Ceder, 2014). This optimization model presented an algorithm for maximizing the travel time reduction resulting from the use of priority lanes given a predefined budget. However, the major disadvantage in investigating a wide range of scenarios is that the policymaker is required to execute the algorithm multiple times with different budget constraints, as larger budgets lead to the construction of more priority lanes and increased travel time reduction. The repeated executions are time consuming and cumbersome.

This paper introduces a multi-objective and multi-criteria framework with three components: 1) a multi-objective algorithm that with one execution provides a set of solutions for the decision-maker to choose from; 2) a multi-criteria model that assists the decision-maker to rank a solution based on specific preferences; (3) joint group ranking for selecting the solution ranked highest by all decision-makers.

2. Literature review

2.1. Public transport network design

Numerous studies have been published regarding the design of public transport networks. Baaj and Mahmassani (1991, 1992,

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1995) developed methods based on artificial intelligence with minimum frequency, load-factor, and fleet-size constraints. Ramirez and Seneviratne (1996), proposed models with multiple objectives, taking into account passenger flow and distance travelled. Yan and Chen (2002) developed a model for designing routes and timetables that optimizes the correlation between supply and demand. Bagloee and Ceder (2011) developed a heuristic model in order to solve realistically sized road networks. The model takes into account budget constraints, level of service and attractiveness of the system.

All these models and approaches neglect to incorporate priority schemes as an integral part of PT network design. Many bus priority strategies have been demonstrated worldwide. Traditionally, priority is granted for bus operation at stops, intersections, and by preferential/exclusive lanes. It is known that bus travel times, reliability of service, and vehicle productivity improve 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. et al., 2003).

Skabardonis (2000) reviewed existing control strategies, evaluated them on an actual arterial corridor, identified the major factors affecting transit priority, and formulated both passive and active transit priority strategies. According to the review, both the passive and active priority strategies placed major emphasis on system-wide improvements to transit movements and on minimizing any adverse impact on the rest of the traffic stream. An evaluation technique was also developed to assist in designing signal priority strategies and to predict the impact of the transit priority measures. Turnquist and Bowman (1980) used a set of simulation experiments to investigate the effect on service reliability of several characteristics of network structure in urban bus systems. These experiments primarily focused on the factors which lead to vehicle bunching and on the effect 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 expedite transfers, especially in radial networks. Yao et al. (2014) presented a tabu search-based transit network optimization method that considers travel time reliability. The optimization model seeks to maximize the efficiency of passenger trips in the transit network. The results show that the proposed method can effectively improve the reliability of a transit network and reduce the travel time of passengers in general.

Currie and Lai (2008), who investigated dynamic priority lanes, reviewed a variation of the intermittent bus lanes (IBL) and dynamic transit lanes concept, in the dynamic fairway (DF) adopted for trams in Melbourne, Australia. Their paper documents the world's first practical, ongoing experience with IBL-DF operation. It also presents future plans for a Melbourne bus-based IBL, referred to as the "moving bus lane." 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 their 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 traffic delay increases. 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 cannot be operated, a BLIP can save bus and car occupants together as much as 20 persons-min of travel per bus-km. Xie et al. (2012) describe how dynamic bus lanes with BLIP allocation strategies may improve bus transit. These strategies consist of intermittently opening the bus lane to general traffic when not in use by a bus. Simulated results are consistent with analytical results.

The first to introduce a system-wide approach for designing priority lanes were Mesbah, Sarvi, and Currie (Mesbah et al., 2008, 2011a, 2010, 2011b) who proposed a bi-level model combining priority lane selection and traffic assignment. The model assesses the impact of exclusive lanes on private car travel time and optimizes 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 may be, the following issues have to be considered. a) The model considers two alternatives, exclusive or mixed, while it is possible to consider other alternatives which differ in cost, flow, travel time reduction, etc. b) The priority lanes presented in the model 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 cover the network efficiently since as the model only takes into account travel time reduction. Hadas and Ceder (2014) recently introduced a new approach and modelling for selecting an optimal network of public transport (PT) priority lanes. Their approach is based on a system-wide concept that results in optimal PT network coverage. It develops a model for optimally selecting a set of PT priority lanes that maximizes total travel time savings while also maintaining balanced origin and destination terminals given a budget constraint.

2.2. Multi-objective optimization

Many problems have multiple conflicting objectives, for which there is no single best solution. For example, solution x_1 is said to dominate solution x_2 if x_1 is better than x_2 when measured on all objectives. If x_1 does not dominate x_2 and x_2 also does not dominate x_1, they are referred to as non-dominated solutions. Various multi-objective optimization algorithms provide a set of non-dominated solutions. If the set of non-dominated solutions represents the entire search space, it is called the global Pareto optimal set (or the Pareto set). Otherwise it is called the local Pareto optimal set (Coello Coello, 2006).

Fig. 1 presents an example of a Pareto front. The various points represent feasible choices in which smaller values are preferred to larger ones. Points C and D are not on the Pareto front because point C is dominated by both points A and B, while point D is dominated by point B. Points A and B are not strictly dominated by any other point, and hence lie on the frontier.

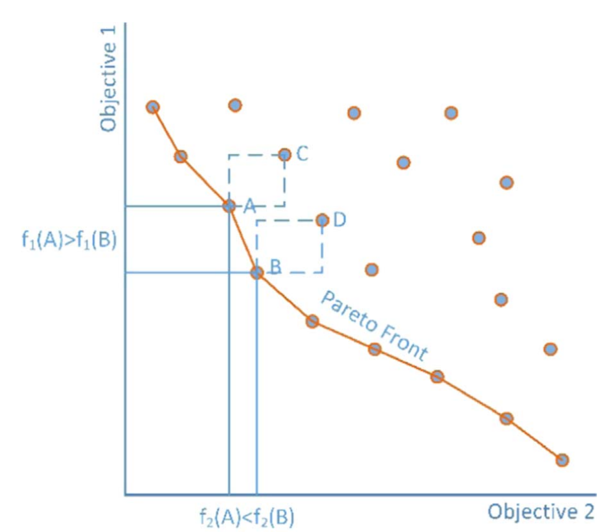

Fig. 1. Example of a Pareto front.

From a practical perspective, users need only one solution from the set of optimal solutions. Therefore, solving Multi-Objective Problems (MOPs) can be seen as a combination of both searching and decision-making (Horn, 1996). Four main approaches are presented in the literature (Miettinen, 1999).

1) **No-preference**
In no-preference methods, where the preferences of the decision-maker (DM) are not taken into consideration, the problem is solved using a relatively simple method, and the solution is presented to the DM. The global criterion is an example of this method (Miettinen, 1999; Zeleny and Cochrane, 1982). The global criterion method transforms MOPs into single objective optimization problems by minimizing the distance between reference points and the feasible objective region.
2) **Decision-making after search/a posteriori**
These methods find all possible solutions of the non-dominated set and utilize user preferences to determine which is the most suitable. The weighted-sum (Cohon, 2013; Miettinen, 1999) and ϵ-constraint (Haimes et al., 1971) methods are examples. 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, a set of optimal solutions will be obtained.
3) **Decision-making before search/a priori**
These methods incorporate the use of a preference before the optimization process. Consequently there is only one solution at the end. An obvious example of this 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 while the result of each optimization process is used as a constraint for the next process.
4) **Decision-making during search/interactive**
These methods are a hybridization of the second and third methods. Using this type of method, a human DM periodically refines the obtained trade-off solutions and thus guides the search.

2.3. Multi-objective evolutionary algorithms

Multi-objective evolutionary algorithms (MOEAs) are stochastic population-based optimization techniques used to find Pareto optimal (or near optimal) solutions for a given problem. MOEAs are similar to EAs (evolutionary algorithms), except for the use of the dominance relation as the criterion for reproduction probability. Thus, at each generation objective values are calculated for every individual in the population and are then used to rank the individuals based on their dominance relationships within the population. Higher ranking individuals are given higher probabilities to produce the offspring population.

Elitism is a mechanism to preserve the best individuals from one generation to another. Using elitism, best individuals found during the optimization process are never lost. Non-elitism MOEAs include VEGA (Schaffer, 1985), MOGA (Fonseca and Fleming, 1993), NPGA (Horn et al., 1994) and NSGA (Deb, 2001). Elitism algorithms include PAES (Knowles and Corne, 2000), SPEA2 (Zitzler et al., 2001), PDE (Abbass et al., 2001), NSGA-II (Deb et al., 2002) and MOPSO (Coello et al., 2004).

2.4. Multi-criteria decision-making

In most cases, when solving a multi-objective optimization problem, the result is a non-dominated solution set from which the DM has to choose his preferred alternative. (Within such a set no solution is better than another with respect to all the objectives.). Selecting a preferred alternative is not a trivial task, and for that reason some decision-making methods have been developed. Accordingly, multi-criteria decision-making (MCDM) methods, some of which are listed below, are automated methods for selecting a preferred solution given a set of feasible solutions, while having conflicting criteria (Ehrgott, 2005; Żak and Kruszyński, 2015). MCDM methods also allow assigning the various solutions to different pre-defined classes and ordering them from best to worst (Vincke, 1992).

A multi-criteria decision problem contains a set, A, of actions, variants and/or solutions (defined using a complete list or set of constraints) and a consistent set, F, of criteria. The consistent set of criteria, which is consistent with the DM's preferences, provides a comprehensive and complete evaluation of the set A. Moreover, no correlation exists between the various criteria domains, and the domains of all criteria are disjointed (Roy, 1990; Żak and Kruszyński, 2015).

The various methods of MCDM can be classified in different ways. A general classification based on the purpose of the algorithm is (1) MC choice/optimization methods, (2) MC sorting methods and (3) MC ranking methods.

The max-min method, for example, can be used when the DM wants to maximize the achievement in the weakest criterion, while the min-max method can be used to minimize the maximum opportunity loss. Compromise programming identifies the solution for which the distance from the ideal solution is the minimum. (The ideal solution is an artificial solution consists of the upper bound for maximization of the criteria set.) The 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 selecting the preferred solution. The second version of this method provides a complete rank ordering of the original set of alternatives. The TOPSIS method (Hwang and Yoon, 1981) assumes that the preferred solution should simultaneously be closest to the ideal solution and farthest from the negative-ideal solution. (The negative-ideal solution is an artificial solution that consists of the lower bound for maximization of the criteria set.) For every solution, TOPSIS calculates an index that combines both its closeness to the positive-ideal solution and its remoteness from the negative-ideal solution. The alternative that maximizes this index value is the preferred alternative. Multi-attribute utility theory (MAUT) (Keeney et al., 1979) is based upon the assumption that every DM tries to optimize a utility function that is not necessarily known at the beginning of the decision process. The utility function is composed of various criteria that enable assessing the global utility of an alternative. For each criterion, the DM gives a score, referred to as 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, which are usually 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 is given a rank of 1.) Next, the weight of each criterion 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 does 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 a method, consider the analytic hierarchy process (AHP) proposed by Saaty (1977, 2008). With AHP, the decision problem is first structured as hierarchal levels. At the top level is the goal of the problem while subsequent levels represent criteria, sub-criteria, and so on with the last level representing the decision alternatives. Next, value judgments concerning the alternatives with respect to the next higher level sub-criteria are calculated based on available measurements. If measurements are not available, the calculation is made from pairwise comparison. After the value judgments of alternatives have been computed, composite values are determined by finding the weighted average values across all levels of the hierarchy. The analytic network process (ANP), a generalization of the AHP method that deals with dependencies, is another example of MCDM methodology (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 directly asking the DM for a numerical weight 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".

According to Żak and Kruszyński (2015), municipal transportation projects, that are aimed at the development and enhancement of the urban transportation system, must satisfy the city's transportation policy and development strategy. The various implications of building and using transportation systems make the task of designing and planning them complex. Therefore, in addition to using multi-objective optimization methods in order to obtain a set of optimal alternatives, multi-criteria decision methods are used to order the alternative solutions and, eventually choose the preferred one (Pérez et al., 2015).

The following are a few examples of MCDM in the field of transportation. Roy and Hugonnard (1982) used ELECTRE IV in order to rank 12 suburban line extension projects on the Paris metro system. Wey and Wu (2007) worked on transportation infrastructure (TI) project selection, where multiple factors such as project risk, corporate goals, limited availability of a firm's TI resources, etc., had to be considered. The problem was approached using fuzzy Delphi, analytic network process (ANP) and the zero–one goal programming (ZOGP) model. The use of this model was demonstrated using an ongoing decision-making project in Taichung City, Taiwan. Awasthi et al. (2011) presented a multi-criteria decision-making approach for planning the location of urban distribution centers under uncertainty. Using fuzzy TOPSIS, various potential locations are evaluated based on a set of evaluation criteria, and the best location is selected for an urban distribution center. Angulo et al. (2014) addressed the problem of highway network expansion. They proposed an extended. multi-objective, bi-level, and continuous location model, The model that considers demands, budget and user behavior is capable of handling uncertainty in demand.

3. The framework for the multi-objective and multi-criteria model

The present study introduces a combined Multi-Objective (MO) and Multi-Criteria (MC) approach for selecting a compromise solution (in the MC stage), based on a feasible, non-dominated solution set (from the MO stage). The framework illustrated in Fig. 2 is comprised of: 1) an optimization stage, which based on the PT network structure, costs, etc., finds the optimal solution set; 2) a ranking stage, where the optimal solution set, along with the DM's preferences serve as the input for the MCDM process which orders the solution set based on each DM preferences; and 3) a group selection process which combines the ordered solutions of each of the DMs and selects one solution acceptable to them all.

3.1. Data and parameters

The following parameters are used as input for the model:

$G(N,A)$ a directed network that comprises all road segments traversed by PT routes

I a set of all nodes from which a priority lane starts or ends, $I \subseteq N$ (i.e. the circled nodes in Fig. 3)

i, j nodes of network G, $i \in N, j \in N$

P a set of all possible paths (shortest, quickest, etc.) starting at node s and terminating at node t (i.e. 15-14-32-13-12-11-33. Such a path is shown in Fig. 3). Matrix P can be easily calculated, as described in Hadas and Ceder (2014).

s, t nodes of network G, serving as end points for $p \in P, s \in I, t \in I$

$p_{i,j}^{m,s,t}$ an indicator whether road segment (i,j) is part of path m that starts from s and terminates at t (of set P)

k priority lane alternative index (i.e. mixed traffic, semi-exclusive, exclusive, grade separated)

$c_{i,j}^{k}$ the construction costs of road segment (i,j), for alternative k (of set C)

$v_{i,j}^{k}$ the travel time saving per passenger along road segment (i,j), for alternative k. The time saving is the estimated reduction of travel time as a result of implementing priority lane alternative k (of set V).

$f_{i,j}$ the total passenger flow of all routes passing through road segment (i,j)

dm a decision-maker (of set DM)

w_{dm}^{of} decision-maker dm weight for each objective function of (set W)

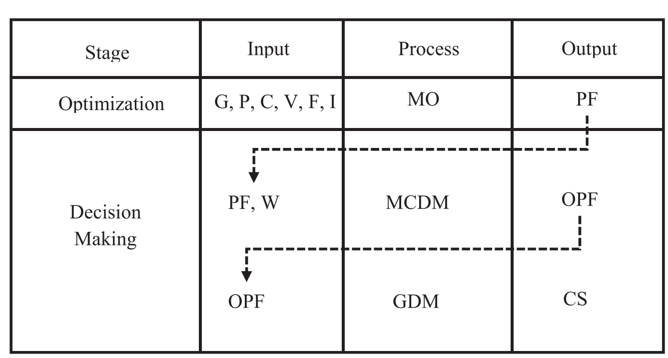

Fig. 2. The framework's components interactions.

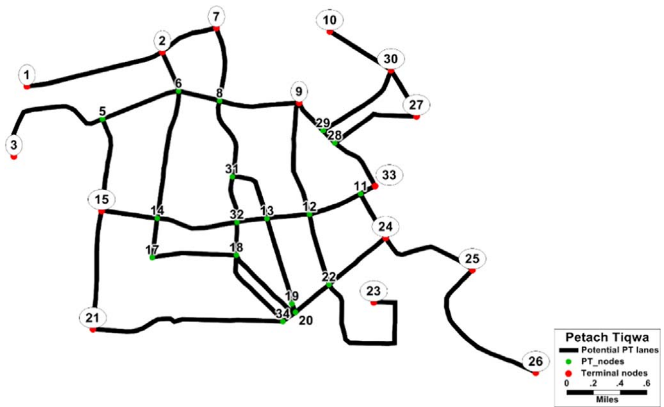

Fig. 3. Potential priority lanes and terminal nodes.

3.2. Decision variables

$x_{i,j}^{k}$ such that "1" represents the selection of priority lane alternative k for road segment (i, j), and "0" otherwise. $x_{i,j}^{k} \in PF$

$px^{m,s,t}$ such that "1" represents the selection of path m that starts from node $s \in I$ and terminates at node $t \in I$, and "0" otherwise.

3.3. Objective functions

OF-s maximizing the total travel time savings for PT users, caused by the selected set of priority lanes (the saving objective).

OF-d maintains a balanced connectivity between the selected terminal nodes – represented by maximizing the minimal degree for all terminal nodes $s \in I$. The degree represents the number of priority lanes connecting node s to other terminal nodes. A higher degree corresponds to better connectivity for a single node, while balanced degree corresponded to better overall connectivity (the degree objective).

OF-b minimizing the budget allocation for construction of priority lanes (the budget objective).

3.4. Solution sets

PF the Pareto-front solution set

OPF_{dm} the ordered solution set of the decision-maker dm

CS the compromise solution set

4. Multi-objective model for connected urban bus priority lanes

The model's objective is to select a set of priority lanes that optimize OF-s, OF-d, OF-b. This multi-objective model is developed based on the single objective model presented by Hadas and Ceder (2014), Each priority lane will start from a node and end at a node serving as terminals of the PT network. A connected, urban bus priority lane network is a system-wide approach for PT planning. Such an approach increases the PT connectivity level and thus improves the attractiveness of the PT service. Moreover, efficient transfers can enhance the overall PT network performance by providing better coverage and connectivity. The network presented in Fig. 3, 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 savings). 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, route 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 experience traffic bottlenecks in the form of non-prioritized sections.*"

The three objective functions (OF-s, OF-d, and OF-b) are good representatives of social welfare, design qualities, and economic considerations, respectively. Thus, they are non-redundant and also cover the major aspects of PT network projects. Furthermore, these objective functions represent the traditional PT stakeholders including user, authority, and operator. The user seeks a well-connected network (OF-d), which is attractive (OF-s), and can compete with the private vehicle. The authority is concerned with efficient budget allocation (OF-b) and its effect on the network characteristics (OF-s, OF-d). Finally, the operator is concerned with revenues which are affected by the network quality (represented by OF-d, and OF-s).

4.1. The formulation of the multi-objective problem

Objective functions

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

$$\max \min_{i|x_{i,j}^{k}=1} \left\{ \min_{j|x_{i,j}^{k}=1} \left(\sum_{t} px^{j,t}, \sum_{s} px^{s,j} \right) \right\} \tag{2}$$

$$\min \sum_{i} \sum_{j} \sum_{k} x_{i,j}^{k} \cdot c_{i,j}^{k} \tag{3}$$

subject to

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

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

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

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

* For clarity, the index m was omitted.

Eq. (1) maximizes total time saving that results from using the selected PT priority lanes (OF-s). Eq. (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 (OF-d). An unbalanced priority lane set will impact the overall reliability of the PT network and reduce the level of service. Eq. (3) minimizes budget allocation (Of-b) and constraint (4) maintains the selection of one alternative. Constraint (5) ensures that if at least one path ($\sum_s \sum_{s \neq t} (p_{i,j}^{s,t} \times px^{s,t}) \geq 1$) from s to t is selected ($px^{s,t}$=1), then one alternative ($x_{i,j}^{k}$) for road segment (i, j) must be selected given that the road segment is part of a path from s to t ($p_{i,j}^{s,t}$=1). This constraint also maintains the continuity of each selected priority lane. Constraints (6) and (7) define binary decision variables.

The model described above cannot be solved optimally for two main reason: 1) The problem is a multi-objective optimization problem; and 2) The problem is defined as an integer linear programming problem, which is NP-Hard. This requires the use of a heuristic algorithm for solving the problem.

4.2. The multi-objective evolutionary algorithm

In this paper, the Strength Pareto Evolutionary Algorithm 2 (SPEA2) (Zitzler 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 solutions. The algorithm which was tested using the single objective formulation and test cases presented in the original paper (Hadas and Ceder, 2014), was 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 used to create offspring for the next generation. To avoid a situation in which 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 the archive and population, is calculated. For 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 is incorporated, based on the kth nearest neighbor.

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=∅. 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.

For the problem studied, a candidate solution must specify the selected paths and the selected alternative for each node belonging to the selected paths. A solution can be encoded using an array of integers of a size equal to the number of nodes plus the number of paths. This array is composed of two parts. The first part contains information about the selected alternative for each node: when 0 represents an unselected node, 1 indicates that the first alternative was selected and so on. The second part contains information about the selected paths when 1 represents a selected 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 about the selected paths, is used to create two new chromosomes that 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 of 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 in information about its associated nodes to a given solution; and (3) Change information – This operation randomly changes the information of a node belonging to a selected path in a given solution.

5. Multi-criteria approach for ranking and selecting solutions

5.1. Multi-criteria decision-making

This section demonstrates the use of multi-criteria decision-making as a tool for aiding the DM to rank and select a preferred solution based on the DM's preferences. Three such methods are used in this section, AHP, TOPSIS, and a combined AHP-TOPSIS method.

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, H^*, and farthest from the negative-ideal solution, L_*. 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). Mathematically, given a payoff matrix, θ, of size n by m, when n are the alternative solutions and m are the values of criteria for alternative, the first step of the TOPSIS method is normalizing this matrix, getting a new matrix, R, such that $r_{ij} = \theta_{ij} / \left(\sum_i \theta_{ij}^2 \right)^{0.5}$. Next, a weighted pay-off matrix, Q, is computed such that $q_{ij} = \lambda_j r_{ij}$, when λ_j is the relative importance weight of the j^{th} criteria. Next, the ideal and anti-ideal solutions are calculated as follows, $H^* = \left\{ q_j^* j = 1,2, \ldots, n \right\} = \left\{ Max q_{ij}, \forall\ i, j = 1,2, \ldots, n \right\}$ and $L_* = \left\{ q_j^* j = 1,2, \ldots, n \right\} = \left\{ Min q_{ij}, \forall\ i, j = 1,2, \ldots, n \right\}$. Then, for each solution, separation measures (the distance from the ideal and negative-ideal solutions) are calculated, meaning $P_i^* = \left[\sum_i \left(q_{ij} - q_j^* \right)^2 \right]^{0.5}, i = 1,2, \ldots m$ and $P_{*i} = \left[\sum_i \left(q_{ij} - q_{*j} \right)^2 \right]^{0.5}, i = 1,2, \ldots m$. TOPSIS identifies the preferred solution by minimizing the similarity index, D, which equals the ratio between the distance from the negative-ideal solution and the sum of distances from the ideal and negative-ideal solutions in the following way: $D_i = P_{*i} / (P_{*i} + P_i^*), i = 1,2, \ldots, m$. All solutions are ranked by their index values. A solution with a higher index value is preferred over one with index values smaller than its value.

TOPSIS is a good method due to its simplicity and ability to consider a non-limited number of alternatives and criteria in the

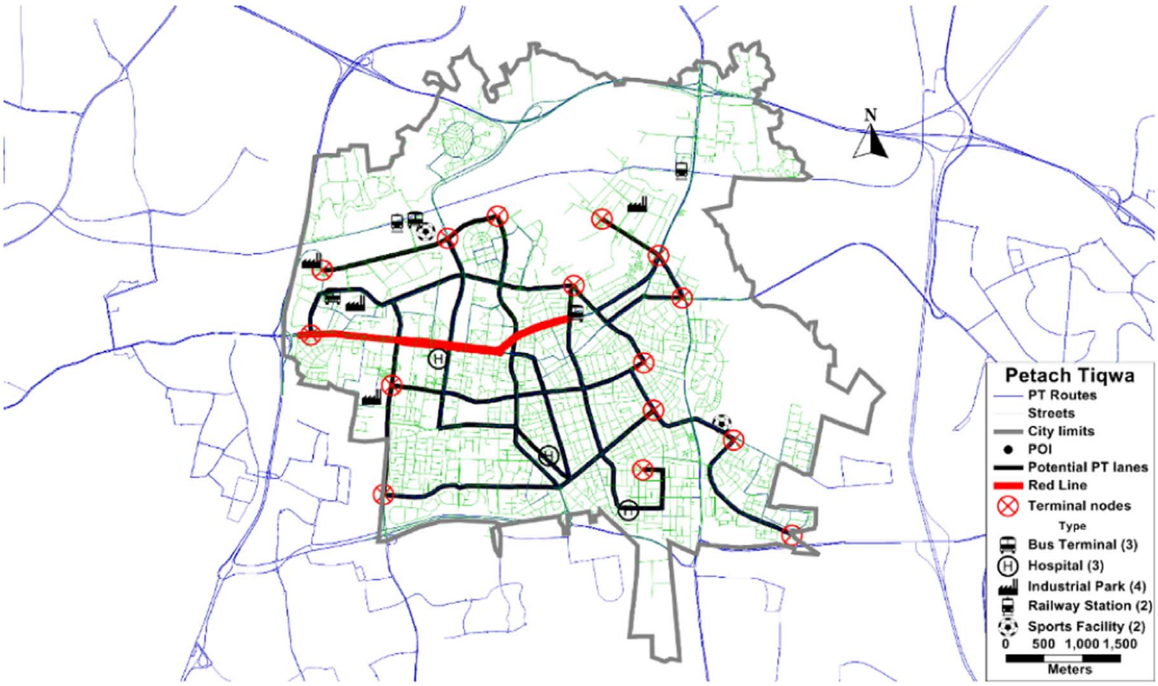

Fig. 4. Petah Tikva's street and PT network with potential road segments and terminals.

decision making process. On the other hand, the TOPSIS method requires a weight vector, stating the importance of each criterion compared to all others. For large number of criteria, the weight vector might include inconsistencies. Therefore, the AHP method, described next in this chapter, is used as well.

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. It is assumed that there are n alternatives, $C_1,\ldots,C_n$, to be compared, and m criteria for evaluating each alternative. First, a pairwise comparison between all alternative solutions is performed with respect to the first criteria. This means that every two alternatives, C_i and C_j are assigned a relative weight to each other (or priority or significant) denoted as a_{ij}, which eventually form a square matrix $A=\left(a_{ij}\right)$ of order n with the constraints that $a_{ij}=1/a_{ji}$ for $i \neq j$, and $a_{ii}=1$, for all i, known as the pairwise comparison matrix. The matrix A s considered consistent if $a_{ik} = a_{ij}a_{jk}$ for all i, j and k. Next, a vector ω of order n such that $A\omega=\lambda\omega$, is found. In the case of AHP, ω is an eigenvector (of order n) and λ is an eigenvalue, which, for a consistent matrix, equals n. When the matrix A is not consistent, the ω vector has to satisfy $A\omega=\lambda_{max}\omega$ and $\lambda_{max}\geq n$. Since human nature is often inconsistent, the entries are checked to detect possible contradictions. When several successive pairwise comparisons are presented, they may contradict each other. This may, among other causes, be due to insufficient or uncertain information, vaguely defined problems, or lack of concentration. AHP defines a measurement called the "Consistency Ratio" (CR) which is the ratio between the inconsistency found in the entries (*CI*) and the average inconsistency of 500 randomly filled matrices (random index). If the value of the CR is smaller or equal to 10%, the inconsistency is acceptable. The Consistency Index, *CI*, can be calculated from $(\lambda_{max}\text{-}n)/(n-1)$. To create a full AHP model, the process should be repeated for all criteria. In the last step the synthesis is obtained by multiplying preferences for all criteria by the choice selections within each criteria (Kniaz, 2015; Saaty, 1977; Teknomo, 2015).

Finally, a *combined AHP-TOPSIS method* is introduced. Following the advantages of AHP's pairwise comparison over traditional weight assignment methods, the present approach proposes basing the TOPSIS ranking on the AHP weight vector.

5.2. Group decision-making

One of the main obstacles for implementing a transportation plan is the different objectives set by the stakeholders, specifically both the local and national authorities as well as users. This can lead to disagreement concerning the recommended plan (or solution). As a consequence decisions might not be made or stakeholders might be dissatisfied. The problem is intensified if multiple available solutions are all feasible and non-dominated. On the other hand, it is possible to utilize group decision-making (GDM) in order to select a compromise solution. Hwang and Lin (2012) provide a comprehensive review of GDM techniques and models. They classify GDM in three groups: social choice theory, expert judgment, and game theory. According to social choice theory, each decision-maker casts a vote to select an alternative. Each alternative is analyzed by each voter based on multiple criteria and the selection is based on the group voting process. Expert judgment (or group participation) is characterized by the suggestion of solutions by experts; the consideration of different points of view; and the selection of a solution based on a joint agreement, polling, surveys, brainstorming, etc. When a conflict of interest arises, Game theory is useful as the players deploy strategies in order to address the payoff function of the game.

GDM and MCDM share some common characteristics. MCDM problems aim at finding good performance of the complete set of criteria, while GDM problems aim at obtaining a ranking which satisfies all players. Both types of problems share the concept of an ideal solution, which is often unfeasible. This also applies to the concept of dominance. When the ideal solution is not feasible, a decision-maker's preferences must be modeled on multiple criteria (in MCDM), or the group decision-maker's preferences on multiple players (in GDM), in order to find the best solution (Leyva-Lopez and Fernandez-Gonzalez, 2003).

Our selection model is based on a voting mechanism (social choice) for the following reasons: 1) It combines the final decision of each of the DMs, not his judgment, which Saaty (2008) found highly important; 2) Each DM previously ranked an optimal

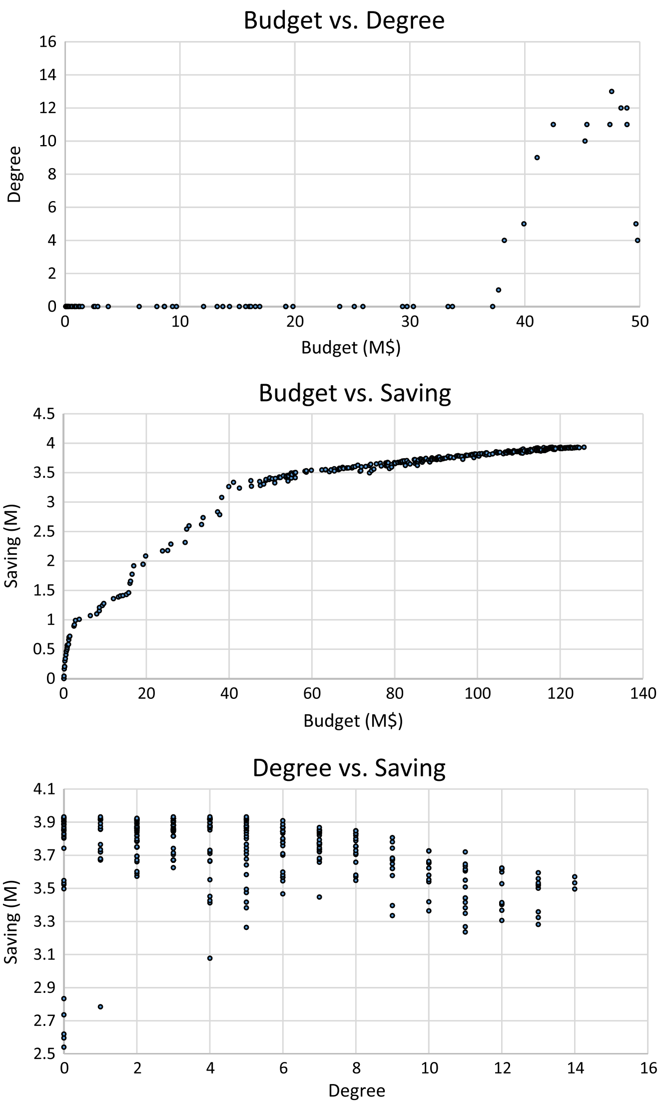

Fig. 5. the Pareto-front solution set and the relationship between budget, degree and saving.

Table 1
Optimal results for different scenarios.

Budget	Degree	Saving
	Fixed Saving	
118M	0	3.9 M
121M	1	
122M	2	
123M	4	
124M	5	
126M	7	
	Fixed Degree	
53M	6	3.4M
75M		3.6M
96M		3.8M
106M		3.8M
119M		3.9M
	Fixed Budget	
100M	3	3.8M
	7	3.8M

solution set based on his or her preferences; 3) The present approach seeks a solution that will be easily accepted by all DM's.

In cases in which a group of voters are supposed to choose a preferred alternative over the set of alternatives and each voter ranks the alternatives in a different order of preference, an aiding mechanism can be used. In such cases, rather than choosing an alternative preferred by a majority, a consensus-based alternative is chosen. One of the best, if not among the best consensus-based voting procedures is the Borda Count method (Zahid and de Swart, 2015). The Borda function is homogeneous, monotonic, Pareto optimal, anonymous, and neutral (Hwang and Lin, 2012).

The Borda Count (BC) method defines consensus functions by mapping a set of individual rankings to a combined ranking, called *Risk Rank* (RR). To do that for every voter $j \in N$, each alternative solution $i \in M$ is given a ranked value, R_{ij}, such that the most important alternative is given the value of one, the second important alternative is given the value of two and so on. If two or more alternatives are considered equally important, they all are given the same value, which is the average value of their rankings. After all alternative solutions are ranked by all votes, the *Risk Rank* of each alternative $i \in M$ can be calculated such that $RR = \sum_{j=1}^{N} M - R_{ij}$. The most preferred alternative is the alternative with the highest value of RR. Similarly, the least preferred alternative is the alternative with the lowest value of RR.

The Borda Count method is easy to implement and does not require any training. The method treats all classifiers equally and does not take into account individual classifier capabilities, a disadvantage that can be addressed by applying different weights for every classifier (which may require additional training), and calculating the BC as a weighted sum of a number of classes (Ruta and Gabrys, 2000).

6. Case study

6.1. Highlights from the original case study

The present case study re-examines a previous study (Hadas and Ceder, 2014). That study was conducted as part of a proposal submitted to the Israeli Ministry of Transport and Road Safety (Ministry of Transport and Ministry of Treasury, 2011). For the sake of clarity, the following is a brief description of the earlier case study.

Petah Tikva is the fifth largest city in Israel with 211,000 residents, and an area of 36 km^2. The city is located in Israel's largest metropolitan area (Gush-Dan). As of 2010, the compound annual growth rate of the Petah Tikva population was 3.3% (compared to 1.5% for the entire population of Israel). Based on the 2008 census (Central Bureau of Statistics, 2008), 49% of Petah Tikva's residents worked in the city (~50,000), while an additional 84,000 individuals commuted from other cities. As of 2008, 26% of these commuters travelled on public transportation (PT). One bus operator serves the city's urban PT network. All routes share the road with private and commercial vehicles. A light rail transit (LRT) line is being developed to connect the city's central bus station to other municipalities in the metropolitan area. This is indicated in Fig. 4 by a red line. Some of the major points of interest, such as bus terminals and industrial parks are illustrated as well. The following steps were implemented in the previous case study: 1) Possible road segments were selected for use as priority lanes, as well as terminals to serve as start and end points for these lanes (see Fig. 4). 2) Costs and benefits were estimated based on the proposal guidelines of the Ministry of Transport and Ministry of Treasury (2011). Costs and benefits were calculated as construction costs (USD) per km, and annual time saved (ATS) for distance travelled,

Table 2
Decision-maker preferences.

DM	Criteria	Weights	Pairwise comparison				Range (M$)	Solution set size
			Budget	Saving	Degree	CR		
1 (authority)	Budget	3	1	5	3	0.4%	30–50	14
	Saving	10	0.2	1	0.5		> 0	
	Degree	8	0.333	2	1		> 0	
2 (user)	Budget	7	1	5	8	0.6%	40–60	31
	Saving	8	0.2	1	2		> 0	
	Degree	10	0.125	0.5	1		> 0	
3 (authority)	Budget	3	1	5	5	0%	30–50	14
	Saving	10	0.125	1	1		> 0	
	Degree	10	0.125	1	1		> 0	
4 (user)	Budget	1	1	9	7	8.4%	45–60	29
	Saving	10	0.111	1	0.333		> 0	
	Degree	7	0.142	3	1		> 0	

Table 3
DM #1 - Solutions ranking.

No.	Budget	Degree	Saving	AHP	TOPSIS	AHP-TOPSIS
9	47,560	13	3,281,674	1	1	1
5	42,479	11	3,236,502	2	4	2
4	41,071	9	3,335,523	3	9	9
7	45,406	11	3,268,631	4	6	6
11	48,880	12	3,367,782	5	2	3
10	48,366	12	3,305,832	6	3	5
8	47,405	11	3,349,103	7	5	4
6	45,242	10	3,363,844	8	8	7
12	48,894	11	3,382,294	9	7	8
3	39,924	5	3,263,791	10	11	10
2	38,224	4	3,077,972	11	14	13
13	49,668	5	3,382,540	12	10	11
1	37,721	1	2,784,613	13	13	14
14	49,817	4	3,412,336	14	12	12

respectively. 3) A set of solutions based on the single objective model was constructed for several budget and degree combinations. 4) A preferred solution was selected based on a qualitative assessment by the DMs.

6.2. Multi-objective model results

The optimal multi-objective model for priority lane 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. The following conclusions can be drawn from the two Pareto-front graphs presented in Fig. 5: 1) When the budget is low, up to about \$38M, the degree for all solutions is 0. This indicates that not all terminals are connected because when the budget is low, it is impossible to connect them all. As the budget increases, more options are available for selection. 2) As the budget increases, the saving increases as well. 3) The benefits of the minimal connected network (degree = 1) are at least a saving of 2.8M. 4) Connectivity of degree 6 and higher has a negative effect on savings, as the budget is shifted from high saving segments to low saving segments in order to increase the degree. Table 1 summarizes the results of selected scenarios. Each scenario includes a budget, saving, and degree. The selected scenarios provide the decision-maker with three clusters of solutions. In each cluster, one objective is set as fixed while the other two are variable. For example, for a fixed saving (3.9M), and a degree range of 0–7, the required budget is presented. It can be observed that for higher connectivity (degree), a larger budget is required.

Table 4
DM #2 - Solutions ranking.

No.	Budget	Degree	Saving	AHP	TOPSIS	AHP-TOPSIS
2	42,479	11	3,236,502	1	10	1
1	41,071	9	3,335,523	2	21	2
6	47,560	13	3,281,674	3	1	5
4	45,406	11	3,268,631	4	11	3
3	45,242	10	3,363,844	5	18	4
7	48,366	12	3,305,832	6	3	7
5	47,405	11	3,349,103	7	12	6
8	48,880	12	3,367,782	8	4	8
13	51,028	13	3,324,070	9	2	10
9	48,894	11	3,382,294	10	13	9
14	51,173	12	3,401,525	11	6	11
22	54,235	13	3,357,861	12	5	14
16	52,164	11	3,415,455	13	14	13
29	56,070	13	3,500,749	14	7	19
25	55,023	12	3,407,849	15	8	18
20	53,788	11	3,441,195	16	15	16
12	50,445	9	3,396,230	17	22	12
28	55,985	12	3,413,562	18	9	22
23	54,397	11	3,442,082	19	16	20
19	53,775	10	3,419,026	20	19	21
30	58,637	11	3,508,101	21	17	26
10	49,668	5	3,382,540	22	25	15
18	53,120	7	3,447,309	23	23	23
31	59,879	10	3,539,263	24	20	27
11	49,817	4	3,412,336	25	29	17
17	52,411	5	3,416,734	26	26	24
27	55,175	6	3,466,875	27	24	29
15	52,134	4	3,426,225	28	30	25
24	54,865	5	3,474,573	29	28	30
26	55,025	5	3,494,307	30	27	31
21	54,134	4	3,451,799	31	31	28

6.3. Multi-criteria ranking and selecting

An online questionnaire was distributed among PT decision-makers and stakeholders (authorities, operators, and users). This process was aimed at simulating the ranking and selecting of preferred solutions from the above-mentioned set of non-dominated solutions. The DMs were asked to assign weights to the three criteria (to be used with TOPSIS) and to provide a pairwise comparison of these criteria (to be used with AHP), and the range of feasible solutions. Table 2 summarizes the preferences of the DMs. The first two DMs were only asked to assign weights to the criteria, while the last two were requested to rank the solutions independently and later asked to comment on the three automatic ranking methods.

The first three DMs share a low CR, while the fourth DM has a

Table 5
DM #3 - Solutions ranking.

No.	Budget	Degree	Saving	AHP	TOPSIS	AHP-TOPSIS	USER
14	49,817	4	3,412,336	1	1	12	12
13	49,668	5	3,382,540	2	2	11	10
1	37,721	1	2,784,613	3	9	14	14
2	38,224	4	3,077,972	4	11	13	13
3	39,924	5	3,263,791	5	10	10	11
12	48,894	11	3,382,294	6	14	7	4
8	47,405	11	3,349,103	7	6	6	5
11	48,880	12	3,367,782	8	3	3	2
6	45,242	10	3,363,844	9	7	8	8
10	48,366	12	3,305,832	10	13	2	3
7	45,406	11	3,268,631	11	12	5	6
9	47,560	13	3,281,674	12	4	1	1
4	41,071	9	3,335,523	13	5	9	9
5	42,479	11	3,236,502	14	8	4	7

Table 6
DM #4 - Solutions ranking.

No.	Budget	Degree	Saving	AHP	TOPSIS	AHP-TOPSIS	USER
13	59,879	10	3,539,263	1	7	25	1
5	58,637	11	3,508,101	2	4	5	3
24	55,025	5	3,494,307	3	17	17	4
17	54,865	5	3,474,573	4	13	16	5
26	54,134	4	3,451,799	5	12	18	10
3	55,175	6	3,466,875	6	10	8	6
9	52,134	4	3,426,225	7	6	13	12
28	52,411	5	3,416,734	8	9	9	15
20	55,985	12	3,413,562	9	23	1	14
11	53,120	7	3,447,309	10	8	20	7
21	56,070	13	3,500,749	11	11	11	2
22	55,023	12	3,407,849	12	3	24	17
14	54,397	11	3,442,082	13	27	19	8
15	53,775	10	3,419,026	14	15	15	11
8	53,788	11	3,441,195	15	2	27	9
19	54,235	13	3,357,861	16	29	23	24
18	49,817	4	3,412,336	17	15	6	16
12	49,668	5	3,382,540	18	14	29	20
7	52,164	11	3,415,455	19	20	2	13
23	50,445	9	3,396,230	20	24	3	19
4	51,173	12	3,401,525	21	16	14	18
10	51,028	13	3,324,070	22	5	22	26
27	48,894	11	3,382,294	23	26	28	21
2	48,880	12	3,367,782	24	19	4	22
6	48,366	12	3,305,832	25	22	7	27
25	47,405	11	3,349,103	26	28	26	25
16	47,560	13	3,281,674	27	1	10	28
1	45,406	11	3,268,631	28	21	21	29
29	45,242	10	3,363,844	29	18	12	23

Table 7
The Borda Count overall ranking.

No.	Budget	Degree	Saving	AHP-TOPSIS				BC Score
				DM 1	DM 2	DM 3	DM 4	
1	47,560	13	3,281,674	1	3	1	4	27
2	48,880	12	3,367,782	2	6	3	1	24
3	48,366	12	3,305,832	4	5	2	3	22
4	45,406	11	3,268,631	5	1	4	6	20
5	47,405	11	3,349,103	3	4	5	7	17
6	45,242	10	3,363,844	6	2	7	5	16
7	48,894	11	3,382,294	7	7	6	8	8
8	49,817	4	3,412,336	9	9	9	2	7
9	49,668	5	3,382,540	8	8	8	9	3

borderline CR. The following analysis explains the fourth DM's inconsistency. Both AHP and TOPSIS methods were used to sort the solutions based on DM preferences. Weights were also calculated from the pairwise comparison matrices and were used with the TOPSIS algorithm, (AHP-TOPSIS). The results are listed in Tables 3–6.

As can be seen from the results, the AHP and TOPSIS recommendations are inconsistent with similar extreme rankings. This is due to the different weighting techniques used. TOPSIS is based on a traditional weighting of all objective functions while AHP is based on a pairwise comparison. The latter has the benefit of a more focused weighting technique and consistency analysis. This is evident from the combined TOPSIS-AHP ranking that incorporates the AHP weighting with the TOPSIS ranking. This method, which has similar results to AHP, strengthens the advantages of AHP.

For an in-depth analysis, the third and fourth DMs were asked to independently rank the solution set (column "USER" in Tables 5,6), and upon completion to comment on the TOPSIS-AHP ranking results.

For the third DM, the results show that the TOPSIS-AHP method is very similar to the DM's rankings. Next, the DM was asked for his opinion about the results of both the AHP and TOPSIS-AHP methods. The DM stated that both rankings are logical, and that he agrees with the prioritization they offer in which savings in time are elevated and costs are minimized. Moreover, the DM said that the difference between the methods is the weight of connectivity [degree]. (TOPSIS-AHP gives more emphasis to the connectivity objective than TOPSIS.) In this context, the DM said that he tended to agree with the TOPSIS ranking because he thought that a good network should first of all offer a good connectivity, as passengers do not like to make transfers.

The fourth DM analysis is less conclusive, with dissimilarities between the rankings. When asked to comment on the differences, he admitted that his own ranking was based solely on the savings aspects with his weights (both AHP and TOPSIS) accounting for the importance of connectivity (degree). It can be argued that the DM did not fully understand the objective functions, as the CR clearly indicates.

Finally, the Borda Count method was used to provide a consensus ranking of the various alternatives selected by the four DMs. The first stage was to select all alternative solutions that the DMs had ranked. Next, for each DM, the alternatives were ranked based on the results of the AHP-TOPSIS analysis, which in turn was used by the Borda Count method to obtain an overall ranking. Table 7 summarizes the ranking based on the Borda Count score. The highest ranked solution was selected as the 1st solution by two DMs, and as the 3rd and 4th solutions by the other two. This solution can easily be accepted by all stakeholders as a viable compromise solution.

7. Concluding remarks

This study presents a novel, multi-objective and multi-criteria approach for finding a compromise solution in selecting priority lanes for a public transport network.

This framework has the following advantages. 1) It provides a multi-objective model that incorporates several objective functions representing the different perspectives of relevant stakeholders. It is well-known that disagreement among stakeholders can hamper and delay the selection of a transportation alternative from a set of solutions. The proposed framework provides an analytical approach which systematically selects an optimal solution set, ranks the solution set for each DM, and chooses a solution acceptable to all DMs. The use of an optimal solution set for the MCDM model has a clear advantage over the traditional use of an alternative set. The alternative set is not necessarily a non-dominated solution set. Therefore it is possible that the ranking will be based on non-optimal solutions. 2) It introduces an original AHP-TOPSIS ranking methodology which can easily rank a solution set based on the stakeholder's multi-criteria preferences, while assessing the stakeholder's consistency in prioritizing the objectives; 3) It provides a GDM tool for selecting a solution that will be acceptable to all parties involved.

The applicability of the model was demonstrated by the case study. The DMs easily adopted the methodology of weighting each objective function and assessing the ranking. They also accepted the results. Furthermore, the framework is transferable to other domains, since the MO, MCDM, and GDM components are generic in nature.

Future research can pursue several directions. 1) Other objective functions can be added, such as minimizing parking space reduction, or minimizing delay of other transport modes. This is possible since the optimization model can easily handle numerous objective functions, while the ranking models eliminate the need to manually assess the Pareto front. 2) The model can be integrated with an assignment model. The proposed model lacks the direct assessment of the impact on other modes of transport (specifically private vehicles), but an extended model can be developed in order to overcome that issue. The extended model will have an additional stage (after the optimization, and before the MCDM and GDM). Since the model provides the complete Pareto front, which is only a subset of all feasible solutions, traffic assignment can be performed much more efficiently. Furthermore, the assignment results will be represented by an additional objective function, the effect on other modes of transportation. Therefore, in contrast to the common aggregation of total time change, the suggested model will provide the policymaker the opportunity to assess the complete non-dominated set by the MCDM and GDM stages. 3) The model can be integrated with route design and time-tabling.

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