The Railway Network Design, Line Planning and Capacity Problem: An Adaptive Large Neighborhood Search Metaheuristic

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Abstract. In this chapter, we propose a model for the Railway Network Design and Line Planning (RNDLP) problem, integrating the two classical first stages in the Railway Planning Process. The network design problem incorporates costs relative to the network construction, proposing a set of candidate lines. The line planning problem is in charge of determining optimal frequencies and consequently train operations, taking into account rolling stock, personnel and fleet acquisition costs. Both problems are intertwined because the line design influences the selection of frequencies and the corresponding fleet size. We consider the existence of an alternative transportation mode for each origin-destination pair in the network. In this way, the rapid railway mode competes against the alternative mode for a given certain demand, represented by a global origin-destination matrix. Passengers choose their transportation mode according to their own utility. Since the problem is computationally intractable for realistic size scenarios, we develop an Adaptive Large Neighborhood Search (ALNS) algorithm, which can handle the RNDLP problem. As illustration, the ALNS performance is demonstrated in an artificial instance using estimated data from literature.

Keywords: Railway Rapid Transit · Network design · Line planning · Adaptive Large Neighborhood Search

1 Introduction

Railway Rapid Transit (RRT) is a high-capacity public transport that usually operates on an exclusive right-of-way in urban areas. The general aim of a RRT

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system is to improve the mobility of the population in big cities and metropolitan areas, but other purposes like decreasing private traffic congestion and pollution has become relevant nowadays. RRT systems are the most effective transportation mode since in a very short time they can carry considerable more people at a higher speed than other public transportation modes.

The RRT planning process is a very complex task involving strategic, tactical, operational and real-time decisions. Among these decisions are the selection of the location of stations and the connections between them, the itinerary and the frequency of the lines, the capacity of the trains, the timetable, the scheduling of the trains, the crew and other staff planning, and the management of delays and disruptions. Several agents are implicated in this process. They can be grouped into local authorities and transportation agencies, potential travellers and construction and operating companies. These problems are complex due to several factors: large-scale, uncertainty in data, different criteria to be taken into consideration because of the different viewpoints of the involved agents, competition with other transportation modes and computational complexity of the optimization counterpart problems. For these reasons a sequential approach was traditionally proposed for the whole RRT planning process.

Knowing the current mobility patterns and the predictions over a period of time, the first phase consists in choosing from an underlying network the location of the access and the egress points to the system, and the links between pairs of them. The traditional non-optimization methodology is based on the selection of a set of corridors, combining them, and choosing the best combination according to several criteria. However, this approach could eliminate in a very early phase good alignments that do not are considered any more. The second step consists in selecting the itinerary of the lines and the frequency of them in each period of time of the day, day of the week and season of the year. An issue closely related with the frequency is the determination of trains' capacity. The first idea is that the higher the capacity is, the lower the required frequency. However, in the presence of competing modes the relationship between capacity and frequency is non-linear and, even more, it becomes non-continuous. Based on the knowledge of the hourly demand the timetable is designed. Then, the last step of the sequential process consists in the scheduling of rolling stock and personnel.

In this work we integrate the two first steps adding the determination of the capacity of the trains. Thus, we consider the problem of simultaneously determining the line network design, the frequency of the lines and the capacity of the trains, considering also a competing transportation mode.

RRT network design [15,26], can be classified depending on whether a single or multiple alignments are to be planned, and whether they are completely new or extensions of already existing ones. The main criteria used to design rapid transit alignments are described in [24]. For the problem of locating one single alignment, a tabu search was proposed in [19] in order to maximize the population covered, [7] proposed a bicriterion model for the location of a rapid transit line minimizing construction cost and passenger travel time, [6] developed a two-phase heuristic for the problem of designing an alignment in a urban context maximizing the population coverage, [30] presented a heuristic for the construction of a rapid transit alignment maximizing trip coverage, and [29] addressed the problem of locating a metro line in a historical city maintaining a minimum distance between the alignment to be designed and protected buildings. In [32] the problem of locating the stations, determining the headway and the fare of a transit line in a linear corridor when maximizing the profit is addressed using a heuristic algorithm.

Regarding the multiple alignment problem, [28] solved the rapid transit network design problem of maximizing the trip coverage by using simulated annealing (SA), in [23] the infrastructure railway network design problem as well as its robust version are solved by using a Greedy Randomized Adaptive Search Procedure (GRASP), [31,35] used the demand coverage as objective function. Based on an a priori geometric configuration, in [31] a metro network design is proposed under the criteria of maximizing population coverage and minimizing construction cost. With a similar methodology, but considering traffic capture instead of population coverage, [27] proposes a mixed integer tractable model formulation. Regarding papers dealing with the extension of existing networks we highlight [3], that proposed a model and a heuristic for the problem of expanding the infrastructure of a railway network.

The second phase of the railway planning process is line planning, in which a set of itineraries or lines is selected from the resulting network after the first phase or from a line pool. Moreover, the frequency of each line at each period of time is determined. Usually in this phase the capacity of the trains is supposed to be known. The line planning problem has been tackled in several papers, among them [8,13] propose branch-and-cut algorithms to select lines from a previously generated set of candidate lines (line pool). In [9] linear and non-linear integer programming models are proposed for the line planning problem with minimum cost. In [25] lines can have different halting patterns. [21] considers the problem of designing the frequencies of a regional metro with elastic demand by minimizing the total cost. For more information on line planning we refer to the recent reviews by [4,33,38].

As mentioned, we integrate the first two phases of the planning process taking also into account aspects of capacity and personnel cost. We assume there is a competing mode of transportation. The number of trips captured by the railway rapid transit system, which is determined by using a logit modal split function, depends on the difference between the utilities of both transportation modes. The utility of each pair of origin-destination demand for the rapid transit system depends on the fare, waiting time-cost at stations, in-vehicle time-cost and transfer time-cost between lines. The objective function is the profit, that is the difference between the revenue and the total cost. The revenue depends on the number of passengers captured by the railway network (RN). The total cost includes construction cost, fixed and variable operating costs, crew cost and the fleet acquisition cost as a function of the rolling-stock required to cover the demand captured by the RN system.

A related model was proposed in [11]. However, in this paper the variables defining the flow of passengers differ from those of [11]. Here, for each origin-destination pair, we use binary variables for the use of links instead of variables representing fractions of the demand, as in the former model. As consequence, the solutions proposed by this model are less favourable to the service provider but more favourable to the travellers than in the previous one, because in this situation, passengers follow the best path to reach their destination give rise to more loaded trains. In [12] we analyse the RNDLP problem in terms of complexity by comparing the exact solution of small instances using commercial solvers against an ALNS. In that work train capacity is determined by means of integer variables defined in order to obtain the number of carriages needed in each line. The modal split considers only the travel time as a key factor to select the railway or an alternative mode instead of passengers utility. Others aspects like railway fare do not influence the mode choice. As illustration, the ALNS is applied to designing a RRT network for the city of Seville.

Since the RNDLP problem is obviously NP-hard, a metaheuristic is needed to solve medium and large instances. In this paper an adaptive large neighborhood search (ALNS) metaheuristic is applied.

The remainder of the chapter is structured as follows. The next section introduces a non-linear mixed integer model for the RNDLP problem that simultaneously determines the most convenient network topology and the most appropriate set of lines, determining line frequencies and selecting a specific train model for each one in presence of an alternative transportation mode. Section 3 presents an ALNS algorithm designed to manage real-size instances of the RNDLP problem. Section 4 illustrates the computational performance of the ALNS considering different experiments in a medium-size artificially generated instance of the RNDLP using estimated values of time data from literature. The last section provides some conclusions and point out some still open questions.

2 Description of the RNDLP Problem

Consider a set $N = \{1, \ldots, n\}$ of potential nodes for locating stations and a set of arcs $A \subseteq N \times N$ representing potential connections between nodes. Both sets define a potential graph used as a basis for the building of the railway rapid transit network. We define the edge set $E = \{\{i, j\} : i, j \in N, i < j, (i, j) \ or \ (j, i) \in A\}$. Thus, the underlying network is topologically described as a graph $G_E = G(N, E)$. The alternative transportation mode network (private car), competing with the railway rapid transit system, is represented by an undirected graph $G_{E'} = G(N, E')$. As is usual in the network design, there exists an upper bound C_{max} on the total construction cost of the railway network RN.

Let $W = \{w_1, \ldots, w_{|W|}\} \subseteq N \times N$ be the set of ordered origin-destination OD pairs $w = (o^w, d^w)$, where o^w and d^w represents the origin and destination of pair w, respectively. Without loss of generality, we assume that all trips occur between nodes belonging to the underlying network, that is, potential stations acts as demand origins and destinations. The expected number of passengers

g_w associated with each OD pair $w \in W$, as well as the corresponding utility U_w^{ALT} of pair w using the alternative mode are known. Let d_{ij} be the length of edge $\{i, j\}$, and λ, the average speed of trains measured in km/h. In order to obtain applicable results, we work with a discrete set $\mathcal{H}$ of headways which are measured in minutes. Note that if $h \in \mathcal{H}$, then the line *frequency* is equal to $60/h$, measured in number of trains per hour. We consider a parameter γ representing the maximum number of lines that can circulate on any edge of the network. This is a topological constraint frequently used in order to not over saturate some open tracks, which would result in excessively long headways (low frequencies). We assume known train capacities, according to different models $m \in M$ available in the market with capacities K_{train}^m. We consider all trains of a line operate at the same capacity, i.e., each line is operated by an specific model. The transfer time is considered as the sum of two terms: the time spent between platforms uc_i, which is supposed to be known, and the average waiting time for taking the next train of the line to transfer. The last term can be approximated as the average headway of the line to transfer. For each line, the main variable to be determined is the headway. As previously mentioned, no a priori line pool is defined, and since a constructive approach is followed, a lower and an upper bound, N_{min} and N_{max}, on the number of stations of each line are considered [10]. In order to compute the expected utility of pair w, parameters β_{tt}, β_{tr}, β_{wt}, are used to denote respectively the monetary cost of travel time, transfer time and waiting time at the initial station (see [21]). The index $\ell \in \mathcal{L}$ denotes each line, being $\mathcal{L}$ a set used to describe the possible lines and $|\mathcal{L}| = \mathcal{L}^{\max}$.

The considered objective function obj_{NET} maximizes the net profit, expressed as the difference between the revenue obj_{REV} and the total system cost obj_{SC}. In order to calculate the revenue, we consider two parameters: the first one, ξ, denoting the passenger fare and the second one, η, a public subsidy per trip [5,17]. The fare is also considered in the modal split model as part of the passengers' utility. We also consider a parameter t_{final} representing the time horizon employed to finance the construction of the network and to amortize the rolling stock investment. The number of years spent to build the network is denoted by $t_{initial}$. Obviously, $t_{initial} \leq t_{final}$. Furthermore, in order to obtain a realistic model, we have incorporated a discount rate r. Finally, we denote by h_{year} the number of hours during which a train operates in a year.
Therefore, the revenue can be expressed as:

$$obj_{REV} = \sum_{k=t_{initial}}^{t_{final}-1} \frac{1}{e^{rk}} \left[(\xi + \eta) \sum_{w \in W} g_w \cdot \text{ pp of pair } w \text{ using the RN} \right],$$

where *pp* represents the proportion of passengers.

The system cost obj_{SC} is composed of three main terms as follows (for more details see [11]).

$$obj_{SC} = obj_{BC} + obj_{OC} + obj_{FAC}.$$

The first term obj_{BC} corresponds to the cost for building stations and edges. This term is obtained considering two parameters: c_{ij} and c_i, corresponding to the cost of the built stretch on edge $\{i, j\}$ or the constructed station i, respectively. For the sake of simplicity, we assume that both, edge and station construction costs, are independent of the number of lines traversing edges or reaching stations. Concretely, this cost can be computed as:

$$obj_{BC} = \frac{1}{t_{final}} \sum_{k=0}^{t_{final}-1} \frac{1}{e^{rk}} \left[\sum_{\{i,j\} \in Eb} c_{ij} + \sum_{i \in Nb} c_i \right],$$

where Eb and Nb are the constructed-edge set and the constructed-station set.

The second term obj_{OC} is the operating cost, which includes fixed obj_{FOC} and variable costs obj_{VOC}:

$$obj_{OC} = obj_{FOC} + obj_{VOC}.$$

The term obj_{FOC} is related to maintenance and overheads of rails $ORlc_{ij}$ and stations $OStc_i$, measured in monetary units per year

$$obj_{FOC} = \sum_{k=t_{initial}}^{t_{final}-1} \frac{1}{e^{rk}} \left[\sum_{\{i,j\} \in Eb} ORlc_{ij} + \sum_{i \in Sb} OStc_i \right].$$

The variable cost takes into account the cost of operating trains as well as the crew cost $cost_{crew}$ per train and year, which is closely related with line headways. The operating cost $cost^m_{train}$ of a train of model m per unit of length, is given. Therefore, the variable cost is defined as:

$$obj_{VOC} = \sum_{k=t_{initial}}^{t_{final}-1} \frac{1}{e^{rk}} \left[(h_{year} \cdot \lambda) \sum_{\ell \in \mathcal{L}} FS_\ell (\sum_{m \in M} cost^m_{train}) - cost_{crew} \sum_{\ell \in \mathcal{L}} FS_\ell \right],$$

in which FS_ℓ is the required fleet of line ℓ, measured as the number of trains required per hour. This number can be expressed as a function of the headway (h_ℓ) and the length of the line:

$$FS_\ell = \lceil 120/(h_\ell \lambda) \sum_{i,j \in E_\ell} d_{ij} \rceil, \; \ell \in \mathcal{L}.$$

The last term in the system cost expression is the fleet acquisition cost obj_{FAC} which is determined by the investment in trains Inv^m_{train}. Note that the size of the rolling stock and the choice of specific train models will be a consequence of the passenger demand and the frequency of the lines. A parameter χ is used in order to include a set of reserve trains that will be needed as consequence of train maintenance operations. So, this cost can be represented as

$$obj_{FAC} = \sum_{k=t_{initial}}^{t_{final}-1} \frac{1}{e^{rk}} \left[\frac{\chi}{(t_{final} - t_{initial})} \sum_{\ell \in \mathcal{L}} FS_\ell (\sum_{m \in M} Inv^m_{train}) \right].$$

The line capacity imposes an upper bound on the maximum number of passengers that each line can carry per hour on each edge:

$$h_\ell \sum_{w\in W} g_w \cdot (pp\ of\ pair\ w\ traversing\ \{i,j\}\ in\ line\ \ell) \leq 60 \cdot K^m_{train}.$$

The modal split is described by means of a logit model in order to determine the volume of passengers captured by the RN, similarly to [34]. The logit function compares the expected passengers' utility U_w^{RN} with the corresponding utility U_w^{ALT} in the competing mode.

$$f_w^{RN} = \frac{1}{1+e^{(\alpha-\beta(U_w^{ALT}-U_w^{RN}))}},\ w \in W.$$

The expected passengers' utility has three terms that correspond to the waiting time at stations ($u_w^{RN,wt}$), in-vehicle time ($u_w^{RN,tt}$), and transfer times ($u_w^{RN,tr}$).

$$u_w^{RN,tt} = \frac{60}{\lambda}\sum_{\ell\in\mathcal{L}}(\sum_{\{i,j\}\in E}(pp\ of\ w\ traversing\ \{i,j\} in\ line\ \ell)\cdot d_{ij}), w\in W,$$

$$u_w^{RN,tr} = \sum_{\ell\in\mathcal{L}}\sum_{\ell':\ell'\neq\ell}\sum_{i\in N}(pp\ of\ w\ transferring\ from\ \ell\ to\ \ell' in\ i)\cdot(\frac{h_{\ell'}}{2}+uc_i),\ w\in W,$$

$$u_w^{RN,wt} = \frac{1}{2}\sum_{\ell\in\mathcal{L}}\sum_{j:\{o^w,j\}\in E} h_\ell\cdot(pp\ of\ w\ traversing\ \{o^w,j\}\ in\ line\ \ell), w\in W.$$

Parameters β_{tt}, β_{tr} and β_{wt} represent the value of ridding, transferring and waiting time respectively (see [21]).

$$U_w^{RN} = \xi + \beta_{tt}\cdot u_w^{RN,tt} + \beta_{tr}\cdot u_w^{RN,tr} + \beta_{wt}\cdot u_w^{RN,tw}, w\in W.$$

Finally, the Railway Rapid Transit Network Design and Line Planning (RNDLP) consists of choosing the line to be constructed ($\mathcal{L}_c$, the stations of each line (N_ℓ), the edges of each line (E_ℓ), the headway of each line to be constructed (h_ℓ), and the kind of train to be assigned to each line (M_ℓ), such that the net profit is maximized:

$$max\ obj_{NET} := (obj_{REV} - obj_{SC}).$$

3 An Adaptive Large Neighborhood Search Metaheuristic for the RNDLP Problem

The RNDLP is an NP-hard non-linear problem. In [12] we formulated and solved a quite similar Network Design and Line Planning problem. The main differences with respect to the problem here treated are on the modal split sub-model and the line capacity constraints. In that paper we demonstrated the inability of the state-of-the-art commercial solvers to solve real size instances. Moreover, we compared an ALNS (very similar to the one considered in this chapter) with fully linearised versions of the RNDLP for small instances (linear MIP solvers cannot manage large instances), reporting the superiority of the ALNS technique. As consequence, in order to tackle real size instances efficiently, for the current problem, we develop an ALNS metaheuristic which provides a powerful algorithmic framework capable of simultaneously handling the network design and line planning problems. The ALNS metaheuristic was introduced by [37] to solve variants of the vehicle routing problem. Basically, this algorithm tries to improve iteratively an initial solution using destroy and repair operators. The ALNS belongs to the category of large scale neighborhood search techniques defined in [1] but only examines a relatively low number of solutions. The main difference between the original work of [37] and the proposed by [39] concerns the probability of selecting an operator. Concretely, in our ALNS implementation, we consider several destroy and repair operators which are independently applied as in [14].

3.1 The ALNS Metaheuristic

As mentioned, the ALNS starts with an initial solution which is modified at each iteration by means of operators. This initial solution is formed by one line or a set of connected lines randomly defined but holding the problem constraints. We remark that a line is characterized by two different terminal stations, the intermediate stops or itinerary, the headway and the capacity of each train. In this situation, when the initial solution is defined, we can compute the amount of people travelling on the current network, the corresponding construction and operation costs and, consequently, the associated profit, which represents the quality of the solution. This calculation is done using a heuristic local search algorithm (for more details see [18]). Given a network configuration, the local search solves the problem of maximizing the net profit of a line plan by selecting the headway and the train model of each line, assuming that all passengers interested to travel in the RN can be transported.

At each iteration, one or two lines are randomly modified by means of an operator. An operator is a heuristic method which modifies a solution, keeping feasibility conditions. We consider six operators: two destroy operators, two repair operators and two operators combining destroy and repair operations. The repair operators insert new lines or extend existing ones. The destroy operators remove part of a line or a full line. Concerning the combined operators, the first one eliminates an existing line and then, inserts a new one. The second one removes part of a line and extends a randomly selected line.

In order to apply these operators, the lines are randomly selected and the operators are chosen with a certain probability which depends on their performance in the past iterations. As in other random algorithms, the acceptance of new solutions is controlled by means of a SA technique, diversifying the search in this way. The procedure ends when a certain stopping criterion is satisfied.

3.2 Outline of ALNS

In order to define the ALNS algorithm, we include the following elements:

- A set of heuristic methods (operators). The ALNS considers two kinds of operators, namely, repair and destroy operators. The repair operators build a new solution from a given solution while maintaining the feasibility whereas the destroy operators remove part of the solution.
- A set of variables in order to keep information about the best solution, the solution accepted by the SA and the current solution.
- A set of parameters whose values define the algorithm behaviour.
- A procedure to compute the quality of each solution.
- An initialization phase in which an initial solution and a set of initial values of the parameters are set in order to start the algorithm.

The key ideas of the ALNS can be described as follows:

Step 1: Initialization phase Construct a feasible solution and set the initial value of the parameters;
All operators have the same probability of being selected;
The stopping and the acceptance criteria are defined;
Step 2: Select an operator according to the roulette wheel mechanism;
Generate a new feasible solution and compute its profit;
Step 3: Compare the new profit against the stored profits. Apply the SA acceptance mechanism;
Keep information on the operator performance;
If a determined number of iterations are performed, update the probability of selecting each operator according to the SA results;
Step 4: Inspect the stopping criteria;
If the stop criteria is not met, go to Step 2, otherwise, the ALNS is finished.

Algorithm 1. Steps in the ALNS implementation.

3.3 The ALNS Components

The main components of our ALNS implementation are the following:

1. Neighborhood size
   Two networks G_{RN} and G'_{RN} are considered as neighbors if they have at most two different lines. Hence, the number of nodes and edges in the underlying network determines the size of the neighborhood.
2. Adaptive selection of operators
   The selection of a specific operator is made through a roulette wheel mechanism. Concretely, we associate a weight p_j with each operator j. This weight measures how well the operator has performed in the past iterations. Assuming h operators, the probability of selecting the operator m is $p_m/\sum_{j=1}^{h} p_j$.

3. Adaptive weight adjustment
   The weights p_j are updated at each iteration according to the quality of solutions. At the beginning of the ALNS execution, all weights are fixed to one and as a consequence, all operators have the same probability. At each iteration, once an operator j has been selected and applied, its score σ_j may be increased using three parameters θ_1, θ_2 or θ_3 with the next meanings:
   θ_1 : the new solution G_{RN} is better than the best global solution G_{best};
   θ_2 : the new solution G_{RN} is better than the incumbent solution G_{curr};
   θ_3 : G_{RN} is worse than the incumbent solution but it is still accepted.
   Obviously, the better the solution is, the higher the score is, i.e., $\theta_1 \geq \theta_2 \geq \theta_3$.

   After each block of s iterations, the performance of each operator j is observed and its weight is updated using the expression

$$p_j := \begin{cases} p_j & \text{if } o_j = 0 \\ (1-\varepsilon)p_j + \varepsilon\sigma_j/\nu_j o_j & \text{if } o_j \neq 0, \end{cases}$$

   where $\varepsilon \in [0, 1]$ is a parameter called the reaction factor which allows controlling how quickly the weight adjustment algorithm reacts to changes in the scores. The parameter o_j is used for controlling the number of times operator j is used in the incumbent s iterations. The factor $\nu_j \geq 1$ represents the computational effort required by the operator.

   Finally, once all weights have been updated, all scores are reset to zero in order to store the performance information for the next block of iterations.
4. Acceptance and stopping criteria
   Our acceptance criterion is based on SA. We consider a standard exponential function to describe the SA, which uses two parameters: the current temperature $T_{start} > 0$ and the cooling rate $0 < \phi < 1$. At the beginning of the ALNS implementation, the temperature starts with T_{start} and after certain number of iterations, it is decreased (cooled) using the cooling rate ϕ ($T = T_{start} \cdot \phi$). The parameter T_{start} may be computed by inspecting the initial solution. In [37] T_{start} is defined in the way that a solution 5% worse than the initial solution has 50% probability of being accepted. Let G_{RN} be the current solution and $obj_{NET}(G_{RN})$ be the corresponding objective value, then, a new neighbor solution G'_{RN} is accepted if $obj_{NET}(G'_{RN}) > obj_{NET}(G_{RN})$ and is accepted with probability $e^{(obj_{NET}(G'_{RN}) - obj_{NET}(G_{RN}))/T}$ otherwise. In our case, if the difference between $obj_{NET}(G'_{RN}) - obj_{NET}(G_{RN})$ is less than ϱ% of $obj_{NET}(G_{RN})$, the acceptance probability is 0.5, i.e.,

$$e^{(obj_{NET}(G'_{RN}) - obj_{NET}(G_{RN}))/T_{start}} = 0.5$$

   or, equivalently,

$$T_{start} = (obj_{NET}(G'_{RN}) - obj_{NET}(G_{RN}))/\ln(0.5).$$

   The parameter ϱ is selected by the user.

With respect to the stopping criteria, we distinguish three different methods to control the end of the execution: the maximum number of iterations φ is reached, the final temperature T_{final} is reached or the running time exceeds a user-controlled threshold.

3.4 The ALNS Operators

The proposed ALNS considers six operators, defined as follows:

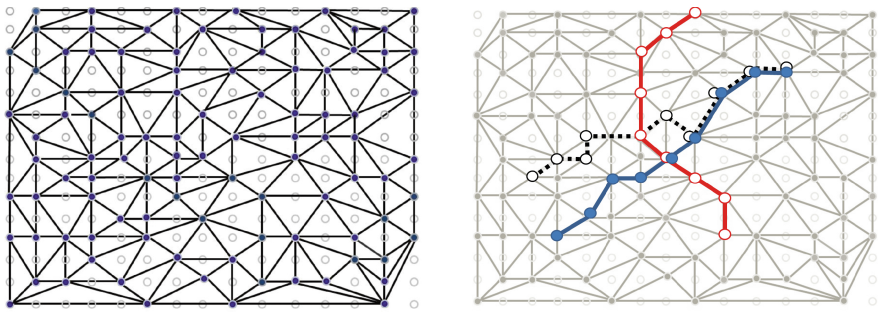
- Inserting-line operator. This operator aims at inserting a new line in the RN. To this end, two nodes representing the terminal stations, are randomly selected from the underlying network. Then, a shortest path connecting these stations in the underlying network is computed. This path configures the itinerary of the new line if the lower and upper bounds on the number of nodes of a line is fulfilled. Otherwise, a different couple of nodes are selected and the procedure above described is repeated. Once the itinerary have been set, the construction cost as well as the fixed operating cost can be computed. Since each operator has to ensure feasibility, a line is not inserted if
  - there exists an edge in the itinerary exceeding the upper bound imposed on the number of possible lines connecting each pair of adjacent nodes,
  - the itinerary is part of other existing line in the current RN solution,
  - the itinerary contains an existing line,
  - it is not connected with the existing lines in the RN.

  If finally the line is inserted, the corresponding profit is computed by means of a local search heuristic (see [18]).
- Extending-line operator. This heuristic randomly extends an existing line. First, the operator randomly choose a line and then, randomly selects the position (at the beginning or at the end in the itinerary) in order to extend the selected line. Once the line and the terminal station have been selected, a node (not belonging to the selected line) of the underlying network is randomly selected. A shortest path between this node and the terminal station of the line is computed. The itinerary of ℓ is extended according to the resulting path. A line is not extended if it reaches the maximum number of permitted nodes or there exists an edge in the itinerary exceeding the upper bound imposed on the number of possible lines connecting each pair of adjacent nodes. Finally, if the line ℓ is extended, its profit is computed using the local search heuristic.
- Delete-line operator. The delete-line operator randomly removes a line from the current RN provided the network is connected.
- Delete-part-line operator. This operator randomly selects a line ℓ to be partially removed. To do this, an intermediate node of the itinerary of ℓ and a terminal station of ℓ are randomly selected. The sub-path between both nodes is removed from ℓ. The lower bound on the number of nodes of ℓ is inspected. If the line is contained in an existing line or the network becomes unconnected after eliminating the sub-path, the removal is not considered.

- Delete-part-line and Extending-line operator. This method applies a delete-part-line and an extending-line operators in the same iteration. In case that the delete-part-line can be applied, the extending-line is later used. As can be observed, both operators work independently and, therefore, the selected line can be different for each one.
- Delete-line and Inserting-line operator. The idea of this operator consist on removing a line by means of the delete-line operator and then, if possible, apply the insert-line operator with the aim of adding a new line. As the reader can note, this method replaces a line with another line.

4 Computational Experiments

In this section, in order to show the performance of the proposed ALNS algorithm, we conduct a set of computational experiments on a medium-sized artificially generated network. The network contains 100 nodes (potential stations) and 275 links (edges). The node set was randomly selected from a 15×15 square grid with 225 nodes covering a surface of 14^2 km^2. The coordinates of each node were randomly chosen by considering a uniform distribution $U(-0.5, 0.5)$ around each coordinate (x,y) of the selected nodes in the grid, that is, by using the intervals $(x - 0.5, x + 0.5)$ and $(y - 0.5, y + 0.5)$. The edge set was then defined by using the Voronoi diagram, linking adjacent nodes and avoiding edge crossings (see Fig. 1). The length of each edge was computed as the Euclidean distance between its adjacent nodes. In order carry out the bed of experiments, an arbitrary initial solution was defined as depicted in Fig. 1.



(a) Artificial generated network (b) Initial solution

Fig. 1. Experimental scenario and initial solution

With respect to the passengers' demand, for each one of the 9900 OD pairs (100×99) among the different potential stations, the expected number of trips was obtained following a discrete uniform distribution $U(0, 43)$, given rise to an hourly OD demand matrix with a total of $107,269$ trips.

As explained previously, the modal split is described through a logit function. To this end, we need to introduce the utility associated to the competing mode (private car) as well as the associated to the railway system. Basically, the utility U_w^{RN} of using the RN, is compared pair by pair with the utility of the private car, U_w^{ALT}. As the reader may note in the following expression, U_w^{RN} is expressed in terms of monetary costs:

$$U_w^{RN} = \tau + \beta_{tt} \cdot u_w^{RN,tt} + \beta_{tr} \cdot u_w^{RN,tr} + \beta_{wt} \cdot u_w^{RN,wt}, \ w \in W.$$

All parts of the trip (access, waiting, riding, transfer) were estimated in terms of time assuming a commercial speed of 40 km/h, and converted into monetary values using parameters β_{tt}, β_{tr} and β_{wt}. As a consequence, U_w^{RN} is a function of the fare and the set of edges and lines selected to perform the trip as well as the line frequencies. In this illustration, the values of time are taken from the work of [21], as shown in Table 1.

The utility of the alternative mode, U_w^{ALT} for each pair $w \in W$ is described as follows:

$$U_w^{ALT} = fc + d'_{o^w,d^w} \cdot vc + d'_{o^w,d^w} \cdot \frac{60}{v} \cdot tvc + Pt \cdot tvp + pc, \ w \in W.$$

where:

- fc, denotes the fixed cost per trip corresponding to the private car mode.
- v, represents the average speed.
- vc, defines the variable cost per km.
- tvc, denotes the unitary value of travel time.
- Pt, corresponds to the average time needed to park at destination.
- tvp, is the unitary value of parking time.
- pc, is the average cost of parking per trip.
- d'_{o^w,d^w}, corresponds to the modified Euclidean distance between the origin and destination of pair w.

In particular, each Euclidean OD distance has been multiplied by a factor 1.2, representing the impossibility of follow straight lines connecting the origin and destination of the pair. The specific values used in our experiments are included in Table 1. We want to remark that the goal of these experiments is to show the performance of the ALNS rather than the proper estimation of all these scenario-dependent parameters. Interested readers in modelling private car and public transport preferences can consult the books [20,40] and the work of [2,16,21,36,41]. [41] shows a general analysis of the value of time and [16,21] present the specific case of modelling the value of time in railway systems.

Costs concerning operation and rolling stock acquisition are taken from [22], considering the family of trains "Civia", recently used by the National Spanish Railways Service Operator (RENFE) for commuter/regional railway passengers transportation in Spain. Concretely, we have considered three different models:

Civia-463, Civia-464 and Civia-465, with 607, 832 and 997 passenger capacities (seating and standing) respectively. The remaining model parameters are shown in Table 1.

Concerning the ALNS execution, in order to select the most appropriate values for the algorithm parameters, we run consecutively the same instance three times until the coefficient of variation (the sample average divided by the sample standard deviation) reached a value of 0.1, which indicates a strong stability

Table 1. Input parameters for the computational experiments.

Parameters		
Name	Description	Value
t_{final}	Years to recover the purchase	20
h_{year}	Number of operative hours per year	6935
$t_{initial}$	Number of years spent to build the network	10
m	Model of train	463, 464, 465
$cost^m_{train}$	Costs for operating one train model m per kilometer [€/km]	$3, 3.1, 3.2$
$cost_{crew}$	Per crew and year for each train [€/ year]	$75 \cdot 10^3$
Inv^m_{train}	Purchase cost of one train Civia in €	$4.4 \cdot 10^6, 5.2 \cdot 10^6, 5.9 \cdot 10^6$
K^m_{train}	Capacity of each type of train [Passengers]	$607, 832, 997$
$\mathcal{H}$	Possible headways [min]	{3, 4, 5, 6, 10, 12, 15, 20}
N_{min}	Minimum number of stations for each line	5
N_{max}	Maximum number of stations for each line	16
β_{tr}	Perceived value of time spent transferring in €/min	0.25
β_{wt}	Perceived value of time for waiting at the origin station in [€/min]	0.25
β_{tt}	Perceived value of time for riding in train in [€/min]	0.083
fc	Fixed cost per trip corresponding to the private car mode [€]	1.75
v	Average speed of the private car mode [Km/h]	60.0
vc	Variable cost per km corresponding to the alternative mode [€/km]	0.12
tvc	Unitary value of time travelling in the alternative mode [€/min]	0.05
Pt	Average time needed to park at destination [min]	10.0
tvp	Unitary value of time corresponding to the parking time [€/min]	0.25
$\mathcal{L}^{\max}$	The maximum number allowed in the network	6
pc	Average cost of parking per trip [€]	Table 2

of the algorithm. Then, using the tuned ALNS, a set of 24 experiments were generated by varying fare, subsidy and the ticket price for the alternative mode, as described in Table 2. The first twelve experiments (first block) correspond to a constant value of the sum $fare + subsidy$ equal to 3. For the last twelve experiments (second block) $fare + subsidy = 2$.

Table 2. Definition of computational experiments.

Summary of experiments				
Exp. number	Fare+subsidy	Fare	subsidy	pc
1	3	0.5	2.5	0.5
2	3	0.75	2.25	0.5
3	3	1	2	0.5
4	3	1.5	1.5	0.5
5	3	0.5	2.5	0.75
6	3	0.75	2.25	0.75
7	3	1	2	0.75
8	3	1.5	1.5	0.75
9	3	0.5	2.5	1
10	3	0.75	2.25	1
11	3	1	2	1
12	3	1.5	1.5	1
13	2	0.5	1.5	0.5
14	2	0.75	1.25	0.5
15	2	1	1	0.5
16	2	1.5	0.5	0.5
17	2	0.5	1.5	0.75
18	2	0.75	1.25	0.75
19	2	1	1	0.75
20	2	1.5	0.5	0.75
21	2	0.5	1.5	1
22	2	0.75	1.25	1
23	2	1	1	1
24	2	1.5	0.5	1

The ALNS has been coded using Java and run in a computer with 8 Gb of RAM memory and a 2.8 Ghz CPU. In all cases a value of $\gamma = 3$ (line multiplicity) was considered. The cooling factor was fixed to 0.9997 and the reaction factor to 0.7. The final temperature T_{final} was set to 0.01. The score parameters θ_1, θ_2 and θ_3 were set to 10, 5 and 2, respectively. The acceptance neighborhood parameter ϱ was set to 33%, as in [14]. The rest of model parameters are set as in [11]. In all cases, the time limit (3600s) acts as stopping criterion.

Detailed information on these solutions are collected in Tables 3 and 4. In Table 3 column "Exp. number" refers to the tested experiment. The second column shows the number of captured passengers; the third one represents the number of lines; the fourth column reports (in order) the headway corresponding to each line and the last column contains the model of train selected for each line. As in Table 3, the first column of Table 4 shows the experiment number. Afterwards, column by column, we report the computation time needed to obtain the best solution, the net profit, the network revenue, the operating cost, the building cost (including the fixed operating cost), the crew cost and finally the fleet acquisition cost.

Table 3. Computational results for the ALNS metaheuristic.

Exp. number	Demand	No. of lines	Headway	Train models
1	39493	6	[10, 10, 10, 10, 10, 10]	[463, 465, 463, 464, 464, 464]
2	36377	6	[5, 5, 5, 5, 5, 5]	[463, 465, 465, 465, 465, 465]
3	44682	6	[6, 6, 6, 6, 6, 6]	[463, 463, 463, 463, 463, 463]
4	28812	6	[15, 15, 15, 15, 15, 15]	[465, 464, 463, 463, 464, 463]
5	29547	6	[6, 10, 10, 10, 10, 10]	[464, 464, 463, 465, 464, 464]
6	28185	6	[10, 10, 10, 10, 10, 10]	[465, 463, 463, 463, 463, 464]
7	41726	6	[5, 5, 5, 5, 5, 5]	[465, 464, 463, 463, 463, 463]
8	30851	6	[12, 12, 12, 12, 12, 12]	[465, 465, 463, 464, 463, 465]
9	30851	6	[10, 10, 10, 10, 10, 10]	[464, 464, 463, 465, 463, 463]
10	31208	6	[10, 10, 10, 10, 10, 10]	[464, 465, 463, 463, 464, 464]
11	34047	6	[10, 10, 10, 10, 10, 10]	[465, 463, 463, 463, 464, 463]
12	36690	6	[10, 10, 10, 10, 10, 10]	[464, 464, 465, 465, 464, 464]
13	37201	6	[10, 10, 10, 10, 10, 10]	[465, 464, 464, 464, 464, 463]
14	37373	6	[6, 6, 6, 6, 6, 6]	[464, 463, 463, 463, 463, 463]
15	32668	6	[12, 12, 12, 12, 12, 12]	[465, 464, 464, 463, 464, 465]
16	31603	6	[12, 12, 12, 12, 12, 12]	[465, 463, 463, 464, 463, 464]
17	36520	6	[10, 10, 10, 10, 10, 10]	[465, 465, 464, 464, 463, 463]
18	40219	6	[10, 10, 10, 10, 10, 10]	[464, 463, 465, 463, 464, 463]
19	39949	6	[10, 10, 10, 10, 10, 10]	[465, 464, 463, 463, 465, 464]
20	30408	6	[12, 12, 12, 12, 12, 12]	[465, 465, 464, 463, 463, 464]
21	43361	6	[6, 6, 6, 6, 6, 6]	[463, 463, 463, 463, 464, 463]
22	28108	6	[10, 10, 10, 10, 10, 10]	[463, 463, 464, 465, 463, 463]
23	27698	6	[15, 15, 15, 15, 15, 15]	[464, 463, 464, 463, 464, 465]
24	36070	6	[6, 6, 6, 6, 6, 6]	[464, 464, 463, 463, 463, 463]

Table 4. Computational results for the ALNS metaheuristic.

Exp. number	Time	Profit	Revenue	Operating cost	Building cost	Crew cost	Acquisition cost
1	3192.90	3.70E9	7.11E9	2.91E8	2.86E9	7.65E7	1.82E8
2	3437.87	3.29E9	6.55E9	4.71E8	2.38E9	1.26E8	2.75E8
3	3481.97	3.85E9	8.04E9	5.08E8	3.26E9	1.37E8	2.82E8
4	3206.59	2.74E9	5.19E9	1.54E8	2.16E9	4.05E7	9.51E7
5	3600.82	2.34E9	5.32E9	2.82E8	2.44E9	7.36E7	1.79E8
6	2017.74	2.48E9	5.07E9	2.05E8	2.20E9	5.44E7	1.25E8
7	3561.55	3.70E9	7.51E9	5.13E8	2.85E9	1.36E8	3.09E8
8	3212.30	3.49E9	6.26E9	1.92E9	2.39E9	4.98E7	1.24E8
9	3543.65	2.69E9	5.55E9	2.32E8	2.43E9	6.10E7	1.43E8
10	2342.42	2.88E9	5.62E9	2.23E8	2.31E9	5.87E7	1.37E8
11	2428.17	3.25E9	6.13E9	2.28E8	2.45E9	6.07E7	1.35E8
12	3519.16	3.57E9	6.61E9	2.49E8	2.56E9	6.43E7	1.64E8
13	2091.95	1.27E9	4.46E9	2.80E8	2.66E9	7.32E7	1.79E8
14	3529.52	1.09E9	4.49E9	3.92E8	2.67E9	1.05E8	2.24E8
15	3167.72	1.09E9	3.92E9	2.02E8	2.44E9	5.24E7	1.33E8
16	3467.02	1.19E9	3.79E9	1.78E8	2.27E9	4.69E7	1.11E8
17	2713.09	1.19E9	4.38E9	2.49E8	2.72E9	6.50E7	1.60E8
18	3227.82	1.75E9	4.83E9	2.48E8	2.60E9	6.55E7	1.52E8
19	3484.67	1.74E9	4.80E9	2.50E8	2.58E9	6.55E7	1.59E8
20	964.50	7.67E8	3.65E9	1.98E8	2.51E9	5.21E7	1.25E8
21	3651.22	1.81E9	5.20E9	4.19E8	2.62E9	1.13E8	2.39E8
22	3552.36	8.59E8	3.37E9	2.08E8	2.13E9	5.50E7	1.25E8
23	2571.30	9.21E8	3.32E9	1.32E8	2.15E9	3.46E7	8.19E7
24	3631.94	1.32E9	4.33E9	3.73E8	2.32E9	9.98E7	2.17E8

Figure 2 resumes the different terms concerning the objective function for all the experiments. As expected, incomes are bigger for the first twelve instances. Experiments number 3 and 21 produce the best results in terms of profit for the two different blocks of experiments respectively. The structure of costs depicted in the figure denotes the complexity of the RNDLP problem. Specifically, it could be expected a higher captured demand for experiment 1 in comparison with experiment 3 as consequence of a minor fare (the RN becomes more attractive for passengers). However, as revenue is lower, a lower income gives rise to a less extensive network, given service to a minor number of O-D pairs, which translates in a minor captured demand (see Fig. 3). Moreover, the best solution (experiment 3) also corresponds to the higher construction costs and to one of the experiments with high operation costs (with exception of experiment 7).

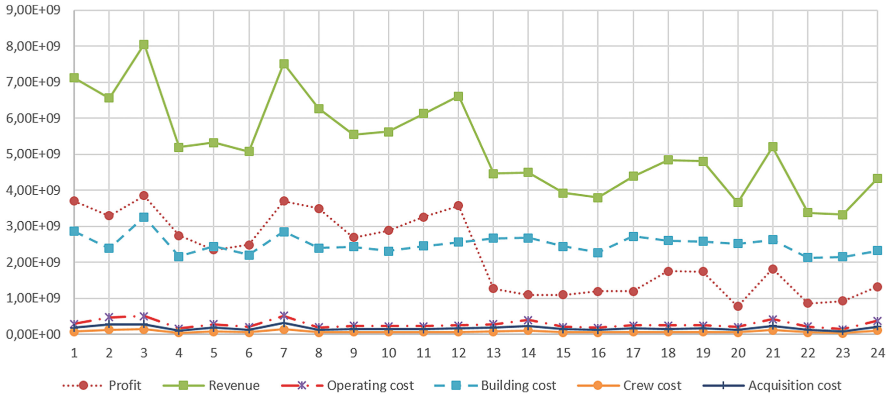


Fig. 2. Representation of costs for the set of experiments.

In order to obtain a deeper insight in the best solutions, experiments 3 and 21, Fig. 4, representing Network Profit versus time, illustrate the convergence process of the ALNS in both cases. As the reader may note, the algorithm attain a 70% of the best profit in approximately 1000 s for the experiment 3 and a 50% in 2400 s for the experiment 21. In general, the convergence in the second block of experiments (with lower sum of $fare + subsidy$) is slower than in the first one. Figure 5 shows the topology of both solutions.

Figure 6 presents a comparison between the topology of both networks, giving an idea about the coverage of the two solutions. This picture also illustrates the complexity of making the most appropriate design. As depicted, Experiment 3 covers a greater number of nodes which translates in a higher number of served O-D pairs.

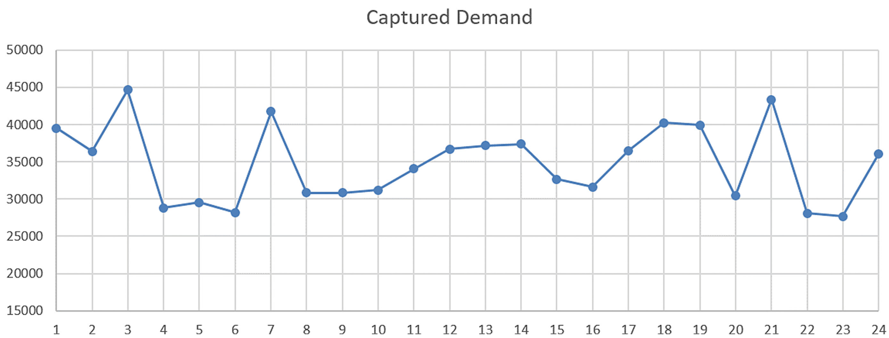
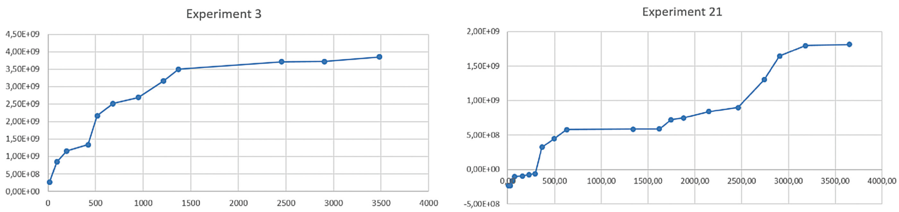
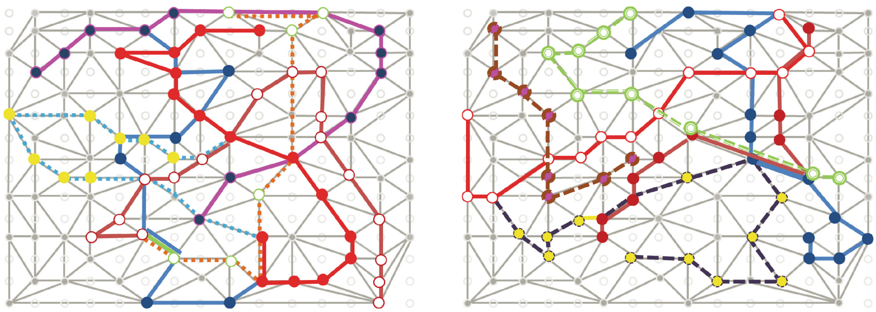


Fig. 3. Captured demand for the set of experiments.



(a) Profit evolution for Exp. n. 3 (b) Profit evolution for Exp. n. 21

Fig. 4. Improvement of the ALNS with time



(a) Network of Exp. n. 3 (b) Network of Exp. n. 3

Fig. 5. The RN solutions

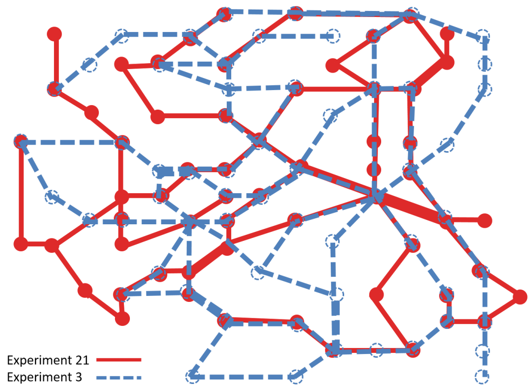


Fig. 6. Comparison of coverage Exp. 1 and 23.

5 Conclusions

In this chapter, we have presented a MINLP formulation for the integrated Railway Rapid Transit Network Design and Line Planning (RNDLP) problem, considering simultaneously the two first stages of the railway planning process. The model incorporates all relevant costs, including the network building, fleet acquisition, train operation, rolling stock and crew costs, taking into account the temporal nature of the network deployment. The proposed model reflects both, the service provider and the user points of view. The line planning phase includes line frequency and train model selection decisions, determining the final level of service for each line. The proposed formulation considers the existence of an alternative mode (private car) providing service to all origin-destination pairs. Users select the railway or the alternative mode by comparing its respective utilities by means of a logit probabilistic sub-model that include RN fare as a decision parameter. In order to solve realistic size instances of the RNDLP problem, an Adaptive Large Neighborhood Search (ALNS) metaheuristic is proposed. The ALNS performance was assessed by means of a parametric analysis in a medium-size artificial generated network. As reported in Sect. 4, the ability of the ALNS in obtaining good solutions within short computation times is demonstrated. Computational experiments provide yield useful insights into the different interactions among all the aspects related to this long-term and complex decision problem.

Nowadays, the integration of different stages of the railway planning process continues being a challenge and further research is needed in order to model and solve real and big instances. Although several attempts have been made to solve rolling stock and scheduling problems jointly, there still exists a gap in integrating strategic and tactical problems. This chapter contributes to this end.

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