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Network design and vehicle routing problems in road transport systems: Integrating models and algorithms

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ABSTRACT

In this paper, an integrated approach is proposed that incorporates the road network design problem and the vehicle routing problem, which are very often studied separately. This approach can be adopted when the routes to follow in a transport system have to be designed (e.g., for public transit with fixed and variable routes, or for freight distribution) jointly with the network topology and capacity. The goal is to minimise congestion and the impacts on the network from passengers and freight vehicles. The design (control) variables consist of the optimal vehicle routes and optimised road network; they are both discrete (link topology for passenger and freight, routes for passengers and freight vehicles, etc.) and continuous (link capacity in terms of reserved lanes, signal settings, etc.). The problem is modelled in congested transportation networks (e.g., in an urban centre). A heuristic algorithm is adopted to find the best network configuration and the best vehicle routes. The proposed model and the adopted algorithm are applied in a test system to analyse the limits of the methodology, to verify the advantage obtained from the joint method and its applicability. In the test system, the joint procedure gives good results in terms of cost decreases. The reported methods can help public and private stakeholders in making decisions regarding transportation policy, especially in the urban environment.

1. Introduction

In recent years, many cities have proposed measures for designing public transit systems (for passengers) with paths and frequency optimisation and for reducing the number of trucks (for freight) in urban centres, forcing suppliers and retailers to consider significant changes in their behaviour. The two problems are studied in a predefined transport network: the optimal routing for passengers and freights and the optimal transport network could be studied jointly.

In the literature, (i) the road Network Design Problem (NDP) and (ii) the Vehicle Routing Problem (VRP) (for public transit and freight transport) are studied as separate problems.

(i) The road NDP consists in finding the optimal configuration of an existing road network according to certain criteria (e.g., minimization of total delay, minimization of vehicular pollution, etc.), and can range from optimisation of link direction and lane allocation (discrete problems) to optimisation of the capacity at junctions (continuous problem). In urban areas, the capacity can be treated as a function of signal regulation at the final node of the link, so its optimisation can be treated as node regulation. The NDP was first proposed for uncongested systems and has been extended to congested systems and other applications. A detailed account of the literature on NDP is given in Section 2.1.
(ii) The VRP consists in finding the optimal set of vehicle routes with respect to some constraints. The VRP for optimising the routes of a fleet of vehicles (cars, buses, trucks) was first formulated by Dantzig and Ramser [1]. Primarily used in the freight field, the VRP can be extended to the field of passengers. As an example, the dial-a-ride transit service can be formulated as a pickup and delivery vehicle routing problem with time windows. In the rest of this paper, the term "public transit" is used with the means to include in the definition also the dial-a-ride and its variations. A detailed account of the literature on VRP is given in Section 2.2.

Although the literature has treated NDP and VRP separately, the two problems are naturally related through the influence of network optimisation on vehicle paths.

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The advancement proposed in this paper is related to the proposal of a joint problem named Network Design and vehicle Routing Problems (NDRPs). Traditional approaches focused on optimising vehicle routes using the configuration of the road network as a fixed input. The main purpose of the proposed method is to design vehicle routes in an optimised road network (in terms of link layout and junction regulation), providing some reserved lanes to improve the service. The alternative response proposed in this paper relates to optimisation of the transportation system to minimise the time spent by both passenger and freight vehicles on urban road networks. The system is designed to improve the quality of service in public transit and freight distribution without reducing the level of service for road drivers. The objective function relates to the general cost for users (for passengers and drivers), cost for operators and impacts for citizens. The objective of the paper is to propose an integrated model to solve with a well-defined and efficient algorithm (in this paper a classical genetic algorithm, but other algorithms could be selected). Note that the reference is to road network design and not to any service network. The proposed NDRP considers discrete variables (that is, link orientation, lane allocation, route for vehicles) and continuous variables (that is, junctions capacity and vehicle capacity); it generates the best configuration, in terms of network layout, regulation at junctions, best route, and best capacity for vehicles. The NDRP is defined as a two-level model: in the outer level the road network is designed; in the inner level, a route optimization is performed. The two levels are integrated mainly for the following reasons: a single objective function is used; in the iterative solution procedure, the two problems are solved sequentially with feedback on the first problem.

The proposed model can:

- be applied both for freight and public transit; besides, considering that the approach foresees reserved lanes, the routes (or at least a portion of them) can be forced in using such lanes;
- support public and private decision makers in making decisions concerning the transport policy at the urban level; as an example for the design of corridors that ensure an efficient public transit and a freight distribution with a low impact on the other traffic components.

The paper is structured with six sections: after Section 1, Section 2 reports a literature review; Section 3 specifies the NDRP; Section 4 describes a solution procedure; Section 5 experiments the proposed method in a test system; finally, Section 6 reports some discussions and conclusion remarks and plans for future developments.

The main original contributions proposed in this paper are as follows:

- the integration of NDP and VRP and the specification of the NDRP in a two-level weighed problem where vehicle routing comes out together with best road configuration (Section 3);
- the specification of a solution procedure (Section 4);
- the experimentation of the proposed method in a test case (Section 5).

In Sections 3, 4, and 5, the model, procedures and results are reported in the sub-sections *.1 in relation to the general joint aspects and in the sub-section *.2 in relation to the NDP and VRP aspects. The main original contributions (mainly reported in Sections 3, 4, 5) are supported by a state of the art (Section 2) and some final considerations (Section 6).

2. Literature review

The NDP and VRP problems can be applied for: designing the configuration of the road transport system used by passenger and freight vehicles [2] and for planning [3]; designing public transit systems for passengers [4–6]; reducing the trucks in urban centres [7,8]; forcing freight decision makers to change their behaviour [9–13]; supporting information and communication technology and control centre [14–16]. The two problems are studied separately.

Given the separate treatment of the NDP and VRP in the literature, this section will divide the discussion into the NDP-related literature (i, subsection 2.1) and the VRP-related literature (ii, subsection 2.2) (Fig. 1).

2.1. Network Design Problems

The classification of the state of the art concerning NDPs considers the decision variables:

i.A. discrete variables (discrete NDP);
i.B. continuous variables (continuous NDP with rigid or elastic path choice);
i.C. discrete and continuous variables (mixed NDP).

i.A) Discrete NDPs design lanes allocation and lanes direction. In discrete NDPs, the first heuristic algorithms were proposed by Billheimer and Gray [17] on uncongested networks and by Chen and Alfa [18] on congested networks. Foulds [19] introduced the option that a set of possible network configurations can be added by the analyst; Gao et al. [20] introduced the possibility of the construction of new infrastructures (within a budget constraint); Xie and Turnquist [21] introduced the possibility of adding lanes for emergency vehicles and assigning them priority at junctions; Shanmugasundaram et al. [22] proposed an approach to design the link direction with the aim of minimising the travelled distance. Other discrete NDPs were considered in Poorzahedy and Turnquist [23] and Kalafatas and Peeta [24].

i.B) Continuous NDPs have generally been identified with signal setting optimisation. A sub-classification [2] involves the path choice (1. rigid or 2. elastic) and junction optimisation (I. isolated junction or II. interacting junctions).

i.B.1) Assuming rigid path choice, two forms of junction have been explored: i.B.1.I) isolated junction [25–30]; i.B.1.II) interacting junctions [31–36].

i.B.2) Assuming an elastic path choice, two forms of junction have been explored: i.B.2.I) isolated junctions [2, 37–43]; i.B.2.II) interacting junctions [29,44–46].

i.C) Discrete and continuous NDPs include the cases i.A and i.B. In NDPs, Cantarella et al. [2] proposed a set of heuristic approaches (tabu search, simulated annealing, and genetic algorithms) to optimise link topology and junctions under rigid supply and demand. Russo and Vitetta [47] proposed a three-step method (topological similarity, cluster analysis, and solution selection) for solution in a multi-criteria approach. Caggiani and Ottomanelli [48] proposed a fuzzy approach to uncertainty evaluation in the constraints, and Luathep et al. [49] proposed a mixed integer linear programming formulation, solved by a cutting constraint algorithm. Guthrie *et al.* [50] incorporated in the problem definition the concept of social equity linked with accessibility analysis.

In recent years, the authors have proposed some works in network design problem. In the paper by Cantarella et al. [2], some heuristics for NDP were specified and used singularly or jointly. Respect to the NDP reported in this paper, the reserved lanes were not considered. In the paper by Polimeni and Vitetta [51] a mixed (discrete and continuous variables) NDP joint with a VRP was reported. The network was optimised considering the transport demand related to road and freight. With respect to this paper, a mono-level and non-weighed problem formulation was proposed, and a basic genetic algorithm was

- **i. Network design problem**
  - A Discrete variables
  - B Continuous variables
    - 1. Rigid path choice (I. Isolated / II. Interacting junctions)
    - 2. Elastic path choice (I. Isolated / II. Interacting junctions)
  - C Discrete and Continuous variables
    - 1. Rigid path choice (I. Isolated / II. Interacting junctions)
    - 2. Elastic path choice (I. Isolated / II. Interacting junctions)
- **ii. Vehicle routing problem**
  - A. Transit scheduling design
    - 1. Route
    - 2. Frequency/Timetable
  - B. Dial-a-ride problems
    - 1. Route
    - 2. Schedule
  - C. Route design for freight vehicles
    - 1. Exact solution approach
    - 2. Heuristic solution approach

Fig. 1. State-of-the-art classification

implemented. The paper Musolino et al. [52] proposed a model to support the system manager in the Mobility as a Service (MaaS) design.

2.2. Vehicle Routing Problems

The classification of the state of the art concerning VRPs considers the type of problem:

ii.A. Transit scheduling design (with fixed routes);
ii.B. Dial-a-ride problems;
ii.C. Route design for freight vehicles.

ii.A) In transit scheduling design problems, the general goal is to design a set of routes, to assign the vehicles to the routes, to design the frequencies and the timetable also considering the needs of passenger. As an example, Arbex and da Cunha [53] proposed a multi-objective optimisation approach to define the dimension of the fleet and minimise the travel costs. Buba and Lee [54] proposed an approach to solve simultaneously the design of the transit network and the frequency setting problem with the aim of minimising travel time and the unmet demand. The bus allocation problem is tackled by Gkiotsalitis et al. [55], who proposed an approach to minimise the operational costs and the user waiting time. The frequency setting problem is solved by Ahern et al. [56] where an approach is proposed to minimise both the passenger costs and the bus operating costs. Nnene *et al.* [57] used an agent-based approach to design the transit network and to solve the scheduling problem in the case of demand-responsive services. Montella et al. [58] proposed a method to optimise the fares of the transit system with the goal of minimising social costs.

ii.B) The dial-a-ride problem (DARP) consists of designing vehicle routes and schedules for a set of users considering both the delivery and the pick-up [59–61]. Cordeau [62] proposed a branch-and-cut algorithm to solve the static version (the case in which all users' requests are known in advance) of DARP, it is suggested to apply the procedure to low dimension problems. A tabu search heuristic is reported in Laporte and Cordeau (2003); a procedure for exploring the neighbourhood of each solution is proposed, the aim is to minimise the route travel time. Melis and Sörensen (2021) developed a neighbourhood search algorithm to design the routes, minimising the total travel time of all users. Similarly, Pfeiffer and Schulz [63] designed the routes with the aim of minimising waiting time. A heuristic approach was proposed by Luo and Schonfeld [64] with the aim of minimising the number of vehicles and serving all users, ensuring the quality of the service. In dynamic DARP, Tafreshian et al. [65] proposed a local search heuristic to design the routes of the vehicles with historical data. Maalouf et al. [66] proposed a fuzzy approach, the objective is to design the service to respect the desired arrival time at the destination. Hyland and Mahmassani [67] extended the problem to autonomous vehicles, the aim is to manage the fleet to minimise the overall travelled distance.

ii.C) An extensive literature is available on route design for freight vehicles. Without claiming to be exhaustive, a brief literature review on VRP is reported. For further information, see Laporte [68] and Lin *et al.* [69]. VRPs can be classified according to the solution method, considering: ii.C.1) exact solution approaches; ii.C.2) heuristic solution approaches.

ii.C.1) Exact solution approaches have been applied both to problems based on Lagrangian relaxations and to problems based on the Dantzig-Wolfe decomposition. Regarding the first set of problems, Fisher [70] specifically proposed a branch-and-bound technique, solving a Lagrangian problem that provides the lower bounds. Kallehauge et al. [71] proposed a method based on Lagrangian relaxations and a branch algorithm. Other papers based on the Lagrangian approach include those by Desrosiers et al. [72] and Fisher et al. [73]. With regard to the second set of problems, Choi and Tchab [74] proposed a VRP for a heterogeneous fleet, the solution approach being a branch and bound algorithm; Qureshi et al. [75] proposed a VRP with semi-soft time windows and a branch and price algorithm to solve the problem; Kohl et al. [76] proposed a VRP with time windows solved with a branch and bound approach.

ii.C.2) In heuristic solution approaches, Tasan and Gen [77] used a genetic algorithm to solve the VRP with simultaneous delivery and pick-up, Allahviranloo *et al.* [78] and Abbassi *et al.* [79] proposed a parallel genetic approach, evolving different populations simultaneously, and Hanshar and Ombuki-Berman [80] proposed a genetic algorithm to optimise travel cost. Gribkovskaia et al. [81] proposed a tabu search algorithm to solve the pick-up and delivery problem, and Nanry and Barnes [82] proposed a tabu search using strategies favourable to convergence. Osman [83] proposed a simulated annealing algorithm to minimise the total distance travelled; Tavakkoli-Moghaddam et al. [84] used simulated annealing to minimise the vehicles used and the management cost; Syrichas and Crispin [85] proposed the quantum annealing algorithm to solve large scale problems. Other heuristics have been reported in the literature. Ant colony was proposed by Dorigo and Stützle [86], Jabir et al. [87], Kyriakakis *et al.* [88]. The local search was proposed by Rivera et al. [89], Arnold and Sörensen [90], Andelmin and Bartolini [91]. The swarm optimisation algorithm was implemented in Marinaki and Marinakis [92], Chen et al. [93], Islam et al. [94].

In recent years, the authors have proposed some works in vehicle routing: Polimeni and Vitetta [95] proposed a model to analyse the freight distribution considering the change in travel costs with the road congestion; Musolino et al. [96] proposed a procedure based on reliable link travel times by means of the network fundamental diagram; Musolino et al. [97] proposed a methodology to evaluate the position of urban centres for the freight distribution where the VRP solution is a component of the objective function in the location problem; Polimeni and Vitetta [98] and Napoli et al. [99] formulated a VRP in the specific case of electric vehicles.

2.3. Limits and integration

The two problems, NDP and VRP, studied separately have had extensive development in the scientific literature in terms of models and solution procedures; they are proposed assuming different basic hypotheses. Sections 2.1 and 2.2 highlight the numerous papers published and the numerous areas studied. However, in reality, the two problems coexist, and joint study is necessary.

Advanced procedures for solving a single problem can also provide optimal solution for one of the two problems but do not consider the effects that can be obtained by optimizing the other problem as well. Joint optimal procedures provide optimal solutions that consider the desired effects of both problems.

Therefore, in this paper, a joint solution procedure of the NDRP with vehicle routing optimization developed in an optimized bidding system configuration is proposed. The joint problem allows for transport networks optimized in terms of topology and capacity and, on the same optimized network, optimized vehicle routing. Therefore, an overall problem that considers an optimized transport network for vehicles (for passengers and/or freights) and optimal routing of vehicles (for passengers and/or freights).

3. Models

The NDRP, as reported in this section, incorporates the NDP and the VRP. It is structured as a constrained problem, with route optimisation (VRP, inner level) after network optimisation (NDP, outer level). The overall formulation must consider the contribution of the two problems to the final objective. The symbols used in the following paragraphs are shown in Table 1. In any case, each time a symbol is introduced, its definition will be given.

In the model, the variables considered are as follows:

(transport system variables)

- a: link of the network;
- i, j: two consecutive nodes visited in a route;
- v: public transit and/or freight vehicle;
- $\mathbf{f}$: link flow vector in congested conditions, with entry f_a the flow on link a; this vector should take into account all the components of the traffic (n is the generic component, i.e. buses, freight vehicles, cars and so on), one way to achieve this result is a weighted sum of the traffic components n as:

$$\mathbf{f} = \Sigma_n \beta_n \cdot \mathbf{f}_n \tag{1}$$

where

- ■ β_n is the weight of the traffic component n; each vehicle (buses, freight vehicles, cars and so on) has a different size and therefore must be added with a different weight to obtain an equivalent flow in equivalent cars;
- ■ $\mathbf{f}_n$ is the link flow vector of the traffic component n, with entry $f_{n,a}$ that is the flow on the link a relative to the component of traffic n;

- $\mathbf{c}$: VRP link cost vector, with entry c_a the cost for public transit and freight vehicles on link a;
- $\mathbf{h}$: VRP path cost vector, with entry h_{ij} the cost for public transit and freight vehicles users on the path connecting the pairs i-j;
- $\delta_{a,ij}$ binary variable, equal to 1 if link a belongs to the path between i and j, and 0 otherwise;

(decision or control variables)

- $\mathbf{y}$: network configuration vector, with entry the variables y_i that describes the network topology (the number of lanes allocated for passenger vehicles and the number of lanes allocated for transit and/or freight vehicles) and the signal setting (the cycle duration and the green duration for each lane at a junction) related to the NDP;
- $\mathbf{\Omega}$: vehicles route matrix, related to the paths used by the vehicles in VRP, with entry $\omega_{ij,v}$ equal to one if the vehicle v uses the path between i and j, and 0 otherwise;

Table 1
Symbols

Symbol	Short Definition
a	link of the network
$\mathbf{c}$	VRP link cost vector
c_a	cost for public transit and freight vehicles on link a
$\mathbf{d}$	travel demand vector
$\mathbf{E}$	set of network links
$\mathbf{E1} \subseteq \mathbf{E}$	subset of shared network links
$\mathbf{E2} \subseteq \mathbf{E}$	subset of reserved network links
$\mathbf{f}$	link flow vector in congested conditions
$\mathbf{f}^*$	optimal value of the vector $\mathbf{f}$
f_a	flow on link a
$\mathbf{f}_n$	link flow vector of the traffic component n
$\mathbf{f}_{SNL}(\gamma(\mathbf{f}, \mathbf{y}))$	vector of the stochastic network loading function
$\mathbf{h}$	VRP path cost vector
$\mathbf{h}_{ij}$	cost for public transit and freight vehicles users on the path connecting the pairs i-j
i, j	two consecutive nodes visited in a route
$\mathbf{S_f}$	set of feasible link flows
$\mathbf{S_y}$	set of feasible network configurations
$\mathbf{S_\Omega}$	set of feasible routes
v	public transit and/or freight vehicle
V	set of public transit and/or freight vehicles
$\mathbf{y}$	network configuration vector
$\mathbf{y}^*$	optimal value of the vector $\mathbf{y}$
$z(\mathbf{f}, \mathbf{y}, \mathbf{\Omega})$	function related to the objectives of the NDRP
$z_1(\mathbf{f}, \mathbf{y})$	function related to the objectives of the NDP
$z_2(\mathbf{\Omega})$	function related to the objectives of the VRP
α	homogenization factor for the objective function
β_n	weight of the traffic component n
$\gamma(\mathbf{f}, \mathbf{y})$	vector of functions related to the user cost for each link
$\gamma_a(\mathbf{f}, \mathbf{y})$	cost function on link a
$\delta_{a,ij}$	binary variable, equal to 1 if link a belongs to the path between i and j, and zero otherwise
Λ	passenger and freight origin and destination set
$\omega_{ij,v}$	Binary variable, equal to one if the vehicle v uses the path between i and j, and zero otherwise
$\mathbf{\Omega}$	vehicles route matrix
$\mathbf{\Omega}^*$	optimal value of the vector $\mathbf{\Omega}$

(transport system functions)

- γ(f, y): vector of functions related to the user cost in each link, with entry $\gamma_a(\mathbf{f}, \mathbf{y})$ the cost function on link a (it gives the cost vector c);
- $\boldsymbol{f}_{SNL}(\gamma(\mathbf{f}, \mathbf{y}))$: vector of the stochastic network loading function, dependent on the cost functions;

(transport system sets)

- **E**: set of network links;
- **E1**$\subseteq$ **E**: subset of network links shared by different transport modes;
- **E2**$\subseteq$ **E**: subset of network links reserved for commercial vehicles or public transport; note that **E1** and **E2** are disjoint sets and **E1** $\cup$ **E2** =**E**; if an infrastructural link has both reserved and unreserved lanes, it is split into two links;
- $\mathbf{S_y}$: set of feasible network configurations, such that each configuration is connected, and respects lane allocations and proper signal settings;
- $\mathbf{S_f}$: set of feasible link flows (containing feasible and non-negative vectors, $\mathbf{f} \geq 0$);
- $\mathbf{S_\Omega}$: set of feasible routes;
- $\mathbf{\Lambda}$: passenger and freight origin and destination set (point points where users request to pick up and get off public transport or delivery and/or pick-up freight operations);
- **V**: set of public transit and/or freight vehicles;

(objective functions)

- $z(\mathbf{f}, \mathbf{y}, \mathbf{\Omega})$: function related to the objectives of the NDRP;
- $z_1(\mathbf{f}, \mathbf{y})$: function related to the objectives of the NDP;
- $z_2(\mathbf{\Omega})$: function related to the objectives of the VRP;
- α homogenisation factor for the objective function.

3.1. General model

The problem studied concerns the search for the optimal configuration of the transport network, in terms of topology (directions of travel) and capacity of the links (regulation at junctions and number of lanes), and of vehicle routing, in terms of topology (paths to follow) and capacity (capacity and number of vehicles).

The supply system considers the transport infrastructure, vehicles and organization adopted to allow the movement of passengers and freight. The supply model is defined through a transport network composed of links and cost functions associated with each link dependent on the traffic flow which takes into account the different demand components (i.e, passengers and freights).

The demand components consider different components in term of quantity and users' decisions for passengers mobility and freights movement. The demand vector must consider the different traffic components present in the system. It is commonly considered to be divided into passenger flow and freights flow. Within each component, different sub-components can also be considered (i.e.: for passengers the demand can be considered divided in relation to the vehicles used (individual, semi-collective, collective), the scope of the journey, etc.; for freight the demand can be considered divided by size of the vehicle used, the freight category, the transport service, etc).

Eq. (2) formalises the proposed NDRP in term of a constrained optimisation problem:

$$\begin{cases} \mathbf{f}^*, \mathbf{y}^*, \Omega^* = arg\,min_{\mathbf{f},\mathbf{y},\Omega} \quad z(\mathbf{f}, \mathbf{y}, \Omega) \\ \text{subject to} \\ \text{Technical and external constraints} \\ \text{Behavioural constraints (related to the NDP)} \\ \text{Routing constraints (related to VRP)} \end{cases} \tag{2}$$

The solutions of the problem (2) are the vectors **f*** and **y*** and the matrix **Ω***, respectively, the optimal values of the vectors **f, y, Ω**.

The constraints of the problem can be grouped into three sets: the first is described below and refers to technical and external input respecting the optimisation problem; the second (NDP) concerns the behavioural constraints related to the user choice at path level in congested systems; the third (VRP) concerns the vehicle routing problem.

Technical constraints refer to technical characteristics, such as the range of vehicles, the vehicle capacity, and the road width. The technical constraints to consider are of a different nature for NDP and the VRP. For the NDP, the technical constraints to be considered concern, for example, the geometric characteristics of the infrastructures which are pre-established (slope, width of the roads, etc.), regulation constraints at junctions for traffic safety, and characteristics of the vehicles. For the VRP, the technical constraints to be considered concern, for example, the dimensions of the vehicles used for the transport of passengers (buses) and goods (vans, trucks), pick-up/delivery constraints (time windows), capacity of the vehicles.

External constraints refer to budget limitations or mobility limitations (e.g., limited traffic zones) or normative limitations (e.g., use of electrical vehicles in the city centre). The external constraints to be considered are similar for the two problems because they are above all constraints provided for by national or local norms and rules. These constraints define the rules for circulation, time constraints for access to certain areas in terms of vehicle type or prohibition in certain time slots, limits to be respected for polluting emissions and noise, etc.

The objective function can be expressed as a linear combination of two components:

$$z(\mathbf{f}, \mathbf{y}, \boldsymbol{\Omega}) = z_1(\mathbf{f}, \mathbf{y}) + \alpha \cdot z_2(\boldsymbol{\Omega}) \tag{3}$$

The α value, greater than zero, is a relative weight for the two components of the objective function. The unit value guarantees an identical weight to the two components. If optimization has the main purpose of optimising the topology and capacity of the transport network (NDP), weight values lower than 1 must be adopted; at most the null value leads to optimizing only the NDP. Conversely, to give greater weight to the routing (VRP), weight values greater than 1 must be adopted. The choice of weight is not easy and can be defined in agreement with the decision maker based on the policies to be implemented in the transport system.

Other specifications for the objective function can be adopted considering the sustainability components, economic, social, and environmental.

Eq. (3) expresses the union between the two problems treated, its components take into account the influence of the two single problems on the overall formulation. The two objective functions z_1 and z_2 and the related specific constraints are reported respectively in the subsections 3.2.1 and 3.2.2.

3.2. Sub-models

In this subsection the two sub-models (NDP and VRP) are specified.

3.2.1. Network Design Problem

The vector of equilibrium flow **f***, together with the best supply configuration **y***, is obtained as the solution of the NDP (inner level). The inner-level mixed NDP is based on equilibrium concepts in the constraint, because the link costs considered are those related to the equilibrium point of the assignment problem. The link costs are flow dependent: if the link is used for both passenger vehicles, public transit, and freight vehicles, the cost depends on all flow components; if the link is only used for public transit and or freight vehicles, the cost depends on the vehicles allowed to use the link.

Starting from the infrastructural supply and demand flows for passenger and freight, the optimisation procedure can be formulated as in Eq. (4):

$$\begin{cases} \mathbf{f}^*, \mathbf{y}^* = arg\,min_{\mathbf{f},\mathbf{y}} \quad z_1(\mathbf{f}, \mathbf{y}) \\ \text{subject to} \\ \text{Technical and external constraints} \\ \text{Behavioural constraints} \end{cases} \tag{4}$$

The solutions of problem (4) are the vectors **f***and **y***; from the vectors obtained, the variable adopted for the VRP is the value of the link cost $\boldsymbol{\gamma}(\mathbf{f}^*, \mathbf{y}^*)$.

The objective function for the NDP can be expressed in several forms considering mono criteria or multi criteria approach. In the case of multi criteria approach non dominated solutions are generated and the solution could not be unique. The objective function can be specified as the total general cost for users:

$$z_1(\mathbf{f}, \mathbf{y}) = \sum\nolimits_{a \in \mathbf{E}} \gamma_a(\mathbf{f}, \mathbf{y}) \cdot f_a \tag{5}$$

If some lanes are reserved for public transit or/and freight vehicles, problem (5) can be modified to consider that, for a subset of links, the link cost will depend on the network configuration (**y**) but not on the flow. In this case, the link cost can be expressed as $\gamma_a(\mathbf{0}, \mathbf{y})$, assuming that the link cost is the free flow cost ($\mathbf{f} = \mathbf{0}$):

$$z_1(\mathbf{f}, \mathbf{y}) = \sum\nolimits_{a \in \mathbf{E}_1} \gamma_a(\mathbf{f}, \mathbf{y}) \cdot f_a + \sum\nolimits_{a \in \mathbf{E}_2} \gamma_a(\mathbf{0}, \mathbf{y}) \cdot f_a \tag{6}$$

Note that the problem can be extended to different time slices by modifying Eqs. 5 and 6: this would make it possible to consider the variability of demand (both for passengers and for freight) over time, obtaining a cost matrix for each time slice.

For the users behavioural the constraints are:

$$\mathbf{y} \in \mathbf{S}_\mathbf{y} \tag{7}$$

$$\mathbf{f} \in \mathbf{S}_\mathbf{f} \tag{8}$$

$$\mathbf{f} = \boldsymbol{f}_{\text{SNL}}(\boldsymbol{\gamma}(\mathbf{f}, \mathbf{y}), \mathbf{d})) \tag{9}$$

Constraint (7) indicates that the allocated lanes do not exceed the available lanes, that for each pair of centroids, there is at least one path and that the signal setting vector has admissible values. Constraint (8) indicates that the flow vector has admissible values. Constraint (9) indicates that the flow vector must be an equilibrium flow vector (behavioural constraints). The costs and the flows considered for all users are those obtained from the equilibrium point of the assigned problem, and it depends on the circular dependency from flows, costs, and travel demand, **d**. The travel demand can be obtained by means of stochastic models [100], considering the time slice. In addition, an approach with elastic demand is possible and, in this case, there would be a further dependence of demand on costs and flows. Considering that there are multiple demand components (i.e. passenger and freight), a general approach to multimode and/or multiuser equilibrium assignment must be adopted by obtaining multiple flow $f_{n,a}$ components (n) in each link (a), considering the Eq. (1). In order not to burden the notation, the multimode multiusers model is not reported in this paper (for more details see [101]).

The costs for the VRP are obtained from the equilibrium point with flow vector **f*** (that respects the behavioural constraints) at the optimal point for the network configuration **y***. For this reason, the vector of link costs **c** to be adopted for the VRP is obtained from the function:

$$\mathbf{c} = \boldsymbol{\gamma}(\mathbf{f}^*, \mathbf{y}^*) \tag{10}$$

The proposed models could be extended to the case of time-dependent networks; this would require dynamic assignment in the NDP and continuous cost functions implementation in VRP.

3.2.2. *Vehicle Routing Problem*

The matrix of optimal routes **Ω*** is obtained as the solution to the problem of the outer level. Starting from the link cost obtained from Eq. (10), the optimisation procedure can be formulated as in Eq. (11):

$$\begin{cases} \Omega^* = arg\,min_{\Omega} \quad z_2(\Omega) \\ \text{subject to} \\ \text{Technical and external constraints} \\ \text{Routing constraints} \end{cases} \tag{11}$$

The solution to problem (11) is the matrix **Ω***; this matrix associates the sequence of nodes with the vehicles.

The objective function allows minimisation of the travel cost for the vehicle fleet, assumed as the sum of the travel time for each route, which depends on the node sequence and the path cost. The objective function of the VRP can be specified as the total general cost for transit and freight vehicles:

$$z_2(\Omega) = \sum_{v \in V} \sum_{i \in \Lambda} \sum_{j \in \Lambda} h_{ij} \cdot \omega_{ij,v} \tag{12}$$

with $h_{ij} = \Sigma_{a \in \mathbf{E}} \delta_{a,ij} \bullet \mathbf{c}$

For VRP the constraint indicates that only one vehicle can visit a node, that all vehicles leave from the depot and come back to it, and freight demand cannot exceed vehicle capacity. The solution of the problem also depends on the level of freight demand, and approaches to evaluate such a demand can be applied [102]. The feasible solutions can be grouped into a set as:

$$\Omega \in \mathbf{S}_\Omega. \tag{13}$$

4. Procedures

The computational complexity of the problem does not allow the use of exact procedures for solving real size problems. In this paper, network and route optimisation problems are solved using heuristic procedures based on genetic algorithm. Note that the objective of this paper is not the proposal of a solution algorithm, for this reason the genetic algorithm is adopted considering that it is a consolidated and efficient procedure for solving the transport design problems (the state of the art reported in Section 2 can be considered).

In this section, the words reported in *italics* character refer to the labelled text reported in the nodes of the Figs. 2, 3 and 4.

4.1. *General procedure*

Fig. 2 reports the general flowchart related to the heuristic procedure adopted for the solution of the proposed NDRP.

First, note that the inputs of the heuristic NDP component include the *initial supply* (in terms of link *costs* and *infrastructures*, such as available roads) and the *demand* (in terms of *passengers* and *freight*). The supply characteristics of the network are the values obtained from feasible network configurations, whereas the demand is the number of travels of individual and transit passengers and freight divided by the modes that move on the network during a typical day. Some links in the network can be reserved for public transit and freight vehicles (preferential lanes) to improve the service.

The *heuristic NDP* is solved considering users, system manager, and social *objectives*, along with technical, behavioural (demand/flow/cost consistence), and external *NDP constraints*. Since it is not possible to

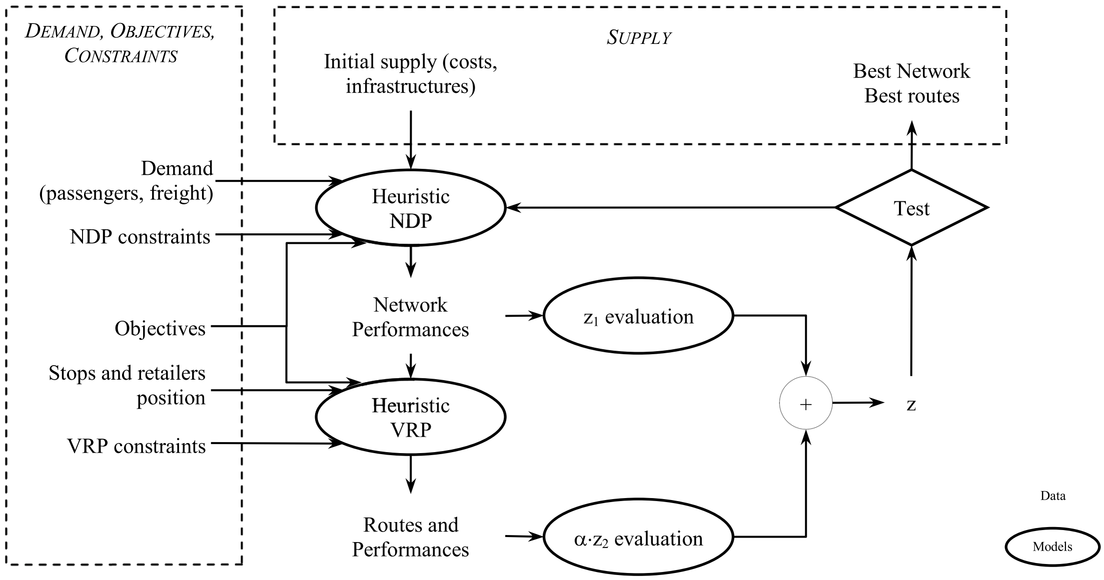


Fig. 2. Whole heuristic procedure proposed for the NDRP

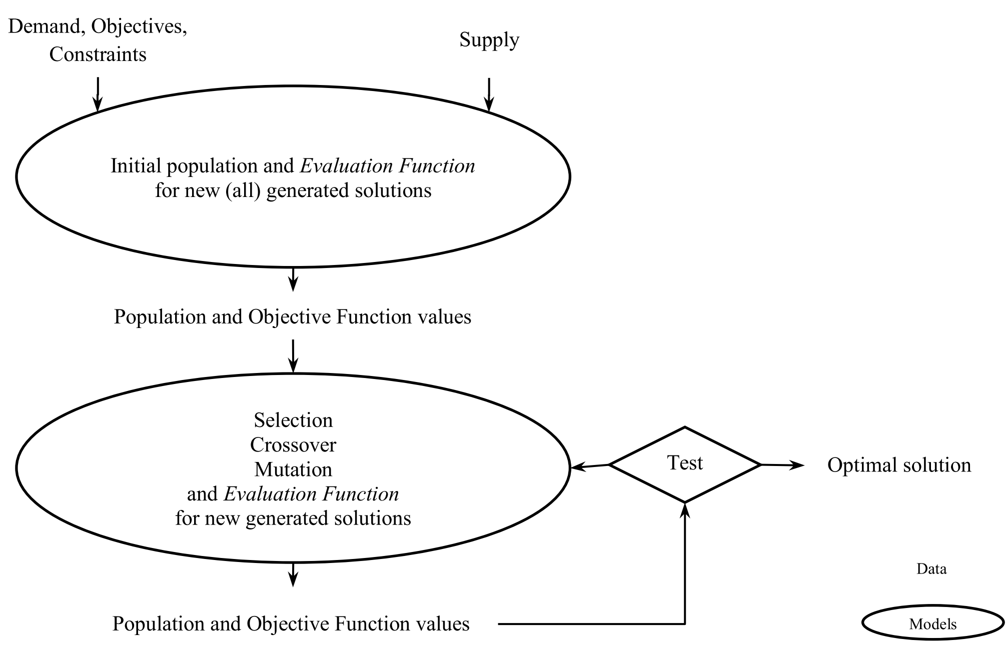


Fig. 3. Heuristic procedure for NDRP solution

guarantee the convergence [2], the *heuristic NDP* is stopped after a fixed number of iterations. The temporary output are the *network performances* (link costs and flows), related to a supply configuration from which it is possible to begin evaluating route costs. Knowing costs and flows, it is possible the *evaluation* of the component z_1 of the objective function.

The *heuristic VRP* includes the *network performances* (mainly the link costs), the passenger *stops and retailers position,* and a set of *VRP constraints*. Since the solution algorithm is heuristic, the VRP is stopped after a fixed number of iterations. The output is the set of *routes and* related *performances*, allowing for the *evaluation* of the component z_2 of the objective function.

The *test* of the whole procedure could be done considering the value of objective function or considering the maximum iteration number defined a priori, or when, after a predefined number of iterations, no new solution has not been generated. In the case of this paper, the maximum number of iterations will be used.

The output of the procedure as a whole is as follows:

- *best network,* for passengers: the road network (topology and optimal regulation at junctions) obtained by removing the lanes reserved;
- *best routes*, for public transit and/or freight distribution, including reserved lanes on the road network.

4.2. Sub-procedures

In this subsection, the sub-procedures adopted for the optimisation and for evaluation function are reported. Network and route optimisation problems are solved using a genetic algorithm. Fig. 3 summarises the heuristic procedures applied to solve the mixed NDP and VRP problems.

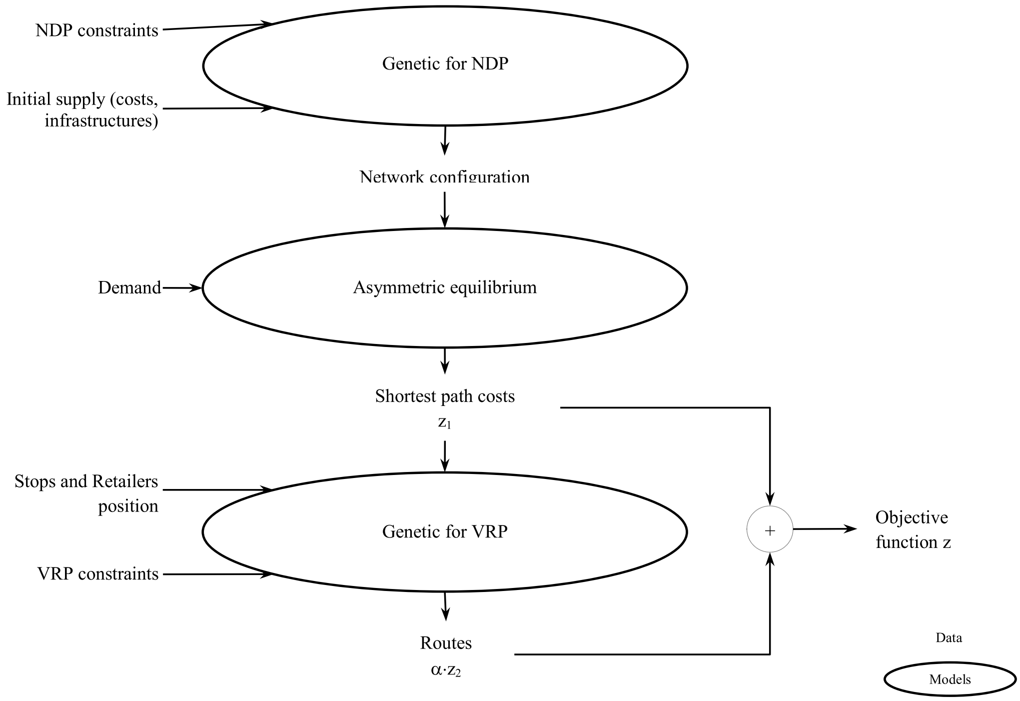


Fig. 4. Evaluation Function

Starting from *supply* and *demand, objectives* and *constraints*, an initial population composed of a fixed number of solutions is generated (e.g., randomly). Each solution consists of two parts: a road network configuration and a set of routes. An *Evaluation Function* allows evaluating the objective function (3) for new (all) generated solutions. The outputs are a set containing the *population* and *objective function values* (a value for each element in the population). The population is subject to some operations (*selection, crossover,* and *mutation*, that respect the constraints) and generating new solutions. The *Evaluation Function* allows us to evaluate the objective function for *new generated solutions*.

The input of the algorithm are or the initial supply (that is, the actual configuration of the road network), the passengers' demand and the position of the retailers and the quantities to be delivered (picked up). The parameters are the population size, the iterations number, the rate of crossover, and mutation. The constraints depend on the problem: i.e., lane number, lane capacity in network configuration; i.e., vehicle capacity, length (time) of each route for route optimisation. Starting from an initial population, as an example randomly generated, the population set is subject to some operators (selection, crossover and mutation) with the aim to improve it (generally the new solutions replace the old in the population). The test could generally be performed on the maximum number of iterations or when, after a number of iterations, the solution is not improved. In the case of this paper, the maximum number of iterations will be used.

Since each solution consists of an optimized road network and a set of routes, the evaluation of the objective function should consider both aspects. The *Evaluation function* for new generated solutions (Fig. 4) is a key aspect of the procedure. It allows one to evaluate the objective function for each generated solution, considering the evaluation of the network configuration and the optimisation of the routes in VRP.

Focusing on the component due to the network configuration, we consider as it is generated and as it is evaluated. The generation of a new *network configuration* is made with a genetic algorithm (genetic for NDP): considering an *initial supply* (defined by *costs* and *infrastructures*) and the *NDP constraints* this algorithm allows merging current configurations obtaining the new *network configuration*. Its evaluation implies an *asymmetric equilibrium* procedure that, taking as input also the *passenger demand* provides (among other indicators) the *shortest path costs* and the component z_1 (Eq. 5) of the objective function. Focusing on the component due to the vehicle routing problem, the input are the previous *shortest path costs*, the *retailers position* and the *quantity* to deliver (pick-up). A *genetic for VRP* is applied to optimise the set of routes, the genetic algorithm gives as output the routes and the component $\alpha{\cdot}z_2$ (Eq. 3) of the objective function.

The final output is the value of the *objective function* z. In this section the weighted sum of the two components is considered; other specifications for the objective function can be adopted without changing the structure of the proposed procedure.

In the Sections 4.2.1 and 4.2.2 some specifications of the procedures adopted for the NDP and for the VRP are reported.

4.2.1. Network Design Problem

The genetic algorithm used to solve the NDP is an extension of that proposed by Cantarella et al. [2], sharing the basic idea. The population will consist of feasible network configurations (the population size is set to 40 elements). To ensure the generality of our problem, the solution is coded starting from the infrastructural supply. The proposed optimisation procedure allows, for each infrastructural element, the insertion of one or two links and their lane allocations. Thus, for an infrastructural element *(i, j)* the allocation of one or more lanes in one direction means inserting a link in that direction. For example, for the first line in Fig. 5, there are two links (1-2 and 2-1) with two lanes for direction 1-2 (one lane for passengers and the other reserved) and a single lane for direction 2-1.

A standard roulette wheel selection is performed, on the basis of solution fitness.

Crossover and mutation could introduce violations of the constraints and a test is needed to check the admissibility.

In this work, two mutation methods were tested: the first consists of alterations in the number of lanes in a link, and the second consists of inverting the link direction.

After crossover and mutation, an asymmetric equilibrium procedure (Section 4.2.2) is needed to evaluate the signals at junctions and the component z_1 of the objective function. Signal setting design is an internal process of the asymmetric equilibrium procedure [103]. Stochastic *network loading* is performed, assigning the demand flow to each

Infrastructural element	Not reserved lanes		Reserved lanes	
	i-j	j-i	i-j	j-i
1-2	1	1	1	0
1-5	2	0	0	1
2-4	2	1	0	0
2-7	1	1	1	0
…	…	…	…	…

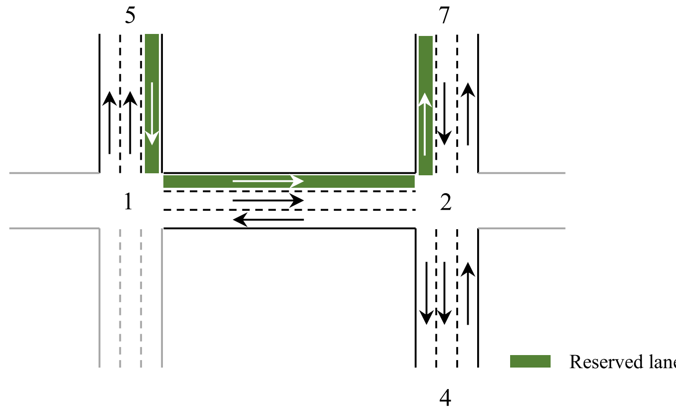


Fig. 5. Solution coding

link. The link costs are then updated based on these flows and the signals at the junctions are optimised using the Webster procedure [26], taking actual network link costs into consideration. The Webster procedure optimises the signals by minimising the maximum saturation among all green accesses (or, equivalently, maximising the capacity factor of the junction). Other optimisation methods could be adopted at junctions. Hence the flows are updated given that the new signals at the junctions have changed the link cost (by changing the wait time at those junctions). The procedure is repeated until a stop test is verified: in this case, the test is on the maximum number of iterations.

4.2.2. Vehicle Routing Problem

Route optimisation is performed using a genetic algorithm based on that proposed by Polimeni et al. [104], sharing the basic idea. However, the solution coding is changed, with the aim of improving the genetic operators.

Formally, the procedure follows the same logic as the genetic algorithm proposed for topology design, but for a different problem type and solution coding in the population. In route design, a solution is coded as a string of values, each representing a user (Fig. 6).

This approach prevents loss of generality and allows one to consider the constraints in decoding solution. The *selection* follows a standard approach, while the *crossover* can be one of three options:

(1) "append", indicating that the blocks selected in the first parent are added to the end of the second, and vice versa (see Fig. 6 for a schematic representation);
(2) "sprawl", indicating that the users in the selected block are inserted in random positions;
(3) "optimum", indicating that the users in the selected block are inserted in positions that minimise cost.

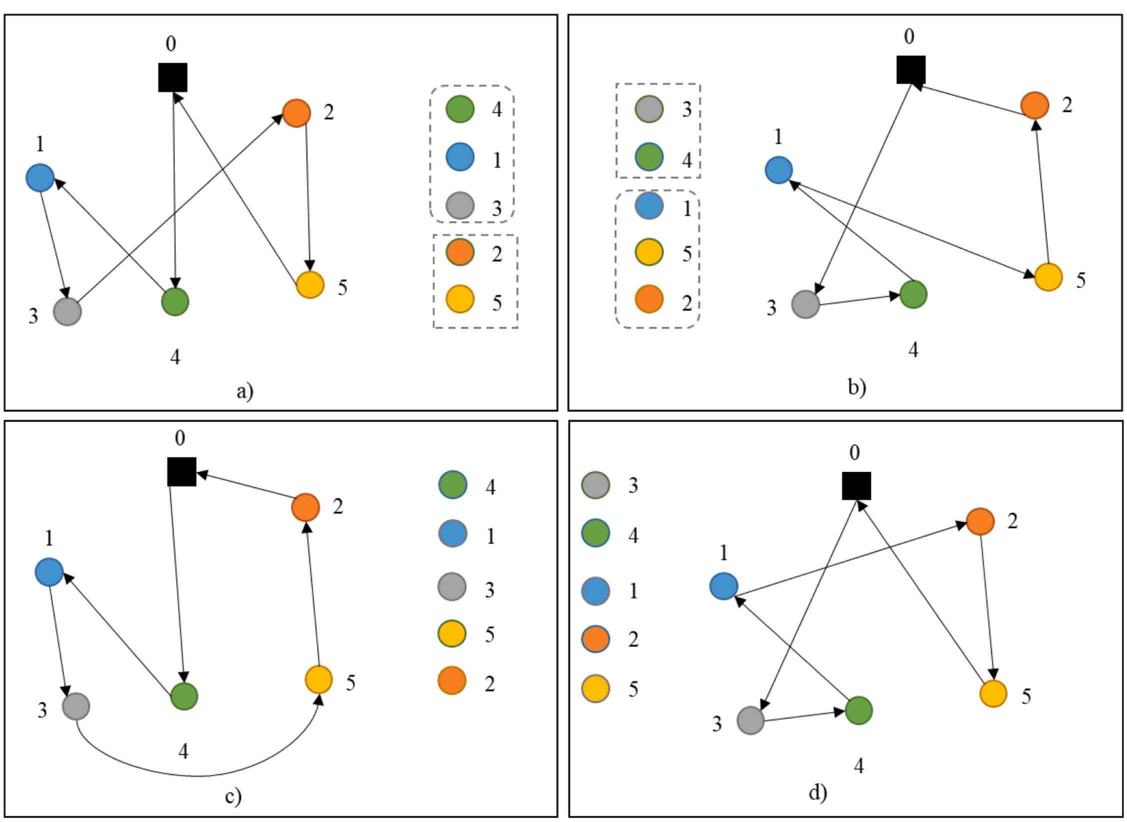


Fig. 6. Genetic algorithm in route optimization: a schematic example of append crossover

In our approach, the genetic algorithm, starting from two parents, gives two children (other assumptions are possible).

Since some nodes can be duplicated in this operation (violating the constraints), a further test is needed. Note that in options 1 and 2 above, the solution decoding must be done after the crossover (only once), while in option 3 it is necessary to decode the solution for each node insertion (to evaluate the cost), thus significantly increasing the computation time.

The mutation generates a variation in some solutions to expand the search space. Examples of mutation include changes in the position of two nodes in a route, route inversion, and so on.

The test is on the maximum number of iterations.

5. Experimentation

To evaluate the proposed approach, an application is reported in a test system, in particular it is considered the Sioux Falls test network (Fig. 7). The purpose of this application is to test the functioning of the procedure; for this reason, a test network that is not too large and a limited number of clients to visit were chosen, this allows the experiment to be kept under control. In addition, it was decided to consider the case in which the delivery / pick-up service is carried out by a single vehicle. The experiment can be replicated on larger networks and considering a larger number of clients and a fleet of vehicles, but with a much higher computational time.

5.1. General assumptions

It is assumed that:

- the supply consisted of three demand centroids, 20 nodes, and 36 infrastructural resources;
- the freight vehicles were required to deliver/pick-up goods to/from customers located at nodes 109, 112, 114, 116, 119 and 122, starting out at node 108;
- the demand is assigned at the network supposing it note and unelastic at emission (i.e., the demand does not depend on costs and flows), departure clock time, distribution, and modal split levels;
- the NDRP is applied with the objective of the network configuration and routes for freight vehicles optimisation;
- the objective was to minimise the total time spent in the network assuming that for the related weight the value $\alpha = 0.4$.

The network is optimised in three scenarios:

- Scenario 0), or reference scenario, with disjoint optimisation of the two problems; the NDP is applied without considering the routing; a VRP is applied on the optimised network; the value of the objective function is then calculated, which can be assumed as a reference value if the two problems are solved in a disjoint way;
- Scenario a), all of the lanes of all the links in the network are for mixed use - i.e., available to both freight vehicles and passenger vehicles;

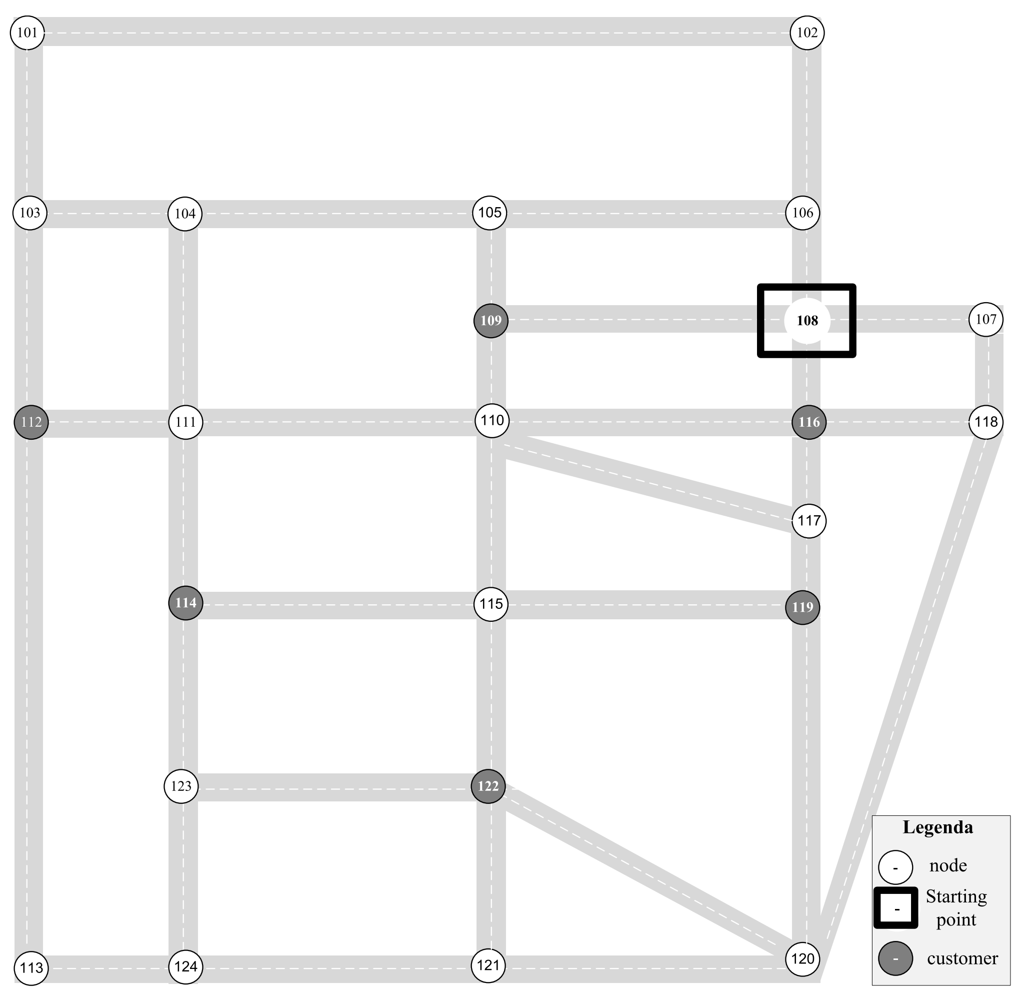


Fig. 7. Sioux Falls test network (adapted from [105])

- Scenario b), some lanes obtained from the optimization are reserved for freight vehicles only.

The possibility of designing the route, integrated with the possibility of also defining the reserved lanes (scenario b), is one of the potentialities of the application of the integrated procedure.

The genetic algorithm is a stochastic algorithm. In Garcia et al. [106] a statistical analysis of several runs is reported. Thus, the costs reported is the best solution found among the multiple runs (30 in this paper).

In Cantarella et al. [2], in relation to the specific problem of network design an analysis of different kinds of heuristics (hill climbing, genetic algorithms, simulated annealing, tabu search, hybrid methods) are tested. The genetic algorithm results the best. In the same paper, results related to different algorithm parameters are tested in order to obtain the best values. Considering that the proposed procedure refers to the network design integrated with routing, the best values obtained in Cantarella et al. [2] are adopted. In particular, the algorithm parameters are as follows:

- Population size: 40,
- Crossover rate: 0.4,
- Mutation rate: 0.1.

Instead, to solve the VRP, the parameters of the algorithm are as follows:

- Population size: 30,
- Crossover rate: 0.6,
- Mutation rate: 0.1.

5.2. Specific results

Since the proposed procedure is heuristic in nature, a test of its stability is needed. The test consists of several runs of the algorithm to evaluate the range of founded solutions. The test reported refers to the scenario a. The values of the objective function range from about 937 to 812 seconds, with a standard deviation of 32,43 (Fig. 8). The statistics indicate that the values of the objective function are stable with respect to the runs.

The results obtained in the considered scenarios are reported in Table 1 (the costs reported are based on the best solution found among the 30 runs).

Initially, NDP and VRP are applied separately, and the value of the reference objective function was calculated (Table 2). Subsequently, NDRP is applied (joint solution of the two problems) in the two scenarios a) and b). By comparing the reference scenario with scenario a) it was emerged that the joint optimisation allows reducing the overall cost of 30.80%, with cost reduction in both the components of the objective function. The routes found in the two scenarios are different, the change in the shortest paths caused a different sequence of users to serve.

NDRP solutions vary in topology and cost depending on whether the reservation of the lane is considered (scenario b) or not (scenario a). Compared to the reference scenario (Table 1), the cost of the solution decreased by 30.80% in scenario a) and by 25.05% in scenario b). Referring to reservation *vs.* no-reservations, lane reservation reduces the cost of the routes for freight vehicles (8.81% of reduction in this test, see Table 1), but the total cost in the network increases of 8.31% (i.e., the cost of routes for commercial or public vehicles is reduced at the expense of the path cost of private vehicles). Table 1 provides a route cost comparison for optimisations with and without reserved lanes, and

Table 2
Comparing route cost without and with reserved lanes

Scenario	z_1 *(seconds/ users)*	z_2 *(seconds/ vehicle)*	$z = z_1 + \alpha\, z_2$ *(seconds/ vehicle)*	*Route*
0) Reference	898.28	688.37	1173.63	109-112-114-122-119-116
a) Without reserved lanes	622.75	473.52	812.16	116-119-122-112-114-109
b) With reserved lanes	706.95	431.81	879.68	116-119-122-114-112-109
0) Reference vs a) Without reserved lanes	-30.67%	-31.21%	-30.80%	-
0) Reference vs b) With reserved lanes	-21.30%	-37.27%	-25.05%	-
a) Without reserved lanes vs b) With reserved lanes	13.52%	-8.81%	8.31%	-

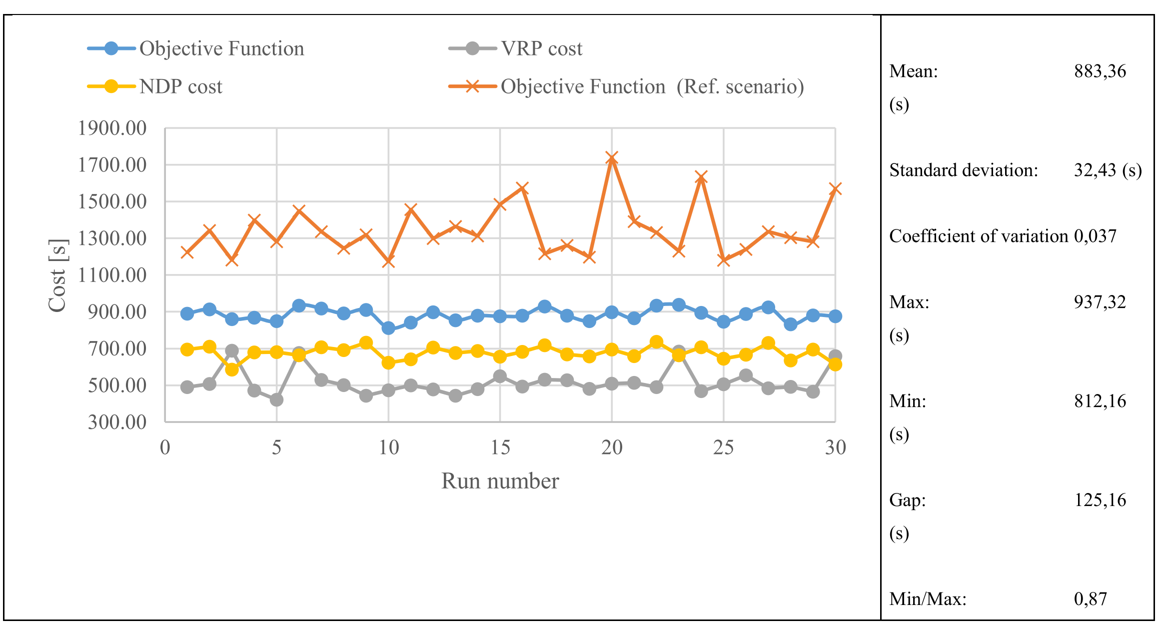
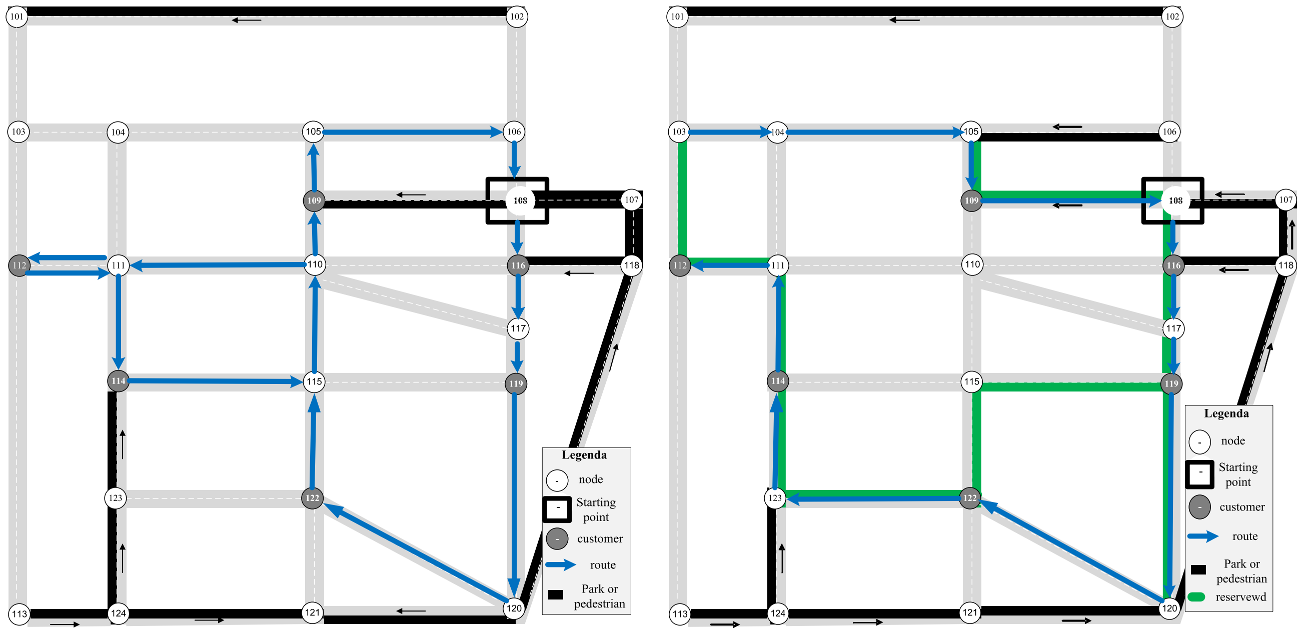


Fig. 8. Stability test for the proposed algorithm (scenario a)



(a) (b)

Fig. 9. Route-schematized network without and with lane reservations

Fig. 9 (a-b) shows the test network schematised for the two cases.

Note that, because the network configuration is changed, the paths between the nodes could be changed. Then, although the solutions are similar in topology (it is remarked that the inversion between users 112 and 114) the route cost decreases because of the use of reserved lanes.

6. Discussions and conclusions

In this paper a model and a procedure for the joint solution of the NDP and the VRP are reported. The model and procedure are defined in an integrated way to allow for the system of optimal routes in an optimised transport network configuration. The proposed problem integrates two consolidated design problems into a single one. In fact, network and route optimisations are modelled as two different levels of the same overall problem (NDRP). A genetic algorithm provided solutions at both levels.

The transport system is composed of elements that interact with each other: because of this interaction, the decisions to be taken to define the optimal configuration cannot be based only on the experience. The use of quantitative approaches to support the decision maker is well established. In this paper, two different optimisation problems, which are generally adopted separately for the design of the road network topology and capacity (including the identification of reserved lanes) and for the routing of vehicles, are considered.

The support through optimisation models, also with heuristic solution approaches, allows the search for solutions to be implemented in the system, in some cases even in real time (for example, regulation of traffic light regulation parameters, updating of vehicle routing).

In this paper the two problems NDP and VRP have been combined trying to integrate the benefits deriving from each of the two problems, and the relative feedbacks, obtaining a further benefit in terms of reduction of the objective function.

In a test application, two scenarios are considered and compared with a reference scenario (where the NDP and the VRP are solved separately). The joint procedure seems effective in finding a better solution than the disjoint case, in fact, the cost decreases by about 31% if the network configuration does not foresee reserved lanes, of about 25% otherwise. When comparing the case of reserved and not-reserved lanes, it was revealed that the reserved lanes allowed for a (approximately) 8% decrease in the travel time of the routes. Such a reduction could have significant secondary effects, such as reduced emissions and/or accident rates, although in the performed experiment, an increase in the overall time spent in the network was registered. The test carried out does not want to demonstrate that a network configuration with reserved lanes is better than one with non-reserved lanes (or vice versa), the aim is to propose a procedure that allows one to solve the problem and evaluate, case by case, the configuration to adopt. It can support decision-makers to assume policy decisions.

The results obtained are related to the test system and could be extended in other realities after further tests on the reported method. The application of the proposed methodology in real and large-scale systems requires in-depth analysis of problems that are already present even when the two individual problems are solved. The solution requires high processing times, and cannot be obtained in real time. This is not a limitation in the cases where the problem is applied to planning on a tactical and strategic scale. The solution algorithms are heuristic to obtain a solution close to the optimal one. The use of heuristic procedures such as those reported in the article supports the application even in large networks because they provide a solution close to the optimal one already in the first iterations and the same solution can be improved as the algorithm progresses and over processing time.

There are some limits of the proposed procedure: the optimum procedure is implemented in two levels and therefore the solution found may not be that of absolute optimum; the solution is heuristic and there is no guarantee of the distance with respect to the exact solution; the problem may take a long time to process on full-sized systems and therefore cannot be applied in real time. NDP generally does not apply in real time (the change of travel directions and the allocation of reserved lanes cannot change continuously), while VRP may require the application in real time.

Possible developments could be obtained by putting in the procedure a model to better consider the interaction between vehicles of different classes, multicriteria evaluation, and by solving the procedure with different algorithms in order to compare the performances. Also, the problem needs to be tested in full-size systems and extended in time-dependent networks.

CRediT authorship contribution statement

Antonio Polimeni: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Antonino Vitetta:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare no competing interest.

Data availability

Data will be made available on request.

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