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Optimization of downstream fuel logistics based on road infrastructure conditions and exposure to accident events.

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Abstract

The paper analyses a practical case of study related to the distribution of fuels for the Total Erg Oil Company to the service stations located in the Province of Rome (Italy).
The problem is formulated as a capacitated vehicle routing problem with time windows, where several heuristic procedures have been tested, considering both fixed and time-dependent travel times.
With respect to the standard operational costs, a multivariable objective function is proposed which takes into account: 1) the risk associated with an incidental event involving a fuel tank; 2) that not all the roads are suitable for heavy vehicles transporting fuel products. These two additional terms permit to better quantify the costs for the operator, since it is assumed that roads with higher number of accidents or with specific infrastructure conditions have also higher probability of making the fuel tank experiences at least a delay during the day.
Results demonstrate how an accurate planning of the service based on our multivariable objective function saves up to 40 km on a daily basis compared to a benchmark. Moreover, the distribution company can parameterize the configuration of the service, by varying the weights adopted in order to include the additional parameters with respect to the standard operational costs, thus assuring a higher safety route planning.

Keywords: downstream fuel logistic; vehicle routing problem; hazardous materials; hazmat transportation

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1. Introduction

"Logistics" is the science that allows to determine and manage a complex of elements and their activities by managing processes efficacy and efficiently. In the oil sector, logistics provides and coordinates the necessary infrastructure for stockpiling, inventory management and transport of goods, from storage to the consumer, in the timing and in the prescribed manner, efficiently and at the lowest possible cost. Within the general framework of distribution logistics, fuel distribution belongs to the hazmat transportation sector, as fuels are classified as dangerous goods (Accord Dangereuse Routiers, ADR 2017) and are subject to particular restrictions, calling for special applications of quantitative modelling (see e.g. Batta and Known, 2013 for a general overview).

Present work focuses on the optimization and planning of the fuel distribution by road from the depot to the petrol service stations (petrol station replenishment problem), which includes both the trip generation (routing in what follows) as well as the choice of times and assignment trips-vehicles (scheduling in what follows).

The routing phase is considered as a fundamental issue in logistics costs. The analysis of the most convenient itineraries that a vehicle should fulfill, following a defined network (Ghannadpour and Zarrabi, 2019), can be reached by using Vehicle Routing Problem (VRP) approaches, which are broadly adopted in various research applications (Hoff et al. 2010, Reihaneh and Ghoniem, 2019, Zhen et al. 2019; Li et al. 2018; Breuning et al. 2019; Bruglieri et al., 2019).
The literature on VRP applied to fuel distribution is rich of contributions. Dell'Olmo et al. (2005) used a methodology for finding a set of alternative paths between an origin and a destination site on which routing one or a set of dangerous goods. They considered Pareto-Optimal paths between an origin and a destination, by implementing a multicriteria shortest path algorithm. Cornillier et al. (2008, 2009) realized an optimization of the delivery of several petroleum products to a set of petrol stations using a limited heterogeneous fleet of tank-trucks. Vidal et al. (2011) considered a hybrid genetic algorithm for multi depot and periodic vehicle routing problems. Also, Triki (2013) and Carotenuto et al. (2017) identified some heuristic solution methods for the periodic petrol station replenishment problem.

In our paper, the solution of the fuel distribution problem is based on several heuristic procedures, considering both fixed and variable travel times (respectively static and dynamic environment). In the last case, thus considering the problem within a time dependent setup (similar to Toumazis and Kwon, 2016), we complicate further the setting compared to a-priori, offline routing as seen for instance in Bula et al. 2017.

Moreover, since most of research in hazardous material transportation are based on finding the best and safest routes (Bula et al., 2019; Androutsopoulos and Zografos, 2012), we added in the vehicle routing problem the minimization of a risk term. This risk term measures the probability of incurring in an incidental event involving a fuel tank and the fact that not all the roads are suitable for heavy vehicles transporting fuel products.
In this way, we aim to properly quantify the costs for the operator, since the routes with higher number of accidents or with specific infrastructure conditions present a higher probability to generate a delay for the fuel tank. In the comprehensive terminology of Hamdi et al. (2014), we solve routing and scheduling considering a composite measure in the optimization; this leads to an inherent multi-objective problem where the minimization search for a tradeoff regarding costs, distance travelled, time spent, or a combination of them (similar to Alexiou, Katsavounis, 2015).

One final practical contribution of our works is the integration and usability within the process of a company. In fact, we consider a practical context related to the Total Erg Oil Company, seeking for support in planning the distribution phase downstream of the refining process, i.e. Downstream Logistic, for the whole territory of the Province of Rome in Italy. The output is the actual route planning and vehicle scheduling with the assignment of each route to the truck-tanker commissioned to perform the service.

The paper is structured as follows: firstly, the real case study, the input database and the methodological process are described. Secondly, the main parameters reported in the objective function formulation of the VRP are highlighted.

Adopted solution algorithms and performance indicators for the evaluation of the service are presented. Finally, the computational results and the assessment of the costs of the service are underlined and discussed.

2. Case study and methodology

The case study presented in this paper is a real-life scenario, with the main stakeholders being the Total Erg Oil Company and “Raffineria di Roma”. Currently, “Raffineria di Roma” operates as a depot for refined petroleum products located in the West side of Rome, Italy, outside the main ring road of the city. The geographical area analyzed covers the whole Province of Rome (5,363.28 km²), where Total Erg owns about 199 petrol stations (Figure 1). The fuel replenishment is carried out with tank-trucks, equipped with liter counters and 3 compartments, with a total load capacity of 22,000 liters. This kind of vehicles are both usable for urban and extra-urban fuel transportation services. The company has been looking for optimized the set of routes, the scheduling of vehicles, and the sizing of the fleet needed to perform the service. These derive by the minimization of the operational costs related to the service time and composed by travel times and fuel load/unload times. Moreover, considering the importance of security of road freight transport at both national and European level (Carrese et al., 2014) and that the utilization of the road network exposes the trucks to accidents, we have introduced additional costs within the objective function: i) a cost based on a composite function of population exposure and incident probability (here in after called Risk Index) ; ii) two additional measures of road infrastructure characteristics: the Altimetric Index and the Planimetric Index.

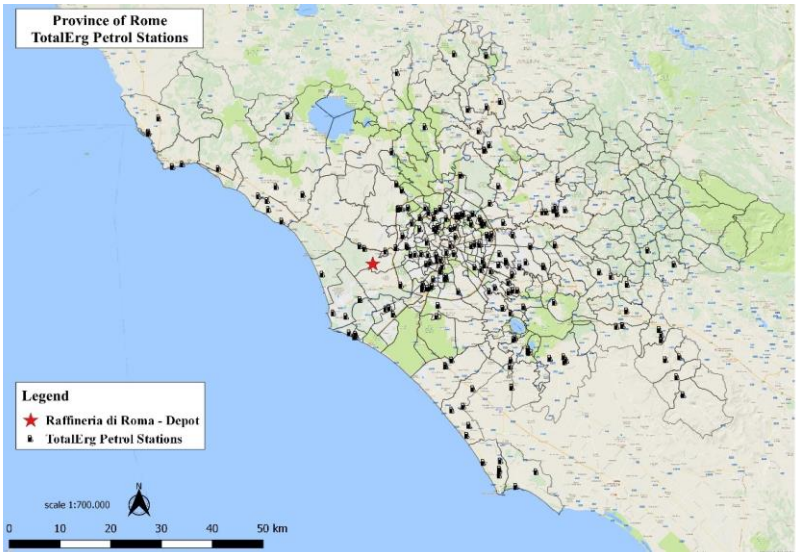


Fig. 1. Location of fuel stations and depot (Total Erg case study)

The information sources we used to setup and solve the overall downstream logistics optimization (Figure 3) is composed by data (TDSPP in Figure) related to time dependent travel times between all pairs of nodes (stations and depot). These data are computed and validated by the Mobility Agency of Rome, and consist in travel times and distances travelled on shortest paths for the specified time interval, as well as in estimated annual car accidents. Car accidents evaluation is carried out by the Mobility Agency of Rome using *ad hoc* calibrated Safety Performance Functions, linking the annual car accidents on a path with the annual average daily traffic and road characteristics (Basile and Persia,2015). Several routing algorithms derived by literature have been adopted and the results have been evaluated adopting specific Key Performance Indicators (KPIs, Figure 3). We first evaluated the best algorithm concerning a benchmark, representing a static condition, with fixed travel times matrices having no variations during the day, based on a constant flow representing the morning peak hours (off-line static data). We could not use the current routes adopted for the service as benchmark due to industrial secret. The best VRP algorithm found this way has been then adopted in a route planning based on variable travel times (off-line time dependent data -

dynamic method, Figure 3. In this last case, the vehicles routes are optimized in relation with the actual traffic conditions experienced along the day on the network. In fact, it is well known that a detailed representation of road network congestion is required to assure reliable logistic costs, while the static assumption may often lead to no optimal solutions (Figliozzi, 2010). Figure 2 reports the average OD travel times and a description of their variation across OD and time. The fuel demand is varying in the range of 5,000-10,000 liters per customer, while the time windows are randomly generated, within either a morning delivery round (7:00-12:00), or an afternoon round (15:00-20:00).

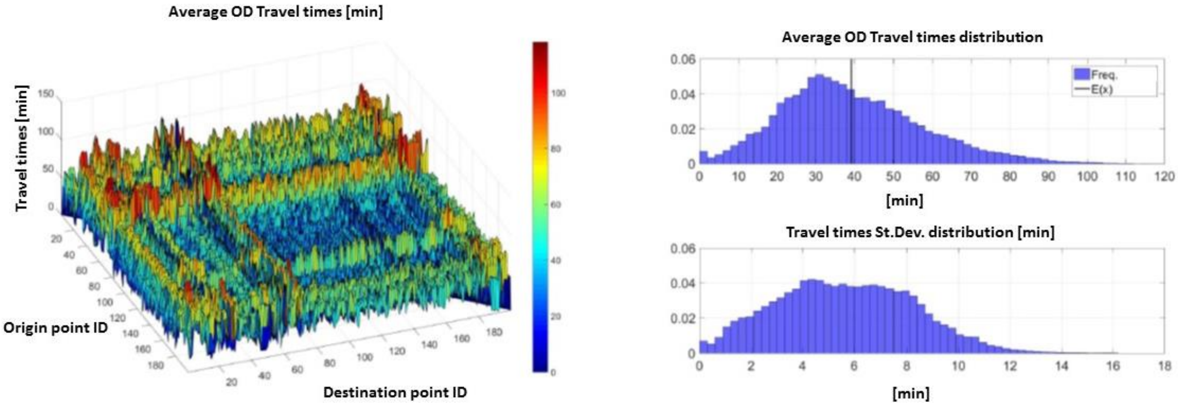


Fig. 2. Average OD matrix (left); distribution and standard deviation of travel times (right)

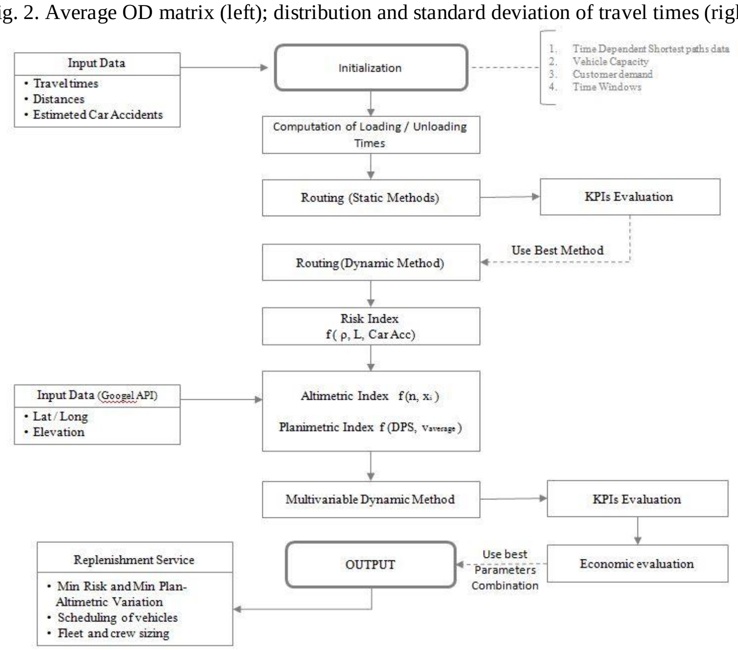


Fig. 3. Workflow of the methodological procedure adopted.

In addition to travel times, time perturbations are introduced to correctly represent fuel loading and unloading operations (respectively, in the depot and in the petrol stations) as a function of the time required to secure the areas. In the following sub-sections, the problem is formulated in terms of service cost minimization for both the dynamic case and the off-line static benchmark; then, the multi-variable optimization including the Risk Index, the Altimetric index and the Planimetric Index is presented only for the dynamic case; we also review all the KPIs adopted for the evaluations.

2.1. Problem formulation and solution methods

The off-line distribution problem is formulated as a capacitated vehicle routing problem with time windows (VRPTW) of [earliest, latest] delivery times (Kumar and Panneerselvam, 2015). The depot D must distribute the fuels to a given set S of petrol service stations by using a given set V of vehicles of given capacity. An unlimited number of vehicles is available at the depot D with a capacity of 22,000 liters. The maximum load factor reachable for each vehicle is no more than 95% for safety reason (i.e. gas emission during the unloading fuel process). Each station s requests a certain quantity of fuel d_s to be delivered within a given time window $[t_r, T_r]$.

A feasible solution of the problem consists of a route for each vehicle starting and ending in D such that (*i*) the demand of each station is satisfied, (*ii*) each station is served by exactly one vehicle, and (*iii*) the maximum load factor of each vehicle is not exceeded.

Let r be the set of routes in a solution, each associated to the vehicle $v(r_m)$ used for the m-th route. The cost of route r_m is considered as the variable cost c_m associated to the travel time of route r_m.

If static travel times are adopted for the computation of the variable cost, a matrix containing the average travel times (over a relevant interval, we considered 7-11 am) between each pairs of nodes t_{ij} is the input of the problem; the objective function of the static VRPTW will be:

$$\min \sum_{m=1}^{|r|} \left[c_m \left(\sum_{(i,j)\in r_m} \bar{t}_{ij} \right) \right] \tag{1}$$

If dynamic travel times are adopted for the computation of the variable cost, a tridimensional matrix containing the travel times between each pairs of nodes t^h_{ij} for each time interval h is the input of the problem; the objective function of the dynamic VRPTW will be:

$$\min \sum_{m=1}^{|r|} \left[c_m \left(\sum_{(i,j)|_h \in r_m} \bar{t}^{\,h}{}_{ij} \right) \right] \tag{2}$$

In both cases, the goal is to serve all the service stations with the available fleet at the minimum cost.

The literature on VRPTW is rich of contributions both for the static version (Solomon, 1987, Russell 1997, Bramel and Simchi-Levi, 1996, Potvin et al., 1996, Taniguchi et al., 1998, Cordeau et al., 2002) and for the time-dependent version (Ichoua et al. 2000, Flamini et al., 2011, Kritzinger et al., 2011, Ehmke et al., 2012, Flamini et al.,2017).

In this paper, several heuristic procedures have been adopted to compute the initial solution for the static VRPTW. Specifically:

- Savings Heuristic by Clark and Wright (1964): it is a constructive method based on the computation of the savings derived by the join of two or more routes;
- Sweep Method by Gillett and Miller (1974): it is a cluster first – route second procedure, where the routing phase is approached as a Travelling Salesman Problem (TSP) for each cluster;
- Insertion Method (Solomon, 1987, Kai, 2017): the procedure is based on the savings method joined with the insertion of the farthest node at the initialization step of the routes.

The static solutions have been improved following several intra-route and inter-route node's exchange as the 2-opt Neighborhood, the 2-opt* Neighborhood (2 Vertex Exchange) and the Crossover Exchange Neighborhood (Lin and Kernighan, 1973, Savelsbergh, 1988, Vigo, 1996, Toth and Vigo, 2014, Popovic et al., 2012).

The solutions are evaluated in terms of Key Performance Indicators (KPI) and the solution method associated to the best static solution is applied to the dynamic case.

2.2. Multi-variable objective function

A multi-variable objective function is proposed for the construction of the routes in the dynamic case, extending (2):

$$\min \sum_{m=1}^{|r|}\left[\left(c_m\left(\sum_{(i,j)|_h\in r_m}\bar{t}^{\,h}{}_{ij}\right)\right)+\alpha\ RI_{r_m}\right] \tag{3}$$

where the Risk Index RI_{r_m} for each route r_m is computed as the sum of the risk index between each pair of nodes *(i,j)* of the route: $\sum_{(i,j)\in r_m} RI_{ij}$.

The risk index between each pair of nodes RI_{ij} depends by the average daily value of accidents $CarAcc_{ij}$ along *(i,j)* and by the average value of the population density ρ of the zones encountered along *(i,j)* weighted for the percentage of the length L of the path *(i,j)* inside each zone:

$$RI_{ij} = CarAcc_{ij}\ [\Sigma_{zone}\,\rho_{zone}\ \%L^{zone}{}_{ij}] \tag{4}$$

In order to compute the Risk Index, the path traces between each couple of nodes have been extracted using the Google Direction API platform on a sub-problem of the initial instance. Then, the path traces have been matched with Census Data of the Province of Rome (2016) to retrieve the associated population density.
A further evolution of the OF involves the insertion of descriptive indices of the path features, modifying the (3) as follows:

$$\min \sum_{m=1}^{|r|}\left[\left(c_m\left(\sum_{(i,j)|_h\in r_m}\bar{t}^{\,h}{}_{ij}\right)\right)+\alpha\ RI_{r_m} ++\beta\left(AI_{r_m}+PI_{r_m}\right)\right] \tag{5}$$

The Altimetric Index AI_{rm} derives by considering that a continuous number of "up and downs" along the route may deteriorate the attention of the driver. Moreover, routes with homogeneous altimetric features lead to reduced fuel consumption. Thus, considering the shortest path connecting two nodes, AI_{rm} is computed as the standard deviation of the elevation of all the points of the path. As in the Risk Index, also for AI_{rm} elevation of all the points is derived by the Google Direction API platform (see Figure 4).

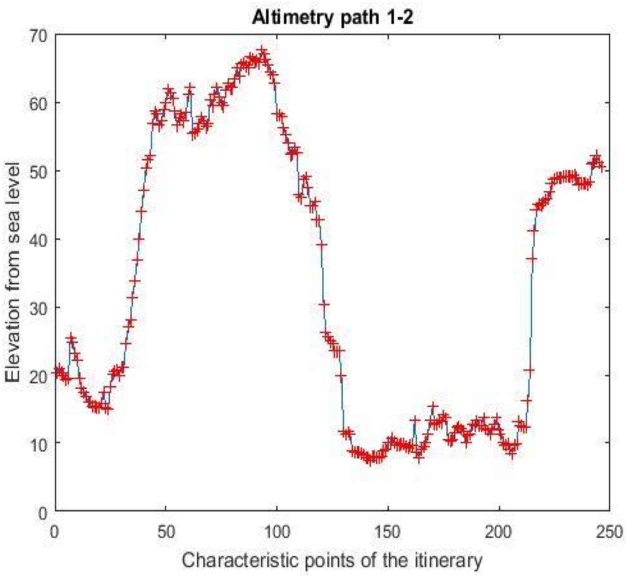
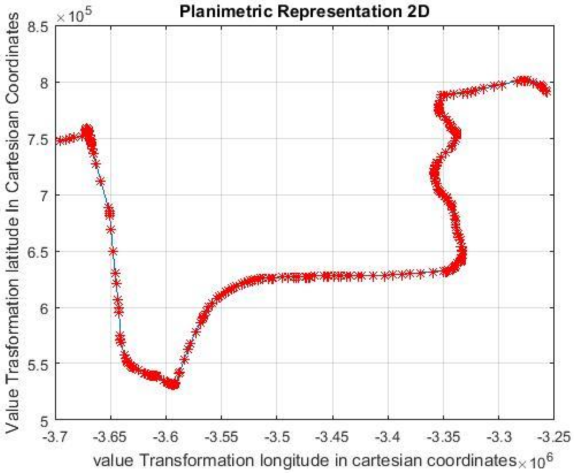


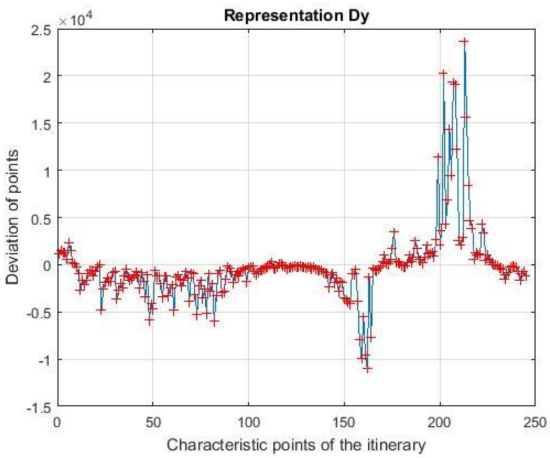
Fig. 4. Elevation of all the points between the nodes 1-2 and computation of standard deviation.

The Planimetric Index PI_{rm} is introduced to take into account geometrical constraints related to the road radius along the path. In order to compute PI_{rm}, for each pair of nodes:

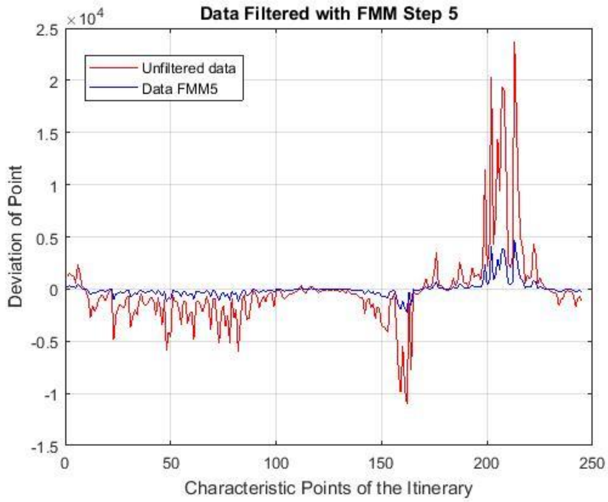
- All the points related to the shortest path between the two nodes are derived by the Google Direction API platform together with their geographic coordinates;
- The points are represented on a Cartesian plan (Figure 5a) and its first derivative is computed (Figure 5b);
- Derivatives values are filtered through a moving average process (FMM5, Figure 5c) and average value as well as standard deviation (STD) of FMM5 is computed (Figure 5d);
- The sum of the deviations (in absolute value) between the FMM5 values exceeding STD with respect to the average value.



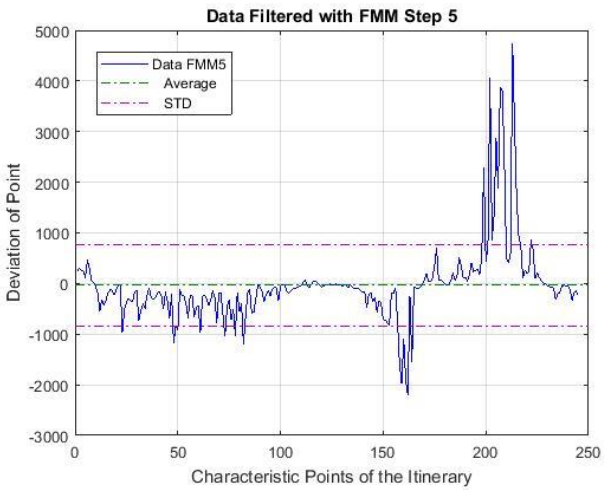
a)



b)



c)



d)

Fig. 5. Planimetric representation of the path between the nodes 1-2 (a); representation of the deviation of the points given by the first derivative with respect to y (b); comparison of first derivatives and data filtered with FMM step 5 (c); data filtered with FMM5 and representation of the Standard Deviation and average value (d).

The parameters α and β in (5) are tuning parameters with the purpose of modifying the weights of the variables.

2.3. Key Performance Indicators (KPIs)

The KPIs adopted for the evaluation of the service have been divided into 4 groups: Route Structure; Transport; Load capacity; Under-utilization of the service. In order to make possible the comparison between the different outputs of the optimization, each KPI has been normalized in the range [1,10], where the best condition refers to 10. Then, for each KPI of each group, a weight w_i has been defined such that $w_i > 0$ and $\sum_i w_i = 1$.

Also each KPI group has a weight c_{KPIg} such that $c_{KPIg} > 0$ and $\sum_{KPIg} c_{KPIg} = 1$.

The weight w_i of each indicator belonging to each group was set as a project parameter with the purpose of highlighting the most significant magnitudes affecting the quality of the organized service as the group and the KPI change. The KPIs for "Route Structure" (N. Route: number of generated routes; N. Nodes: average number of nodes visited on the route) group have a homogeneous coefficient of 0.5, as it has been assumed that the number of constructed routes and the average number of visited nodes are likewise within the performance of the service.

The group "Transport" includes 5 indicators (Avg Time: Average travel time of the route; Total time: Total time spent; Avg Distance: Average distance travelled of the route; Total distance: Total kilometres travelled; Speed: Operating speed), each of which has its own coefficient: the indicators for the service operating times, i.e. average travel time of the route; and total time spent, have higher weights with respect to the other indicators (0.2 and 0.35 respectively), since minimizing operating times is considered a major goal of the problem. With regard to the "Load capacity" group (Liters: Average number of liters of fuel transported; Tons: Average number of tons transported; Ton-km: Total number of tons per kilometer; Load factor: Average load factor), the largest weight (0.6) was attributed to the "Load Factor", as the maximum load factor allows for a good quality service, reducing the unit production costs of the service and at the same time maximizing the use of the vehicle. The liters and tonnes transported have an equivalent weight of 10%, while the productivity of the service, expressed in tons-km, is 20%. Indicators of the category "Underutilization of the service" (% Empty km: Percentage of kilometers travelled with empty vehicle; % Empty Time: Percentage of time travelled with empty vehicle; % Load Time: Percentage of time spent for loading/unloading operations), respectively, account for weights of 15% in terms of kilometers and travel times, and equal to 70% with regard to the loading / unloading time at the customer node.

Considering the weight c_{KPIg} of each group, a greater value was assigned to the "Transport" group, as the economic cost of service production is determined based on the indicators contained therein. KPIs of "Load Capacity" and "Under-utilization" were assigned a coefficient of 0.2 and 0.3 respectively, while the "Structure" category was assigned a weight less than 0.1. The performance values of individual groups, normalized with respect to the minimum-maximum value, were compared to determine the solution method that returns the best overall performance.

3. Computational results

We report the solution performances of the distribution planning firstly considering the three heuristic methods adopted to compute the initial solution for the static case (first three rows of Table 1, where not shaded columns report the indicator’s values, while shaded columns the corresponding total group’s KPI):

- The routes generated by the Insertion Method showed a better structure of the service and load capacity performances when compared with the other methods;
- The transportation service is approximately the same in case of Insertion and Savings methods;
- The underutilization of the service is better in case of adopting the Sweep method; however, the difference in terms of single KPIs of the group is negligible;
- Insertion Method reaches the highest performances, and it is adopted as the algorithm for the dynamic case.

Finally, the Risk Index, as well as the Altimetric and the Planimetric Index have been added in the objective function of the dynamic case together with the service costs and solved by the Insertion Method for different values different values of the tuning parameters α and β (Table 2). In this case, the test instance considers a subset of service stations (43 nodes) and the depot due to the computational expensive phase of matching the effective path with the census zones.
Computational times are 122.44 sec for the static insertion method [199 nodes]; 4,913.62 sec for the dynamic insertion method [199 nodes]; 45.33 sec for the dynamic insertion method on the subset of nodes [43 nodes] on an Intel Core i7-6700HQ, 2.60GHz, 8.00 GB RAM. Improvements from a computational point of view can be reached by introducing parallel computing.

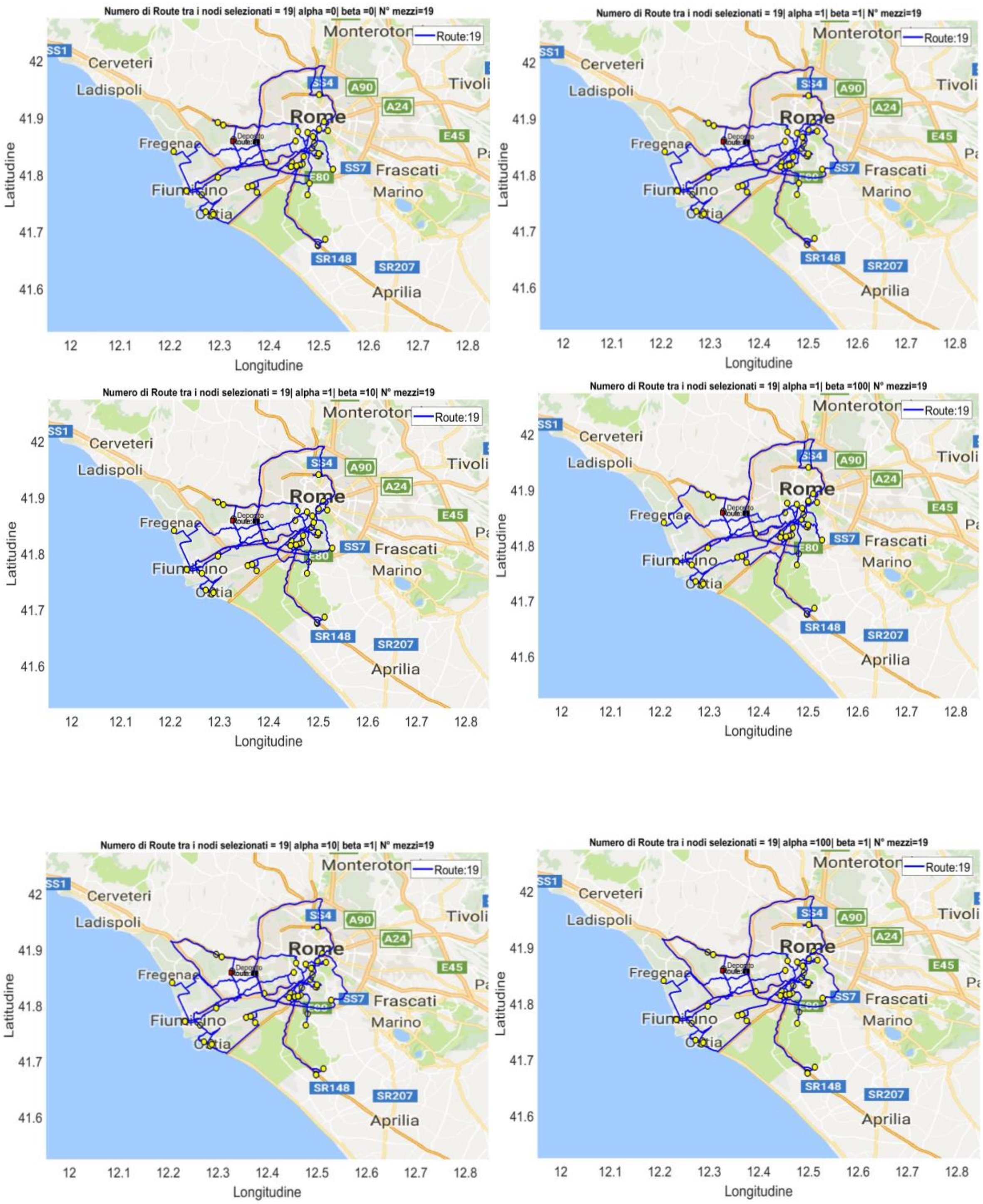


Fig. 6. Example of routes generated by varying α and β

Table I. Evaluation of best algorithm

Group	Route Structure			Transport						Load Capacity					Underutilization of the service				Grand TOTAL
c_{KPIg}	10%			40%						20%					30%				
KPIs	N Route	N Nodes	Total KPI	Avg Time [h]	Total Time [h]	Avg Distance [Km]	Total Dist. [km]	Speed [Km/h]	Total KPI	Liters	Tons	Ton-Km	Load Factor	Total KPI	% Empty Km	% Empty Time	% Load Time	Total KPI	
wi	50%	50%		20%	35%	15%	20%	10%		10%	10%	20%	60%		15%	15%	70%		
Static Savings Method	87	2,29	0,10	3,20	278,39	79,54	6919,89	57,62	3,46	17109,25	12,32	994,12	86%	0,20	44%	43,0%	58%	0,70	4,46
Static Sweep Method	87	2,29	0,10	3,48	302,68	81,03	7049,86	57,92	1,04	17109,25	12,32	1010,03	86%	0,32	44%	43,0%	57%	2,59	4,05
Static Insertion Method	84	2,37	1,00	3,52	295,94	80,79	6826,80	57,90	2,09	17720,30	12,76	1042,22	89%	2,00	45%	43,0%	58%	0,71	5,79
Dynamic Insertion Method	84	2,37	1,00	3,59	301,33	81,27	6786,22	57,32	1,08	17720,30	12,76	1042,36	89%	2,00	44%	40%	57%	2,99	7,07

Table II. Sensitivity to α and β, dynamic insertion method

Group	Route Structure			Transport						Load Capacity					Underutilization of the service				Grand TOTAL
c_{KPIg}	10%			40%						20%					30%				
KPIs	N Route	N Nodes	Total KPI	Avg Time [h]	Total Time [h]	Avg Distance [Km]	Total Dist. [km]	Speed [Km/h]	Total KPI	Liters	Tons	Ton-Km	Load Factor	Total KPI	% Empty Km	% Empty Time	% Load Time	Total KPI	
wi	50%	50%		20%	35%	15%	20%	10%		10%	10%	20%	60%		15%	15%	70%		
α=0 β=0	19	2,26	0,86	3,79	71,96	107,72	2046,63	64,04	3,42	16660	11,995	1281	83,3%	1,64	43%	39%	56%	1,00	6,92
α=1 β=1	19	2,26	0,86	4,11	78,01	106,02	2014,47	53,54	3,00	16660	11,995	1325	83,3%	1,90	43%	41%	53%	1,22	6,98
α=1 β=10	19	2,26	0,86	4,30	81,67	107,39	2040,48	50,26	2,24	16660	11,995	1298	83,3%	1,74	42%	41%	50%	1,91	6,74
α=10 β=1	19	2,32	1,00	3,86	73,40	105,30	2000,73	52,87	3,65	16660	11,995	1304	83,3%	1,77	44%	42%	49%	1,79	8,22
α=1 β=100	20	2,15	0,10	4,61	92,29	105,13	2102,69	41,01	0,94	16660	11,995	1298	79,1%	0,66	46%	41%	45%	2,32	4,02
α=100 β=1	19	2,26	0,86	4,37	83,05	110,67	2102,67	50,05	1,33	16660	11,995	1343	83,3%	2,00	43%	42%	49%	1,98	6,16

3.1. Scheduling results

Scheduling of departures and arrivals times of vehicles for each service station has been computed simultaneously with the routes construction phase; the procedure returns also departure/return time from/to the depot. Each route has a service starting time (beginning of the fuel filling phase by the tank-truck), and a service finish time (vehicle returns to the depot). For each visited node there is an arrival time, a starting time for unload operation, and a departure time. Between two nodes, a travel time is computed. The sum of the partial times between all nodes represent the total cost, or total time, of the route.

The vehicles scheduling outcome is summarized with a Gantt Diagram, determining a timetable for the delivery service. The Gantt Diagram provides, for each route, the lead-time, represented by two different time slots: 1) the earliest start (ES) and earliest finish times (EF); 2) the latest start (LS) and latest finish (LF) times of the service. The service can be performed in one of this two time slots or in a combination of them, but it cannot be executed outside these ranges, to fit the required time windows. Figure 5 (top) shows the ES-EF time slots for each of the 19[th] route obtained for the instance of 43 nodes concerning the scenario with α=1 and β=10. Starting from the vehicle scheduling, the fleet size has been obtained, maximizing the number of possible routes for vehicle. The (greedy) criteria for performing this step allocates the route *r* to the vehicle *k* if the starting time of the operations of route *r* in the depot *D* begins later than the return time to the depot of route *r-1*. Thus, a list containing the routes in ascending order of starting time of operations at depot is required. If the merge of more routes is feasible in terms of times, routes are assigned to the same vehicle, otherwise a new vehicle is required and the allocation procedure must be repeated: the number of vehicles needed to perform the service for a subset of nodes equal to 43 resulted to be 12.

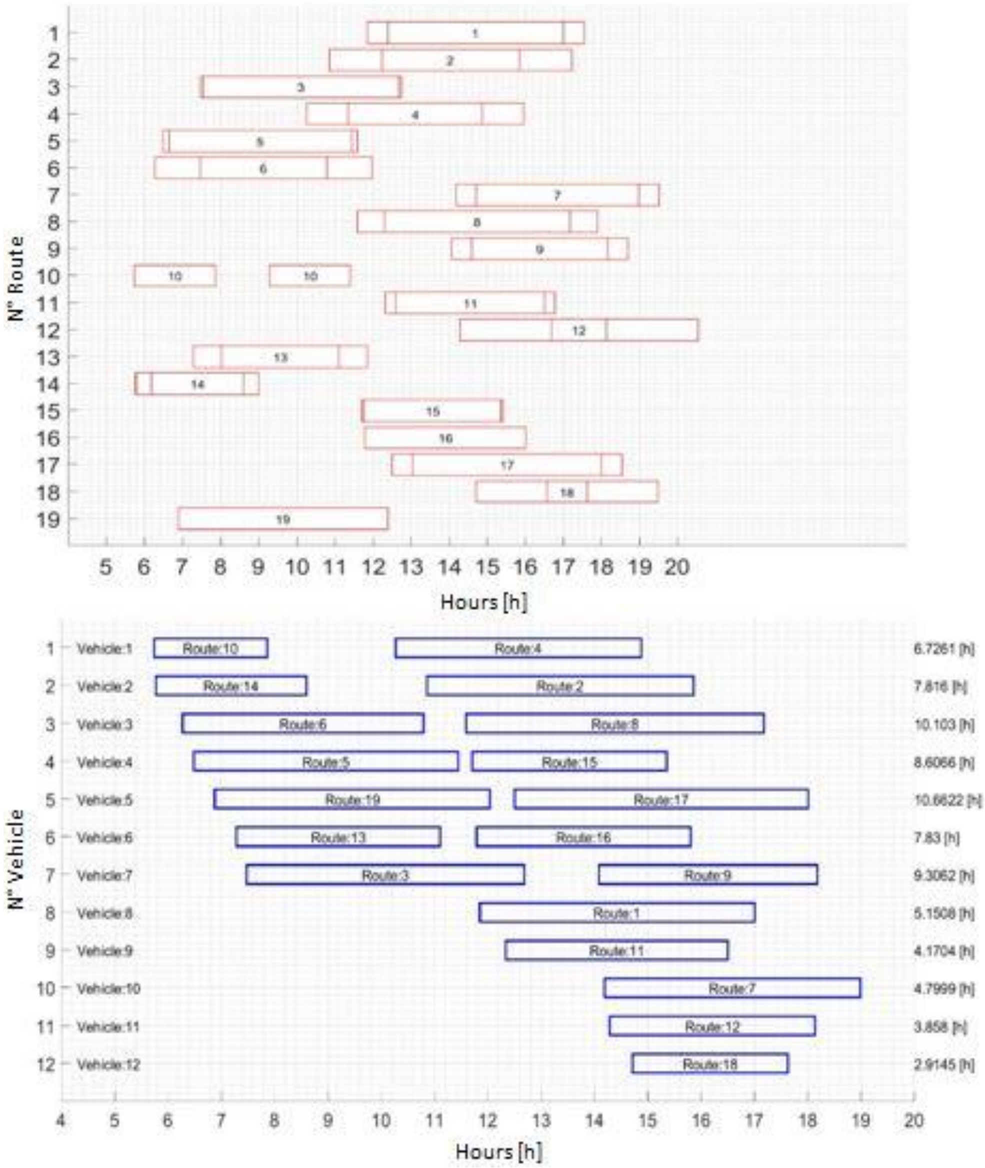


Fig. 7. Vehicle scheduling for 43 nodes, α=1 and β=10 .
Top: Gantt Diagram with ES and EF time slots; Bottom: Vehicle assignment

3.2. Economic evaluation

A quantification of impact indexes that composed the objective function from the economic aspect, referring to the unitary costs adopted by the Italian Ministry of Transport for the evaluation of the minimum production cost in the case of a transportation service of fuel products (with a maximum length of 150 km for each route) is developed.

Table III. economic evaluation of the service

Scenario	Total Km [km]	Total Cost [€]	Cost Var. [%]
α=0 β=0	2046.63	5’192.29 €	+2.29 %
α=1 β=1	2014.47	5’110.71 €	+0.69 %
α=1 β=10	2040.48	5’176.70 €	+1.99 %
α=10 β=1	2000.73	5’075.85 €	n.a
α=1 β=100	2102.69	5’334.54 €	+5.10 %
α=100 β=1	2102.67	5’334.48 €	+5.10 %

The total unit cost is composed by several terms (namely: Truck cost: 0.250; Tanker cost: 0.216; Maintenance cost: 0.100; Crew cost: 1.043; Insurance Cost: 0.238; Tires cost: 0.010; Tolls cost: 0.035; Fuel cost: 0.375; Management cost: 0.270, respectively in EUR/km), leading to a total unitary cost, equal to 2.54€/km. In Table 3, we report the total cost of production, given the total kilometres travelled by all vehicles on all the planned routes for the different scenarios as a function of α and β.

The minimum cost service obtained with the configuration $\alpha = 10$ and $\beta = 1$ allows the minimization of the risk index with an aware choice of the plano-altimetric conditions. Giving higher weights to the two new components can increase the total cost of about +5%.

4. Conclusions

This paper reports on a study with the real case of downstream fuel logistics for Total Erg Oil company and its respective 199 service stations located in the considered territorial context of the province of Rome, Italy. The problem is formulated as a capacitated vehicle routing problem with time windows, and dynamic travel times taking into account congestion phenomena.

Different heuristic VRP solution approaches available from literature have been evaluated. Compared to an optimization based on static travel times, which we consider a benchmark of current operations, a saving in the service of about 40 km can be obtained on a daily basis.

A multi-variable objective function has been proposed, which includes a new risk index able to evaluate the population exposure to possible accidents involving the tank-truck, as well as indices related to the plano-altimetric development of the route.

The multi-variable objective function has been tested on a subset of nodes with respect to the starting instance. With weight parameters, more or less weight can be given within the tradeoff between the service costs and the new indices.

The best performances of the service have been obtained given more weight to the to the risk index (tuning parameter equal to 10) and introducing the plano-altimetric conditions (tuning parameter equal to 1).

Further developments of the study are required to improve the procedure: 1) from both a computational side: reducing the computational times by adopting parallel computing; 2) from an operational side: introducing quantitative approaches to fix the values of the weights adopted in both the objective function and in the evaluation phase.

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Dear Editor,

here is attached a revised version of the paper "Optimization of downstream fuel logistics based on road infrastructure conditions and exposure to accident events"

by
Valerio Cuneo, Raffaele Pizzuti, Marialisa Nigro, Stefano Carrese, Cosimo Federico Ardito, Guido Marseglia*.

Authors would like to thank the Reviewers for their valuable opinion and especially for having appreciated the work. An effort has been done in revising the manuscript according to the received comments and to improve the readability of the text.

Answers to each specific observation are given in the following, with modifications to the text highlighted in red.

Best regards

The authors

REVIEWER 1

The topic of this paper is interesting.

We thank the reviewer for the positive comment.

However, there are several aspects which should be improved. My comments are shown as follows. The section of introduction should be improved, and not like this status.

Authors thank reviewer for the suggestion. We improved the introduction. Moreover, the state of the art has been enriched and the literature reference has been enlarged. Some actual references are added, concerning the main research topic.

Some figures and tables in this manuscript should be stated more clear, e.g. Fig. 6 of page 9, Table 2 of page 10.

Authors thank reviewer for the suggestion. Figures 5 and 6 and Table II are now improved.

The dynamic model in this manuscript considers the dynamic travel times in different time slots. So the risk index of route should be considered as a time-dependent variable.

No, the risk index (as well as the altimetric and planimetric index) is not time-dependent, since it is function of the average daily value of accidents, the average value of the population density, the length of the path: these are not time-dependent variables.

REVIEWER 2

This is an interesting case-oriented paper, well written. The literature review makes sense. The authors combine well-known methods and tools, covering several aspects, including the "up and downs" along the routes. The result is an interesting piece of work that could be published in an "applied" journal.

We thank the reviewer for the positive comment.

The way the several KPI's are combined / interpreted is unclear. Where do the "weights" presented in the last paragraph of section 2 come from? Should a multicriteria analysis not be useful in this context?

The weights are actually fixed, where higher values are assigned by the authors to KPIs assumed rilevant for the considered transport engineering application. A sensitivity analysis is definitely needed in order to derive the set of solutions according to different weights. Moreover, as suggested by the reviewer, a multicirteria analysis can help in defining the best settings for their values. We have added it as a further development of the work.

It would be interesting to give more details on the computational times. Which software packages are used? Are the algorithms parallelized (knowing that a Core i7-6700HQ has 4 cores and is hyperthreaded). Which OS is used?

Yes, the reviewer is right. Actually, the algorithm is not parallelized, but it could be a refinement for further development, thus reducing the computational times. The package adopted is MATLAB. Google API are called by MATLAB. The OS used is Windows.

The dynamic insertion method needs 4913 seconds, i.e. almost 1.5 hours. Can this be considered as reasonable? Is the marginal benefit of this method large enough, knowing that the static insertion method is solved in 2 minutes?

We think that the marginal benefit of the dynamic insertion is mainly in its capacity to take into account the change in congestion conditions for different time slices of the day, getting closer to reality as much as possible. The static method is very fast, but it works with data that can be very far from the real state of the traffic network.

One could regret that the "economic evaluation" section is rather simplistic compared to the refinement of the core model. I suppose that, in real life situation, the economic aspects are an important element of the decision...

Yes, the reviewer is right. It has been a decision of the authors to focus more on the transport study than on the economic evaluation. However, although simplistic, the economic assessment was carried out using a procedure given by the Italian Ministry of Transport and Infrastructures, thus using a "certified" method.

Small suggestion: the visual quality of some equations and figures is rather low. See equation 4 or figure 4 and 5 for instance.
The images and equation 4 are now improved according to the reviewer suggestion.