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Risk based, multi objective vehicle routing problem for hazardous materials: a test case in downstream fuel logistics

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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 static and dynamic travel times. With respect to the standard operational costs used typically, a multivariable objective function has been proposed which takes into account also a new risk index. The risk index proposed is function of the population density of the zones covered by each path and of the estimated number of road accidents on each road link. In such a way, we take into account the population's exposure to the risk associated with an incidental event involving a fuel tank.
The obtained output is the set of planned routes with minimum service cost and minimum risk. Results demonstrate how an accurate planning of the service saves up to 3 hours and 30 km on a daily basis compared to a benchmark. Moreover, the distribution company can parameterize the configuration of the service, by varying the weight adopted in order to include the risk index. Including the risk index may bring to a higher safety route planning, with an increase of the operating costs of only 2%.

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

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1. Introduction

Logistics is defined as 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 distributions belong to the so-called hazmat transportation, 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 Kwon, 2013, for a general overview).

We focus on the optimization of the distribution of fuels by road from the depot to the petrol service stations, in terms of trip generation (routing in what follows). Several heuristic procedures have been tested for the solution of the problem in both static and dynamic environment.

The problem is very interesting and characterized by a specific and extensive literature highlighting its complexity (Cornillier et al, 2008-2009, Vidal et al., 2012, Triki, 2013, Carotenuto et al., 2017).

Differently from other papers also dealing with vehicle routing problem (VRP) for hazmat routing, we both include time-dependent setup and a risk based assessment, which have been so far mostly treated separately in the literature (with regard to risk assessment: Erkut and Verter, 1988, Dell'Olmo et al., 2005, Carotenuto et al., 2007). In the comprehensive terminology of Hamdi et al. (2014), we consider routing and scheduling, minimizing in a multi-objective fashion a composite function of population exposure and incident probability, within a time dependent setting with time windows. In fact, considering the problem within a time dependent setup (similar to Toumazis and Kwon, 2013) complicates further the setting compared to a-priori, offline routing as seen for instance in Bula et al. (2017). Thus, a multivariable objective function has been defined which takes into account standard service costs and a risk index to include the population exposure to possible accidents involving the tank-truck along the route. Considering a composite risk-based measure in the optimization leads to an inherent multi-objective problem where a risk-based measured is to be minimized, with a tradeoff regarding costs, distance travelled, time spent, or a combination of them (similar to Alexiou and 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 to perform the service.

The paper is organized as follows. The next section describes the practical case of study, the input database and the methodological process. Then, the objective function is formulated together with the definition of the risk index. 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 reported. Some conclusions follow.

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.

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 optimizing the set of routes, 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 car accidents, we proposed an innovative Risk Index inside the objective function in order to consider also minimization of risks in the optimization.

The information sources we used to setup and solve the downstream logistics optimization (Figure 1) 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.

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, 2012), carries out car accidents evaluation.

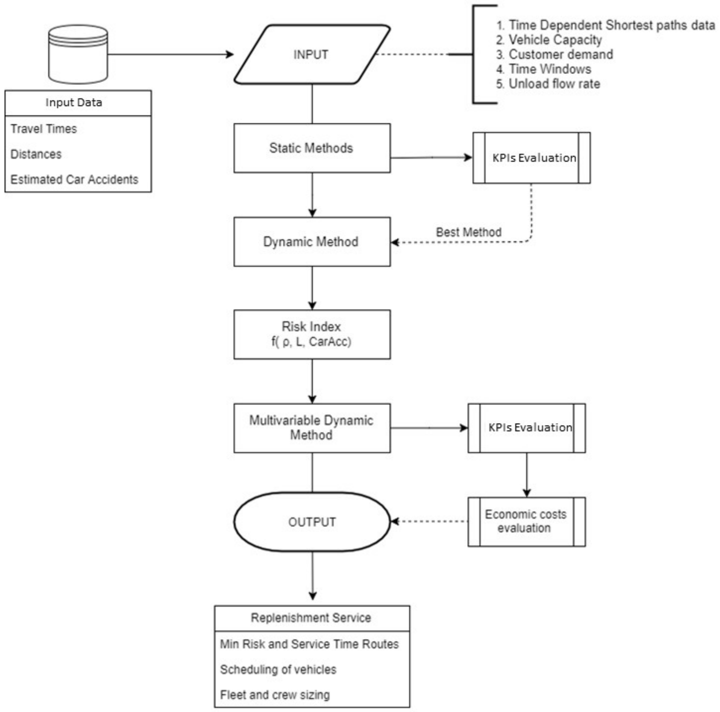

Fig. 1. Workflow of the methodological procedure adopted

Several routing algorithms derived by literature have been adopted and the results have been evaluated adopting specific Key Performance Indicators (KPIs, Figure 1). We first evaluated the best algorithm with regards to a benchmark, representing a static condition, with fixed travel time 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 1).

In this last case, the vehicles routes are optimized in relation with the actual traffic conditions experience 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). The fuel demand varies in the range 5,000-10,000 liters per customer, while, due to the lack of data, the time windows are randomly generated within either a morning delivery round (7:00-12:00) or an afternoon round (15:00-20:00), thus respecting the opening and closing times of the petrol stations.

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 is presented only for the dynamic case; we also review all the KPIs adopted for the evaluations.

3. 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). Using a VRPTW, one can reproduce in the easiest way the operational condition of the fuel distribution, where vehicle's capacity and opening times of the petrol stations heavily influence the service planning.

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 litres.

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 $\bar{t}_{ij}$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 3-D matrix containing the travel times between each pairs of nodes $\bar{t}^h{}_{ij}$ 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, 1995, 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 Clarke 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, Kay, 2017): the procedure is based on the savings method joined with the insertion of the farthest node at the initialization step of the routes.

Once the initial static solution is computed, it is 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 static solutions derived are then evaluated in terms of KPIs and the best one, together with the corresponding solving procedure, has been adopted as the benchmark for the dynamic case.

3.1. Multi-variable objective function: the Risk Index

A multi-variable objective function is proposed for the construction of the routes, extending (2) with an innovative Risk Index. Thus, the multi-variable objective function assumes the following expression:

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

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 of the census zones encountered along *(i,j)* weighted for the percentage of the length L of the path *(i,j)* inside each zone:

$$RI_{ij} = CarAcc_{ij} \cdot \left[\sum_{zone} \rho_{zone} \ \%L^{ij}_{zone} \right] \tag{4}$$

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.

The proposed multi-variable objective function allows getting a set of routes at minimal operational cost and minimum risk. Minimizing the two components makes it possible to obtain efficient and cost-effective service while at the same time limiting the population's exposure to the risk associated with an incidental event involving a fuel tank. RI_{ij} values have been normalized within a range of [0,1]. This standardization process allows obtaining values comparable with the timescale of the operational costs expressed in hours, thus making the Risk Index as a time penalty. The parameter α inside (3) is a tuning parameter given by the route planner in order to give more or less importance to the risk index with respect to the operational costs.

3.2. 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 kilometre; 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 kilometres 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 kilometres 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.

4. 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 (Table 1):

- 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.

When the Insertion method is adopted in the dynamic case (Table 1, TD Insertion Method), the dynamic insertion method is able to work better than the static one in terms of transport indicators with a saving of about 3 hours (total time) and 30 km in the service (total distance).

Finally, the Risk Index has been added in the objective function of the dynamic case together with the service costs and solved by the Insertion Method, for different values of the tuning parameter α (Table 2). In this case, the test instance considers a subset of service stations (43 nodes), due to the computational expensive phase of matching the effective path with the census zones.

When the Risk Index is considered, also the possible reduction of the population exposure to the accidents is evaluated as a KPI. The c_{KPIg} value of the Risk Index is assumed equal to 0.3 and equal to the c_{KPIg} of the transport KPIs group. If α is equal to zero, the solution obtained is the one with the minimum service cost. Increasing α means to give higher importance to the minimization of the risk: in this case, also solutions with higher service cost can be obtained. The increase of α might result in a completely different choice of the paths, especially to reach service stations located inside the city of Rome, avoiding road links closest to the downtown or to the highest populated zones of the city (where possible), see Figure 2 for an example. The solution found with an α value equal to 1 seems to be the best compromise between service times and risk.

All the procedures have been implemented in MATLAB and in case of adoption of the Risk Index an interaction is required with Google Direction API platform and QGIS. 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 with Risk Index [43 nodes] on an Intel Core i7-6700HQ, 2.60GHz, 8.00 GB RAM.

4.1. Economic evaluation

We quantify the impact of the adoption of the risk index from an economic point of view, 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).

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.

Table 1. Evaluation of best algorithm

Group	**Route Structure**		**Transport**				
c_{KPIg}	**10%**		**40%**				
KPIs	**N°Route**	**N°Nodes**	**Time [h]**	**Total Time [h]**	**Distance [Km]**	**Total Dist. [km]**	**Speed [Km/h]**
wi	**50%**	**50%**	**20%**	**35%**	**15%**	**20%**	**10%**
Insertion Method	84	2.37	3.12	262.44	80.78	6785.70	57.89
Savings Method	87	2.29	3.07	267.27	79.53	6919.40	57.63
Sweep Method	87	2.29	3.09	268.92	81.03	7049.90	57.92
TD Insertion Method	84	2.37	3.08	259.13	80.41	6754.50	59.39

Family	**Load Capacity**				**Underutilization of the service**		
c_{KPIg}	**20%**				**30%**		
KPIs	**Liters [Liters]**	**Tons [Ton]**	**Ton-Km [Ton-Km]**	**Load Factor**	**% Empty Km**	**% Empty Time**	**% Load Time**
wi	**10%**	**10%**	**20%**	**60%**	**15%**	**15%**	**70%**
Insertion Method	17720.30	12.75	1042.15	89%	44%	43%	58%
Savings Method	17109.25	12.32	994.10	86%	44%	43%	58%
Sweep Method	17109.25	12.32	1010.03	86%	44%	43%	57%
TD Insertion Method	17720.30	12.76	1037.76	89%	45%	46%	59%

a. Statics Methods - Normalized and weighted KPIs

Family	**Route Structure**	**Transport**	**Load Capacity**	**Underutilization of the service**	**Total**
Insertion Method	1.00	2.79	2.00	1.11	6.90
Savings Method	0.10	2.34	0.20	1.11	3.75
Sweep Method	0.10	1.19	0.32	3.00	4.61

b. Insertion Method vs TD Insertion Method - Normalized and weighted KPIs

Family	**Route Structure**	**Transport**	**Load Capacity**	**Underutilization of the service**	**Total**
Insertion Method	1.00	0.40	1.82	3.00	6.22
TD Insertion Method	1.00	4.00	1.64	0.30	6.94

Table 2. Sensitivity to α, Dynamic Insertion Method.

a. TD Insertion Methods Performances at the variation of α

Family	Route Structure		Transport				
c_{KPIg}	10%		30%				
KPIs	**N°Route**	**N°Nodes**	**Time [h]**	**Total Time [h]**	**Distance [Km]**	**Total Dist. [km]**	**Speed [Km/h]**
wi	**50%**	**50%**	**20%**	**35%**	**15%**	**20%**	**10%**
$\alpha = 0$	19	2.26	2.70	51.27	48.91	929.26	51.91
$\alpha = 1$	19	2.26	2.72	51.62	49.90	948.08	51.23
$\alpha = 10$	20	2.15	2.69	53.74	51.74	1034.80	52.14
$\alpha = 100$	20	2.15	2.68	53.53	51.79	1035.70	52.17

Family	Load Capacity				Underutilization of the service			Risk
c_{KPIg}	20%				10%			30%
KPIs	**Liters [Liters]**	**Tons [Ton]**	**Ton-km [Ton-Km]**	**Load Factor**	**% Empty Km**	**% Empty Time**	**% Load Time**	**Risk index**
wi	**10%**	**10%**	**20%**	**60%**	**15%**	**15%**	**70%**	**100%**
$\alpha = 0$	17512.21	12.61	636.77	88%	41%	38%	66%	n.a.
$\alpha = 1$	17512.21	12.61	636.43	88%	43%	41%	64%	5.72
$\alpha = 10$	16636.60	11.98	635.45	83%	41%	39%	64%	5.16
$\alpha = 100$	16636.60	11.98	634.05	83%	41%	40%	64%	4.77

b. TD Insertion Method - Normalized and weighted KPIs

	Route Structure	Transport	Load Capacity	Underutilization of the service	Risk	Total
$\alpha = 0$	1.00	2.66	2.00	0.37	0.30	6.33
$\alpha = 1$	0.55	1.82	1.96	0.73	2.51	7.57
$\alpha = 10$	0.10	0.98	0.39	0.96	2.80	5.22
$\alpha = 100$	0.55	1.19	0.20	0.91	3.00	5.85

Table 3. Economic evaluation of the service.

Scenario	Risk	Total Km [km]	Total Cost [€]	Cost Var. [%]
$\alpha = 0$	n.a.	929.26	2,357.53 €	n.a.
$\alpha = 1$	5.72	948.08	2,405.28 €	+2.03%
$\alpha = 10$	5.16	1034.80	2,625.29 €	+11.36%
$\alpha = 100$	4.77	1035.70	2,627.57 €	+11.45%

Comparing the total cost with respect to the Risk Index it is evident how a decrease in risk (higher α) increases the total cost of the service: this increment is due to a higher overall travelled distance in order to search for a less risky path, with direct implications on the service cost. However, analysing the Scenario α = 1, *i.e.* the best compromise between the minimum service cost and the minimum risk, a low increase in the operating cost (only 2%) guarantees an adequate distribution planning with a less overall hazard.

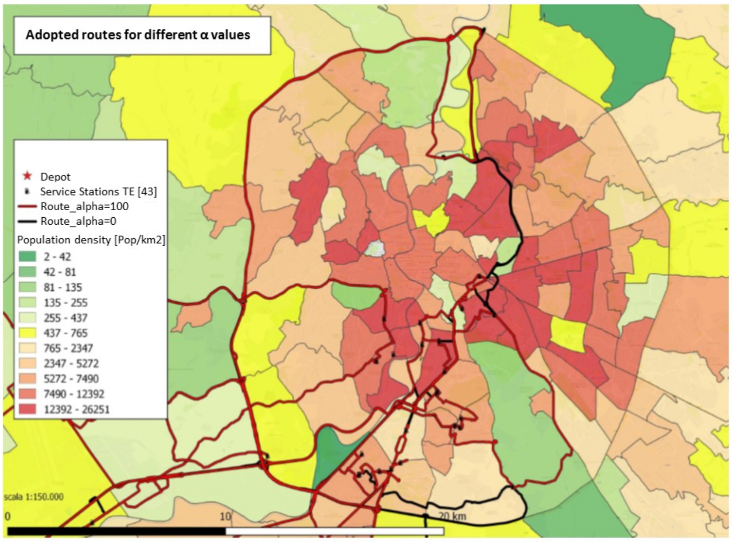

Fig. 2. Example of risk-based routes with different α (dark red: α =100, black: α = 0): green to yellow to red shows increasing population density of the zones

5. 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 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 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 3 hours and 30 km can be obtained on a daily basis.

Since the transport of fuels is considered a transport of dangerous goods, a multi-variable objective function has been finally proposed, which includes a new risk index able to evaluate the population exposure to possible accidents involving the tank-truck. The risk index is a function of the average daily value of accidents along the road links and by the average value of the population density of the zones encountered along the route weighted for the percentage of the length of the route inside each zone.

The multi-variable objective function has been tested on a subset of nodes with respect to the starting instance. With a weight parameter, more or less weight can be given within the trade-off between to the service costs or to the risk index, when longer travel times, distances and operational costs, are chosen to result in lower risk routes (possibly longer and having detours of densely populated, high accident areas).

The best performances of the service have been obtained given the same weight to the service costs and to the risk index (tuning parameter equal to 1). Moreover, the economic analysis conducted underlines as this scenario differs in terms of operating costs of only 2% with respect to the scenario without risk index.

Further research will be required to analyse the effects of different values of KPI's weights in terms of service's evaluation. Finally, other interesting features as vulnerable areas (historical areas or green areas) or specific road infrastructure characteristics can be added inside the decision process.

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