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A multi-objective time-dependent route planner: a real world application to Milano city

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Abstract

The past decades have seen a great deal of research on algorithms for shortest path problems. However, real-world systems like route planners and mobile navigation systems require to take into account some additional conditions. Our work concerns a truck route planner for real-time navigation developed for an Italian firm and tested on real world data of Milano road network (about 61,000 nodes and 106,000 arcs). Given the vehicle GPS position and the destination, the route planner allows to find in a few seconds a path between them which minimizes simultaneously travel time, travel cost and risk. Beside the multi-objective optimization and the CPU efficiency, other challenging features faced by the algorithm that supports the route planner are the time-dependency of some attributes (e.g. the travel costs due to the congestion charge ruling the access to limited traffic zone in the Milano centre) and the presence of forbidden turns. Results on the real network of Milano are obtained and discussed.

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1. Introduction

Congestion is one of the major problems in urban centres, and the transport of goods is one of the main problem to be tackled. The vision of the problem has changed over time, both for the growing awareness of the chaotic processes to govern, and because the traditional measures have proved not to be effective. A new integrated

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approach (Ciccarelli et al., 2006), based on the use of Intelligent Transport Systems (Sussman, 2005, Bruglieri et al., 2011, and Azzone et al., 2014), tackles the critical issues of mobility systems even in the aspect of safeguarding the investments already made.

Different organizational and technological frameworks for the integrated management of urban freight transportation based on ITS have been proposed, see for instance Crainic et al. (2004) and Taniguchi et al. (2001). In such situations, the introduction of better decision support software could very significantly improve the performances of urban freight transportation (Crainic et al., 2009).

The authors worked in IMPULSO, a project granted in the context of the Innovation Program of the Ministry of Industry called “Industria 2015”, in collaboration with Project Automation. IMPULSO proposed solutions for the integration between ICT systems and logistic operators for the distribution in urban and metropolitan areas, for the transport of goods at medium and long range. Inside the project, we developed a route planner to assist the navigation of vehicles for freight transportation, which is able to take into account the vehicle characteristics such as category (motorbike, car, truck, etc), type of transported freight (hazmat or non-dangerous goods) and availability to use roads with fees. A multi-attribute road network is given. The considered attributes are the following: travel times, travel costs and risks. All the attributes are associated with the road arcs. Travel times are obtained from Tele Atlas Data Base. Travel costs are given by the sum of three components: fuel consumption (that - we assume - depends linearly on the road length), the car toll and the congestion charge for the access to limited traffic zone (so called Area C in Milano). Note that this third component makes the travel costs of some roads time dependent since usually the congestion charge is only active in certain time windows (e.g. the Area C holds every working day from 7.30 a.m. to 7.30 p.m.). The risk attribute represents the need to avoid that vehicles pass too near to sensible places like hospitals, schools, important buildings. Also this attribute is time dependent since the risk associated with some sensible places may vary over the time (e.g. the risk associated with schools slumps to zero during the night when they are closed). The road network is also connoted by a set of forbidden turns consisting in a list of forbidden sequences of nodes.

Given the characteristics of the vehicle, the current GPS position and the destination, the route planner returns, within a few seconds, a path from the estimated origin to the destination that minimizes at the same time the total travel time, cost and risk, taking also into account forbidden turns.

Concerning the multi-objective path problem, several algorithms to determine the set of non-dominated (or Pareto-optimal) paths have been proposed. Martins (1984) presents a non-polynomial label setting algorithm, while Guerriero and Musmanno (2001) give a non-polynomial label correcting algorithm. Multi-objective shortest path problems are also examined in Azevedo and Martins (1991), Climaco and Martins (1981), Corley and Moon (1985), Tung and Chew (1992), Luè et al. (2008), Luè and Colorni (2015), Sastry et al. (2003, 2005). None of these algorithms can be used to solve our problem since their computational complexity is incompatible with the request of yielding a solution within a few seconds. Hamacher et al. (2006) present different algorithms to solve the time-dependent bicriteria path problem but they cannot be applied to a graph of big dimension like that one derived from the Milano road network since their CPU time would be prohibitive. Vice versa Nannicini et al. (2008) and Nannicini et al. (2012) present algorithms that can be applied to time dependent road networks of big dimension with reasonable CPU time but they consider only one objective and neglect the forbidden turn constraints. At the best of our knowledge, no algorithm of the literature solves a path problem with the same features that we address, although they are significant from a practical point of view.

2. Problem description

A directed graph $G=(N,A)$ representing the road network, with node set N and arc set A , is given. Three criteria are defined on the arcs: travel time, travel cost and transport risk. Each vehicle is identified by a triplet (h,k,s) indicating that concerning the travel time criterion the kind of vehicle is h (e.g. motorbike), concerning the travel cost criterion the kind is k (e.g. electric vehicle) and concerning the transport risk criterion the kind is s (e.g. the vehicle is transporting an explosive substance). For each arc (i,j) , t_{ij}^h indicates the travel time, c_{ij}^k indicates the travel cost and r_{ij}^s the transport risk. Note that since on some arcs the values of some criterion can change during the time, we consider a discretization of the day in η time slots in such a way that each criterion can be considered constant on

each time slot. Given a criterion, for instance the cost, $c_{ij}^k[\sigma]$ indicates that such a criterion is considered for the time slot σ . (Sometimes we omit to specify the time slot if we do not want to stress the time dependency of the criterion). On the graph G , a set $F \subset N \times N \times N$ of forbidden turns is also defined, where each (p,q,r) in F indicates that the arc (q,r) cannot be traveled after arc (p,q) .

Given a vehicle v identified by the triplet (h,k,s) , given its current GPS position o' at the instant time τ and its destination $d \in N$, we want to determine a minimum multi-objective path from the guessed vehicle origin $o \in N$ to the destination d taking into account forbidden turns and the vehicle departure time τ . We call such a problem the Multi-Objective Time Dependent Shortest Path with Forbidden Turns Problem. Moreover it is required that the solution of the problem is found within a few seconds in order that it can be useful to the vehicle driver, since the query is made when the travel is already in progress.

In the following, we summarize the nomenclature used in the paper.

Nomenclature

$G=(N,A)$	directed graph representing the road network
N	set of the nodes
A	set of the arcs
t_{ij}^h	travel time on arc (i,j) of vehicle of type h
c_{ij}^k	travel cost on arc (i,j) of vehicle of type k
r_{ij}^s	transport risk on arc (i,j) of vehicle of type s
l_{ij}	length of arc (i,j)
o'	vehicle GPS position
Θ	vehicle movement direction
o	guessed vehicle origin
d	vehicle destination
τ	vehicle departure time
η	number of time slots for the time discretization

3. Solution algorithm

The first problem that the route planner has to solve consists in finding the node $o \in N$ that in the graph representation of the road network corresponds to the vehicle GPS position o' considering that the vehicle is moving on the direction Θ . Such a problem is solved with a map matching algorithm inspired by Quddus et al. (2003) and Velaga et al. (2009). The algorithm consists of the following steps:

1. Detect the candidate arcs considering the arcs of G inside a circle centered on o' ;
2. For each candidate arc a compute a Total Weighted Score (TWS) taking into account both the distance from o' to a and the movement direction Θ ;
3. The vehicle is assigned to the candidate arc a^* with maximum TWS;
4. The head of a^* is returned as guessed vehicle origin node o .

Once that the estimated vehicle origin o has been determined, the aspects that make hard the path search in the routing problem are the following: i) Pareto optimality; ii) feasibility with respect to the forbidden turns; iii) time dependency; iv) fast computation (a few second CPU time is at most allowed).

We face the first feature solving the multi-objective path problem with the weighted sum method. For each criterion, a weight is introduced to represent the relative importance of the criterion (we assume that the sum of such weights is 1). Let $\lambda_1, \lambda_2, \lambda_3$ the weights used for the criteria time, cost and risk, respectively. In this way for each vehicle v of kind (h,k,s) the following generalized cost can be defined

$$C_{ij}^v = \lambda_1 \frac{t_{ij}^h}{T^h} + \lambda_2 \frac{c_{ij}^k}{C^k} + \lambda_3 \frac{r_{ij}^s}{R^s}, \quad \forall (i,j) \in A \quad (1)$$

where T^h , I^k , R^s are the normalization constants for the criteria time, cost and risk, respectively, in order to ensure that the total generalized cost of every elementary path belongs to the interval $[0,1]$. The determination of the normalization constants is a problem that needs to be treated carefully since the computation of the longest path is an NP-hard problem and estimating them with an upper bound too large may make too small the contribution of some criterion compared to the others.

We propose two heuristic methods to estimate the normalization constants. The first one (that we call NCM1) consists in computing the minimum path from o to d , for the vehicle v , with respect to each criterion separately. Then, for each criterion, the corresponding normalization constant is obtained considering the maximum value that the criterion achieves on the three mono-criterion paths computed before.

The second method proposed (NCM2) allows to improve the CPU time of the route planner, since it does not require the computation of the mono-criterion paths for the specific origin-destination pair (o, d) of the vehicle v . The normalization constants are differentiated for three possible sizes of the distance between the origin and the destination of the vehicle query (small, medium and large). The method consists in computing, for each size, for each vehicle type v , the mono-criterion paths over a set of randomly chosen origin-destination pairs of that size: for each criterion, the normalization constant is obtained taking the maximum value that the criterion achieves over such paths. In this way the normalization constants can be computed before the vehicle query and therefore their computation time does not impact on the answer time of the query.

Concerning the second feature of the routing problem addressed, i.e. feasibility with respect to the forbidden turns, two kinds of approaches are possible (Gutiérrez & Medaglia, 2008). In the first one, turn prohibitions are handled by transforming G into a larger graph that accounts for these extra constraints. Once transformed, a classical shortest path algorithm is applied on the new graph. Due to the significant graph expansion (in general, turn prohibitions at an intersection can take up to eight node replications), these approaches demand large memory requirements and may be time consuming since the computational complexity of a classical shortest path algorithm, like Dijkstra's one, is $O(m \log n)$ where m is the number of arcs and n is the number of nodes. In the second kind of approach, a labeling algorithm that works directly on the original graph G , is proposed, yielding high performance and low memory requirements. In order to satisfy the CPU time requirement of the route planner we follow the second kind of approach. The labeling algorithm consists in an extension of Dijkstra's one where information is maintained about labels and distances of visited arcs, instead of nodes as the classical Dijkstra's algorithm does. In other words a label L_{ij} is defined for each $(i, j) \in A$. At the beginning of the algorithm, temporary labels are assigned to those arcs emanating from the starting node (i.e. $L_{oj} := C_{oj}^v, \forall (o, j) \in A$). In every iteration (main loop), the algorithm chooses the temporarily labeled arc with minimal label value. This arc is labeled permanently and the labels of its reachable arcs are updated, taking into account the forbidden turns (i.e., if (p, q) is the arc labeled permanently, $L_{qr} := \min\{L_{qr}, L_{pq} + C_{qr}^v\}, \forall (q, r) \in A: (p, q, r) \notin F$). The algorithm stops when an arc incident to the final node is reached or there are no more arcs with temporary labels.

Concerning the third feature of the route planner (i.e. time dependency) we notice that the computation of a minimum time dependent path is an NP-hard problem (Nannicini et al. 2008). Therefore we consider a heuristic algorithm given by an extension of the Dijkstra's one where the arc labels are computed considering the generalized cost values updated at the instant time when the tail of the arc to label is reached. Therefore at the beginning the algorithm assigns to the arcs emanating from the origin node o the temporary labels $L_{oj} := C_{oj}^v[\hat{t}], \forall (o, j) \in A$, where \hat{t} is the time slot corresponding to the vehicle departure time τ . Then, at each iteration if (p, q) is the arc labeled permanently (i.e. the arc with minimum label), the labels are updated according to the rule $L_{qr} := \min\{L_{qr}, L_{pq} + C_{qr}^v[t_{pq}]\}, \forall (q, r) \in A: (p, q, r) \notin F$, where t_{pq} is the time slot corresponding to the arrival time at node q , considering the path used to obtain the label L_{pq} .

Concerning the last feature of the route planner, i.e. fast computation, we introduce a modification to the algorithm described so far, exploiting the main idea on which is based the A^* algorithm introduced by Hart et al. (1968). A^* is a goal-directed search technique that is similar to Dijkstra's algorithm but that add a potential function ρ_u to the priority key of each node u in the queue. This potential function applied on a node u should be a lower bound to the distance to reach the destination node from u : in this way, priority to nodes that are supposed to be closer to the destination, is given. For instance, for the shortest path problem, ρ_u can be estimated considering the Euclidean distance between the node u and the destination. Concerning our routing problem where we have introduced the generalized costs C_{ij}^v , we could compute ρ_u considering the value δ given by

$$\delta = \max_{(i,j) \in A} \frac{l_{ij}}{c_{ij}^v} \quad (2)$$

where l_{ij} is the length of arc (i,j) . In fact in this way ρ_u is obtained dividing the Euclidean distance between the node u and the destination by δ . However, if the normalization constants necessary to compute the generalized costs C_{ij}^v are obtained through the NCM1 approach, the value δ needs to be computed during the query and determining it by formula (2) can be time consuming since in the real application the number of arcs is huge. In this case a faster procedure to obtain an estimation of ρ_u , although less tight of the previous one, is given by

$$\rho_u = \lambda_1 \frac{\rho_u^{time}}{Th} + \lambda_2 \frac{\rho_u^{cost}}{rk} + \lambda_3 \frac{\rho_u^{risk}}{Rt} \quad (3)$$

where ρ_u^{time} , ρ_u^{cost} and ρ_u^{risk} represents the estimation of ρ_u obtained applying the same idea to the criterion time, cost and risk, respectively (with ad hoc values of δ). Through the formula (3) the computation of ρ_u is faster since the values of δ , necessary to compute ρ_u^{time} , ρ_u^{cost} and ρ_u^{risk} , do not require to use the normalization constants and then they can pre-computed before the query. In the experimental campaign ρ_u is always computed via formula (3).

Finally, here we report the pseudo-code of the Time Dependent A^* with Forbidden Turns (TD- A^* -FT) algorithm used to solve the Multi-Objective Time Dependent Shortest Path with Forbidden Turns Problem.

Algorithm TD- A^* -FT

```

1. begin
2.   set  $U := \emptyset$ ,  $L_{ij} := \infty \forall (i,j) \in A \setminus \delta^+(o)$ ,
3.   set  $L_{oj} := c_{oj}^v[t]$ ,  $Pred[o,j] := o$ ,  $\forall (i,j) \in \delta^+(o)$ ;
4.   while ( $\delta^-(d) \cap U = \emptyset$ ) do
5.     begin
6.       find  $(p,q) \notin U$  such that  $L_{pq} + \rho_q = \min\{L_{ij} + \rho_j : (i,j) \notin U\}$ ;
7.       set  $U := U \cup \{(p,q)\}$ ; ( $L_{pq}$  becomes definitive)
8.        $\forall (q,r) \in A: (p,q,r) \notin F$ 
9.         if  $L_{pq} + c_{qr}^v[t_{pq}] < L_{qr}$  then
10.          set  $L_{pq} := L_{pq} + c_{qr}^v[t_{pq}]$  and  $Pred[q,r] := p$ ;
11.     end
12. end

```

In the algorithm TD- A^* -FT, symbol $\delta^+(o)$ indicates the forward star of node o , $\delta^-(d)$ indicates the backward star of node d , set U represents the set of arcs that are permanently labeled and $Pred[q,r]$ represents the predecessor of node q when the arc (q,r) is permanently labeled.

Note that the mono-criterion paths are computed applying the Algorithm TD- A^* -FT where the generalized cost is substituted by the attribute of the criterion that needs to be optimized.

4. Experimental campaign

The algorithm TD- A^* -FT has been implemented in Java language and the numerical experiments have run on a PC Intel Core i5, 2.5Ghz, 3.85Gb RAM. The experimental campaign has been carried out on the road network of Milano (Italy) using the Tele Atlas Data Base (2012, 22-nd March version). The corresponding graph G has $|A|=106,755$ arcs, $|N|=61,595$ nodes and $|F|=17,034$ forbidden turns.

The information on the travel time of each arc has been obtained directly from the Tele Atlas Data Base and they are independent on the vehicle departure time. While the travel cost has been computed considering the sum of three components: i) *fuel consumption*, estimated as a cost linearly dependent on the arc length with a factor of 0.367 €/Km, derived from the average mileage reimbursement for a commercial vehicle in Italy; ii) *highway toll*, estimated as a cost linearly dependent on the arc length with a factor of 0.1 €/Km, derived from the current kilometric toll values on Italian highways; iii) *congestion charge cost*, given by a fixed cost of 5 € if the arc traveled is a gate of access to limited traffic zone (so called Area C in Milano) and it is traveled between 7.30 a.m. and 7.30 p.m. of a working day. The risk of each arc has been estimated considering the sum of two components: i) a *risk default value*, linearly dependent on the arc length with a factor of 0.50 Km⁻¹; ii) risk associated with *sensible places*, defined on arcs that are within a circle of 0.3 Km radius centered on sensible places, that in the experiments are supposed to be all the nursery schools of Milano: it holds only when the arc is traveled between 7.30 a.m. and 4.30 p.m (when the nursery schools are open) and can assume values either 3 or 5 (according to the size of the school). Finally the time has been discretized in $\eta = 96$ time slots of 15 minutes.

We have generated 24 instances of the Multi-Objective Time Dependent Shortest Path with Forbidden Turns Problem considering 3 classes of randomly generated origin-destination (OD) pairs with different distances: the class 1 includes OD pairs with distance less than 5 Km, the class 2 those with distance between 5 and 10 Km and class 3 those with distance between 15 and 20 Km. The average and the standard deviation values of the distances of all the OD pairs generated in each class are summarized in Table 1. Each class is formed by 8 instances and, hereafter, each instance is identified by a progressive number (from 1 to 24) counting them in increasing order of class.

Table 1. Characteristics of the instances, subdivided in three classes of OD distance (in Km).

Class	Average distance	Standard dev
1	2.56	0.95
2	6.33	0.76
3	13.26	2.09
All classes	7.12	4.63

In the first group of experiments we consider a congestion charge free vehicle with departure time equal to 7.30 a.m. In this way all the arc attributes can be considered static because the time dependent component of the cost attribute is null and the one of the risk is constantly active during the trip since it is reasonable that the trip ends before 4.30 p.m.

In the first experiment we consider $\lambda_1 = 1$ and $\lambda_2 = \lambda_3 = 0$, namely we only optimize the travel time criterion, and we compare the results obtained with two values of δ : the first one, $\delta' = 41.67$ m/s, is obtained considering the maximum speed on the whole road network (150 Km/h in the highways); the second one, $\delta'' = 16.67$ m/s, considering the maximum urban speed (60 Km/h, according to the Tele Atlas DB). The results are summarized in Table 2, where the columns represent respectively the instance number, the time criterion value of the solution returned by the TD- A^* -FT algorithm with the two values of δ , their relative percentage variation passing from δ' to δ'' (i.e., $100 \cdot (\text{Time}(\delta'') - \text{Time}(\delta')) / \text{Time}(\delta')$), the CPU time of the Map Matching phase in milliseconds (ms), the CPU times of the TD- A^* -FT algorithm with the two values of δ (in ms) and their relative percentage variation passing from δ' to δ'' . We can observe that the solution found with δ'' coincides almost ever with that one obtained with δ' but, with this parameter tuning, the algorithm becomes by far quicker since its CPU time is in average the 65% lower.

Table 2. Comparison of the Time objective function and the CPU times depending on two different values of δ .

Instance	Time [s] (δ')	Time [s] (δ'')	Δ Time [%]	CPU Map Matching [ms]	CPU routing [ms] (δ')	CPU routing [ms] (δ'')	Δ CPU routing [%]
1	161.5	161.5	0%	1289	179	10	-94%
2	172.8	172.8	0%	512	389	22	-94%
3	136.4	136.4	0%	462	152	15	-90%
4	242.1	242.1	0%	439	865	185	-79%
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
21	983.3	983.3	0%	477	3539	1113	-69%
22	1044.9	1044.9	0%	423	4632	1723	-63%
23	1364.8	1364.8	0%	1991	8130	5158	-37%
24	1049.9	1049.9	0%	442	3982	2144	-46%
Average			0.05%	595	2040	840	-65%

In the second experiment we consider $\lambda_1=\lambda_2=\lambda_3=1/3$ and we compare the two methods for computing the normalization constants described in Section 3 (NCM1 and NCM2). The results are summarized in Table 3, where the columns represent respectively the instance number, the value of the three criteria, time, cost and risk, on the solution returned by the TD- \hat{A} -FT algorithm with NCM1, their relative percentage worsening with respect to the corresponding mono-criterion optimal path and the CPU times (in ms) of the TD- \hat{A} -FT algorithm with NCM1 and NCM2. We notice that the average CPU time of NCM2 is 1.36 s against 3.60 s of NCM1, with an average decreasing of 52.82%. Moreover, concerning the quality results, for each criterion, the average percentage worsening, with respect to the corresponding mono-criterion optimal path, of the solution obtained with NCM2 is 4.77%, 4.51%, 3.18%, respectively (against 6.04%, 3.64%, 2.29% of NCM1). Hence, compared to NCM1, NCM2 seems also to yield fairer solutions.

Table 3. Results with $\lambda_1=\lambda_2=\lambda_3=1/3$ and comparison of the two methods to generate the normalization constants

Instance	Time [s]	Cost [€]	Risk [-]	Δ Time [%]	Δ Cost [%]	Δ Risk [%]	CPU routing [ms] (NCM1)	CPU routing [ms] (NCM2)
1	161.46	0.68	0.93	0.00%	1.02%	1.02%	48	160
2	172.80	0.88	1.20	0.00%	0.48%	0.48%	198	102
3	136.44	0.76	1.03	0.00%	3.43%	3.44%	344	116
4	242.10	1.29	1.76	0.00%	3.13%	2.07%	1632	460
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
21	1148.16	6.37	8.68	16.77%	14.56%	4.36%	6966	2666
22	1066.92	5.93	8.08	2.11%	2.93%	3.27%	7019	2063
23	1398.54	7.40	10.09	2.48%	3.91%	2.89%	13482	3491
24	1096.98	5.30	7.21	4.48%	2.03%	1.07%	6660	2171
Average				6.04%	3.64%	2.29%	3604	1360

For testing the efficacy of the TD- A^* -FT algorithm also in time-dependent scenarios we build four instances of our routing problem where the vehicle considered is not congestion charge free, its origin is outside the congestion charge area while the destination is inside it. We want to observe how the solution changes by varying the departure time of the vehicle. The features of the instances are reported in Table 4, while the paths returned by the TD- A^* -FT algorithm is reported in Figure 1 where a black circle indicates the origin (labelled “O”), a white circle the destination (labelled “D”), and a crossed white circle stands for the gate of entrance into the toll area (Area C).

In instance #1, the departure time is set 10 minutes before the toll area shutdown. The algorithm returns the fastest and cheapest path from origin to destination, entering the toll area from gate A. Therefore, a 5€ cost of toll is charged besides default linear costs. In instance #2, departure time is delayed of 3 minutes (from 19:20:00 to 19:23:00), the algorithm returns the same solution, same gate (A) and same path: all other alternative paths are still dominated. A further delay of 2 minutes sets instance #3 departure time at 19:25:00. In this case, since departure time is closer to the shutdown, it is expected that algorithm would somehow consider to lengthen the path in order to enter the toll area after the shutdown time, possibly from another gate. In fact, solution to instance #3 shows a different path: vehicle enters the toll area from gate B at 19:31:29, one minute and a half after the toll area shutdown. In this case, the time criterion is worsened of about 10%, the vehicle needs 40 seconds more to get to destination but the money criterion is improved of more than 60%: no toll is charged on the vehicles and driver saves around 4.4€. Solution to instance #4 and #5 show the same behavior: the solution is based on lengthening the path to enter the toll area after 19:30:00. Since departure times are very close to shutdown it is not needed to go so far from gate A: gate C is selected as entrance point respectively at 19:35:26 and 19:35:52. Solutions to instance #4 and #5 look very similar, the difference is in the path towards the gate: it is straight forward for #5 while for #4, whose departure time is earlier than #5, vehicle is invited to reverse travel direction in order to spend few seconds “waiting” for toll area shutdown. In both cases, a gain in terms of costs is pursued against a small loss in terms of travel time.

5. Conclusions

We introduced a new challenging routing problem arising from a real world application: the Multi-Objective Time Dependent Shortest Path with Forbidden Turns Problem. We propose an heuristic algorithm that addresses all the features of the problem and solves it within a few seconds. Although the algorithm is heuristic, it performs well since in the experimental campaign is able to find solutions, whose average percentage worsening, with respect to the mono-criterion optimal path, is 4.77%, 4.51%, 3.18%, for each criterion time, cost and risk, respectively. Moreover it is able to decide to slightly lengthen the path of a vehicle if its departure time is close to the end of the congestion charge time window in order to enter the toll area when the congestion charge is not active.

Table 4: Results for some time-dependent instances

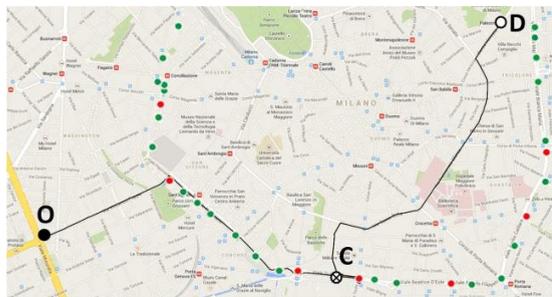
Instance	Departure Time [hh:mm:ss]	Time at Gate [hh:mm:ss]	Arrival Time [hh:mm:ss]	Cost [€]	Time [s]
1	19:20:00	19:21:54	19:26:40	7.01	400.62
2	19:23:00	19:24:54	19:29:40	7.01	400.62
3	19:25:00	19:31:29	19:32:20	2.57	440.58
4	19:28:00	19:31:30	19:35:26	2.33	446.58
5	19:29:00	19:31:56	19:35:52	2.16	412.86



Path of instance #1 and #2



Path of instance #3



Path of instance #4



Path of instance #5

Figure 1: Path returned by the TD-A*-FT algorithm for five time-dependent instances

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