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Assessing the value of information for retail distribution of perishable goods

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ABSTRACT

This paper addresses quantitative methods for estimating the value of information from ITS in urban freight distribution. A real-life application on the retail distribution of perishable goods is considered. The problem is formulated as a vehicle routing problem with soft time windows and time-dependent travel times, and solved by using information affected by different degrees of detail and reliability. The practical performance of these solutions is then evaluated by simulation, to assess the joint benefit of using more reliable and detailed information with different solution algorithms.

Keywords: information reliability, city logistic, ITS, vehicle routing, time-dependent travel times.

1 Introduction

The increase of congestion in transport system requires innovative approaches to face the need for sustainable mobility. In this context, limiting the impact of freight transport on road congestion is specifically important. In fact, the European freight road transport is expected to increase by 55% by 2020 [5]. The traditional measures to accommodate this growth, such as the expansion of the existing transport networks, cannot be pursued, at least in urban areas. The recent trend is for the development of intermodal logistic platforms in the city neighborhoods, where goods incoming from different transport modes (rail, maritime, large trucks) are stored, and small vehicles are used for the distribution of freights towards the urban area.

Intelligent Transportation Systems (ITS) and technologies can play a key role to optimize the organization of intermodal platform and to reduce the impact of freight traffic on urban congestion. In 2008, the European commission planned several actions aiming at the introduction of the *eFreight* concept [4], consisting of the collection of real-time information on the location and condition of transported goods, and of its integration with other supply-chain activities and technologies, such as radio frequency identification (RFID).

In this paper we focus on the best use of ITS information for the distribution of goods from an intermodal platform to the retailers located in an urban area. Specifically, we are interested in the development of a quantitative method to estimate the value of such information in the optimization process of the retail distribution of perishable goods. The perishable goods market is characterized by the short life time of products, sometimes limited to few days, which turns out in a rapid depreciation of the product value. The distribution must therefore comply with strict restrictions on the delivery times. This challenge requires, on one hand, effective optimization algorithms to plan punctual deliveries to the retailers at sustainable cost. On the other hand, there is a need for reliable and accurate data on the road network to produce solutions that can be implemented in practice.

Network traffic conditions deeply influence the link travel times that constitute the main input of distribution problems. Travel times are affected both by systematic variability (traffic condition in the different time slices) and stochastic variability (unforeseen events, such as accidents or maintenance operations). Therefore, in order to effectively plan the deliveries, time-dependent travel times should be taken into account. Tracking systems based on the RFID technology or GPS offer a new opportunity to collect reliable real-time information about network traffic conditions. Such information can be used both in real time, to locate the position of a vehicle, and off line to estimate the travel time of each element of the network with high level of precision and reliability. However, while the cost of implementing such measurement systems can be easily computed, estimating the value generated by advanced tracking systems is more difficult [17]. In fact, there is a need for scientific studies on the evaluation of the added value generated by advanced tracking systems in distribution. This need motivates the present work.

The problem is formulated as a vehicle routing problem with soft time windows for the deliveries, in which the objective function includes the transportation costs and the cost of late deliveries. We focus on a real case study, namely an intermodal logistic platform located in the suburban area of Rome (Italy), and in particular on the distribution of fresh products in the historical center of Rome. The center of Rome is characterized by

narrow streets and high density of commercial activities, which makes the distribution quite decoupled from the rest of the city since specific small vehicles have to be used in this area (smaller than 3.5 tons).

The solution approach consists of the development of simple greedy and tabu search algorithms. An innovative aspect has been introduced in one of the tabu search algorithms, taking into account information about the geographical position of customers and routes to construct effective neighborhoods.

The paper is organized as follows. In Section 2 we revise some relevant related works. The research methodology to assess the information value is described in Section 3. Section 4 deals with the formal description of the vehicle routing problem. Solution algorithms are described in Section 5 and the computational results are reported in Section 6. Some conclusions follow in Section 7.

2 Literature review

In this section we review the recent literature related to this paper. The approach followed in this paper is based on (*i*) choice of methods and technologies for data collection, (*ii*) choice of solution algorithms for solving the vehicle routing problem described in the previous section, (*iii*) computation of the added value generated by data reliability in combination with the chosen solution algorithms. While an increasing number of papers addresses the first two points, there is a substantial lack of scientific research as far as the the third point is concerned. Therefore, while this paper focuses on the third issue, we next review the recent literature related to the first two points.

In the last years, there is an increasing interest in the literature on commercial vehicle tour data collection and modeling [8]. Jarugumilli and Grasman [13] use RFID technology to enable efficient control of inventory distribution by exchanging real-time information upon arrival at each location. Wang et al. [29] use real time information from different ITS such as RFID and GPS to optimally route and schedule vehicles in logistic and distribution services. Kim *et al.* [15] propose effective algorithms for data estimation, to be used once measures from the field have been collected.

As for the literature on the vehicle routing problem with time windows (VRPTW), a large number of papers address the static case in which travel times are time-independent. We cite, among the others, Solomon, 1987 [23]; Russell, 1995 [22]; Bramel and Simchi-Levi, 1996 [3]; Potvin et al., 1996 [21]; Taniguchi et al., 1998 [25]. Cordeau et al. [6] consider soft time windows to take into account late and early delivery.

Time-independent travel times do not adequately represent all the real cases, since in practice travel times can be affected by strong variability both systematic (traffic condition in the different time slices) and stochastic (unforeseen events, such as accidents or maintenance operations). Limited research has been carried out on vehicle routing problems with variable travel times. We cite, among the others, Laporte et al., 1992 [18]; Malandraki and Daskin, 1992 [20]; Taniguchi et al., 1999, 2000 [26]-[27]; Kenyon and Morton, 2003 [14]; Taniguchi and Shimamoto, 2004 [28]).

Ahn and Shin [1] are among the first researchers who studied the vehicle routing problem with time windows and time-dependent costs. Malandraki and Daskin [20] give a formulation of the VRPTW and time-dependent costs, modeling the travel time fluctuation with a step function.

Ichoua et al. [16] propose a time-dependent model for a VRPTW, based on time-dependent travel speeds. They extended the tabu search heuristic developed by Taillard et al. [24] to solve the problem and performed some experiments to evaluate the model in static and dynamic environments. Fleischmann, Gietz e Gnutzmann [9] consider the Time-Dependent Vehicle routing problem (TDVRP), defining the travel time function with a linearized step funtion. The authors show that all the models excepted the one by Ichoua et al. are inconsistent since they do not represent the no passing (FIFO) property. Ando and Taniguchi [2] presents a model for minimising the total costs incorporating the uncertainty of link travel times with the early arrival and delay penalty at customers who set up designated time windows.

3 Research methodology

This section describes the procedure adopted for estimating the value of information in our vehicle routing application. The basic idea behind the procedure is that the discrepancy between planned and implemented solutions is only in minor part due to the inherent stochastic nature of travel times. Major differences are due to the mismatch between the observed data, used to build the planned solution, and the actual travel times occurring in practice. In other words, the actual travel time t_{ij} for a link (i, j) can be expressed as $t_{ij} = d_{ij} + s_{ij}$, where d_{ij} is the deterministic part and s_{ij} is a stochastic variable due to perturbation events on transport demand and supply. The deterministic part d_{ij} is the desired value for solving the vehicle routing problem, such as the mean value of t_{ij} or a value achieved with a given probability ψ (i.e., such that the probability of the event $t_{ij} \leq d_{ij}$ is ψ). In practice, the value d_{ij} is estimated by collecting measures of t_{ij} on the network, which can be affected by measurement errors. We let $t_{ij}^{obs} = d_{ij}^{obs} + s_{ij}^{obs}$ be the estimate of t_{ij}, where d_{ij}^{obs} and s_{ij}^{obs} are the observed values of d_{ij} and s_{ij}, respectively.

We call *discrepancy* the quantity $\delta_{ij} = t_{ij}^{obs} - d_{ij}$. If t_{ij}^{obs} is a rough estimate of t_{ij}, then the measurement error can be much larger than the inherent stochasticity of the travel time, i.e., $|\delta_{ij}| >> |s_{ij}|$.

Collecting more reliable information may help to produce a better estimate t_{ij}^{est} of t_{ij}, i.e., an estimate such that $|t_{ij}^{est} - d_{ij}| << |t_{ij}^{obs} - d_{ij}|$. The value of such information is related to the improved performance of the system that would have been achieved if the planned solution was built using the more reliable t_{ij}^{est} instead of t_{ij}^{obs}. Since the discrepancy may vary over the different routes to be traversed, we introduce an aggregated value ε that we call the *unreliability* of the data set. For a urban network with a set N of links, possible aggregations are the mean value of the discrepancies over all the links, e.g. $\varepsilon = \frac{1}{|N|}\sum_{(i,j)\in N}|\delta_{ij}|$, or the square mean value $\varepsilon = \frac{1}{|N|}\sum_{(i,j)\in N}(\delta_{ij})^2$, or any other aggregated representative of all data discrepancies.

Our procedure computes the value of information with reference to a given vehicle routing algorithms $\mathcal{A}$. It requires the production of several solutions with $\mathcal{A}$ for varying the unreliability ε of the data set. Given the data set and a value for the unreliability ε, we let $\rho^p(\varepsilon)$ be the planned solution obtained with $\mathcal{A}$ on such data set, $\rho^h(\varepsilon)$ be the associated historical solution, obtained by using the same routing as in $\rho^p(\varepsilon)$ and the actual data d_{ij} instead of t_{ij}^{obs}. Since the values t_{ij} are stochastic, also the performance of $\rho^h(\varepsilon)$ is a stochastic variable. We let $\pi(\varepsilon)$ be the mean value of the performance achieved by $\rho^h(\varepsilon)$ for a given ε. Applying the same procedure for varying ε, we get a curve $\pi(\varepsilon)$

associated to the vehicle routing procedure $\mathcal{A}$ being used. If using a certain type of ITS one can decrease the information unreliability from a value ε_2 to $\varepsilon_1 < \varepsilon_2$, there is then a performance improvement $\pi(\varepsilon_1) - \pi(\varepsilon_2)$, like shown by the curves of Figure 1.

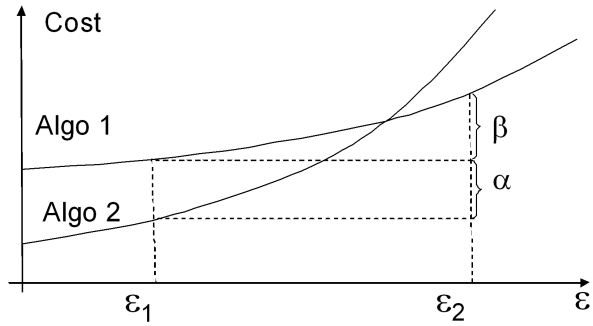

Figure 1: Performance for varying the unreliability

In this paper, we focus on computing the relation between data reliability and distribution costs. We do not address the exact computation of the probabilistic uncertainty of the information before and after the introduction of ITS, which is very much related to the technology and the specific setting, and it is the subject of more technology oriented ITS studies. However, it appears from the literature that there are many settings in which suitable technologies, e.g. the RFID technology, make possible to reduce the unreliability ε nearly to zero (*RFID Journal* October 2002 and August 2008).

It is worthwhile to mention that, very likely, different vehicle routing algorithms may have different degrees of sensitivity to process data information. Therefore, when designing an intelligent transport system, it can also be profitable to develop novel vehicle routing algorithms that will use the more reliable information.

Figure 1 shows the case of two algorithms (Algo1 is more robust, Algo2 is less robust but more performing for reliable data), in which Algo1 is better than Algo2 for highly unreliable data. Before the implementation of an advanced tracking system (for $\varepsilon = \varepsilon_2$) Algo1 is more effective, while Algo2 becomes the best choice after the introduction of ITS (for $\varepsilon = \varepsilon_1$). In other words, it is important to assess the impact of ITS in combination with different (simple and advanced) vehicle routing algorithms. Introducing the advanced tracking system with Algo1 will produce the benefit β in Figure 1. If the vehicle routing algorithm is replaced with Algo2 there is the additional benefit α. Clearly, it is worth paying the cost of implementing the new tracking system and the new algorithm Algo2 only if they generate sufficient ROI (Return On Investment).

4 Problem description

The problem addressed in this work is a vehicle routing problem with soft time windows of [earliest,latest] delivery times. A logistic platform LP must distribute the required amount of perishable goods to a given set R of retailers by using a given set V of vehicles of given capacity. We assume that an unlimited amount of merchandise and number of vehicles is available at LP. Each retailer r requests a certain quantity of goods d_r to be delivered within a given time window $[t_r, T_r]$.

A feasible solution of the problem consists of constructing a route for each vehicle starting and ending in LP such that (i) the demand of each retailer is satisfied, (ii) each retailer is served by exactly one vehicle, and (iii) the capacity of each vehicle is not exceeded. In our model, a vehicle arriving early at a certain retailer will wait until its earliest delivery time.

A vehicle arriving at time $a_r > T_r$ at retailer r incurs a penalty cost w_r for late delivery. This penalty depends on the probability p_r that the delivery is refused by the retailer. We assume $p_r = 0$ for on-time deliveries and up to a small delay τ_{min}, i.e., $a_r \leq T_r + \tau_{min}$. The delivery is refused with probability $p_r = 1$ over a delay τ_{max}, and increases linearly from 0 to 1 in the time window $[\tau_{min}, \tau_{max}]$, as in Figure 2.

If the delivery is refused, the merchandise is returned to the logistic platform and delivered the next day, with an associated cost corresponding to the goods depreciation γ_r. This quantity can be a significant fraction of the goods value, since the time elapsed from the production to the expiry date can range to a week or less for some fresh products. We model γ_r as a function of the demand d_r to be delivered to retailer r, of the good unit price u and of the number of days remaining to the expiry date g as follows: $\gamma_r = \frac{d_r u}{g}$.

The penalty cost w_r is therefore:

$$w_r = (a_r - T_r) p_r \gamma_r$$

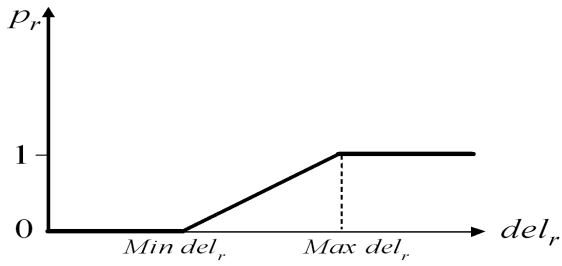

Figure 2: Probability of refusing delivery

Let ρ be the set of routes in a solution, each associated to the vehicle $v(\rho_i)$ used for route i. The cost of route i is given by three quantities: (i) the fixed cost $f_{v(\rho_i)}$ associated to the usage of vehicle $v(\rho_i)$, (ii) the variable cost $c_i(\rho_i)$ associated to length of route ρ_i, (iii) the penalty cost $\sum_{r \in \rho_i} w_r(\rho)$ for late deliveries. The objective function of the problem is therefore:

$$\min \sum_{i=1}^{|\rho|} (f_{v(\rho_i)} + c_i(\rho_i)) + \sum_{r=1}^{R} w_r(\rho). \tag{1}$$

5 Algorithms

In this section we describe the solution algorithms used for our analysis. We assess the performance of different vehicle routing algorithms when varying the data reliability. Specifically, we consider a simple constructive heuristic and two tabu search procedures.

The constructive heuristic groups retailers according to their geographical position and assigns to each group the minimum number of vehicles necessary to accommodate their total demand. Retailers belonging to the same group are ordered for increasing T_r

and then assigned in this order to vehicles. If the demand of retailer r does not fit in any of the available vehicles, a new vehicle is added and r is assigned to it. Otherwise, r is assigned to the available vehicle with the minimum remaining capacity. When all retailers have been assigned to a vehicle, an adaptation of the 3-OPT local search algorithm [19] to the case with time windows is used to sequence retailers served by the same vehicle. This constructive heuristic is similar to the first steps of the procedure currently adopted at the logistic platform to plan vehicle routes.

The first tabu search procedure (hereinafter called ST or *standard tabu search*) implements the main features of the TABUROUTE algorithm introduced by Gendrau, Hertz and Laporte [12]. A solution S in ST is given by the sequence of retailers served by each route. The neighborhood of a solution S is the set of all the feasible solutions obtained by moving one of p randomly chosen retailers from its route in S to another route serving at least one of the q retailers closest to it, where p and q are two parameters of the tabu search. If a move leads to empty an existing route, the route is eliminated. An additional move consists in adding a new route to the set of routes and in assigning to it one of the p retailers. A move can lead to infeasible solutions that violate the capacity constraints of some vehicles. Infeasible solutions are penalized by a factor depending on the violation of the capacity constraints. When the solution does not improve after a certain number of iterations, diversification strategies are used to restart the search from new solutions.

The second tabu search procedure (hereinafter called AD or *advanced tabu search*) differs from ST for the definition of a larger neighborhood of a solution, that is generated by considering an additional move. The new move emulates the behavior of human dispatchers and is based on the geographical properties of the real application considered in this paper and depicted in Figure 3.

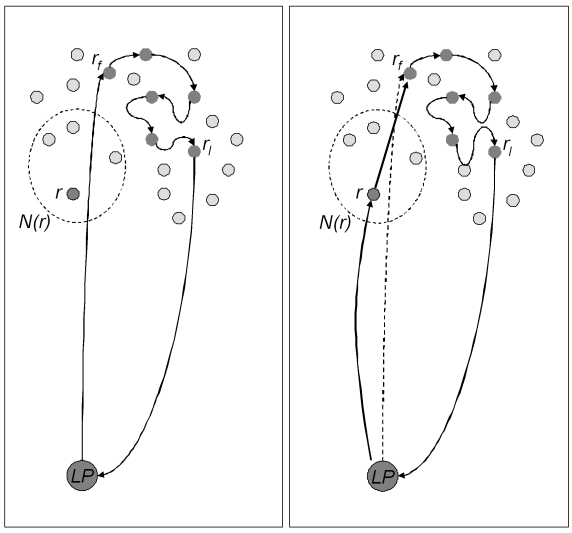

Figure 3: The new move

As described in Section 1, logistic platforms are typically located in the peripheral area of the cities. On the other hand, the retailers can be located in the central area of the city, as in our case study. In such case, each route includes a long path from LP to the first served retailer r_f and a long path from the last retailer r_l to LP. The new move allows moving a retailer r form its current route to another, before r_f or after r_l, even if

r_f or r_l are not included in the q retailers closest to r. The solution S' obtained after the move is included in the neighborhood of S if the cost of S' minus the cost of S is below a given treshold.

6 Computational results

This section reports on the performance of the greedy, AD and ST algorithms on a real test case, located in a subarea of Rome (Italy). The code is implemented in C++ and runs on a PC equipped with a Intel 2 GHz processor and 2 GB of RAM.

6.1 Test case description

The network includes the historical center of Rome, where customers are located, and the south area until the Big Ring Road, where the logistic platform LP is located. The network is shown in Figure 4 and consists of 250 centroids, 425 nodes and 2346 oriented links. The historical center of Rome is characterized by many narrow streets and by

Figure 4: Rome network

a large number of small activities, which translate into specific problem characteristics such as the dimension and the number of customers and low link capacity values. The distribution of merchandise takes place from 4:00 am to 11:00 am. In order to model the traffic conditions within this time window, about 280.000 vehicles are generated on the network considering the variable demand profile shown in Figure 5.

For each hour, link travel times are obtained by simulation using dynamic assignment model where transport demand can change during the simulation interval. For the dynamic simulation we use the DYNAMEQ model: this is a dynamic traffic assignment model which exploits variants of gradient like directions and the method of successive averages to determine pre-trip dynamic equilibrium path choices [10]. As a consequence, the travel times between each pair of retailers, as well as between each retailer and the logistic platform LP, are time-dependent and can be represented by a vector where each component is associated to a certain time slice.

In our study, we consider these travel times values as the actual traffic conditions in the network. To generate errors on the input data, these travel times values have

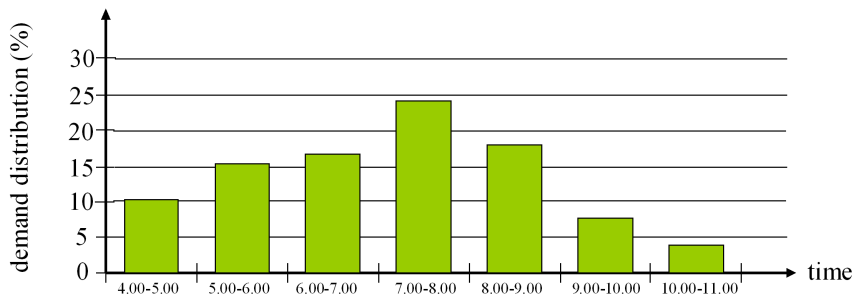

Figure 5: Demand profile

been randomly perturbed using the relation $t_{ij}^{obs} = d_{ij}(1 + \frac{x}{100})$, where x is a random variable uniformly distributed in the interval $[-P, +P]$. We considered 10 values for $P = \{10, 20, ., 100\}$, besides the reference case $P = 0$ in which input data is not affected by error. We consider 10 scenarios for the customer orders, each scenario consisting of one day with 50 deliveries randomly located in the city center. For each value of P and for each scenario, 10 random perturbations of the travel times have been generated, thus obtaining a total of 1010 instances of the vehicle routing problem to be solved with the three algorithms. As an aggregate indicator of the unreliability we use $\varepsilon = \frac{1}{|N|} \sum_{(i,j)\in N} |\delta_{ij}|$.

6.2 Results analysis

For the reference case $\varepsilon = 0$ and for the 10 scenarios, Algorithm AD finds a better solution with respect to Algorithm ST in 8 out of 10 cases. In the following, the best solution obtained either by AD or ST for $\varepsilon = 0$ is referred to as the REF solution.

Table 1 reports the average distances (in percentage) between the solutions found by one of the three algorithms and the REF solution. The greedy algorithm performs very poorly with respect to the two tabu search algorithms, the average distance from REF ranging from 271.34% to 721.96%. With the AD and ST algorithms the average distance from REF is significantly smaller, and reaches the 139% only with a perturbation $\varepsilon = 100$ in the ST case.

A pictorial comparison between AD and ST is shown in Figure 6. On average, AD outperforms ST for all values of ε, which demonstrates the effectiveness of the new neighborhood concept adopted by AD. As for the sensitivity of the algorithms to the unreliability ε, Figure 6 shows that there is a significant increase of the distance respect to the REF solution when passing from $\varepsilon = 0$ to $\varepsilon = 10$. For higher values of ε the distances remain quite stable for AD and slightly increase with ε for ST. This behavior highlights the lower robustness of ST with respect to AD.

The resilience to perturbations of the solutions found by AD and ST can be explained by Figure 7, in which the average estimation error (in percentage) of the different solutions is shown.

For each value of ε and for each instance, the objective function of the solutions obtained by AD and ST with perturbed input data have been compared with the objective function values obtained by the same solutions with no perturbation on link travel times (i.e., with $\varepsilon = 0$). It can be observed that the estimation error increases almost linearly

Table 1: average distances [percentage] between solutions and REF

ε	GREEDY	AD	ST
0	271.34	2.89	33.54
10	448.52	47.23	73.78
20	455.95	53.00	88.43
30	481.06	59.10	90.31
40	512.55	59.09	90.39
50	559.17	59.98	110.99
60	618.46	70.88	111.52
70	647.53	63.43	110.72
80	675.06	64.65	116.69
90	697.54	72.04	118.68
100	721.96	71.87	139.45

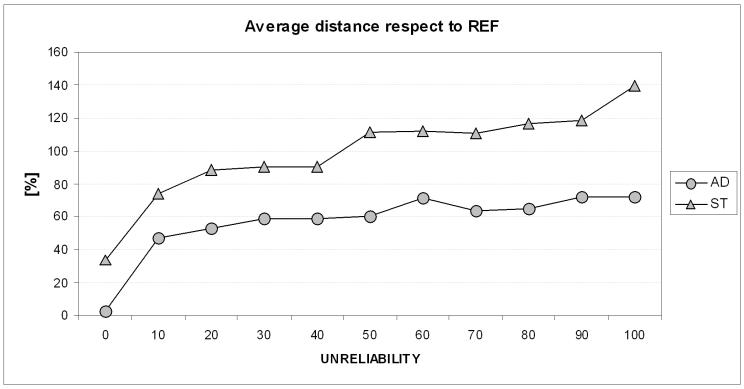

Figure 6: Average distance [percentage] of solutions costs computed by AD and ST respect to REF (7 time slices data input)

with ε for both AD and ST and does not vary significantly with the algorithm but it depends only on ε.
In the remaining part of this section, we study the benefit of using aggregated versus more detailed input data when modeling the traffic conditions in different time slices.

Specifically, we compare the case in which only three time slices are used to model the vehicle routing problem with respect to the more detailed model with seven time slices. In the aggregated case, the link travel times from 4:00 to 7:00 a.m. (and from 7:00 to 10:00 a.m.) are considered constant and equal to the average values during the three hours. Figure 8 shows the average distance of the objective function values from the REF value when using 3 and 7 time slices, for varying ε. The REF value is computed by using 7 time slices and $\varepsilon = 0$. The distance from REF for the case with 3 time slices ranges between 40% and 80% for AD and between 60% and 140% for ST. Such behavior confirms that AD is more resilient to perturbation with respect to ST also when the input data are more aggregated.

It is interesting to compare the performance of each algorithm considering three and seven time slices. This is shown in Figure 9 for the AD algorithm and in Figure 10 for the ST algorithm. As for the AD algorithm, when the input data are very reliable (i.e.,

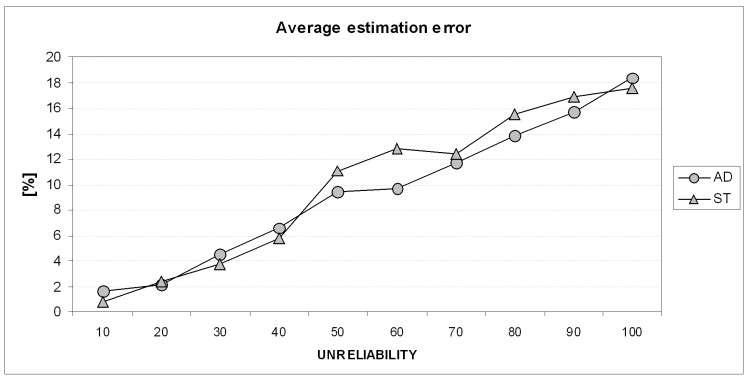

Figure 7: Average estimation error [percentage]

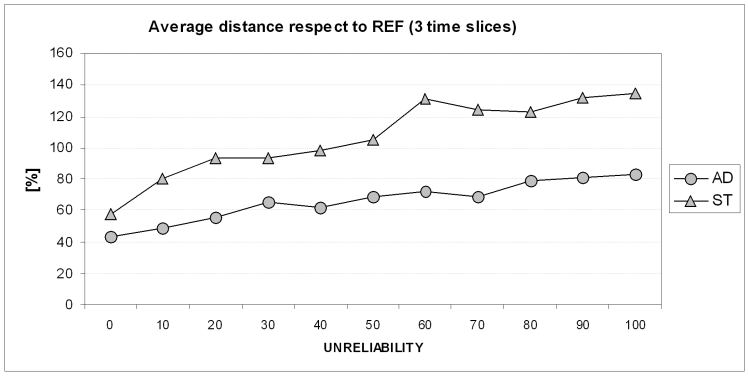

Figure 8: Average distance [percentage] of solutions costs computed by AD and ST respect to REF (3 time slices data input)

when $\varepsilon = 0$) there is a clear convenience in using seven time slices rather than three. On the other hand, for $10 \leq \varepsilon \leq 40$ the difference between the two cases reduces almost to zero, and it is always less than 20% for higher values of ε, so that there is no big convenience in collecting and using more detailed input data for $\varepsilon \geq 10$. When the ST algorithm is concerned, Figure 10 shows that detailed input data (seven time slices) are still preferrable when the perturbation ε is zero and that aggregated input data (three time slices) are slightly preferrable for $\varepsilon \geq 10$.

7 Conclusions

This paper addresses quantitative methods for estimating the value of information from ITS in urban freight distribution. The information adopted are link travel times, that can be deeply influenced by systematic and stochastic variability. Specifically, we developed a quantitative method to estimate the value of such information in the optimization process of the retail distribution of perishable goods. We also developed several solution approaches consisting of a simple greedy algorithms and two tabu search algorithms. A standard tabu seach is derived from the literature on the vehicle routing problem. An

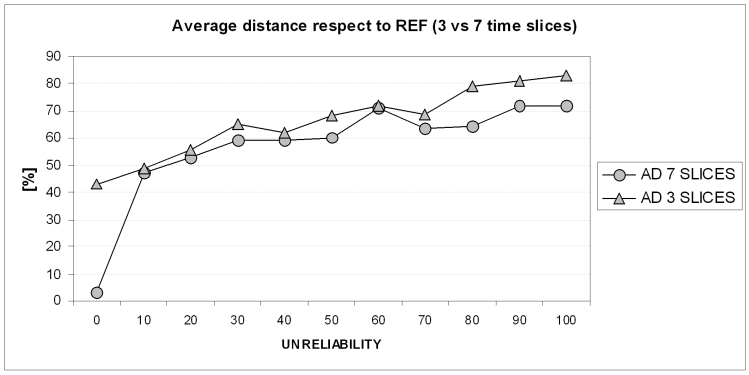

Figure 9: Comparison of the avarege distances of solutions costs computed by AD respect to REF (3 vs 7 time slices data input)

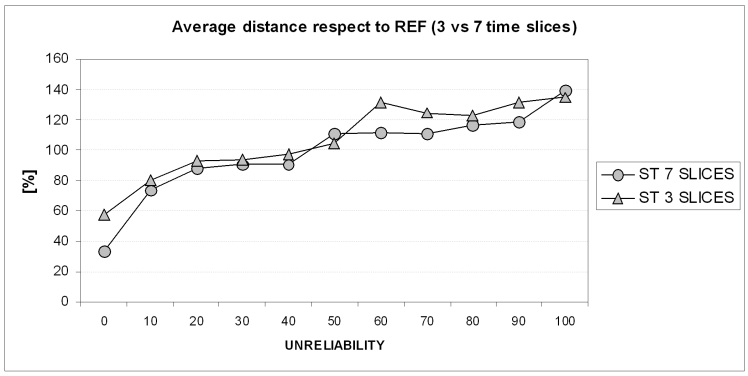

Figure 10: Comparison of the avarege distances of solutions costs computed by ST respect to REF (3 vs 7 time slices data input)

advanced tabu search has been developed by taking into account the geographical position of customers and routes to construct a new effective neighborhood. The results obtained on a real network (a subarea of the city of Rome) shows that the advanced tabu search clearly outperforms the standard one both from the view points of the objective function and the resilience to errors in the input data.

As far as the value of information is concerned, our results show that there is a clear benefit in using detailed and highly reliable data. When reducing the travel time estimation error nearly to zero is not possible (e.g., when travel time values are inherently stochastic in nature) it is important to use an advanced algorithm, able to achieve good performance for a large range of perturbation. Our computational results also show that when the input data perturbation is large, there is no big convenience in using detailed information for the solution of the vehicle routing problem.

Future developments of this work will be possible when practical measures on the network links will be available, and will address the design of the most suitable distributions for the link travel time errors and the definition of the right combination of levels of input data aggregation, information reliability and algorithm to be used in practice.

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