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The Influence of Time Windows on the Costs of Urban Freight Distribution Services in City Logistics Applications

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In freight distribution services a required quality level may have a relevant effect on transportation costs. For this reason an evaluation tool is useful to compare different service settings and support the decision, on the base of quantitative indicators. This paper proposes a method for cost evaluation in this context and presents an application to a case study concerning a freight distribution service, which operates on a wide road network having a city centre, a peripheral urban area and a peri-urban rural zone. A simulation method is proposed to obtain real-life scenarios in order to test the method and its indicators. The performance of each indicator has been evaluated in an experimental context to produce realistic test cases, using a trip planning tool and a demand generator. First, the behaviour of the indicators is analysed with regard to the time windows width planned for the service. Then, their ability in estimating the total transportation cost to satisfy all the requests, under different time period profiles, is shown. The results confirm the ability of the set of indicators to predict with a good approximation the transportation costs and therefore to be used in supporting the service quality planning decisions.

Keywords: urban freight distribution; compatibility indicators; evaluation method; simulation; real-life applications

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1. Introduction

The increase of customer satisfaction approaches in supply chain management imposes to relate the service quality to the logistics costs, making the economic aspects of the last mile an important component of supply chain design. In this context, the new advances in the technologies have been a positive factor for the development of new markets and new consumer needs: the growth of e-commerce and postal shopping, as well as the new trends on shopping trip behaviour (Gonzalez-Feliu et al., 2012), have reinforced the importance of "just in time" policies in freight distribution. Moreover, the service quality of a transportation carrier is often related to travel time, and can vary according to both socio-economic and trip characteristics. The total travel time of a vehicle trip depends on travelled distance, its typical speed and the time spent on each pickup and/or delivery stop (Routhier, 2002), but it is also affected by waiting and access time, congestion, deadlines or service features, etc. In addition, the new constraints of the generalised economic and financial crisis make a readjustment on the freight transportation strategies that have to be included in the main logistics tactical decisions. For these reasons, it is important for a distribution system to ensure the efficiency while maintaining a service quality defined by the time windows or other quality indices. These two factors are usually related: the higher the quality, the higher the cost incurred, but this relation is not trivial and these two factors are not considered in the same manner by the different shippers and transport carriers (Danielis et al., 2005). Moreover, an estimation of the cost level is useful to compare different service settings and support the decision, on the base of quantitative indicators (Taniguchi and Van Der Heijden, 2000).

Detailed cost indicators can be estimated by using various techniques, such as operations research tools, demand models or agent simulators. Specific VRP tools, such as those used for dispatching operations and agent simulation frameworks, are not easily accessible and then properly applicable in a tactical stage. Moreover, other methods, such as macroscopic freight demand estimation models, do not offer the level of detail that distribution companies need for their tactical planning issues. Indeed, the dispatching of the requests is managed by specialised software able to optimise the main operations related to freight distribution. If this kind of software can deal with the needs of each single freight distribution company, methods for supporting the global service planning and cost forecasting are needed when different stakeholders are involved: public authority planners, real estate companies, managers of transport and logistics companies, drivers, associations of retailers, groups of small transporters, etc. This heterogeneous population of stakeholders requires using simple and reliable tools for supporting their decisions and guiding them into the search of common tactical decisions (Raifa et al., 2002).

Although the literature in route optimization and in transport cost estimation is wide, the proposed works deal with theoretical or carrier-based aspects, focusing on cost minimization, in both static and dynamic situations. Several authors propose studies that relate time windows to transport costs. Several works (Taniguchi et al., 1999; Taniguchi and Thompson, 2002; Taniguchi and Kakimoto, 2004) study the impacts of different urban distribution forms on route optimization, taking into account the dynamic nature of travel times. In these works, the cases to test are converted into an optimization problem. From the problem's solution, several cost, time and resource utilization indicators are defined and discussed.

More applied studies of urban deliveries dynamics are also proposed, based on quantitative surveys (Sonntag, 1985; Patier and Routhier, 2008) or on simulation approaches on realistic data (Quak and De Koster, 2005, 2009; Ando and Taniguchi (2006); Zeimpekis et al., 2007; Zeimpekis, 2011a, 2011b). In these works, the aim is to identify and study the dynamics of freight transport in urban areas and the real time optimization when unexpected events are observed by the driver. They are based on in-depth analyses of scenario simulations to show the relations between time windows, optimization dynamics and carrier's performance. Applied research works propose also predictive indicators (Lambert, 2008), but their validation is made qualitatively by asking a panel of potential users about their acceptability or applicability.

This paper aims to study the influence on service quality of time windows characteristics and the geographical and temporal distribution of the requests, using the predictive indicators of Deflorio et al. (2010) to relate service quality to transport cost. Those indicators, although defined to be applied by practitioners, have already been tested only on benchmark problems that do not fully represent real freight distribution applications. More precisely, this analysis will show, as first aim, the indicators' capacity to estimate the total transportation costs trends on a large set of instances served with vehicles operating in a real life road network. Second, a set of scenarios on a City Logistics context are presented, simulated and analysed. A large part of the available literature in this field focuses either on theoretical and conceptual works or on large and medium urban areas. On the contrary, recent trends, mainly in experimentation and pilot testing, focus on small-sized cities and medium semi-urban areas, characterised by a highly variable population density and important geographical constraints. Then, this paper contributes to advance the literature also in this direction, providing a City Logistics case study that considers the area of Ivrea. In fact, this city is a small sized town nearby a highly industrialized medium one (Turin). Moreover, it is in the centre of a surrounding area with accessibility constraints (e.g., mountains areas) and different types of industrial districts.

The paper is organised as follows. Section 2 provides a brief background of the freight transportation problem related to urban distribution with time constraints and the main issues related to time compatibility. Then, the proposed method and its modules are described in Section 3, where we focus on the set of performance indicators and the demand generator . In order to apply the proposed methodology to a real-life distribution network, a case study for the Ivrea region, in North-Western Italy, is proposed in Section 4. Then, the simulation settings and the testing procedure, based on scenarios which consider the network configuration characteristics, are presented. Finally, extensive computational results are given in Section 5. The conclusion of our work is reported in Section 6.

2. Literature Review

Freight transportation costs are nowadays an important component of the overall production costs: the transportation processes involve all stages of the production and distribution systems and represent between 15% and 20% of the final cost of the product (Toth and Vigo, 2002). Moreover, it is estimated that distribution costs account for almost half of the total logistics costs. In this context, routing and scheduling become major aspects in cost reduction strategies.

According to Taniguchi et al. (2010), decision support tools are needed to help public decision makers and practitioners to deal with City Logistics nuisances (mainly traffic congestion, greenhouse gas emissions and air and soil pollution). These tools can take the form of decision support systems. These systems are mainly based on modelling, optimisation, simulation, and evaluation procedures.

Transport demand modelling is a major subject in City Logistics (Ambrosini et al., 2008). Two main types of models can be defined, according to Gonzalez-Feliu et al. (2012): those derived from classical freight transport modelling frameworks (Russo and Comi, 2010), which adapt to urban distribution methods usually applied to O/D estimation, or survey-based models (Sonntag, 1985; Hunt and Stefan, 2007; Routhier and Toilier, 2010). This second category of models use statistics and approximation techniques to represent a reality from rich data sets collected for modelling. Optimisation tools mainly derive from the Vehicle Routing Problem (VRP), largely studied to deal with several real applications (Toth and Vigo, 2002; Golden et al., 2008, Perboli et al. 2008, Groër et al., 2010). This problem presents several variants, to deal with real life constraints and distribution schemes. In congested urban zones, the main VRP variants usually associated with are the following. First is the VRP with Time Windows (VRP-TW), were time constraints are introduced to represent the importance of the freight arrival time(Bräysy et al., 2005a, b). In this context, a Time Window (TW) is defined as the interval of time within which a vehicle must arrive to a node, and it is usually characterized by an early arrival time (EAT) and a late arrival time (LAT). Note than VRP-TW presents a wide variety of sub-variants, such as VRP with soft or semi-soft time windows, where a penalty on transportation cost is applied if the TW is not respected (Qureshi et al., 2010), dynamic VRP-TW (Taniguchi et al., 1999, 2001; Taniguchi and Thompson, 2002), where travel times are evolving over time or VRP with access time windows, where the time constraints are associated to a zone to access and not to a customer to serve (Quak and De Koster, 2005). Another VRP variant concerns two-echelon transport systems, where intermediary facilities are used for cross-docking and transhipment operations (Jacobsen and Madsen, 1980; Crainic et al., 2004, 2011; Gonzalez-Feliu, 2011; Perboli et al., 2011). Urban freight transport is also associated with multi-depot VRP (Toth and Vigo, 2002), where more than one starting depots are considered, or variants of Location-routing problems (Nagy and Sahli, 2005) and pickup-and-delivery problems (Berbeglia et al., 2007), mainly the VRP with backhauls where each vehicle makes two consecutive routes: one for delivery purposes then another to pick-up purposes.

In time constrained freight distribution, the high number of carriers and the strong competition between different companies make quality and cost important aspects. These two factors are usually directly related: the higher the quality, the higher the cost incurred. For a transportation carrier, variable costs are related to transportation times and the total distance travelled by the vehicles. These costs are mainly related to the road network configuration, the nature of the demand and the quality of the transportation service, which is related to several aspects. Since the spatial relations have been well studied, more precisely in land-use and real estate research, the relations with the quality of the service in terms of delivery time windows are less studied.

The impact of geographic, demographic, environmental and policy-driven factors has been studied by several authors (Taniguchi et al., 2010). These works focus either on theoretical or conceptual analyses for city distribution (Taniguchi et al., 1999; Kunze, 2004; Benjelloun et al., 2010; Crainic et al., 2010) or on applied aspects related to large and medium-sized urban areas but only from the public authority's viewpoint (Larrañeta et al., 1999; Visser and van Birsbengen, 1999; Ségalou et al., 2004; Qureshi and Hanaoka, 2006). Note that most of these works focus only on city distribution, although an important part of urban logistics is represented by the peri-urban and rural surroundings of a urban area, according to Patier and Routhier (2008).

Concerning the impact of time constraints and delivery performance, quantitative methods are proposed, mainly tested on theoretical or academic instances. Most of them are based on analyses of vehicle routing problem solutions (Taniguchi et al., 1999, 2001; Taniguchi and Kakimoto, 2004; Nakamura et al., 2010). In these works, a real-life situation, mainly related to city logistics, is represented by an optimization problem. They take into account the dynamic nature of travel times and some works introduce the stochastic behaviour of freight demand.

Other approaches deal with real-life in-depth analyses using operations research tools (Ando and Taniguchi, 2006; Zeimpekis et al., 2007). These works study the relations between time reliability and route optimization dynamics. They belong to the category of Dynamic VRP analyses, and need robust tools and long analyses not always easy to carry out by planners and practitioners. Those stakeholders usually prefer qualitative analyses based on logistics performance indicators (Lambert, 2008). These indicators are in general evaluated by acceptance surveys to their potential users (Lambert, 2008) without a test on their capability of prediction and estimation.

In the last years, the importance of making decision support tools taking into account the various stakeholders involved in urban logistics has increased (Taniguchi et al., 2010). These stakeholders are of different nature (logistics provider or transport carrier managers, specialised consultants, city planners, elected public figures, city technical staff, drivers, real estate decision makers, etc.) and do not always have the scientific and technical background needed to understand complex operations research or modelling frameworks. Moreover, tactical decisions in a group approach need an important communication phase where simpler and quickly obtained information is preferred to long and complex procedures (Gonzalez-Feliu and Morana, 2010). Furthermore, as seen above, it is important to consider all the influence area of a city or a urban zone, not only the dense area, and this aspect is still few studied. As shown above, works dealing with time-constrained freight transport are interested in their dynamics or in optimization issues and the impact of the time windows characteristics has been studied by applying optimization tools. According to Quak and De Koster (2009), the influence of time windows characteristics on freight distribution organization can have an impact on each carrier's performance. However, such analyses are based on complex algorithms which can be difficult to implement by practitioners. In addition, small and medium cities aim to develop new city logistics solutions, and need efficient and adapted decision support, a subject still not proposed in the scientific literature. For this reason, we aim to propose to study the impacts of the temporal distribution of transport demand on the carrier's performance via a scenario analysis. Moreover, we follow a framework easily understandable by any stakeholder related with city logistics and apply it to a particular context: a small urban area with specific geographic and demographic characteristics.

3. The proposed method

In urban freight distribution, the performance of a transport service with time constraints is related to the structure of the demand and its variability in time and space. The sporadic nature of the requests increases the difficulty of tackling the problem with an analytical approach. For this reason, we propose an evaluation method integrating demand simulation on a road network, time compatibility measurement of the entire set of requests and the consequent transportation cost level estimation on the base of some indicators. The framework contains the following two main procedures (see 1 for a detailed description of the general framework):

- Time compatibility and cost estimation: from the scenario characteristics, several indicators can be defined and estimated in order to relate the quality service settings to the difficulty to satisfy the transport requests.
- Demand generation: from the input data (spatial distribution of the customers, quantities to delivery, time constraints of demand, road network characteristics and service characteristics), the scenarios to simulate can be generated.

The framework has to allow testing and changing the established quality settings of a transportation service, in a quick understandable way for both public planners and transport operators.

In the following, we describe first the performance indicators used to evaluate how time windows configurations affect travel time in urban time-constrained freight distribution systems and then the demand generator used to create the scenarios of our simulations.

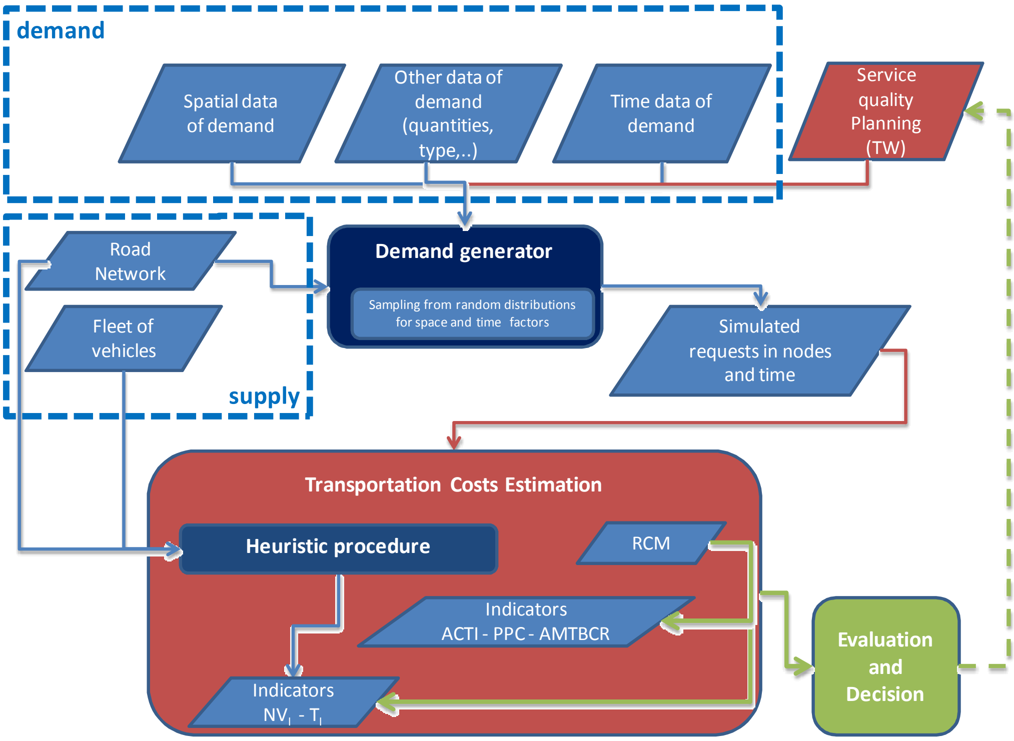

Figure 1. General framework of the evaluation method

3.1 Performance indicators

For the proposed ex-ante evaluation analysis we use the performance indicators proposed by Deflorio et al. (2010). These indicators derive from the concept of Compatibility Time Interval ($CTI_{A/B}$) between two requests, defined as the difference between the earliest delivery time at B of a vehicle serving consecutively A and B, and its latest delivery time. If $CTI_{A/B}$ is positive, then request r_A can precede request r_B directly. The higher the numeric value, the higher the overlapping time interval of the requests and the easier it will be to serve them with the same vehicle. If $CTI_{A/B}$ is negative, request r_A cannot precede request r_B directly. However, this result can have two meanings. If A precedes B, but the vehicle arrives at B before the earliest delivery time (early incompatibility) it is possible to satisfy r_B after r_A in the same vehicle trip, for example delivering to other customers between A and B or making a vehicle stop (slack pause) in order to arrive at B within its TW interval. If B precedes A (late incompatibility) it is not possible to visit A before B in the same vehicle trip.

The compatibility time interval for each pair of requests can be collected into a square matrix of dimension n_R (the total number of requests to be satisfied). This matrix is called Request Compatibility Matrix (RCM). To define this matrix, it has been decided to sort the requests in increasing Earliest Arrival Time, to separate the negative compatibilities with the two different meanings. In this way, the negative compatibilities under the main diagonal identify the late arrival incompatibilities.

From the RCM, several indicators have been defined (Deflorio et al., 2010). We group these indicators into two sets, one containing statistical indicators, which are obtained by statistical calculations applying average operations, and route-based indicators, which are obtained after route construction heuristics. We present below the three chosen statistical indicators, and then we describe briefly the procedure which is used to calculate the two route-based indicators.

The percentage of positive CTIs in the RCM is an easily interpretable indicator. Noted as PPC, it is defined using the following expression:

$$PPC = \frac{number\ of\ positive\ CTI_{A/B}}{number\ of\ elements\ in\ RCM}\ (\%)$$

We can also calculate for each request r_A, the minimum travel time t_{AB}, considering each request r_B compatible with r_A. This value is defined as the Minimum Travel Time between r_A and any compatible request r_B. Then, the average for the overall set of requests is called Average of the Minimum Time Between each request A and any Compatible Request B, and noted AMTBCR.

$$AMTBCR = \frac{\sum_{A} \min_{CTI_{A/B}>0} (t_{AB})}{n_R}$$

Furthermore, we compute another indicator. The overall Average Compatibility Time Interval (ACTI) represents the average value of all the positive CTIs, including those related to the depot. The ACTI indicator can be formulated as follows:

$$ACTI = \frac{\sum_{CTI_{A/B}>0} CTI_{A/B}}{number\ of\ positive\ CTI_{A/B}}$$

The first indicator, PPC, shows the proportion between positive and negative CTI's, the second one, AMTBCR, gives an estimation of the time required to connect two requests in a plan and the third indicator, ACTI, quantifies the average compatibility time intervals between the requests. Two further indicators are also defined: NV_I and T_I. Using the RCM it is possible to apply a partitioning to the set of requests and create a number of subsets which can be served in a feasible sequence. We should recall that here the aim is not to find an optimal solution for the distribution service, but to define a measure for the assessment of the compatibility of different requests, which depends on the demand characteristics also in relation to the road network. We built a greedy algorithm in order to produce such feasible sequences of requests subdivided into different subsets. If each subset in our problem is viewed as a vehicle with a fixed capacity, then each sequence of requests represents a route for the vehicle. From the RCM to each couple A-B we use the values of $CTI_{A/B}$ and assume that request r_B can be satisfied consecutively after r_A if the compatibility time interval $CTI_{A/B}$ is positive, there is not a slack pause between the requests and the vehicle capacity constraints are respected. To generate a realistic configuration for the sub-set of requests, from each request, among all the possible options, we select the next request of the subset according to the best partial solution (minimum route travel time criterion). Finally, the result obtained in this way have been assumed to estimate the further two indicators, namely the number of vehicles (NV_I) and the total transportation time (T_I).

The described indicators have already been tested on the Homberger and Gehring (2005) instances and their performance were promising to describe the difficulty degree of a freight distribution scenario with time windows. However, these standard instances use theoretical transportation times and Euclidean distances. In this work, they have been applied to a realistic road network, where distances could be not Euclidean, but average travel times can be estimated. Also, in the present analysis time windows are uniform within the same experiment, to better explore this factor of the service quality.

3.2 Demand generator

A simulation approach was used to build the demand for the scenarios (Deflorio, 2011). Individual delivery requests have been generated at nodes of the road network at specific times. Each node can be considered as a network node where a vehicle can stop and deliver or pickup the freight. This delivery area can be subdivided into zones, characterized by macro-descriptive variables. These variables are both demographic and socio-economic, and are obtained by statistical data. From these variables, we can estimate the ability to generate or attract freight shipments, defining both generation and attraction indexes.

Using these indexes, and defining the number of requests to generate, the demand can be associated to the physical locations, i.e. the different nodes. To do this, we suppose a uniform distribution of the requests within the same zone.

Then, several attributes can be assigned to each demand. We propose to associate three attributes:

- Time Period Length (TPL): The time period defined by the operating hours of the transportation service.
- Time Period Profile (TPP): The density distribution of requests in a fixed time period.
- Time Window Width (TWW): The time interval which defines each request.

To summarize the demand and scenario generation module, we can define its structure as follows:

1. The geographic and socio-economic data of the study zone has to be entered into the system. In general, these files can be converted into a plain text format in order to simplify their insertion into the system.
2. From the demographic and socio-economic data, the demand is generated in the considered study area.
3. Then, a time window is assigned to each demand request. When assigning a time window to each request, we first define a time period within which all the requests have to be satisfied. Then, the request temporal distribution can be made using different probability laws, in order to represent different TPP cases. Finally, the width of the time windows is defined.

4. Application to a City Logistics case

The proposed method has been applied to a real-life City Logistics case, to examine how the chosen indicators describe the difficulty level to satisfy the requests and the imposed time constraints. Indeed, the performance of a distribution service with time constraints is related to the structure of the demand and its variability in time and space. In this section, we present the main characteristics of the case we will analyse, more precisely the road network, the demand characteristics and the main service features. Moreover, the trip planning tool able to solve routing problems with time windows and used to compare the results of the indicators is also described.

4.1 Road network

The proposed analysis is issued from a case study for parcel distribution in the urban area of Ivrea (Italy). This small urban area is located between the urban areas of Turin (1.500.000 inhabitants) and Aosta (70.000 inhabitants) and presents several particular characteristics. The first is that it presents a big peri-urban and rural ring (the city and the near peripheral surroundings include 55% of the population of the entire urban area). The second is that the city is situated in a mountain context (the Canavese area is an Alpine community where Ivrea is the reference town). The chosen area is located within the Canavese district, in the Northern Piedmont region. This area includes the city of Ivrea and its influence area, which constitutes a urban/rural community of 55.000 inhabitants. Although we can consider this area as a urban community, the peri-urban and rural zones nearby the main town (Ivrea) need to be taken into account, because of the peculiar socio-economic context of the Canavese district (they represent about 45% of the population and more than 80% of Ivrea's urban/rural community overall surface).

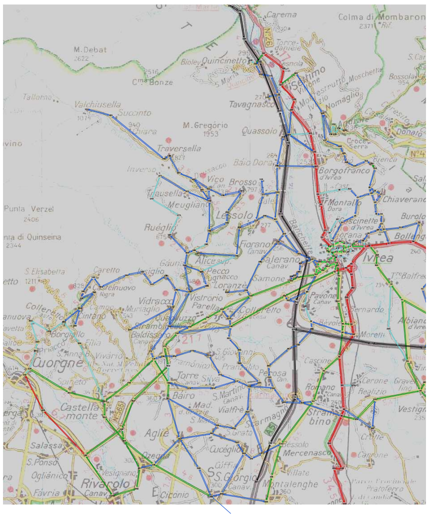

Figure 2. Road network used in experimental analysis

The graph consists of 330 nodes and 836 arcs. For each arc, distances and travel times are provided. Travel time for each arc are assumed to be constant (since congestion phenomena are not relevant here) considering the distance between two nodes and the type of road, which characterises its average speed. The travel times are expressed in hours. Each node represents the location of a potential customer who can make a freight distribution request.

4.2 Demand features

In order to simulate realistic requests we used the demand generator above described. The whole area was subdivided into 9 zones. Attraction and generation indexes used to define the total demand for each zone for the pickup and delivery problem, respectively, have been introduced. Given a demand distribution per zone, it is possible to build up different test cases, where each request is located in a specific node belonging to one of the zones. Each node has the same probability to generate a request as other nodes in the same zone, although any zone can have a different probability according to the attraction and generation indexes.

4.3 Service features

In the organisation of freight distribution services, we observe two conflicting factors: profit and quality of service. In order to increase the profit, the transportation carriers wish to reduce costs, which means increasing service efficiency. However, this can have a negative effect on quality standards and may make it difficult to achieve the level of service expected by the user, who could change provider if the requested quality is not satisfied. The level of service in our study is defined as respect of the Time Window and measured by its width (the shorter waiting period, the higher the quality of the service). Moreover, the number of vehicles is related to the level of service. In general, carriers have a minimum number of vehicles which suppose a fixed cost (even if they are not used) and only the usage of further vehicles will lead to a cost increase. The more complex and restrictive the time windows, the more difficult it becomes to maintain a good level of efficiency.

4.4 The trip planning tool

In order to compare the results of our indicators and assess their validity, a reliable trip planning tool is required to solve routing problems with Time Windows. More precisely, we use the ILOG Dispatcher software (ILOG, 2005), a commercial tool that contains different modules to quickly develop customized trip planning solutions. We built a VRP-TW heuristic procedure, able to solve instances of 200 customers or more with a limited computational effort. More in detail, we implemented a Tabu Search procedure with a composite neighbourhood including 2-OPT (exchange of two arcs between routes), request swap (exchange of two nodes) between routes and request movement to different vehicles. The Tabu Search stops after 5 non-improving iterations (for further details, see ILOG, 2005).

This tool is configured according to the parameters tuning presented in De Backer et al, (1997). This parameter setting, in fact, has been obtained by replicating state-of.-the-art results in standard instance sets, including the well known Salomon instances. In this way we emulate the typical behaviour of a practitioner, who may use commercial software to plan his delivery operations (Hall and Partyka, 2008).

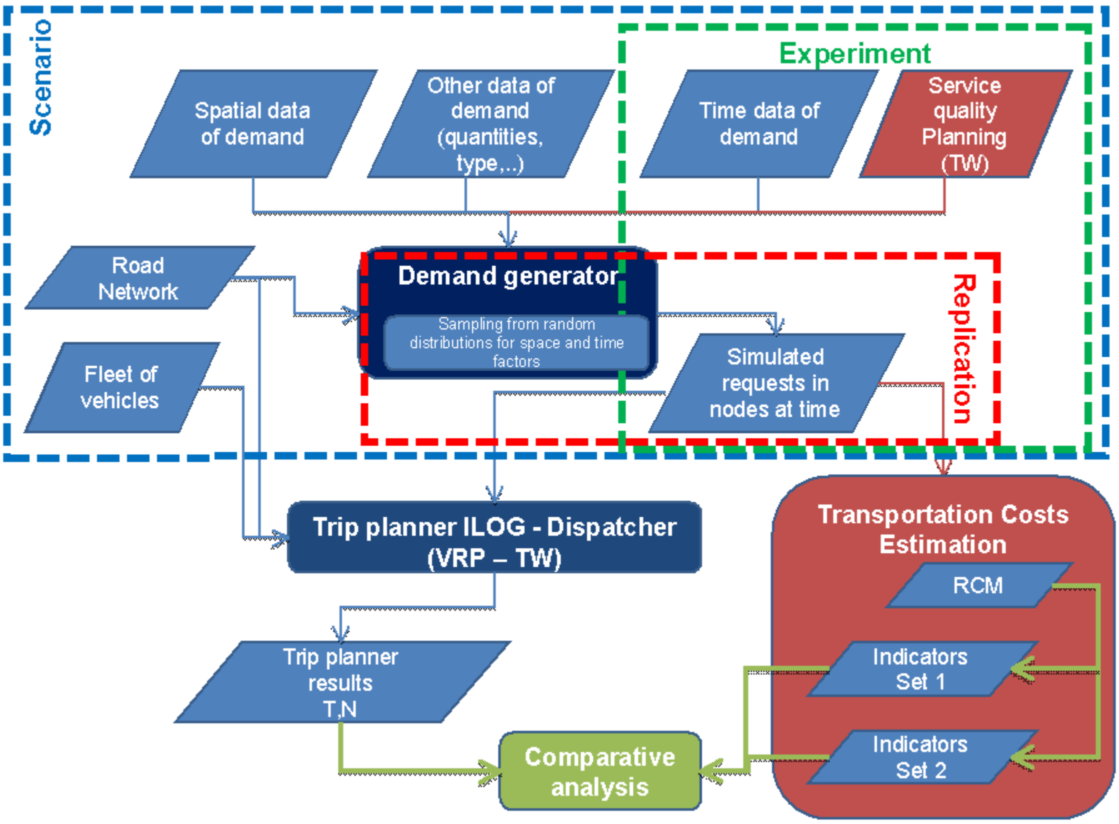

Figure 2. Chart of the comparative analysis

5. Computational results

In this section we present the main computational results of the two sets of experiments in order to test the chosen indicators in real-life scenarios based on data taken from the area of Ivrea (Italy). The analysis considers two axes. First, we analyse the behaviour of the indicators on the

Time Windows Width experiments. Then, we show how they behave in forecasting the total cost of the requests under different Time Period Profiles.

5.1 Methodology for the experimental analysis

To simulate a realistic case of feature setting phase in last-mile transport planning, we suppose a parcel distribution carrier. In this study we consider only one depot, situated at a node in the road network, and a number of available vehicles for the service equal to 30, in order to allow the complete satisfaction of the request for any scenario. In this phase, we assume that all vehicles have the same capacity, expressed in terms of volume (4.5 m^3). Note that for capacity limitations, constraints due to the disposition of the freight inside the vehicles are not taken into account. The time for loading operations at the request location, in the scenarios analysed, has also been taken into account by assuming it equal to 4′ for any request. Different scenarios are created by considering one or more of the following elements:

- Network and demand characteristics: geographical position, road characteristics, urban area characteristics, density of potential requests, request distribution within the period length.
- Service organization and quality characteristics represented by the time windows width.

These settings correspond to several comebacks from the parcel distribution field, most of them collected by survey methods developed to make a detailed description of the urban freight transportation aspects. The analysis will be based on statistics from the main results from simulation. To do this, we propose two sets of experiments:

- Set 1 - Time Window Width (TWW) based instances. The time interval which defines each request (TWW) has a uniform request distribution profile over time. For each value of TWW between 1 and 4 hours, a set of 100 instances have been created.
- Set 2 - Time Period Profile (TPP) based instances. The second type of experiment (TPP) focuses on the time distribution of the requests in a given time period. All the time windows have the same width equal to 1h. We use four realistic time profile distributions of the requests. The time profile "a" simulates the case where a high concentration of requests occurs in the middle of the time period. Time profile "b" represents a demand distribution where a high concentration of requests take place at the beginning of the period, then this concentration gradually decreases. Time profiles "c" and "d" are complementary profiles to "a" and "b", respectively. For each TPP 100 instances with the requests randomly generated are built.

For each experiment, we have replicated 100 tests. To generate them, we have estimated the demand using the travel demand generator, in order to produce a statistical population which can represent several similar but not identical situations. For these replications, we consider a total fixed demand of 200 requests for each experiment. The average demand attraction for each zone is also known. From these parameters, and using the travel demand generator, we obtain 100 random demand extractions. For each extraction, we build a test replication, identifying the corresponding RCM and deriving all the presented indicators. For the same random extraction of requests, using the trip planning tool we obtain the total travel time T and the number of used vehicles N.

For each experiment, we can estimate average values and the statistical dispersions for the proposed indicators and the trip planning results, for a high number of cases, since the main goal is to explore the indicators validity in realistic scenarios.

After testing the given indicators on the proposed scenarios, using the VRPTW heuristic as a tool to study their precision and accuracy, we have selected the most relevant indicators to describe the interaction between the proposed service quality and the related transportation costs for the considered distribution strategy. The transportation cost has been estimated by means of the number of vehicles required to satisfy all the requests and their total travel time along the routes.

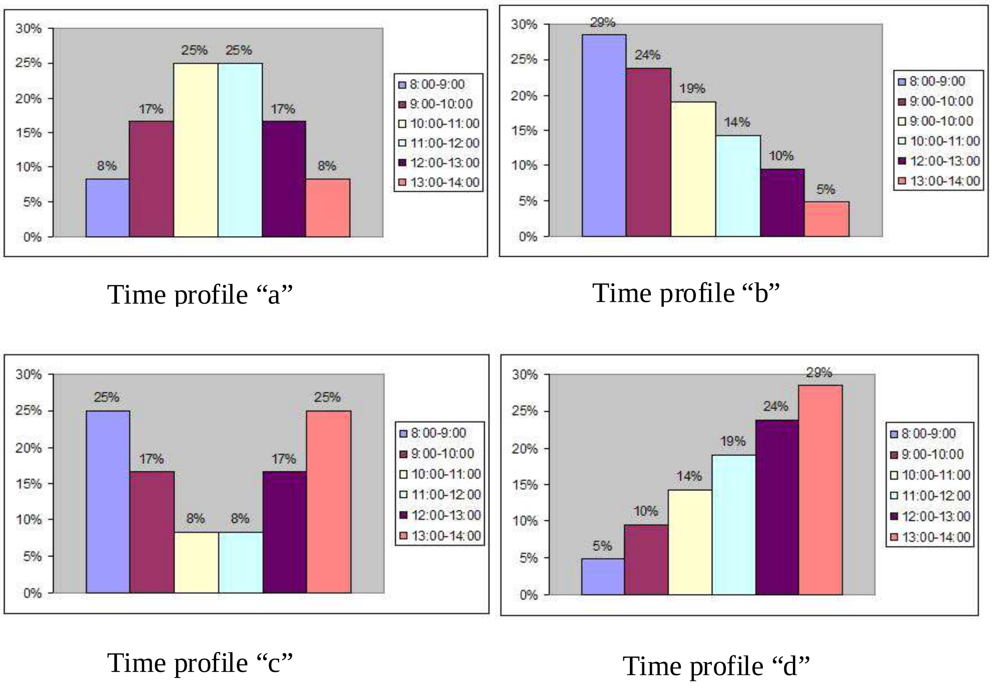

Figure 3. Four realistic cases of time profile

5.2 Time Windows Width analysis

We solved each of the four sets of 100 replications of the TWW experiment type, using the ILOG Dispatcher planning tool (ILOG, 2005). The average values for all the 5 indicators described and the trip planning tool results (in number of vehicles and total travel time, respectively N and T) are reported in the columns of the Table 1 for the 4 experiments. The variation of all average values of indicators is evident over the TWW variation and confirms the expected trends.

Table 1. Average values of the indicators for Set 1

	Indicators					Planning Tool Results	
TWW	ACTI	PPC	AMTBCR	NV_I	T_I	N	T
1h	1888.33	30.94	154.96	40.15	198412	6.22	66554
2h	3871.85	56.07	114.70	18.00	109515	5.70	55822
3h	6038.77	75.47	99.95	8.91	70360	5.32	49381
4h	8446.97	89.27	91.98	6.25	55438	5.25	46248

Moreover, a detailed data analysis of the dispersion of results allows us to distinguish a different behaviour for the 5 indicators represented in 5 graphs, one for each of the selected indicators. Each graph has the total travel cost on Y axis, while the indicator value is reported on X. For each size of TWW, the values of the corresponding instances are reported with a different mark. ACTI and PPC have a similar statistical dispersion, quite low with respect to that one of T. Indeed, if a separation of the 4 data sets is possible, by using the X axis, the same is not possible on the Y axis (total travel time).

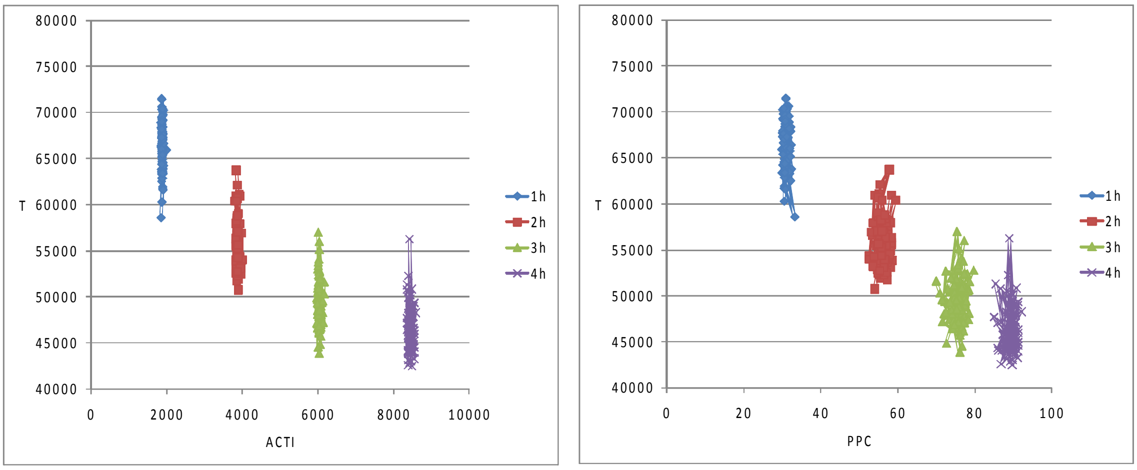

Figure 4. Travel cost (in seconds) related to ACTI and PPC

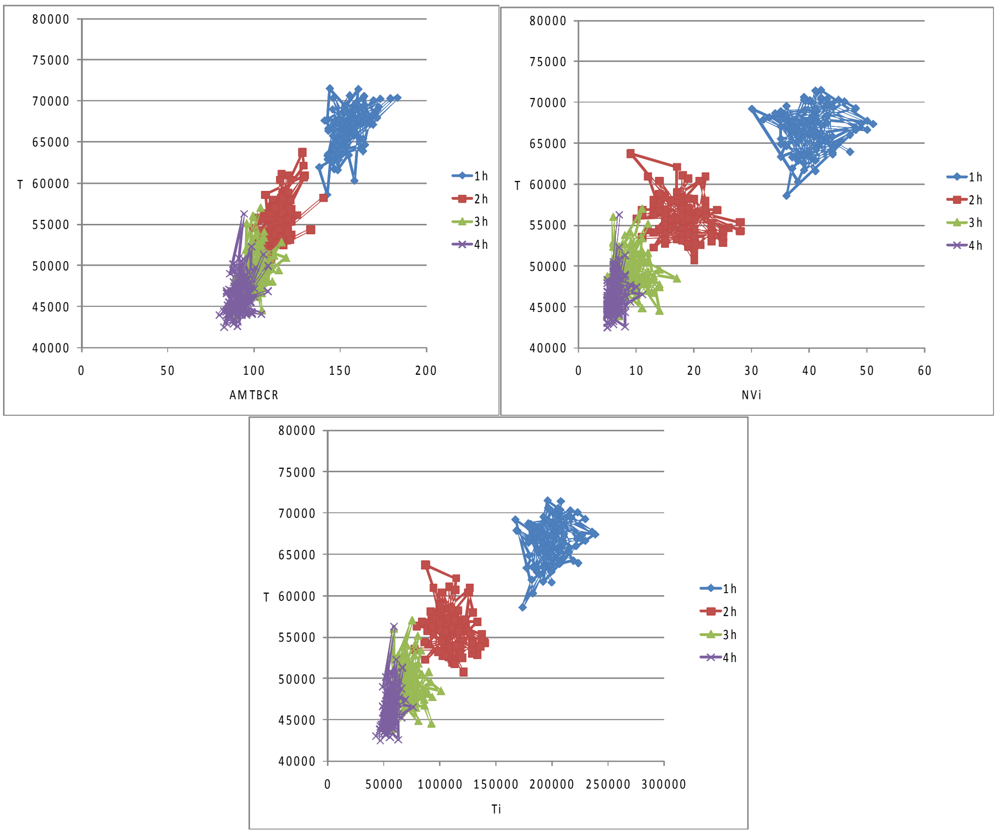

Figure 5. Travel cost (in seconds) related to AMTBCR, NV_I and T_I

On the other hand, AMTBCR, NVI, and T_I have a greater statistical dispersion and describe the same overlapping phenomena observed for T (between the cases 3h and 4h) and a separation of sets for these indicators, as is for T, between the cases 2h and 1h. We can therefore notice how the dispersion of the cost values related to the indicators becomes more and more evident while TWW changes from 1h to 2h. The results also show that AMTBCR, NVI, and TI indicators have a linear-wise increasing trend while the TWW decreases. ACTI and PPC have an opposite trend. Thus, the results confirm the expected behaviour.

5.2 Time Period Profile analysis

We repeated the same simulation method for the four presented time period profiles. In Table 2, we report the average values of the indicators and the planning tool solutions (N, T). The meaning of the columns is the same as in Table 1.

Table 2. Average values of the indicators for Set 2.

	Indicators					Planning Tool Results	
Profile	ACTI	PPC	AMTBCR	NV_I	T_I	N	T
a	1858.41	37.19	149.91	38.21	190768	6.18	65433
b	1904.10	36.57	155,37	38,68	193914	6,28	64955
c	1983.06	31.60	154,65	39,73	195546	6,41	65327
d	1908.69	37.07	144,14	38,31	188625	6,33	64901
u	1888.33	30.94	154.96	40.15	198412	6.22	66554

Each row represents the results obtained with the 4 TPP distributions a, b, c, and d. Row "u" shows the values computed in Set 1, i.e. uniform distribution of TPP and TWW equal to 1h. The transportation cost for all profile cases is in average smaller than the uniform profile case. The tests also confirm the expected behaviour for some indicators. In fact, one can observe that the values of ACTI have, in line with the N results obtained by the planning tool, their minimum value for the case of profile a, followed by the uniform profile "u". Then, similar higher values for the other three profiles are observed. As required, a clear trend can be observed for NV_I and T_I, in line with T results, where for the "u" profile the maximum value has been estimated. For the Set 2 the behaviour of the indicators PPC and AMTBCR is not useful, since its trend is not clear. However, the average values of the indicators are quite similar, as well as the trip planning results, for the non-uniform TPP experiments and not all of the indicators are able to describe this particular feature of the instance.

6. Conclusion

In this paper we presented the application of an evaluation method for freight transportation tactical planning, more precisely for last mile transportation system service configurations. Our method uses several performance indicators, which are based on the definition of Compatibility Time Interval (CTI), and a demand generation model.

The application concerns realistic parcel delivery instances in the influence area of Ivrea (Italy), a particular zone mixing urban and rural spaces with geographical constraints because of the mountain context. We have tested five indicators (ACTI, PPC, AMTBCR, NV_I and T_I) comparing them with the results of a transport planner developed using a commercial tool. We observe that the two first indicators (ACTI and PPC) give macroscopic indications to compare two configurations with different time windows. Moreover, PPC shows the difficulty of distinguishing instances with the same time windows settings, but different random geographical configurations when the time windows width is small, being a first indicator of the difficulty to optimize highly time-constrained instances.

Concerning the other three indicators (AMTBCR, NV_I and T_I), they seem to have more capability to identify the differences of instances with same time windows configuration, so to relate service quality settings (time windows width, distribution period) with the geographic and temporal distribution of requests time windows profile). We also observe that the relation between quality settings and transport cost are not linear, as shown in the case study results. Concerning NV_I and T_I, they represent what a "manual" optimization can lead to, i.e., they are obtained by a "nearest neighbour" procedure that is similar to the behaviour of a driver making a route and going from a customer yet delivered to the further nearest one. Observing these results, we can conclude that more the time windows are wide more it is easy for a driver to optimize his route. However, the results are not linear and some differences are observed between the number of vehicles and the travel time. Indeed, if a carrier wants to increase the customer's availability period (to wait at destination for the delivery) from 1h to 2h, the impact on both travel cost and number of vehicles strongly decreases (as shown in Table 1). The proposed indicators, mainly AMTBCR, clearly describes this trend, and also help to see that the differences between the 2h, 3h and 4h instances are much lower. This behaviour, clearly shown by the AMTBCR, NV_I and T_I, quantifies what already qualitatively observed in practice: highly customized delivery services propose either only last delivery time limits, or time windows of two to four hours (Durand and Vlad, 2011).

The results can be then related to the outcomes of other analyses (Taniguchi et al., 1999; 2001; Quak and De Koster, 2005; Qureshi and Hanaoka, 2006; Zeimpekis et al., 2007) in order to show the application scope and limits of the proposed analysis methodology. These studies show that time windows have an impact on cost, but need to solve the optimization problem. They are then related to the dynamics of freight distribution and aim to understand the links between time windows, travel times (and its dynamics) and route effectuation. They are more addressed to scholars and specialised technical stuff of carriers that can implement and run VRP-TW solution methods and interpret their results. The proposed analysis in this paper is based on predictive indicators, which can be easily interpreted for policy makers and practitioners. They do not need to be compared to a VRP-TW good solution, and are more addressed to managerial and policy-making stakeholders. In any case, the comparison with a VRTP-TW solution shows how each indicator estimates the level cost and the difficulty to reduce costs by using a transport management system or other route optimization software, and help the involved stakeholders to make tactical choices before the route optimization phase of their daily or weekly transport plan configuration.

From a practical point of view, we can identify two main categories of stakeholders interested in the method and results presented in this paper: *transport and logistics operators* and *public authorities*. Considering transport and logistics operators, for small parcel delivery services, a big difference is observed when the service settings change from a 1h TW to a 2h TW. This is confirmed by observing real practices, where many home delivery operators ask for a 2h time customer's availability period for small parcels, and up to 4h for big products like furniture or electronic devices. However, the characteristics of the demand is also related to geographic variables, and the proposed framework can be used by practitioners to identify, for a given demand set, which is the most suitable service quality that the company can offer. This can be expanded by exploring more in-depth the time windows profiles and finding time periods where "personal" time windows, wider or more restricted, can be proposed to the customer. Since access to city centres is often congested during peak-hour periods, some *public authorities* are implementing a time-access regulation. Although this action mainly means adding a time constraints to parcel delivery carriers, the impacts of demand distribution on transport travel time and distance can also be interesting for public authorities. Therefore, the study for simulated scenarios of demand distribution within the allowed access periods, to evaluate how the established access constraint affects the delivery operations, can be carried out by an ex-ante evaluation of measures and policy actions.

Finally, further developments of this research can be discussed. First, a study on the effects of time periods and heterogeneous time windows will give complementary information about how the characteristics of time windows influence delivery costs. A second further research can be focused on experimental analysis in order to explore the behaviour of the evaluation method in predicting cost variations of freight distribution services operating on instances deriving from the fusion of different data sets of requests. This could represent an approximation in a simulated environment of the case where different operators in the same geographical area would share their freight requests in a City Logistics context.

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