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Abstract

This paper introduces a methodology whose aim is to evaluate how the quality of a freight distribution service with time windows, which operates on a given road network to satisfy a number of requests, affects the total cost of the distribution service . The result of a service quality setting, expressed as the width of the time windows, has been assessed using a number of indicators, which are a measure of the service operating costs and based on the request compatibility time interval. Each indicator's performance has been evaluated in an experimental context by using as comparison terms the recent published results of a heuristic algorithm suitable also for the CVRPTW problem . The results enable the selection of the suitable indicators to support the service quality planning decisions.

Keywords

Freight distribution service, time windows, service quality, requests compatibility indicators, experimental analysis.

[*] The main contribution of this author was made during his PhD. course at Politecnico di Torino

Introduction

The freight transportation sector is changing continuously as a consequence of the growth and transformation of the economic activity. In recent years companies have been reducing their storage areas to save resources, but have also sought to offer high quality services to customers in terms of freight availability and the respect of delivery times. In this context, the new advances in 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 pace of life, 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-economics and trip characteristics (Pukkett et al., 2008). The total travel time of a vehicle trip depends on several aspects, like actual travel time, waiting and access time, congestion, deadlines or service features, etc. (Wardman, 1998).

The study reported here relates to time constrained freight distribution planning, like parcel express distribution. In this type of service, one of the customers’ needs is defined by a time interval, known as the *time window* within which the customer wants the freight to be delivered or picked up by the transportation service. The time window’s width can be assumed as a quality factor of the service, since its nature and configuration also affects the total transportation costs (Cordeau et al., 2002).

The aim of this paper is to present a methodology for evaluating how the quality of a freight distribution service with time windows , which operates on a given road network to satisfy a number of requests, affects the total cost of the distribution service, by means of several indicators. The paper is organized as follows. In the first section we report how time windows have been taken into account in existing studies, presenting the related decision and planning problems proposed in the literature. Then, the proposed methodology is described. Before studying the proposed indicators, the general characteristics of the application domain will be described and the instances for testing the indicators are presented. We used then several test scenarios and evaluate the performance of the proposed indicators.

An overview on time constrained freight distribution

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, 2002a). Moreover, it is estimated that distribution costs account for almost half of the total logistics costs (Brewer et al., 2001). In this context, routing and scheduling become major aspects in cost reduction strategies.

The Vehicle Routing Problem (VRP) has become a central problem in the fields of logistics and freight transportation, since in some market sectors, transportation costs constitute a very high percentage of the value added of goods. The utilization of computerized methods for transportation can often result in significant savings, ranging from 5% to 20% of the total costs, as reported in Toth and Vigo (2002a). This problem has been largely studied (Laporte, 1992; Toth and Vigo, 2002b; Cordeau et al., 2007) and several variants have been formulated to represent and optimize different real world distribution cases. One of the best studied is the VRP with Time Windows (VRPTW).

In this problem, time constraints are introduced to represent the importance of the freight arrival in time, which is a common characteristic of applications such as express courier carriers, postal services, newspaper distribution, and e-commerce. 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*). Two types of time window constraints can be defined as follows:

- *Hard time windows*, which are strict constraints where there is no possibility for a vehicle to reach customers if not within the interval defined by the TW. Some variants of the problem offer the possibility for vehicles to have an idle time at destination until the lower time limit is reached.
- *Soft time windows*, which are defined in the objective function, and represented by an increasing cost penalty if the vehicle arrives at the destination outside the time window interval.

A detailed survey of this class of problems has been proposed by Cordeau et al. (2002). Most of these techniques are then oriented to solving these problems through a heuristic approach, since exact solutions are feasible only for limited size problems. These methods, for which Braysy and Gendreau (2005a, 2005b) show the main heuristic techniques in a detailed survey, are usually tested on a group of instances (Solomon, 1987), each of them presents up to 100 freight requests. These requests are grouped into sets following the number of requests and the spatial distribution of the request destinations.

Although frequently the VRP-TW is modeled assuming constant travel times on the network, in some cases, when traffic congestion is relevant, it could be useful to solve the problem assuming variable travel times (Ando and Taniguchi, 2006) .

In time constrained freight distribution, the high number of carriers and the strong competition between different companies make quality and price important aspects. These two factors are usually inversely 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 traveled by the vehicles. These costs are dependent on various factors:

- The road network configuration, which determines the travel time between nodes. This travel time can be translated into costs (working hours, fuel costs, parking fees, etc), and also vehicle emissions that are one of the main causes of air pollution (which also depends on the vehicle characteristics).
- The nature of the demand, expressed in term of quantities, location and delivery (or pickup) time.
- The quality of the service offered, measured as the width of the time windows for delivery (or pickup) time.

To the knowledge of the authors, the existing studies on VRP problems examine both hard and soft time windows which are established a priori and cannot be changed. However, the evaluation of how the service quality in terms of time windows width affects the total cost of the service has not been directly studied.

Methodology

We present here a methodology for evaluating in an initial stage of planning operation, the effectiveness of a time window configuration for a given service quality in relation to a set of freight distribution requests located in specific nodes of the road network .

General definitions

Consider a service which involves a number of freight requests within a given geographical area using a fleet of vehicles travelling on the road network where travel time for each arc is assumed to be constant. Each request R is characterized by a geographical location in a node of the network, the quantity of freight to be delivered and the time interval within which the freight must be delivered, which is defined by an Early Arrival Time (EAT_R), and a Late Arrival Time (LAT_R). The fleet is homogeneous and consists of NV_{TOT} vehicles with an individual capacity equal to K. To satisfy a request the service must deliver the freight satisfying the time constraints. The various requests should be combined by the service provider in order to produce feasible routes for the vehicles available. The result of this planning activity or, in other words, how the requests are combined, depends on the level of compatibility of the requests (which is related to the demand configuration, time windows, network and vehicle characteristics).

To evaluate it, a concept of request compatibility has been proposed by Fischetti et al. (2001). The authors define the compatibility flag of a pair of requests R_i and R_j as a binary attribute whose value is equal to 1 if a feasible circuit that visits the destination point of request R_i before serving request R_j exits; otherwise the flag is equal to 0. Using this attribute we can determine whether request R_i can be served before request R_j with the same vehicle, consecutively or not. However, we cannot use it to compare the compatible cases, in order to establish priorities, or determine how flexible is this compatibility or incompatibility. Therefore, we present the concept of compatibility time interval between two requests, which is defined as follows.

Consider two requests R_A and R_B, each of them defined by their location, respectively A and B, the quantity of freight that must be delivered, respectively d_A and d_B, and the time window, defined by EAT (respectively EAT_A and EAT_B) and LAT time (respectively LAT_A and LAT_B). The distance (expressed as a time measure) between A and B on the road network is noted as t_{AB}. It is also possible to model the time taken for loading and unloading operations at the request location, which can be written respectively as t_A and t_B. The pair of customers A-B

is assumed compatible if a vehicle serving both requests R_A and R_B can visit B after delivering or picking up the freight at A without a slack period and without visiting other customers between A and B, respecting the time constraints defined by the time windows.

Let us suppose that we want to serve A and B consecutively and we want to calculate the earliest arrival time from A to satisfy this condition. The vehicle will arrive at A at least at EAT_A and will not leave A before $EAT_A + t_A$. To ensure request B is satisfied, the vehicle must not arrive at B before EAT_B. The time between arrival at A the arrival at B is therefore $t_A + t_{AB}$. The early arrival time at A of a vehicle serving A and B consecutively can be written in the following way (see Fig. 1):

$$EAT_{A/B} = \max \{EAT_A , EAT_B - (t_A + t_{AB})\}$$

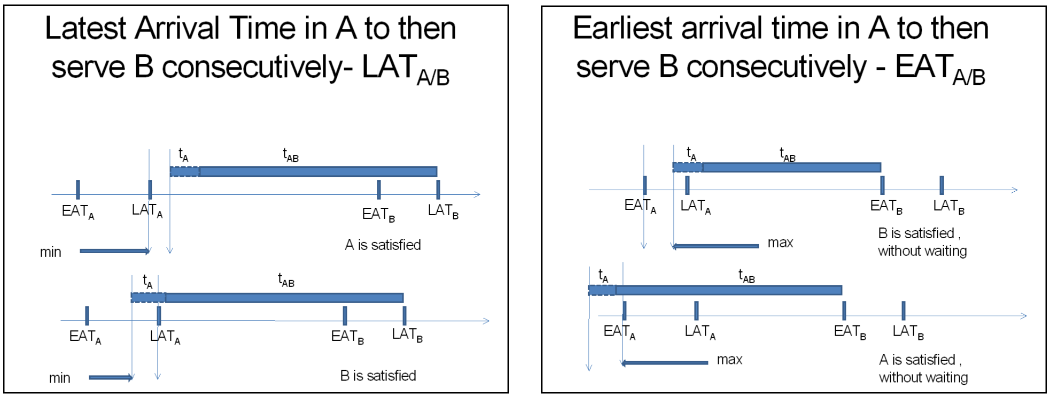


Fig. 1 - Earliest and latest departure time from A to satisfy consecutively requests A and B

In the same case, the vehicle cannot arrive at A after LAT_A and must arrive at B before LAT_B, considering the travel time t_{AB} and the time for loading and unloading operations at A, t_A. The latest arrival time at A which will consent a vehicle to serve consecutively A and B will be as follows (see Fig. 1):

$$LAT_{A/B} = \min \{LAT_A, LAT_B - (t_A + t_{AB})\}$$

The *compatibility time interval* (*CTI*) of the pair of requests *A-B* is therefore defined as the interval between the earliest arrival time and the latest arrival time at A with a vehicle that needs to deliver to A and B consecutively, i.e. $LAT_{A/B}$ - $EAT_{A/B}$. We can write this in the following form:

$$CTI_{A/B} = \min \{LAT_A, LAT_B - (t_A + t_{AB})\} - \max \{EAT_A , EAT_B - (t_A + t_{AB})\}$$

This value defines the time interval which contains a possible actual arrival time at A if the subsequent request along the route is B. The term $CTI_{A/B}$ can be positive or negative. 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 (Fig. 2):

- early arrival at B: A precedes B with a time interval which is bigger than t_{AB}, i.e. $LAT_A < EAT_B - (t_A+t_{AB})$;
- late arrival at B: B precedes A, so it is impossible to carry out the sequence AB in the indicated order, i.e. $EAT_B - (t_A+t_{AB}) < EAT_A$.

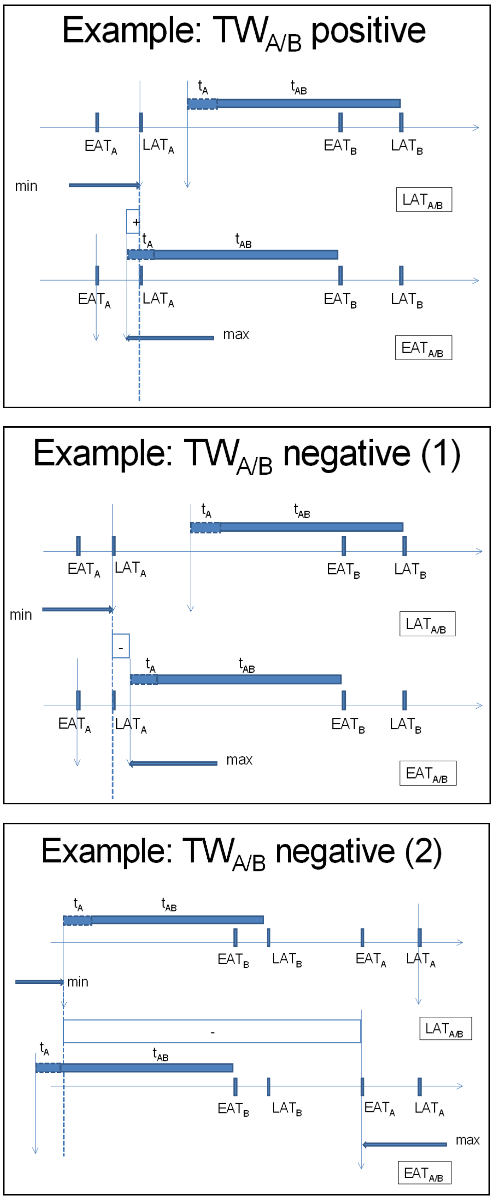


Fig. 2 - Examples of positive and negative pair compatibility time interval cases

In the first case, it is however possible to deliver *A* and *B*'s requests 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 LAT_B . This possibility is quantified by the value of $CTI_{A/B}$: if this value is high, it will be more difficult to serve *A* and *B* using the same vehicle. In the second case, it is not possible to serve *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 order the requests in increasing Earliest Arrival Time, to separate the negative compatibilities with the two different meanings. In this way, the negative compatibilities in the upper diagonal will indicate the early arrival incompatibilities. The negative elements under the main diagonal identify the late arrival incompatibilities.

The *RCM* contains a first relationship between the geographical and service characteristics of the network (links between nodes, maximum high speed allowed, trip times, etc.) and the nature of the demand (*RCM* is affected by node location of requests and time constraints).

Set of indicators

To give a synthetic evaluation of the problem, we need to extract information from the data in the *RCM*. The matrix refers to each pair of requests, but does not give explicit information about the service compatibility (which are the potential requests that can be inserted in the same vehicle trip). From the *RCM*, we can obtain the number of positive $CTI_{A/B}$, which are represented as n_S^+, the number of early negative $CTI_{A/B,}$ noted n_S^{a-}, and the number of late negative $CTI_{A/B}$, which we will call n_S^{r-}. We can therefore define the following simple indicators which express a priori the difficulty of a set of requests for a given network.

ACTI is the Average Compatibility Time Interval of requests, which represents the average value of all the positive pair compatibilities and it contains also *CTI* from and to the depot:

$$ACTI = \frac{\sum_{CTI_{A/B}>0} CTI_{A/B}}{n_S^+}$$

PPC is the percentage of positive compatibilities in *RCM*:

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

For each request R_A, the minimum travel time t_{AB} is calculated 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, and noted $MT_{comp}(A)$. Then, the average MT_{comp} 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*.

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

The first indicator *ACTI* quantifies the average compatibility time intervals between the requests, the second one *PPC* shows the proportion between positive and negative compatibilities and the third indicator (*AMTBCR*) gives an estimation of the time required to connect two requests in a plan . Note that these indicators based on the compatibility are calculated for pairs of requests, so they give an initial idea of how the request configuration fits on the network features. The indicators do not however represent well the entire system complexity and the influence of vehicle capacity .

Therefore in order to extract from the *RCM* information which was more suitable for our problem, we defined two further indicators (NV_I and T_I). These aggregate the information on pair compatibility time interval contained in *RCM*, for a sequence of requests. This makes it possible to extend the request compatibility time interval concept to the whole vehicle trip on the road network. In order to build up these indicators based on vehicle trips, we present a constructive heuristic which allows us to obtain a first estimation of the travel times and the number of vehicles in a simple and fast way.

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 grouped in 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.

In the *RCM* to each couple *A-B* we associate $CTI_{A/B}$. Consider a request R_A and a request R_B. Request R_B can be satisfied consecutively after $\mathrm{R_A}$ if:

- the compatibility time interval $CTI_{A/B}$ is positive;
- there is not a slack pause between the requests;
- the vehicle capacity constraints are satisfied.

The partitioning procedure works as follows: in a first step, we initialize all the routes (i.e. we suppose all the vehicles are empty). We take an empty vehicle starting from the depot, we evaluate all the requests that have not been already served, and add to the route the request R_i with the lowest transportation time from the depot. Then from this request we evaluate each request R_j with a compatibility time interval $CTI_{A/B} > 0$. The request that satisfies this condition with the lowest transportation time from *i* is added to the route.

We repeat this step until there is no request with positive compatibility (with respect to the last request of the route) or if we cannot add a request without violating the capacity constraint. In these cases, the vehicle returns to the depot (to close the circuit and the sequence) and we take another vehicle (creating another set), then the process is repeated.

To generate a realistic configuration for the set of requests at each step we use an approach which chooses the best partial solution (following the criterion of minimum route travel time) among all the candidates that assure the feasibility. However, the result obtained in this way will not be used as the solution of the optimization problem, but as a rapid procedure to estimate the further two indicators, that is the number of vehicles to use and the total transportation time.

The algorithm, implemented using Microsoft Excel and Visual Basic , stops when all requests are assigned to a vehicle, that is when each request belongs to a set. With this procedure the time when each request is satisfied is also computed. Therefore, after obtaining each vehicle trip sequence, the corresponding transportation time is known.

The following definitions have therefore been adopted for the two indicators:

- T_i: the total transportation time as the sum of the time taken for each route;

- NV_i: the number of vehicles that are not empty, i.e. the number of sets created.

In this analysis, no attempt is made to integrate the two indicators, because the impact of these two factors on the total cost depends on the policy of the distribution service company. We will therefore try to analyze these two indicators separately in order to propose a general view of the problem, without referring to specific company objectives or preferences.

Analysis of the indicators' performance

In the organization of freight distribution services, we observe two opposing factors. In order to increase profits, 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 for the time window and measured by its width (the shorter waiting period, the higher the quality of the service). The more complex and restrictive the time windows, the more difficult it becomes to maintain a good level of efficiency.

The time for loading or unloading operations at the request location, in the scenarios analyzed, has been taken into account according to the instance data.

Experimental procedure

In order to evaluate the indicators' performance, a reference VRPTW optimization tool is needed. We chose one of the last developed metaheuristics, the ALNS algorithm of Pissinger and Ropke (2007). The authors propose a general heuristic for different VRP variants based on an adaptive large neighborhood search (ALNS) framework. This method is an extension of the large neighborhood search framework of Shaw (1998) combined with a layer that adaptively chooses among a number of insertion and removal heuristics to intensify and diversify the search. This algorithm, which is robust, provides solutions of very high quality. Moreover, it can be applied to many vehicle routing variants (the algorithm improved 183 best known solutions out of 486 benchmark tests, corresponding to 5 different vehicle routing optimization variants). The best results were obtained for the VRPTW, where the best solutions for 122 out of the 300 large scale instances were improved. For the requests' configurations

, we referred to the CVRPTW benchmark problems of Homberger and Gehring (2005) , obtained by extending the well-known benchmark problems of Salomon (1985) for large networks from 200 to 1000 customers (Homberger and Gehring, 2005).

This test cases can be grouped into 2 different type of scenarios with regards to the time horizon used (short= type 1 and large= type 2). Each set of instances can be divided into three sub sets (R, C, RC) on the base of the nature of the random generation of the requests at nodes of the network. In problems belonging to the C group, the customers are clustered geographically or based on their time windows. In the R group the customers are uniformly distributed, and the RC group combines clustered and randomly distributed customers. Each subset contains 10 instances with various time windows, spatial and temporal distribution of customers.

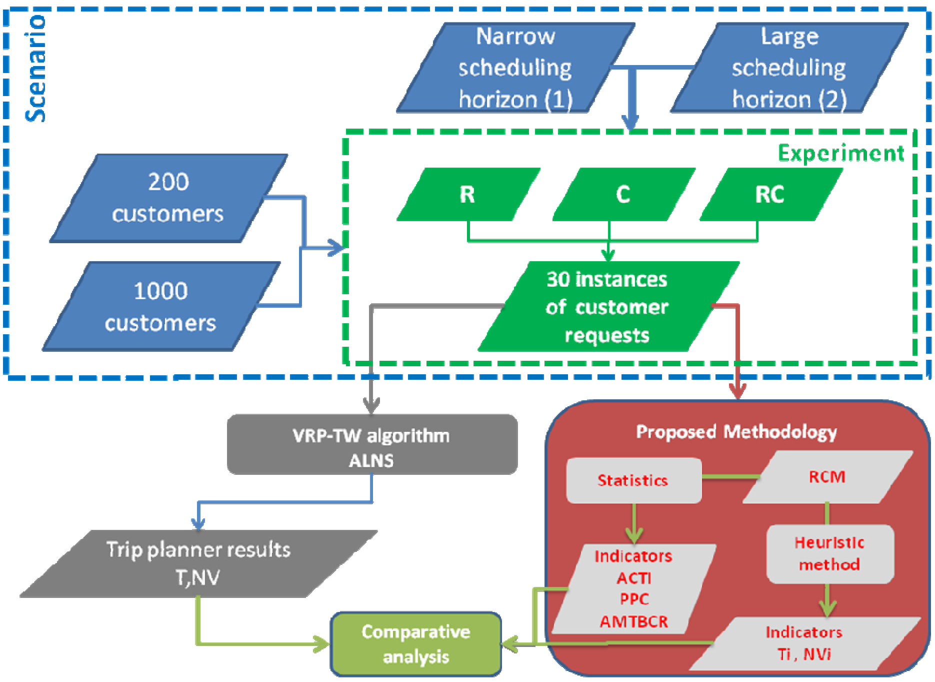


Fig. 3 - A schematic representation of the experimental procedure

Travel times separating two customers corresponds to their relative Euclidean distance. We carried out the analysis for the cases of 1000 customers, after a preliminary test with the instances composed by 200 customers. The fleet size, vehicle capacity and customer service times of the instances chosen for our experiments are reported in table 1.

Tab. 1 – Characteristics of the tested instances

Customers	Scheduling Time	Density	Fleet Size	Vehicle Capacity	Service Time
200	1	R	50	200	10
200	1	C	50	200	90
200	1	RC	50	200	10
200	2	R	50	1000	10
200	2	C	50	700	90
200	2	RC	50	1000	10
1000	1	R	250	200	10
1000	1	C	250	200	90
1000	1	RC	250	200	10
1000	2	R	250	1000	10
1000	2	C	250	700	90
1000	2	RC	250	1000	10

The objective of this experimental phase is to determine which indicators better define the difficult degree of an instance and its consequence on the service cost variations, in order to evaluate a priori, without the need to solve a CVRPTW problem, the demand characteristics related to the service supplied and network configuration.

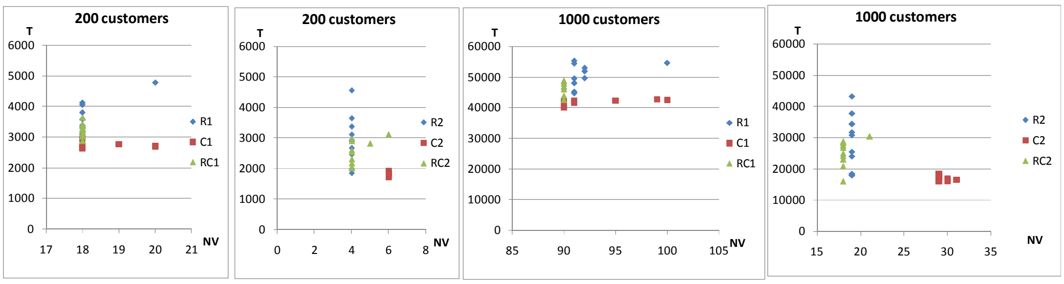


Fig. 4 – Trip planning results (ALNS) for the four scenarios selected and the R,C and RC cases.

Therefore we used the ALNS results to have a reliable estimation of the service cost with which confirm the ability of our indicators to predict the level of difficulty in solving an instance. The comparison has been made by calculating the correlation coefficient ρ (also known as the Pearson coefficient), which shows if there is a linear correlation[1] between the two sets of data. As known, the correlation is 1 in the case of an increasing linear relationship, −1 in the case of a

[1] Other correlation types can be also detected, but for our purpose of identifying a significant trend for such indicators, a linear correlation analysis is considered adequate.

decreasing linear relationship, and these values have been assumed as target depending on meaning of the specific indicator.

Indicator’s performance

Instances with 200 customers

For the first selection of the best indicators, performed with the 200 customer’s cases, as comparison measure for the difficulty of an instance we used the total travel time (*T*). Therefore to work with homogeneous results, we selected the high frequency cases with the same number of vehicles (*NV*): respectively 24 cases with 18 vehicles, for the narrow scheduling horizon scenarios (R1, C1, RC1) and 18 cases with 4 vehicles for R2, C2, RC2.

Tab. 2 – Results for the narrow scheduling horizon scenarios

ID	ACTI	PPC	AMTBCR	Nvi	Ti	ATW	NV	T
C1_2_10	270,8	78,5	2,6	21	3516,8	479,7	18	2644,3
C1_2_2	187,6	47,5	3,5	27	5595,3	347,3	18	2943,8
C1_2_3	389,6	74,5	3,0	26	4517,1	633,1	18	2710,2
C1_2_4	666,7	91,1	2,9	22	3935,5	919,1	18	2644,9
C1_2_9	192,3	61,7	2,7	20	3309,8	360,0	18	2687,8
R1_2_10	66,3	43,5	7,8	22	4519,0	124,5	18	3312,4
R1_2_2	81,9	42,1	8,8	49	8944,1	150,2	18	4059,6
R1_2_3	181,0	70,0	6,2	33	6241,8	290,0	18	3387,6
R1_2_4	314,8	88,7	5,7	21	3986,4	431,0	18	3086,1
R1_2_5	16,7	11,3	14,9	31	7445,4	30,0	18	4125,2
R1_2_6	90,1	46,6	7,6	26	6241,0	165,2	18	3586,8
R1_2_7	186,4	72,9	5,7	26	5158,1	300,0	18	3160,4
R1_2_8	316,8	90,2	5,3	19	3650,5	436,0	18	2971,7
R1_2_9	31,6	21,5	11,0	27	5930,7	60,1	18	3802,6
RC1_2_1	16,3	13,5	10,8	30	6134,5	30,0	18	3647,6
RC1_2_10	80,0	61,5	6,0	20	4002,8	150,0	18	3020,2
RC1_2_2	88,4	47,4	6,0	25	5120,6	165,1	18	3269,9
RC1_2_3	186,3	73,4	5,3	24	4169,4	300,7	18	3034,5
RC1_2_4	315,6	90,6	4,9	19	3409,1	436,1	18	2869,7
RC1_2_5	35,0	27,8	8,7	25	4952,8	64,7	18	3430,0
RC1_2_6	31,8	25,6	8,4	25	4995,9	60,0	18	3357,9
RC1_2_7	48,2	38,7	7,7	22	4365,1	91,4	18	3233,3
RC1_2_8	63,3	49,6	6,5	21	4161,5	119,2	18	3110,5
RC1_2_9	62,9	50,1	6,4	21	4143,5	120,0	18	3114,0
ρ	-0,680	**-0,755**	**0,919**	0,702	**0,869**	**-0,728**		
target	-1	**-1**	**1**	1	**1**	**-1**		

Tab. 3 – Results for the large scheduling horizon scenarios

ID	ACTI	PPC	AMTBCR	Nvi	Ti	ATW	NV	T
R2_2_1	65,8	11,7	14,8	14	6410,0	121,2	4	4563,6
R2_2_10	258,0	41,9	7,9	5	2921,3	476,5	4	2666,1
R2_2_2	397,2	50,7	7,5	12	4876,8	708,7	4	3650,5
R2_2_3	847,5	78,2	5,9	9	3672,9	1296,3	4	2892,1
R2_2_4	1469,1	94,6	5,3	5	2272,6	1883,1	4	1981,3
R2_2_5	126,8	22,5	11,0	7	4552,4	240,0	4	3377,2
R2_2_6	453,5	57,0	7,0	6	3705,4	799,2	4	2929,7
R2_2_7	899,9	81,0	5,8	7	2906,1	1357,3	4	2456,7
R2_2_8	1507,8	95,4	5,3	5	2236,8	1914,1	4	1849,9
R2_2_9	199,0	33,3	8,9	8	3932,4	373,1	4	3113,7
RC2_2_10	381,8	62,5	6,1	5	2708,7	600,0	4	2015,6
RC2_2_3	836,6	79,2	5,5	8	2831,2	1296,3	4	2613,1
RC2_2_4	1466,4	95,0	4,8	5	2140,0	1884,6	4	2052,7
RC2_2_5	157,9	36,5	7,8	10	3472,8	279,1	4	2912,1
RC2_2_6	127,9	31,9	8,2	7	3436,7	240,0	4	2975,1
RC2_2_7	205,3	44,6	7,0	6	2962,1	369,8	4	2539,9
RC2_2_8	286,8	54,3	6,5	4	2808,6	485,4	4	2314,6
RC2_2_9	284,7	55,2	6,4	5	2745,3	480,0	4	2176,0
ρ	**-0,595**	**-0,750**	**0,871**	**0,869**	**0,979**	**-0,588**		
target	**-1**	**-1**	**1**	**1**	**1**	**-1**		

To give a measure of the quality degree offered by a transportation service on a given an instance, we assume the Average value of the Time Windows (ATW) for all the customers (excluding the depot) and to better evaluate if the proposed indicators help the evaluation of service cost variation, we compare their correlation coefficients with those calculated with respect to *ATW*. Observing the values of ρ for both tables we deduce that Ti and *AMTBCR* are the indicators that better describe the variations of travel time among instances for these cases. The tables also show that *PPC* and NV_I give a good result, better than *ACTI*, which however is correlated to the travel time.

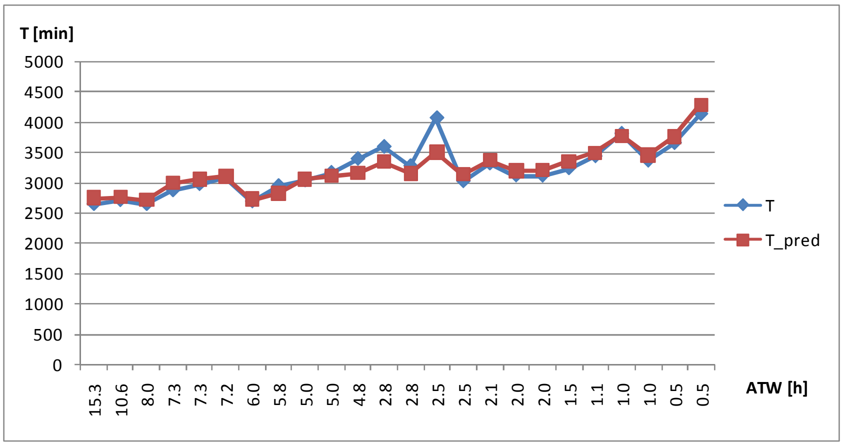
The tables show that the simple measure adopted for the instance quality (*ATW*) is also well correlated with the service cost (expressed here as total travel time), particularly for the cases with narrow scheduling time. Therefore we assume that the reproducibility of the cost variations by means of an indicator has a valid significance if its correlation coefficient is closer to the target value than the *ATW* value (these values are indicated in bold in the tables).

The linear regression model for the estimation of the total travel time for this 200-customer problem on the base of the best simple indicator (*AMTBCR*) can be then calibrated for the two cases (narrow and large scheduling time) as follows:

$T\_pred = 2371.1 + 128.31 * AMTBCR \qquad (R^2 = 0.8454)$

$T\_pred = 930.42 + 245.64 * AMTBCR \qquad (R^2 = 0.7594)$

The results of the application of these models can be observed in diagrams in fig. 8, where instances are ordered for decreasing ATW.



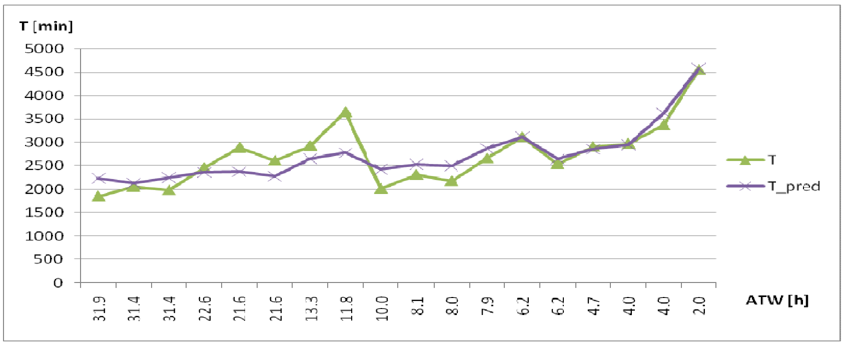


Fig. 5– Comparison between the total travel time by planning (ALNS) and the predicted values for the 2 cases

The 2 diagrams show that the minimum value of T is different for the 2 cases; the one related to type-2 instances, could also be estimated by a VRP algorithm, since when the width of the time windows is so large, it has a limited effect on the trip planning result.

After the selection of the best indicators (Ti, AMTBCR and PPC), we repeat this analysis for all the 30 instances of the two groups, considering also the disaggregation for the 3 types of customers densities (C, R and RC) and observe that a good linear regression can be found, even if the contribution of type- C instances decreases the correlation coefficient in type 1 case. A different behavior can be observed for the indicator PPC, because its trends are related to the type of density (R, C and RC) with a good correlation in general, but here a global trend has less significance. For both types, the slope of the lines is similar, where the RC case is between C and R.

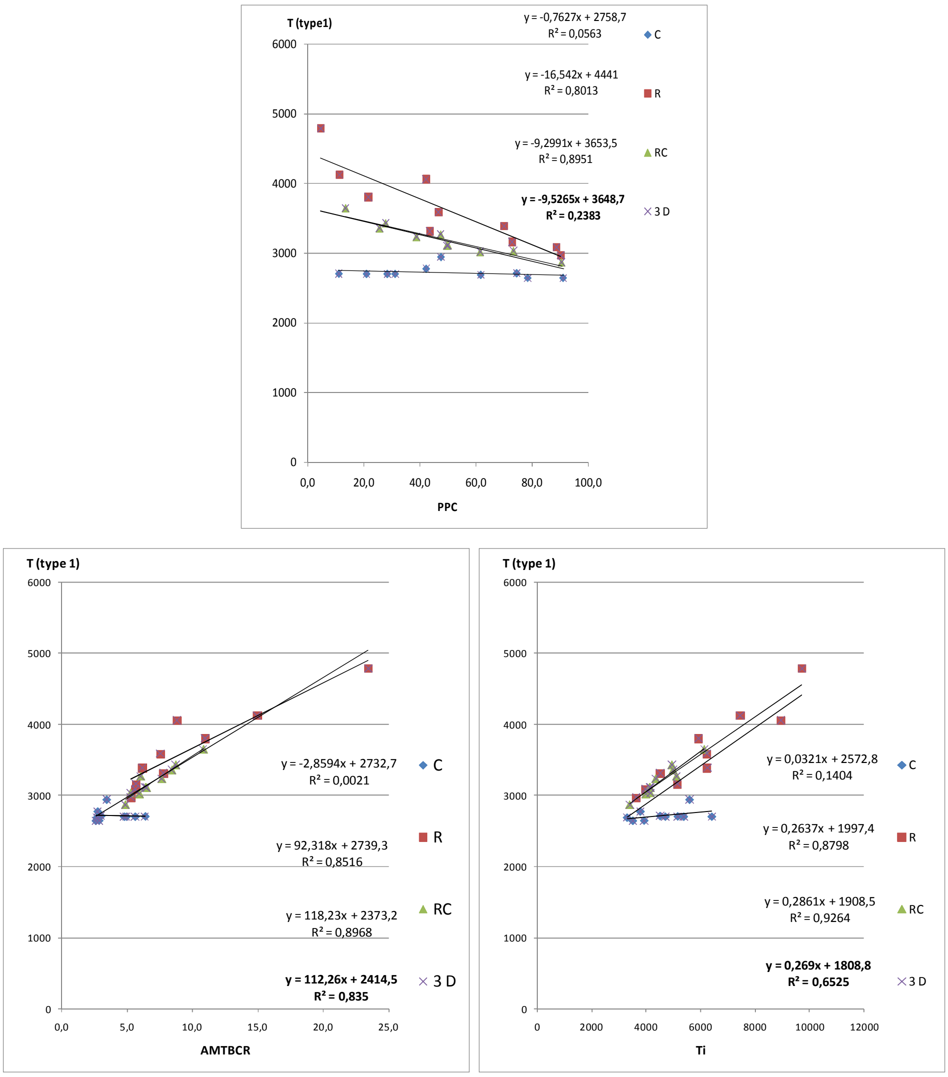


Fig. 6 – Linear regression for total travel time with *PPC*, *AMTBCR* and T_I for type 1

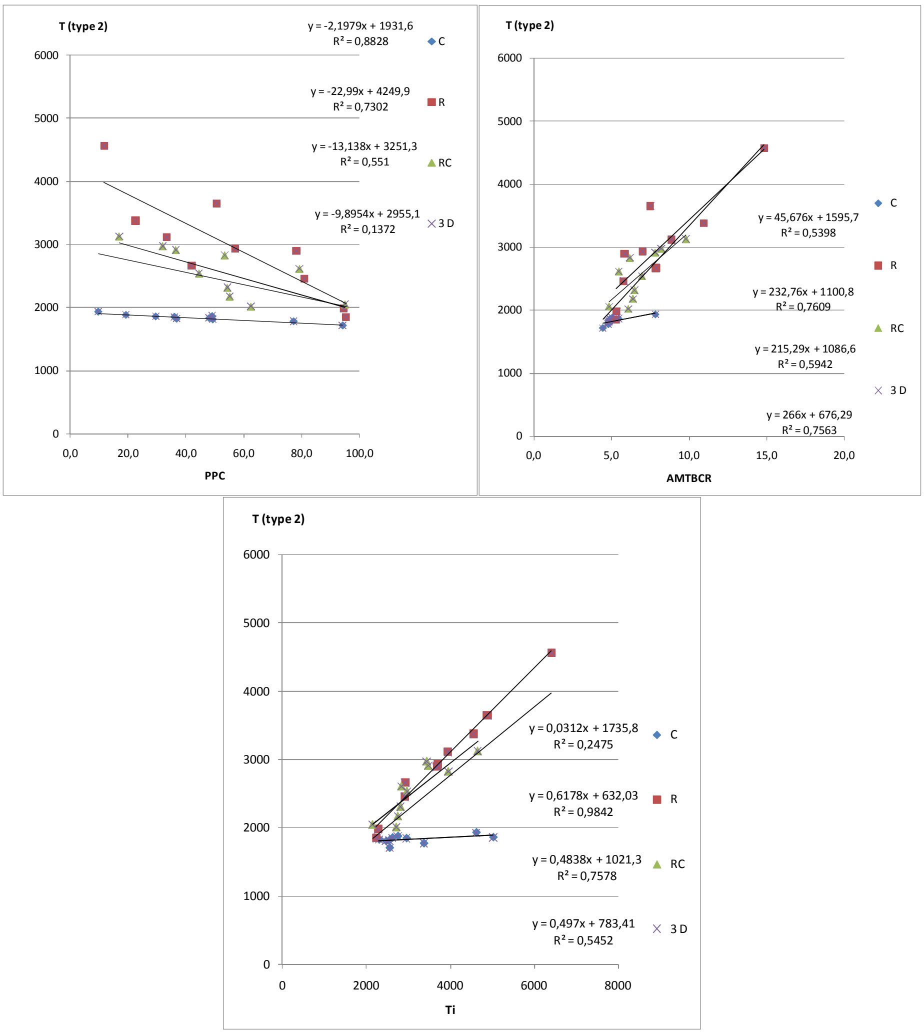


Fig. 7 – Linear regression for total travel time with *PPC*, AMTBCR and T_I for type 2

Instances with 1000 customers

For the 1000-customer problems the ALNS solutions are more heterogeneous with respect to the number of vehicles and the most frequent case (13 times) activates 90 vehicles (Tab. 4)

Tab. 4 – Number of vehicles for ALNS solutions (1000 customers)

Conteggio di NV	type		
NV	1	2	Totale complessivo
18		9	9
19		10	10
21		1	1
29		4	4
30		5	5
31		1	1
90	13		13
91	8		8
92	3		3
95	1		1
99	1		1
100	4		4
Totale complessivo	30	30	60

Therefore to include as more cases as possible we decided to investigate the indicator's behavior considering the instances with a similar number of vehicles *NV* (from 90 to 92 for type 1 and from 18 to 21 for type 2) and to continue in assuming the total travel time as comparison measure of the difficulty degree.

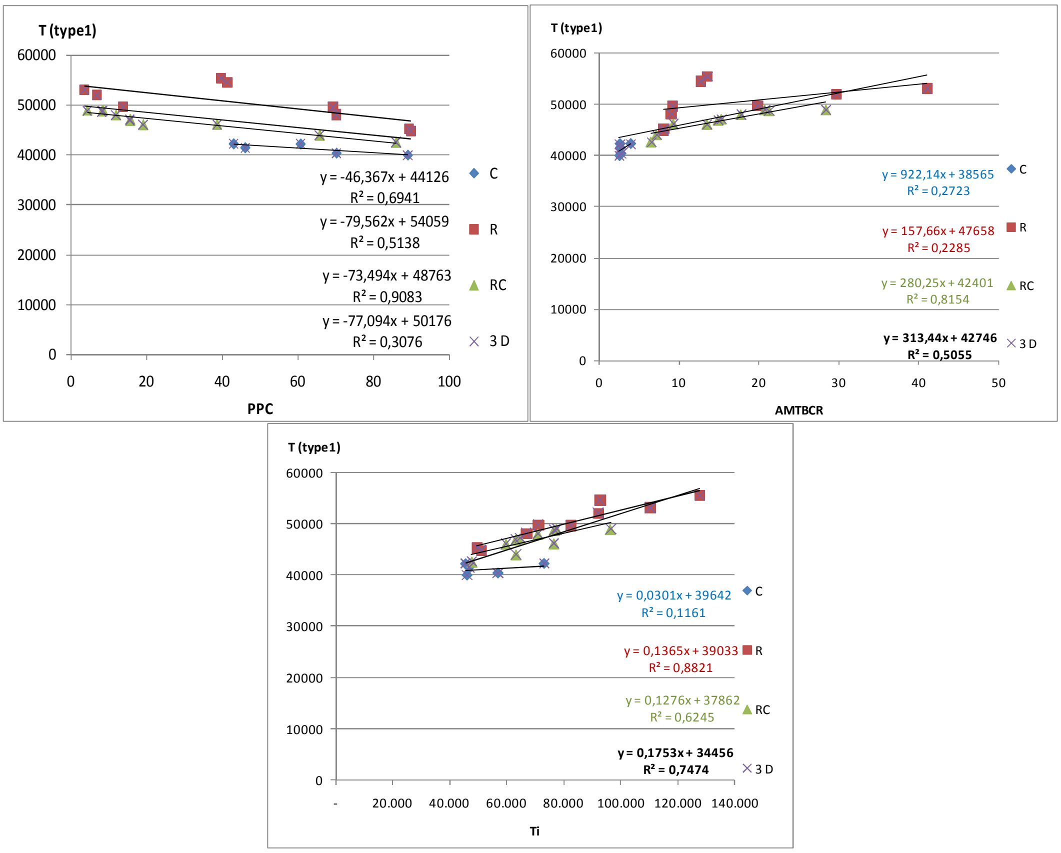


Fig. 8 – Linear regression for total travel time with *PPC*, *AMTBCR* and T_I for type 1

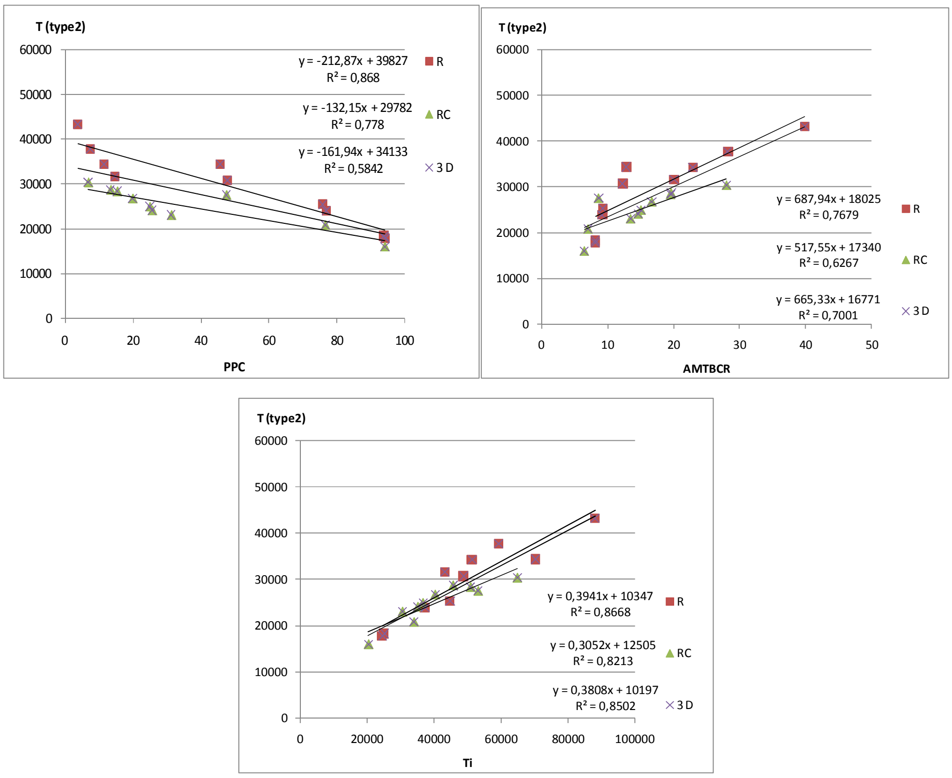


Fig. 9 – Linear regression for total travel time with *PPC*, *AMTBCR* and T_I for type 2

Observing these last diagrams the following points can be outlined:

- instances C are very few cases in type 1 and are completely excluded for type 2 in the analysis because the *NV* is not homogeneous and this is due to the lower vehicle capacity adopted for these cases (700);
- PPC confirms its ability in describing well the difficulty degree, while separating the different densities (R, C and RC);
- AMTBCR describes quite well the RC cases and is useful to represent a density-independent behavior (case 3D);
- Ti better describes R type customer density and confirm its best performance for type 2 horizon scheduling cases.

As for the 200 customers case, in order to verify the errors of a possible linear model with regards *AMTBCR* also for the 1000-cutomers case, we report the diagram in Fig. 10 where the selected instances are ordered for decreasing ATW.

$T\_pred = 42746 + 313{,}44 * AMTBCR \qquad (R^2 = 0{,}5055)\ (type\ 1)$

$T\_pred = 16771 + 665{,}33 * AMTBCR \qquad (R^2 = 0{,}7001)\ (type\ 2)$

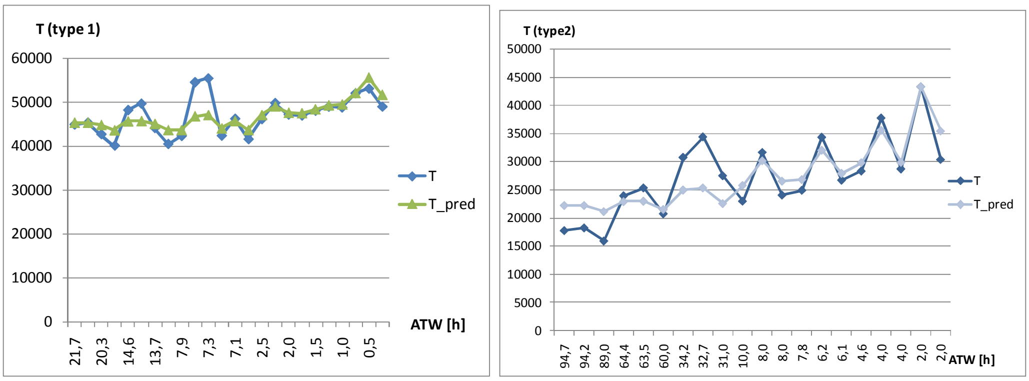


Fig. 10 - Comparison between the total travel time by planning (ALNS) and the predicted values for the 2 cases (1000 customers)

These diagrams show that only few cases do not fit with the model which, therefore, presents in general an acceptable behavior. Finally we remark that instances do not have only time-windows variations but are affected also by other factors (service time, space and time density of requests) and in some cases also they include a vehicle-capacity variation, since they are not specifically generated for this purpose.

However these instances allow a reliable test of indicator performance, for the stability of their results, and a guided selection for practical applications.

We would like also to remark that indicators can be computed very quickly and are defined without the need to set any parameters or calibrate them, since they should be "impartial" measurements and standard references to classifie scenarios that improve the simple information contained in time windows width. On the contrary, any trip planning solution derives from the choice of parameters in the objective function (e.g. the value to weight the waiting time or the vehicle-activation cost).

Conclusions

This study has examined freight distribution planning for services in which the time factor is an important feature of the service quality. In this type of service, one of the customers' needs is defined by a time interval, known as the *time window*, in which the customer wants the freight to be delivered or picked up by the transportation service.

The main contribution of this research is the definition of a methodology for evaluating how the quality of a freight distribution service with time windows, which operates on a given road network to satisfy a number of requests, affects the service cost. The notion of pair compatibility time interval between two requests has been defined and all values have been collected into a Request Compatibility Matrix (*RCM*), where the requests are ordered in increasing Earliest Arrival Time. From this matrix, a first group of three statistical indicators was defined (*ACTI*, *PPC* and *AMTBCR*), following simple statistical rules, and, in a second stage, a further group of two indicators proposed, which follow a planning criterion and therefore need an appropriate computational procedure.

The methodology presented has also been evaluated and the ability of the indicators to describe the level of difficulty in planning the requests has been illustrated in a set of experiments used in scientific literature for large network problems.

A preliminary analysis allowed us to select the indicators with the greatest validity (*PPC*, *AMTBCR* and T_I). An analysis was then performed on these indicators with regard to their ability in describing the difficult to solve instances as consequence of time windows variations and simple linear models have been proposed with regards to *AMTBCR*.

Finally, we note that in the present analysis time windows were not assumed to be uniform within the same experiment. This also means that, for each replication, all the requests do not have the same TW. Further experimental analysis could be carried out to explore requests with homogeneous TW within the same experiment, in order to better control the principal factor that affect the quality of the service. In future research, it would also be useful, by to generate a wider range of instances based on realistic cases, using specific planning tools to test the indicator’s accurancy.

Acknowledgments

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