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*In this paper the problem of finding a computational fast method for pricing of the delivery service in a logistics network has been analyzed. The objective is to develop a supporting method for effective interaction among logistics service providers and customers.*

*We make use of an analytical function to predict the final total cost of distribution and to develop an interaction protocol that, using the function, leads to a final win-win solution in which the most of the customers have agreed to accept a delivery time comporting a reduction of total distribution costs. We also validated the method by use of a simulation software, evaluating the results in terms of cost-efficiency and stability.*

## 1. INTRODUCTION

Logistic activities represent the connection point between goods production and fruition locations, which are separated by time and space (Pareschi et al, 2002). Global competition and tremendous technological progresses, in information technologies and logistics, impose to logistics operators a substantial reduction of their costs, particularly of those originated by the delivery process, when goods must be delivered to customers at right time in the right amounts and positions. The costs sustained by the distributor can be decomposed in three drivers: the variable cost of traveled distance, the variable cost of the vehicles, and their fixed cost. The class of problems studying the minimization of the transportation costs is commonly known as Vehicle Routing Problem (VRP); when customers ask for delivery in a specified time window, the sub-class to which it is referred to is the Vehicle Routing Problem with Time Windows constraints (VRPTW). The presence of a large amount of tight time windows leads to the increase of the number of needed vehicles, and a consequent increase of the transportation cost. On the contrary, if a customer would accept the delivery in a large time window, this would mean an increase on his costs, which originated either by the extra work for unload of the shipment in a unforeseen time window or by the loss of money of a missed sale due to unavailability of goods.

(So and Song, 1998) analyze the interrelations among pricing, delivery time guarantee and capacity expansion decisions. (Basu et al, 2004) extend spatial pricing theory for delivery service to encompass multizone plans. In (Campbell and Salvendy, 2005) an incentive scheme specialized for home delivery service is

proposed. In (Bianco et al, 2005) a formal decomposition of the vehicle routing problem and an interaction protocol is defined while in (Bernardi et al, 2004) a multiagent architecture is described. However, the high number of customers and the huge amount of possible solutions make difficult to resolve this problem to the optimum in a competitive interval of time, given that the problem belongs to the NP - hard in strong sense class of problems (Toth et al, 2002). In this paper we analyze the problem of finding a computational-fast method for the pricing of the delivery service in a logistics network, with the objective to develop a supporting method for effective interaction among logistics service providers and customers. The developed supporting method will help the implementation of an interaction protocol in which the logistics operator is able to price in a time-efficient manner the logistics service.

Given the opposite relationship between costs and windows widths, we have identified the trend of the costs as an analytical function, and then we have analyzed its ability to predict, with an adequately low error margin, the distribution costs using as the only input the measure of the time windows widths. Moreover, upon this analytical function we have built an algorithm for the solution of the delivery problem which leads to a final scenario where the most of the customers agree to broaden out their windows after an economical measurable saving on the transportation cost. On top of this algorithm, a multiagent system can be developed (Shen, and Norrie, 2001). Multiagent systems for supply chain integration and coordination (Durfee, Lesser, and Corkill, 1987; Gerber, Russ, and Klusch, 2003; Julka, Srinivasan, and Karimi, 2002; Karageorgos et al, 2003; Lee, and Whang 1999) can be thought as a building block for collaborative networks (Camarinha-Matos and Afsarmanesh, 2004). The remainder of this paper is structured as follows. In Section 2 problem and model definition are introduced. In Section 3 the proposed solving approach is presented. In Section 4 conclusions and future works are discussed.

## 2. PROBLEM AND MODEL DEFINITION

The problem consists in finding a computational fast method for the pricing of the delivery service in a logistics network, with the objective to develop a supporting method for effective interaction among logistics service providers and customers. The developed supporting method will help the implementation of an interaction protocol in which the logistics operator is able to price in a time-efficient manner the logistics service.

We model the problem as follows:

Given a set of  $n$  customers and an initial time window  $W_i^0 = [e_i^0, l_i^0]$  associated to each customer  $i = 1, 2, \dots, n$ . Let  $W_i = [e_i, l_i]$  be alternatives time windows associated to each customer  $i = 1, 2, \dots, n$  with  $W_i \supseteq W_i^0$ . Let  $s_i^0 = l_i^0 - e_i^0$  and  $s_i = l_i - e_i$  be the width of the time windows in hours with  $s_i^0, s_i \in \{1, 2, \dots, l\}$  where  $l$  be the maximum time width. Let  $\vec{w}^0 = (W_1^0, W_2^0, \dots, W_n^0)$ , and  $\vec{w} = (W_1, W_2, \dots, W_n)$  vectors of the time windows. Let  $n_j$  the number of customers having time

windows width equal to  $j$ . Let moreover  $S = (\sum_{j=1}^l n_j \cdot j) / n$ . Given a market with a set of  $n$  customers and a given resources, network structure, and good requests for customers, we can define  $c_i(s_i) \geq 0$  as the cost for the customer  $i$  for receiving delivery in a time window  $W_i$  and  $tc(\bar{w})$  the total cost of transportation for the logistics operator. We introduce the integer variables  $e_i, l_i \in \{1, 2, \dots, l\}$ . The problem is to find the combination of  $\bar{w} = (W_1, W_2, \dots, W_n)$  such that is

$$\begin{aligned} \min \quad & tc(\bar{w}) + \sum_{i=1}^n c_i(s_i) \\ \text{s.t.} \quad & \\ & W_i \supseteq W_i^0 \quad \forall i = 1, 2, \dots, n \\ & W_i = [e_i, l_i] \quad \forall i = 1, 2, \dots, n \\ & e_i < l_i \quad \forall i = 1, 2, \dots, n \\ & e_i, l_i \in \{1, 2, \dots, l\}, \text{ where } \bar{w} = (W_1, W_2, \dots, W_n) \text{ and } W_i^0 = [e_i^0, l_i^0], \forall i = 1, 2, \dots, n \end{aligned}$$

We notice that for each instance of  $\bar{w}$  the solving of a VRPTW problem is needed.

### 3. THE PROPOSED APPROACH

To solve this problem we apply to the model the following procedure:

1. Find the analytical relationship between  $tc$  and  $S/l$ ;
2. Tune up of the function to prevent error margin;
3. Given an interaction protocol for the pricing of the delivery service, validate it;
4. Implement the interaction protocol in a multiagent based application.

#### 3.1 The Analytical Function

The very first step of our research is made up by a set of tests, carried out with the goal of identifying an analytical function which is able to describe the distribution costs according to changes in customers' delivery time windows  $W_i$ .

We have considered 100 geographically-distributed customers (the position is defined by a couple of Cartesian reference points), with only 1 central depot, where the deliveries begin and end. Let  $p$  the percentage of customers requesting for a tight time windows  $p$ , with  $0 \leq p \leq 1$ , and the measure of such tight time windows be  $w$  hours, with  $0 \leq w \leq l$ ; four scenarios have been considered:

- Scenario 1:  $p = 0.25$ ;
- Scenario 2:  $p = 0.50$ ;
- Scenario 3:  $p = 0.75$ ;
- Scenario 4:  $p = 1$ .

Customers not demanding for a tight time window are supposed to have  $l$  hours wide windows, with  $l = 9$ .

For each scenario, 4 sub-scenarios have been considered:

- Sub Scenario a):  $w = 1$  hour;
- Sub Scenario b):  $w = 3$  hours;
- Sub Scenario c):  $w = 5$  hours;
- Sub Scenario d):  $w = 7$  hours;

Each sub-scenario has been resolved using a VRPTW “ad hoc” solver based on Solomon II heuristic (Solomon et al, 1987): particularly, 10 runs of the solver have been performed for each sub-scenario, randomly assigning the tight delivery windows to different customers, but not changing windows start-times and due-dates. A total of 160 runs have been resolved. The demand of each customer, based on Solomon “R” instances, has been kept constant in all the runs, as well as the service time equal to 90.

The outputs of the solver for each scenario are the total number of vehicles necessary to serve all the customers, and the total cost of distribution.

In Figure 1 a plot for each sub scenario ( $w = 1, 3, 5, 7$ ) is drawn, showing the total cost in function of the percentage  $p$  of time window width. The total cost strongly increases with the increase of the percentage of customers, over the total, demanding for a tight delivery window: moreover, the differences in average total cost don't seem significant for requested delivery windows  $w = \{3, 5, 7\}$  hours, while they are substantial between these 3 spans in which  $w = 1$  hour

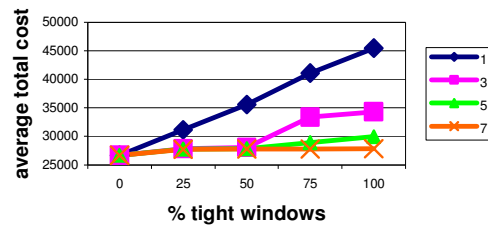


Figure 1 – Average total cost after percentages of tight windows

In order to find out the trend of the total cost in relationship with the  $s/l$  ratio, we used the minimum squares method. Using this method we have chosen as regression function the logarithmical expression:

$$\bar{c} = a \ln(S/l) + b$$

where  $a$  and  $b$  represent model constants with  $a = -9395.7$  and  $b = 24382$ .

In the moment of choosing which function, out of the four produced by the software for each scenario, we will be using for our future experiments, we decided to select the one, shown in Figure 2, produced by the fourth scenario, for the two following reasons:

- the function has the highest  $r^2$  index, equal to  $r^2 = 0.9778$ , of all the scenarios;  
 - the scenario represents the most difficult occurrence to solve, given that the totality of the customers ask for a tight window. The Figure 2 shows the plot of  $\bar{t}c$  for the 4<sup>th</sup> scenario showing the variation of foreseen total costs in function of the  $S/l$ . Dots represent the computed cost  $tc$ .

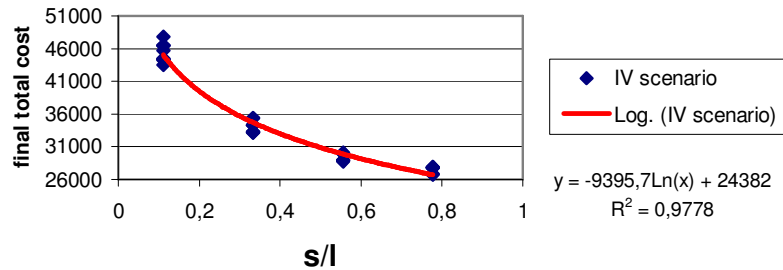


Figure 2 – scenario 4 output regression function

It is possible to see that the maximum distance between the regression function and the observed value corresponds to a  $S/l$  ratio equal to 0.1, then to a 1-hours-wide delivery window. In this point the function is approximately 6% lower from highest observed value (predictable, given that  $r^2$  is very close but not equal to 1), so when we will be using it to predict the total cost of a particular market scenario, we must expect a 6% error on prediction accuracy.

Therefore, we are now able to predict, with a very low error margin, the total cost of a particular market scenario (the output), merely knowing the width of customers' delivery windows (the input), using the just found analytical function.

### 3.2 The function validation

In this section we explain how we assessed the goodness of the prediction made by the analytical function just found: to do this, we firstly resolve some market events with the function, supposing some percentages of tight-windows customers (the input of the function), and then we create solver instances which reflect these percentages, and resolve them, obtaining the exact results from the solver.

To validate the function,  $n_j$  are randomly selected and assigned to customers  $i$ . The average width  $\bar{r}$ , as:

$$\bar{r} = \frac{\sum_{j=1}^l n_j \cdot j}{n}$$

Now, putting this latest value inside the function equation, we finally obtain the predicted total cost  $\bar{t}c$  for each group as:

$$\bar{t}c = a \ln(\bar{r}/l) + b$$

Making use of the percentages and the widths decided in the previous phase, we build VRPTW instances, yet without any change in customers' service time, demand and position, still equal to Solomon's II ones.

We build 10 instances for each group of percentages, again assigning delivery windows to customers in a random way, and then we resolve them using VRPTW solver, which produces the total cost of transportation  $tc$  and the number of vehicles for each instance.

Each group  $\bar{t}c$  and the 10 (exact)  $tc$ 's are compared, and a correction rate that makes  $\bar{t}c$  able to predict (merely, overtop) all  $tc$ 's is evaluated

Looking at the results produced after the 4 groups of percentages, it is possible to observe that 70% of  $tc$ 's are correctly predicted by the function. Thus, just carry a little correction to  $\bar{t}c$  (the maximum needed is of 6%, what is more already expected), making our function able to predict 100% of results.

### 3.3 The interaction protocol

The developed cost function can be used as a tool for measuring the transportation cost based on received orders, and for computing price discounts during negotiation with customers. A basic interaction protocol exploiting these potentialities is structured as follows:

INIZIALIZATION:

--  $i = 1, j = 1; k = 1; \bar{t}c' = 0, \bar{t}c'' = 0;$

-- The  $n$  customers send orders to the Logistics Operator.

-- Computation of the number  $n_j$  of customers having time window width  $j$

-- Computation of transportation cost  $tc'$  through the function and first

assignment to customers as  $tc'_i = tc'/n$ .

**STEP 1:**

**IF:**  $n_j - k > 0$

--  $n_j = n_j - k,$

--  $n_{j+1} = n_{j+1} + k$

-- Computation of new total cost of transportation,  $tc''$ , and of the discount

$\Delta = \bar{t}c' - \bar{t}c''$

-- Send a propose to customers having time window width equal to  $j$  a discount of  $\Delta/n_j$

**IF:** at least  $m > 0$  customers exist for whom is valid  $c_i(j) > c_i(j+1) - \Delta$

-- Enlarge time windows for such customers:  $s_i = s_i + 1$

**ELSE:**

-- Set  $k = k + 1$  and goto STEP 1

**ELSE:**

-- goto STEP 2

**STEP 2:****IF:**  $j < l$ 

- Computation of new  $n_{j+1}$  and  $n_j$ ,
- Set  $j = j + 1$ ; goto STEP 1

**ELSE:**

- Computation of new  $n_{l-1}$  and  $n_l$
- Computation cost  $tc'$  related to final numbers  $n_1, n_2, \dots, n_l$

**STOP****3.4 Simulation**

With the aim of validating the interaction protocol, we implemented it on a simulation software, building a model which reproduces its steps in order to reach a market result where the final percentages of customers asking for tight delivery windows are much less than initial ones, having the customers negotiated to broaden up their windows after a consistent saving. A total of 40 runs have been resolved. In Table 1 we show results of two runs. If the customers' cost structure is feasible, the negotiation will always lead to a final decrease of total costs. In the table this results can be argued from the medium time window width  $S$ .

Table1 – Examples of negotiation results

$j$	Example 1		Example 2	
	Original $n_j$	Final $n_j$	Original $n_j$	Final $n_j$
1	50	49	12	11
2	0	0	11	8
3	20	16	11	8
4	0	0	11	8
5	20	13	11	5
6	0	0	11	2
7	10	2	11	6
8	0	9	11	4
9	0	11	11	48
$S$	2.8	3.47	4.96	6.26

Comparing the algorithm-made with the solver-made results, we can observe that our method has been able to reduce the number of customers asking for a tight, and troublesome, delivery window, carrying a real benefit to the whole system. Furthermore, the final total cost of distribution is always a little higher than the solver one, which means that the algorithm won't ever produce a lower cost than the real, needed one (produced by the solver), avoiding a loss to the distributor.

#### 4. CONCLUSION

In this paper we have found a computational-fast method for the pricing of the delivery service in a logistics network, with the objective to develop a supporting method for effective interaction among logistics service providers and customers. We have developed and tested an analytical function which is able to predict transportation costs and we have shown an interaction protocol for customers and logistics operator to decrease total distribution costs. Future works will regard the ability of the analytical function to predict changes in quantity requests, the use of a better solving algorithm to find function parameters and the development of a multiagent system implementing the described interaction protocol.

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