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From single path to vehicle routing: The retailer delivery approach

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Abstract

In this paper a procedure for simulating goods movement in an urban area is analysed. Assuming that the decision maker is the retailer, a macro-architecture is proposed to simulate retailer movements. The macro-architecture consists of two levels: the first is a commodity-based demand model that simulates goods movement in terms of quantity from wholesalers to end consumers through retailers; the second can shift from a One-to-One Problem (OOP) to a Vehicle Routing Problem (VRP) that simulates the delivery process. The OOP is investigated using the mono-path and multi-path approach, while the VRP is investigated considering a combination of OOP (both in mono-path and in multi-path approaches).

Keywords: Urban goods movements; vehicle routing problem; heuristic

1. Introduction

This paper presents a method to simulate goods movements in urban/metropolitan areas when the decision-maker is considered to be the retailer (Russo and Comi, 2006). It follows on from previous work which explored the case of retailers who chose to restock on their own account (Russo et al., 2007).

Urban goods movement involves two components: demand in terms of goods quantity and vehicle routing with constraints (time windows, number of vehicles and load factors). Here, we propose a demand commodity-based model, which simulates the quantity of goods purchased by a retailer.

There are various models and methods to analyse urban goods movements. The main classifications concern the output considered and the structure. As regards the latter, some models have a structure similar to that used for passengers (multi-step models), while others are based on the macro-economic approach (spatial price equilibrium models) (Harker, 1985). In terms of output, while some models estimate the commodity quantities transported, others estimate the number of vehicles involved in goods transport in urban areas (Ogden, 1992).

In this paper a macro-architecture of goods movements in an urban area is reported. We consider a multi-step model which on two different levels gives as output: 1) commodity flows, and 2) vehicle flows. The first level is a commodity-based demand model that simulates goods movements in terms of quantity; the second is to simulate

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path choice made by the retailer which can shift from a one-to-one problem (OOP) to a vehicle routing problem (VRP). At this level we analyse cases that range from single stop to multiple stops.

Where the retailer chooses to purchase in only one warehouse, the problem can be formulated as the optimum path between one origin and one destination to be determined. This is an OOP. The path search problem in the one-to-one approach, starting from the assumption that just a subset of all the possible topological paths (choice set) between an origin and destination is actually perceived by users, has been treated explicitly by distinguishing two different phases: choice set generation, which identifies the possible alternatives and path choice among the alternatives belonging to the choice set (Ben Akiva et al., 1984; Antonisse et al., 1985; Cascetta et al., 1996; Russo and Vitetta, 2003). Alternatively, the problem of path perception has been simulated implicitly in the choice model. Moreover, the choice set can be simulated as a fuzzy set in which each alternative has a degree of membership to it (Vitetta and Quattrone, 2007).

Where the retailer chooses to purchase from several warehouses (or the carrier must move from more than one retailer), a VRP can be formulated. The VRP has been treated extensively in recent years. The purpose of our investigation is twofold: to formulate the problem taking account of all the possible variables, and to suggest new solution approaches. The VRP was introduced by Dantzig and Ramser (1959) so as to optimize the movements of a fleet of gasoline delivery trucks. Hence, various specifications are proposed for the VRP. Some (Montemanni et al., 2005; Hanshar and Ombuki-Berman, 2007) have proposed the DVRP (Dynamic VRP) given that the number of customers is not known a priori, but is an input that is variable in time. Others have proposed the VRP with Time Windows (VRPTW), in which deliveries are requested to be made within a set time interval. Time windows constraints can be rigid (Hu et al., 2007) or elastic (Ando and Taniguchi, 2006). Others have proposed further specifications: i.e. a VRP in which demand (goods quantity) is elastic (Bianchi et al., 2005), or a modification of the VRP in the inventory routing problem (IRP) (Campbell and Savelsbergh, 2004). In Wisetjindawat et al. (2005) an integrated procedure is proposed: the supply chain is simulated in terms of quantity and distribution process.

The vehicle routing problem and variants can be solved using exact (Fisher, 1994; Toth and Vigo, 2002; Baldacci et al., 2008) or heuristic algorithms (Laporte, 1992; Taillard et al., 1997; Laporte et al., 2000; Jones et al., 2002; Montemanni et al., 2005; Hanshar and Ombuki-Berman, 2007; Laporte, 2007). Exact approaches have some limitations related to calculation times and the limited size of the problems that can be solved. An extended review concerning the VRP, several variants and solution approaches is reported in Laporte (2007). Alternatively, some authors (Holguín-Veras and Patil, 2005; Wang and Holguín-Veras, 2008) analyse the observed trip chain behaviour of commercial vehicles and propose a destination choice and a tour termination model to simulate driver behaviour, independently of path perception. Moreover, the cost involved in goods movements in an urban area can be explored using various models (Holguín-Veras and Brom, 2008). In the literature, the goods distribution problem is often approached in the case in which the decision maker is not the retailer.

In this paper a macro-architecture is proposed to simulate retailer movements. The macro-architecture consists of two levels: the first is a commodity-based demand model that simulates goods movements in terms of quantity from wholesalers to end consumers via retailers; the second can shift from a one-to-one Problem (OOP) to a vehicle routing problem (VRP) that simulates the delivery process.

This paper is structured as follows. In the first section, the proposed macro-architecture of the models is presented. The second section is divided into three parts: the system simulation, in which the method to simulate a transportation system is analysed; the OOP, developed considering path perception in the path choice model, the many-to-one problem in terms of VRP, which is considered as a combination of several OOPs. In the third section, the solution approach is reported, in which the performance of the heuristic algorithms is compared with that of the exact algorithms. Finally, concluding considerations are presented.

2. The Macro-Architecture of Goods Movements

The general macro-architecture of reference is that stated in the literature (Russo and Comi, 2006; Russo and Comi, 2007; Russo et al., 2007). For the purposes of this paper, analysis of the macro-architecture has four subsequent zooms, in which goods movements are analysed from upper macro-levels (commodity and vehicle level) to the path choice model (Figure 1).

At the first zoom the quantity of goods purchased in a zone by a retailer can be analysed on two levels (Russo et al., 2007):

- *commodity level*, consisting of two macro-models:
  - attraction macro-model; this refers to end-consumer quantities;
  - acquisition macro-model; this concerns logistics trips from the retailer's standpoint;
- *vehicle level*, which consists of two macro-models:
  - service macro-model;
  - path macro-model.

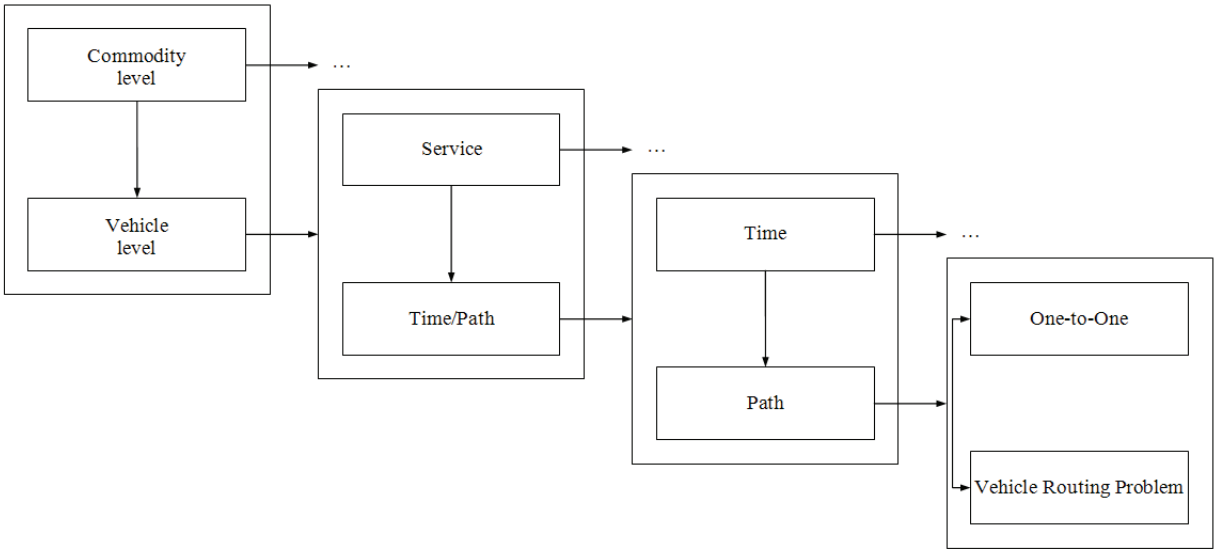


Figure 1 Macro-architecture of goods movements with subsequent zoom

We focus our attention on the *vehicle level* and with the second zoom we find the *service* and the *path/time* macro-model:

- the first (*service*) concerns the quantity of goods delivered at each consignment and the vehicles needed for restocking; in this model we investigate the distribution channels (the definition of distribution channel is used to describe the means by which a product is physically transferred or distributed from the production site to the point at which they are made available to the customers), the service macro-model is investigated when the retailer can be considered the decision-maker; in other words the pull movements of goods are considered, while the push movements are only recalled (Russo and Cartenì, 2004);
- the second concerns the *path/time* choice for each movement of goods; the *path/time* choice model simulate the path and time choice when the retailer moves from her/his standpoint to one or more delivery points (the location of a wholesaler, a producer, etc. is known as a delivery point); this model concerns the case in which the retailer reaches only one delivery point and the case in which the retailer reaches more than one.

We focus on the path/time model and with the third zoom we find the *time choice* and the *path choice* model:

- the first simulates the *time* in which the goods must reach the retailer; with this model the departure and/or arrival time from the retailers standpoint to reach the delivery points at an established time can also be simulated;
- the second concerns the *path* choice made by the retailer (or by the carrier in the push movements); this model can be stochastic or deterministic (whether or not the costs are a random variable), dynamic or static (whether or not the cost depends on time).

With the fourth zoom the *one-to-one* and the *many-to-one* (or the one-to-many) problems are specified. Both problems can be tackled with a deterministic or probabilistic approach, static or dynamic approach depending on the approach to the path choice:

- the *one-to-one* problem concerns the case in which the retailer chooses to pick up goods at only one delivery point;
- the *many-to-one* problem, commonly called VRP, concerns the case in which the restocking is done at various warehouse points; we note that this problem is similar to the case in which a carrier restocks several retailers from one warehouse.

3. The Retailer's Paths

The path choice model allows us to estimate the path choice probability/possibility for retailers in urban and metropolitan areas. As regards the problem of path simulation and design for retail vehicles, two classes of individual users could be considered:

- private users, i.e. those travelling for several reasons (work, shopping, etc.) and following the path of maximum perceived utility, and
- retailers, i.e. those travelling to restock their shops, who can be further distinguished into:
  - Non-Controlled (NC) retailers, those assumed to follow the path of maximum perceived utility in the same way as private users (in accordance with User Equilibrium-UE paradigm);
  - Controlled (C) retailers, those obtaining indications supplied by an external (or internal) authority regarding optimal paths (that satisfy specific criteria, e.g. time minimisation) to follow, who are assumed, rather than to maximise their own utility, to cooperate in minimising total internal costs (in accordance with C-retailer System Optimum-SO paradigm).

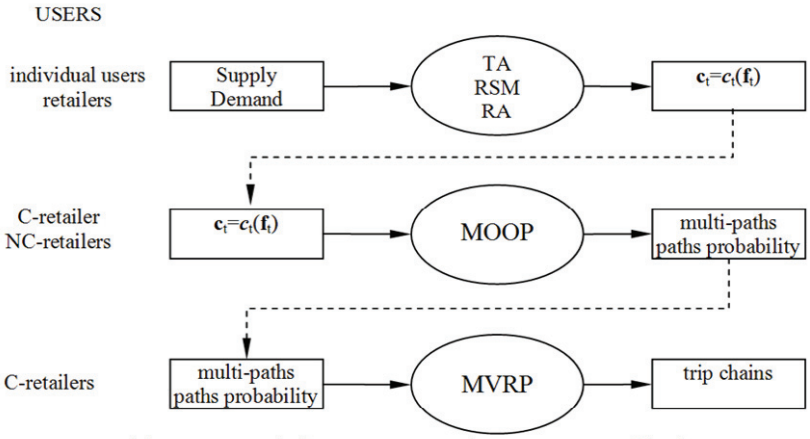
Moreover, if it is assumed that the number of C-retailers is smaller than that of private users and NC-retailers and that therefore their path choice behaviour does not affect system performance (i.e. link/path costs), the behaviour of independent users and NC-retailers could be simulated in accordance with UE paradigm to obtain costs on the network (possibly as a function of flows, assuming that the network is congested and that the system is dynamic). Given the costs on the network the optimal path according to SO paradigm for C-retailers can be designed.

Under these assumptions, in order to solve the restocking problem and identify the optimal paths for C-retailers, three steps could be followed:

- system performance estimation, which can be achieved through Traffic Assignment (TA) (static or dynamic), Real-time System Monitoring (RSM) or Reverse Assignment (RA) (Russo and Vitetta, 2005);
- one-to-one problem solution, which consists of the given the costs on the network obtained by the previous step, in generating alternative paths for every origin-destination pair;
  - in the mono-path case, with a deterministic approach, just one path (equal to the shortest path) with maximum choice probability (equal to 1) is generated; this approach, extensively used in the literature, is not very realistic due to the fact that it does not take into account the uncertainty related to the simulation of user perceptions of the alternatives and the variability of the system states in time, hence its dynamic nature;
  - in the multi-path case (Multi-path OOP, MOOP), with a probabilistic approach, a set of possible paths is generated, each of which has a choice possibility/probability that depends on the user perception of the alternative and the possibility/probability of there being a specific system state that influences the choice process,
- many-to-one problem solution, which consists, given the optimal paths between every origin-destination pair obtained by solving the one-to-one problem, in the solution of a VRP formulated as a classic optimisation problem whose objective is the calculation of the best combination of one-to-one paths in order to visit in succession a certain number of network nodes (freight delivery points) in the least time possible whilst respecting some constraints (e.g. behaviour according to UE paradigm for autonomous users and NC-retailers, number and

capacity of freight vehicles, time windows etc). If the one-to-one problem is solved using a multi-path approach, we have a multi-path VRP (MVRP).

In Figure 2 we report the simulation steps for the case in which the multi-path approach is used.



TA: Traffic Assignment; RSM: Real-time System Monitoring; RA: Reverse Assignment; MOOP: Multi-path One- to-One Problem; MVRP: Multi-path Vehicle Routing Problem

Figure 2 Solving the restocking problem

3.1. System simulation

In this section, the transport system simulation is analysed to evaluate system performance; the users are retailers and private users. The input consists in demand and supply, the output in flows and costs. Three methods may be used: TA, RSM and/or RA.

The TA problem such as the equilibrium or dynamic process models (Wardrop, 1952; Beckman et al., 1956; Sheffi, 1985; Ben Akiva et al., 1998; Cascetta, 2001), has an input, a supply model (simulating network performance) and a demand model (simulating user behaviour). It provides link flows and link performance in terms of costs as output.

The RSM can be obtained with measurement at fixed points in the network with traditional measurement systems like loop detectors and image processing (Hoose, 1991) and floating cars (Torday and Dumont, 2004) in the network (individual cars, taxis, transit system vehicles).

The RA models (Russo and Vitetta, 2005) have link flows and link performance in terms of costs as input and the link cost parameters of the cost-flow functions used in the supply model as well as the value (number of trips) and/or the model parameters of the demand model as output.

The TA problem can be solved with a static or dynamic approach; static assignment models simulate a transportation system in stationary conditions, reproducing the condition in which link flows and link costs are mutually consistent. The output is the link flow vector $\mathbf{f}$ and the link cost vector $\boldsymbol{c}(\mathbf{f})$. Dynamic Traffic Assignment (DTA) models remove the assumptions of static models, allowing transportation system evolution to be represented. DTA models can be analysed as regards the characteristics of the link model adopted. In particular, link flow representation can be continuous or discrete and cost functions can be aggregate or disaggregate. The output is the link flow vector for each time t, $\mathbf{f}_t$, and the link cost vector, $\boldsymbol{c}_t(\mathbf{f}_t)$.

RSM costs and flows are usually made for a percentage of network links. The output consists of the link flow vector $\mathbf{f}$ and the link cost vector $\boldsymbol{c}$ and/or the link flow vector for each time t $\mathbf{f}_t$ and the link cost vector $\boldsymbol{c}_t$ in a subset of links.

RA models, starting from observed costs and flows, supply the link cost parameters of the cost-flow functions used in the supply model, the value (number of trips) and/or the model parameters of the demand model.

3.2. One-to-one problem

As input the OOP has costs and flows and, as output, it supplies the optimal paths; the users involved are C-retailers.

In this paper, we consider C-retailer path choice using two approaches, the mono-path approach and the multi-path approach, which can be mono-criterion or multi-criteria.

The mono-path concerns the generation of only one path between an origin and a destination. This approach, widely used in the literature, is deterministic and the path generated is assumed the best path.

The MOOP concerns the generation of more than one path between an origin and a destination. This approach is probabilistic; the link cost is a random variable, which means each path has a probability to come and the retailer is ill-informed on the system state.

In the literature, only the mono path approach is used, but it is plain that in reality the multi-path approach should be used since it takes into account the uncertainty related to the simulation of the user perception of the alternative and system state variability over time, hence its dynamic nature.

In the MOOP a choice set is generated; in this phase we distinguish:

- formation, concerning the structure of one, or more, potential analytical path set; and
- extraction, concerning the extraction of the choice set.

3.3. Many-to-one problem

The many-to-one problem is formulated as a VRP to simulate the restocking approach when the retailer chooses to restock at some delivery points. This problem can be described as the design of the optimal routes from the retailer's standpoint (retail outlet) to a set of delivery points (e.g. warehouses or producers) where each point can be reached exactly once. The constraints it has to tackle are economic (travel cost or operation costs) and operational (vehicle capacity or time window). The objective is to purchase whilst respecting the constraints and minimising the total cost.

As input, the VRP has the path costs generated from solving the OOP. As output it supplies the optimal trip chain (a trip chain is a combination of several paths). If the OOP is an MOPP, it is possible to formulate an MVRP, given that the MVRP can be shown as the combination of several MOOPs. The MVRP can be static or dynamic: in the first case we have $\mathbf{f}$, $\boldsymbol{c}(\mathbf{f})$, in the second case $\mathbf{f}_t$, $\boldsymbol{c}_t(\mathbf{f}_t)$.

The problem constraints are:

- a delivery point can be reached exactly once,
- vehicle capacity, and
- time windows.

The *time windows* constraint is considered because it is possible that operations at the delivery point can be made only in certain time slices.

4. Solution Algorithms

Several families of exact and heuristic algorithms have been proposed for the VRP. The solution algorithm chosen depends on several factors, such as the size of the problem, the desired solution time and accuracy. Hence increasing numbers of solution approaches are developed (e.g., Branch & Bound, Branch & Cut, for the exact algorithms; Simulated Annealing, Tabù Search, Genetic, for meta-heuristic; hybrid algorithms that combine base algorithms).

The Branch & Bound algorithm allows an exact problem solution to be found. The algorithm searches all possible solutions until it finds the best, but rejects some solutions demonstrating their non-optimality. The algorithm proceeds to partition the solution set and search for the solution only in some sets.

The genetic algorithm allows a problem solution to be found based on the concepts of natural selection and genetic theory. Indeed, starting from an initial population the algorithm evolves through selection, crossover and mutation operators (Vitetta et al., 2008).

However, it is possible to use a high-speed heuristic algorithm to solve the proposed problem. Indeed, from various surveys carried out in some Italian urban and metropolitan areas it emerged that (DIMET, 2006):

- in the city of Palermo (Sicily, about 800,000 inhabitants) in considering distribution channels (Russo et al., 2007), 14% of retailers choose to do restocking on their own account; in the city of Reggio Calabria (Calabria, about 180,000 inhabitants) this percentage is 42%;
- as concerns the restocking zone, in considering only those retailers who do restocking on their own account, it emerged that 82% (Palermo) and 43% (Reggio Calabria) did restocking inside the urban/metropolitan area;
- as regards to retailers who restock inside the urban/metropolitan area, 56% (Palermo) and 33% (Reggio Calabria) using their own vehicle with a load capacity less than 10 m3;
- moreover, 90% of the retailers that do restocking inside the urban/metropolitan area make only one stop, 10% two or more stops.

It is thus admissible to consider that:

- the decision maker is the retailer;
- the study area coincides with the urban/metropolitan area;
- the retailer chooses a vehicle of a certain load capacity (assuming that size choice is independent of zone);

Referring to the retailers that make few stops, a VRP can be formulated, considered as a combination of several OOPs. Moreover, the VRP can be solved using some high-speed heuristics that have a solution probability coinciding with the exact solution. The advantage is the lower computation time with respect to the exact procedure since in most cases the retailer visits a small number of destinations.

The first high-speed heuristic algorithm proposed, also called *nearest insertion* algorithm, consists in an iterative insertion of nodes (delivery points) to minimise the travel cost. At each successive insertion the delivery point nearest the previous one is inserted into the solution. The steps of the algorithm are:

STEP 0 Initialize. The node list W comprises the delivery points and the point where the retailer is located. The *current node* is the point where the retailer is located.
STEP 1 List. The *current node* is deleted from W.
STEP 2 Path. The shortest paths between the *current node* and the delivery points in W are calculated.
STEP 3 Update. The nearest *delivery point* is the new *current node*.
STEP 4 Iterate. Go to step 1 while $W \neq \varnothing$

A variant of the *nearest insertion* algorithm is the *iterated nearest insertion* algorithm, that follows the same logic of nearest insertion, but forecasts some iterations (e.g., the number of iteration is less than, or equal to, the stop number). The nearest insertion is repeated k times with k greater the 1 and less than the number of delivery points. The first is not the nearest with respect to the origin but it is chosen by random procedure. The best trip chain is accepted.

The *nearest insertion* algorithm finds a solution that has a probability to coincide with the exact solution. In using *iterated nearest insertion* algorithms the probability of finding the exact solution increases (by about 75% against *nearest insertion*), in particular for two stops the *iterated nearest insertion* finds the exact solution. The probability of finding the exact solution decreases with an increased number of stops (Figure 3).

5. Conclusion

In this paper, a method to study the retailer's delivery approach was presented. A macro-architecture was reported for a model system to simulate goods movement in an urban area when the retailer is the decision-maker. In the macro-architecture four subsequent zooms were distinguished in which goods movements were analysed from

the upper macro-levels (commodity and vehicle level) to path choice. Path choice was analysed by considering two problems: the one-to-one problem and the many-to-one (or one-to-many) problem. The one-to-one problem was tackled in two cases: the mono-path case (OOP) with a deterministic approach and the multi-path case (MOOP) with a probabilistic approach; we also report some methods (traffic assignment; real time cost measurement and reverse assignment) to analyse the transport system and define the flow and cost vectors. An MVRP was considered, with the many-to-one problem formulated as a classic optimisation problem whose objective is to determine the best combination of one-to-one paths in order to visit a certain number of nodes in succession To solve the proposed problem two high-speed heuristic algorithms were proposed, and their performance was compared with the exact solution.

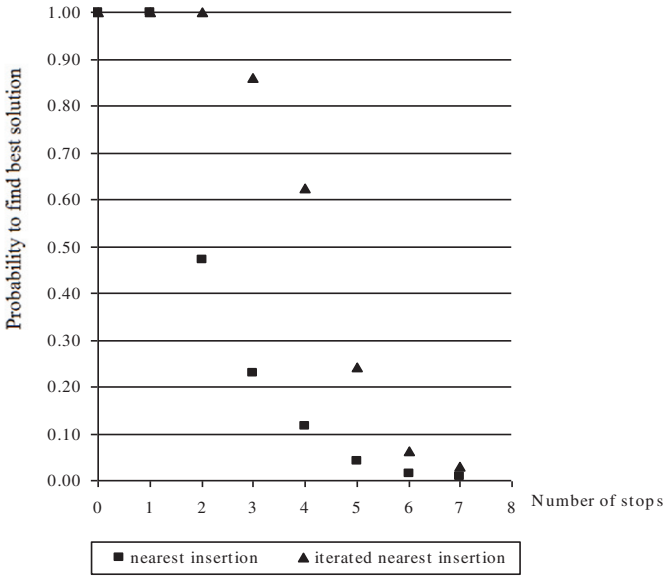


Figure 3 Probability to find the exact solution with insertion algorithm

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