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Solving time-dependent multimodal transport problems using a transfer graph model

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ABSTRACT

In this paper we present an hybrid approach for solving the time-dependent multimodal transport problem. This approach has been tested on realistic instances of the problem providing an adequate balance between computation time and memory space. This solution can be applied to real transport networks in order to reduce the impact of traffic congestion on pollution, economy, and citizen's welfare. A comparison with two previous approaches are given from theoretical point of view as well as experimental performance.

1. Introduction

Nowadays, the daily mobility of passenger and goods has become a very important problem in our society. Traffic congestion produces a direct impact on the economy, causes an increase of pollution, and reduces citizens' welfare. According to the recent data available, in Beijing (China) the road transport sector generates 23% of the total air pollution (Zhao, 2009), close behind the industrial sector, while in the European Union the transport emissions are accounted for around 20% of total greenhouse gas emissions (Bart, in press). In US, urban traffic congestion caused during 2007 a waste of fuel equal to $87.2 billion as well as 4.2 billion hours of transport delay (Schrank & Lomax, 2009).

There are different policy options for dealing with this mentioned problem. In order to avoid that urban development becomes exclusively car-oriented, one of the measures consists in improving the quality of public transport and encouraging its use (Bart, in press). However, greater effectiveness can be reached through combining the different private and public transport means, specially in big cities and in interregional scenarios.

Multimodal transport, the combination of public and private transport modes, has been addressed by several authors in the research community. For solving the multimodal transport problem (MTP) different abstractions are proposed, generally based on the concept of graph theory: hypergraphs (Lozano & Storchi, 2001), hierarchical graph (Bielli, Boulmakoul, & Mouncif, 2006), and classical multigraph (Lo, Yip, & Wan, 2003). Besides, several algorithms to compute the shortest path for the MTP are given in the literature. The Dijkstra algorithm is the most used approach (Kamoun, Uster, & Hammadi, 2005; Zidi, 2006), while other algorithms like the label correcting algorithm (Lozano & Storchi, 2002; Ziliaskopoulos & Wardell, 2000), Breadth-First search (Fragouli & Delis, 2002) and heuristic algorithms (Chang, 2008; Chiu, Lee, Fung Leung, Au, & Wong, 2005; Li & Kurt, 2000) are also investigated.

Despite the great effort done in this field, the complexity of the MTP has not been fully addressed. In realistic scenarios, traveling cost (e.g., time, price, comfort) depends on time, and thus the optimal solution. This time-dependent multimodal transport problem (TMTP) is more complex for solving, since it contemplates different transport modes available and their schedules. In fact, there exist few works that take into account this constraint (Bielli et al., 2006; Galvez-Fernandez, Khadraoui, Ayed, Habbas, & Alba, 2009; Ziliaskopoulos & Wardell, 2000).

In our previous works we have developed a solution for solving TMTP. In Galvez-Fernandez et al. (2009) an alternative abstraction to model time-dependent multimodal networks called *transfer graph* was presented as well as an approach for this abstraction. Two implementations of this approach were proposed. A variant of Dijkstra algorithm was developed in Galvez-Fernandez et al. (2009). It provides better performance in terms of computation time than other algorithms in the literature. Nevertheless, the required memory space makes it unfeasible to apply on big-sized transport networks. In Ayed, Habbas, and Khadraoui (2009), we present a second solution that uses Ant Colony Optimization (ACO) metaheuristic (Dorigo, Birattari, & Stntzle, 2006). It requires less memory space but increases the computation time.

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Nomenclature

MTP	multimodal
Transport problem	
TMTP	time-dependent multimodal transport problem
ACO	ant colony optimization
$G = (V,E,M)$	multimodal directed graph
V	set of vertices for the graph $G = (V,E,M)$
M	set of transport modes for the graph $G = (V,E,M)$
E	set of edges for the graph $G = (V,E,M)$
$p_{v_1.v_k}$	a path from vertex v_1 to vertex v_k
(t_{v_i}, t_{v_j})	travel departing at time t_{v_i} and arriving at t_{v_j}
TDMG	time-dependent multimodal graph
T	set of travels for a $G = (V,E,M,T)$
$c_{e_i}(t_j)$	the cost of the edge e_i at time t_j
SP	the shortest path
$T_g = (C,T_r)$	transfer graph
$C = \{C_1, C_2, \ldots, C_k\}$	the set of monomodal time-dependent graphs
T_r	the set of virtual edges
TV_i	the set of all transfer vertices
P	the set of all paths for a graph
$f(p,t_o)$	the cost function for the path p departing at time t_o
SPP	shortest path problem
$P^{*k}_{s.d}$	the set of SPs from vertex s to vertex d using the component C_k
$P^{*k}_{s.-}$	the set of SPs from the vertex s to all transfer vertex using the component C_k
$P^{*k}_{+.-}$	the set of SPs which start and end at any transfer vertex within C_k
$P^{*k}_{+.d}$	the set of SPs which start at any transfer vertex and end at vertex d within C_k
$R_g = (V_g,E_g)$	relevant graph
V_g	the vertex set of relevant graph
E_g	the edge set of relevant graph
$E^-(v_i)$	the incoming edges of vertex v_i
$E^+(v_i)$	the outgoing edges of vertex v_i
t_o	current time
$p((i,j)^t)$	the probability of choosing the edge (i,j) at time t
$\tau^t_{(i,j)}$	the pheromone value of c_{ij} at t
$\eta^t_{(i,j)} = \frac{1}{cost(c_{ij})}$	a parameter for computing the probability of choosing the edge (i,j) at time t
$cost(i,j)$	the cost of the current path if the edge (i,j) is added
$\tau_{ij}^{(t_{v_i},t_{v_j})}$	the pheromone value for the edge (i,j) within the travel (t_{v_i}, t_{v_j})
γ	pheromone updating rate parameter
δ	pheromone updating rate parameter
ρ	pheromone evaporization parameter
RAM	random access memory
CPU	central processing unit
LP	the set of local paths in all components
$A_g = (VA,EA)$	abstract graph
VA	the vertex set of abstract graph
EA	the edge set of abstract graph
$RI_g = (NI_g,EI_g)$	relevant intergraph
$NI_g = VA \bigcup \{s,d\}$	the vertex set of the Relevant intergraph
EI_g	the vertex set of the relevant intergraph

In this paper a new approach for the TMTP is proposed, which is based on Dijkstra and ACO. Its main contribution is to provide an adequate balance between computation time and space. Therefore, this solution can be scalable and applied to realistic scenarios involving several cities, regions or countries.

The outline of this paper is the following. Section 2 gives some definitions and presents the transfer graph model. Next, in Section 3 we introduce the relevant graph approach for computing the shortest path in *transfer graph* and two implementations based on Dijkstra and ACO, concluding with the benefits and drawbacks of both strategies. Then, we present the new algorithm for TMTP in Section 4 and we prove that is correct with respect to the relevant graph approach in Section 5. Next, in Section 6 some experiments outline the performances of this new approach. In Section 7 we compare the hybrid approach with other existing approaches proposed in the literature. This paper finishes with conclusions in Section 8.

2. The transfer graph model

In this section we present the *transfer graph*, a graphical structure that abstracts the time-dependent multimodal transport network. The main advantage of this model is that it adapts to the distributed nature of real-world transport information providers since it separates and keeps all transport modes in different unimodal networks. Another benefit of this abstraction is that each unimodal network can be easily and independently updated without requiring any further recalculation (Galvez-Fernandez et al., 2009).

2.1. Definitions

Let $G = (V,E,M)$ denotes a multimodal directed graph or network, where $V = \{v_1,\ldots, v_j\}$ is a set of vertices, $M = \{m_1,\ldots,m_k\}$ is a set of transport modes (e.g., train, bus, and car), and $E = \{e_1,\ldots,e_l\}$ is a set of edges. An edge $e_l \in E$ can be identified by $(v_p, v_q)_{m_r}$, where v_p, $v_q \in V$ and $m_r \in M$. The e_l expresses that it is possible to go from vertex v_p to v_q by using transport mode m_r. A value c_{e_l} is associated to each edge e_l, indicating the cost of including the edge in the solution (e.g., distance or time).

Definition 1 (Multimodal path). Given a multimodal graph $G = (V,E,M)$, a path $p_{v_1.v_k}$=($v_1 \to v_k$) is a sequence of edges between a pair of vertices v_1 and $v_k, ((v_1, v_2)_{m_1}, \ldots, (v_{k-1}, v_k)_{m_{k-1}})$, where $\forall i,j \in \{1,\ldots,k\}\, v_i, v_j \in V, (v_i, v_{i+1})_{m_i} \in E, m_i \in M,$ and $i \neq j \Longleftrightarrow v_i \neq v_j$.

Definition 2 (Travel). Given a path $p_{v_i.v_j} = (v_i \to v_j)$ or an edge $(v_i, v_j)_{m_k}$, a travel is defined as a pair of times (t_{v_i}, t_{v_j}) where t_{v_i} denotes the departure time from vertex v_i and t_{v_j} the arrival time at v_j.

Definition 3 (Time-dependent multimodal graph, TDMG). We define $G = (V,E,M,T)$ as a time-dependent multimodal graph, where V is the set of vertices, E the set of edges, and M the set of modes. Each $e_i \in E$ is associated to a set of travels $\tau_{e_i} = \{(t_{s_1}, t_{a_1}), \ldots, (t_{s_k}, t_{a_k})\}$, being $|\tau_{e_i}| = k \geqslant 1$ and $t_{s_j} \leqslant t_{a_j},\ \forall j \in \{1,\ldots,k\}$. T is defined as the set of all travels, $T = \bigcup_{e_i \in E} \tau_{e_i}$.

Definition 4 (Time-dependent cost). If P is the set of paths in a graph G, the function $f(p,t_o)$, $f{:}P \times T \to R$, represents the cost of the path p departing at time t_o. The cost of edges is considered to be time-dependent, i.e., $\forall e_i \in E$ and $j,l \in \{1,\ldots,k\}$ we can have $c_{e_i}(t_j) \neq c_{e_i}(t_l)$.

Definition 5 (Shortest path problem in TDMG). Given a graph $G = (V,E,M,T)$, two vertices $s,d \in V$ and a departure time $t_0 \in \{t_1, t_2, \ldots, t_l\}$, the shortest path problem (SPP) in time-dependent multimodal graph consists in calculating a path p from vertex s to d, departing at t_0 where $f(p,t_0)$ is minimal. This is called the shortest path (SP).