Towards multi-class, multi-objective traffic management based on values

X. Lin[a,*], L.A. Tavasszy[a]

[a] Department of Transport and Planning, Delft University of Technology, Delft, The Netherlands

X.Lin@tudelft.nl, L.A.Tavasszy@tudelft.nl

[*] Corresponding author

Extended abstract submitted for presentation at the 11th Triennial Symposium on Transportation Analysis conference (TRISTAN XI)
June 19-25, 2022, Mauritius Island

March 31, 2022

Keywords: User equilibrium; multi-class traffic; multi-objective optimization; value-based traffic management

1 INTRODUCTION

Freight traffic takes up an important part in the traffic composition. According to Statistics Netherlands (CBS) (2020), road transport within the Netherlands carried 766 million ton of goods in the year of 2019, which was 41% of the total freight being transported. Freight traffic has very different characteristics from passenger traffic. This includes different origin / destinations, vehicle characteristics (length, speed, etc.). In particular, the value of time (VOT) is different for different vehicle (user) classes. According to SP surveys done in De Jong *et al.* (2014), Kouwenhoven *et al.* (2014), the VOT for freight is 38 euros/hour in the Netherlands, and the VOT for passenger car is 9 euros/hour. Despite the differences, freight and passenger are both active participants taking a share in the public traffic infrastructures.

Traffic management can steer the traffic in a way that the road infrastructures are used more efficiently (Wismans (2012), Schreiter (2013). In the meantime, due to the aforementioned differences, freight traffic and passenger traffic can response to the same traffic management approach in different ways. However, freight traffic and passenger traffic are generally not distinguished while implementing traffic management, as traffic managers do not actively consider the differences in vehicle classes. Few research consider freight traffic performance as a separate objective apart from the passenger traffic performance when evaluating traffic management measures.

Literature has addressed multi-objective traffic management Ahn *et al.* (2020), Wismans (2012). Wismans (2012) considers environmental impacts and accessibility. Ahn *et al.* (2020) consider energy consumption as well as travel time with 2 vehicle classes: electric vehicles and conventional vehicles while optimizing traffic management profiles. Both research use 2-level optimization, with the user equilibrium (UE) traffic assignment as the lower level, and the objectives they optimize at the upper level. Neither of the papers consider the VOT of the user classes while designing traffic management measures.

Lin *et al.* (2021) develop an MILP formulation that represents multi-class UE assignment. Based on this new modeling approach, this research provides a theoretical framework of multiple vehicle class, multi-objective optimization for traffic management, which can be solved as a one-level problem. The framework considers the performances of freight traffic and passenger traffic, evaluating the effectiveness of traffic management on these two dimensions by means of multi-objective optimization. The remainder of the abstract presents the core formulation for multi-class traffic management. We also use a simple test case to illustrate a small fraction of what can be achieved with this method.

2 MATHEMATICAL PROGRAMMING FORMULATION FOR TRAFFIC MANAGEMENT

Based on Lin *et al.* (2021), we can now efficiently incorporate traffic management measures considering the behavioral response of different user classes. Assume a network $\mathcal{G} = \{\mathcal{N}, \mathcal{E}\}$, with nodes $n \in \mathcal{N}$, links $i \in \mathcal{E}$, OD pairs $w \in \mathcal{W}$, path $p \in \mathcal{P}_w$ between OD pair w, considering vehicle class $m \in \mathcal{M}$. We formulate the multi-objective traffic management problem as the following:

$$\min_{x,v,c} J = \sum_m \sum_w \sum_p \xi_m x_{mwp} c_{mwp} = \sum_w \sum_p \xi^{\text{truck}} x^{\text{truck}}_{wp} c^{\text{truck}}_{wp} + \sum_w \sum_p \xi^{\text{car}} x^{\text{car}}_{wp} c^{\text{car}}_{wp} \tag{1}$$

subject to:

$$a_{mwp}(c_{mwp} - c^*_{mw}) = 0, \qquad \forall m \in \mathcal{M}, w \in \mathcal{W}, p \in \mathcal{P}_w; \tag{2}$$

$$a_{mwp} = \begin{cases} 0, & \text{if } x_{mwp} = 0 \\ 1, & \text{if } x_{mwp} > 0 \end{cases}, \qquad \forall m \in \mathcal{M}, w \in \mathcal{W}, p \in \mathcal{P}_w; \tag{3}$$

$$c_{mwp} \geq c^*_{mw}, \qquad \forall m \in \mathcal{M}, w \in \mathcal{W}; \tag{4}$$

$$c_{mwp} = \sum_i \left(\delta_{ip} f^{\text{BPR}}_{mi} \left(\sum_{m'} \sum_w \sum_{p'} \delta_{ip'} x_{m'wp'} \pi_{m'} \right) \right), \qquad \forall m \in \mathcal{M}, w \in \mathcal{W}, p \in \mathcal{P}_w; \tag{5}$$

$$f^{\text{BPR}}_{mi}(x) = \frac{L_i}{v^{\text{ff}}_{mi}} \left(1 + \alpha \left(\frac{x}{k_i} \right)^\beta \right), \qquad \forall m \in \mathcal{M}, i \in \mathcal{I}; \tag{6}$$

$$\sum_p x_{mwp} = d_{mw}, \qquad \forall m \in \mathcal{M}, w \in \mathcal{W}, p \in \mathcal{P}_w; \tag{7}$$

$$\xi_m \geq 0, \qquad \forall m \in \mathcal{M}; \tag{8}$$

$$x_{mwp} \geq 0, \qquad \forall m \in \mathcal{M}, w \in \mathcal{W}, p \in \mathcal{P}_w. \tag{9}$$

The objective function sums up the total travel cost (c_{mwp}) over all vehicle flows (x_{mwp}). c^*_{mw} stands for the lowest travel cost of class m, between OD pair w. π_m is the passenger car equivalent (PCE) value for class m. $\delta_{ip} = 1$ stands for that link i is part of path p, otherwise $\delta_{ip} = 0$. d_{mw} is the fixed demand of class m between OD pair w. The BPR function f_{mi} is used for the volume-delay relationship. L_i is the length of link i. v^{ff}_{mi} is the free flow speed of class m on link i. k_i is the capacity of link i. $\alpha = 0.15$ and $\beta = 4$ are constant parameters. The above formulation can be efficiently solved as a mixed-integer quadratic programming (MIQP) problem using packaged/commercial solvers. In the objective function J, vehicle classes are given different weights ξ_m. By adjusting ξ_m, the UE solution gives the optimal value of decision made by speed limits (v^{ff}_{mi}) and lane opening/closure (k_i) that prioritize the different user classes accordingly.

3 A SMALL TEST CASE AND PRELIMINARY RESULTS

Next we use a small test case to illustrate the effect of having traffic management as decision variables in the formulation. A two-path network (Fig.1) is used. Trucks and passenger cars start from the origin on the left to the destination on the right. It is assumed that trucks have strong

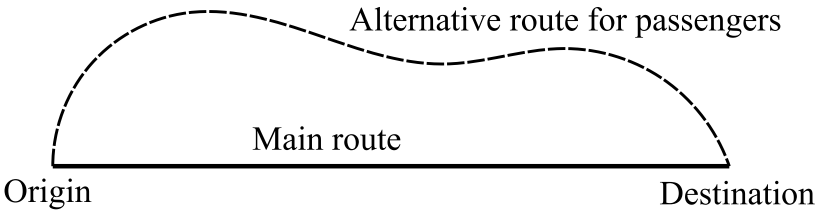

Figure 1 – *A network with 2 routes.*

Table 1 – *Input for the test case*

Input	Description
$(L_{\text{main}}, L_{\text{alt}})$	(200, 200)
$(k_{\text{main}}, k_{\text{main}})$	(20, 20)
$(v^{\text{ff}}_{\text{main}}, v^{\text{ff}}_{\text{alt}})$	Car: (v^{dv}, 120); Truck: (80, 0)
v^{dv}	[80 130]
$\sum_m d_m$	100
ξ_m	$\xi_{\text{car}} + \xi_{\text{truck}} = 1$

preference for the main route; while passenger cars can travel via the main or the alternative route. This also guarantees the uniqueness of the UE status in every solution. (We exclude the discussion on the uniqueness issue of multi-class UE in this document.) The rest of the input is summarized in Table 1.

We use the SCIP solver in Optitoolbox for Matlab to solve the formulation multiple times, with different ξ_m values in each group, with a specific truck/car ratio in demand. We test 6 groups with the truck occupancy of total demand in number of vehicles (7.5%, 10%, 12.5%, 15%, 17.5%, 20%). The results are visualized in Fig.2, in which car / truck total travel time ($x_{mwp} \times c_{mwp}$) are x-axis and y-axis, respectively.

For each group a Pareto line is formed. The 3 stars on each Pareto line marks the speed limit for cars on the main route (from left to right) 130 km/h, 100 km/h, and 80 km/h respectively. Within one group, limiting the free flow speed on the main route causes more cars to switch to the alternative route, leaving more space for trucks on the main route. This results in higher car total travel time and lower truck total travel time.

A comparison between the groups suggests that if the truck occupancy is lower (e.g., 7.5%), a speed limit for cars increases cars' total travel time but does not significantly reduce truck total travel time. The benefit given to trucks of the speed limit becomes more obvious when trucks take a higher occupancy in the travel demand.

We also use two reference lines: $\xi_{\text{car}} : \xi_{\text{truck}} = 1 : 1$ and $\xi_{\text{car}} : \xi_{\text{truck}} = 9 : 38$ De Jong *et al.* (2014), Kouwenhoven *et al.* (2014). The reference given by the SP values can be seen as a reference for the "societal fairness" between passengers and freight, in terms of the usage of infrastructures. Take for an example with a fixed speed limit for cars (100 km/h), when truck occupancy is at around 17.5%, the management is at its fairness. The same traffic management with a lower truck occupancy favors trucks more than cars and vice versa. It also indicates the management measures (in this case, speed limit on the main route) that can be used to steer the mixed traffic closer to its fairness point under different circumstances (e.g., truck occupancy).

We point out that the analysis is preliminary based on simplified models such as an underlying static assignment as well as the BPR function. Nevertheless, we provide a framework for more detailed and realistic analysis on the effectiveness of traffic management with the consideration of values.

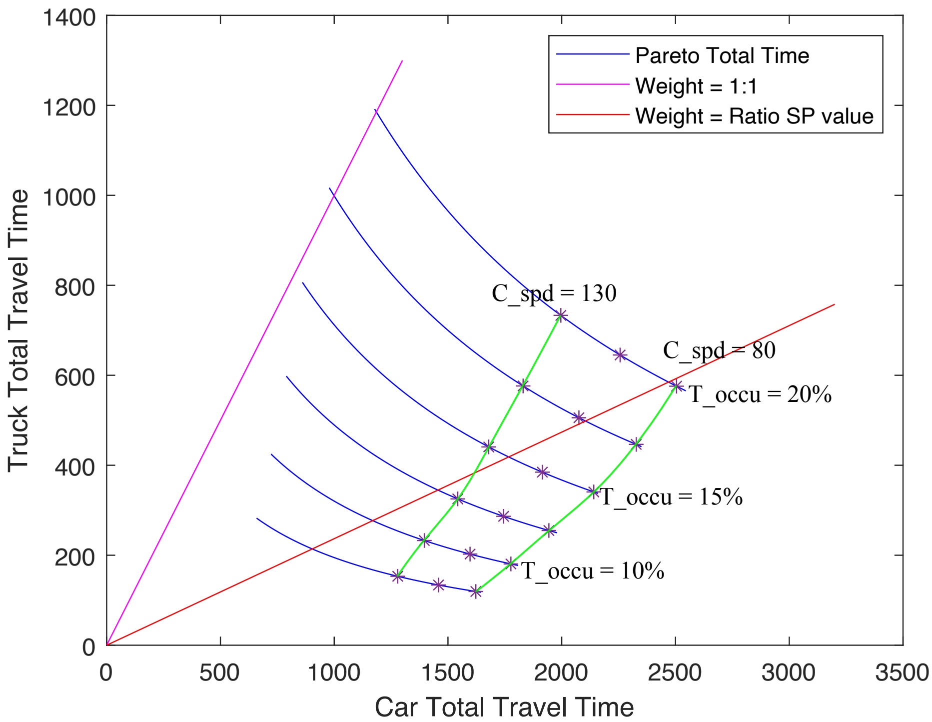

Figure 2 – *Results*

4 SUMMARY

Traffic management rarely connects values to different user classes. With the recent development in modeling UE with mathematical programming, this research builds up an efficient theoretical framework to analyze user class-specific preferences for traffic management measures. A small test case is used for illustration with preliminary analysis based on freight and passenger value of time. The test case indicates that one set of traffic management profile may favor one user class more than another, while this may also turn around as traffic conditions changes. Future research can focus on more detailed and realistic modeling and analysis based on this framework.

References

Ahn, Kyoungho, Bichiou, Youssef, Farag, Mohamed, & Rakha, Hesham A. 2020. *Multi-objective Eco-Routing Model Development and Evaluation for Battery Electric Vehicles.*

De Jong, Gerard, Kouwenhoven, Marco, Bates, John, Koster, Paul, Verhoef, Erik, Tavasszy, Lori, & Warffemius, Pim. 2014. New SP-values of time and reliability for freight transport in the Netherlands. *Transportation Research Part E: Logistics and Transportation Review*, **64**, 71–87.

Kouwenhoven, Marco, de Jong, Gerard C, Koster, Paul, van den Berg, Vincent AC, Verhoef, Erik T, Bates, John, & Warffemius, Pim MJ. 2014. New values of time and reliability in passenger transport in The Netherlands. *Research in Transportation Economics*, **47**, 37–49.

Lin, Xiao, Leclercq, Ludovic, Tavasszy, Lorant, & van Lint, Hans. 2021. *Formulating multi-class user equilibrium using mixed-integer linear programming.* Submitted to a journal.

Schreiter, Thomas. 2013. *Vehicle-class specific control of freeway traffic.* Ph.D. thesis, Delft University of Technology.

Statistics Netherlands (CBS). 2020. *Goods transport; modes and flows of transport to and from the Netherlands.* Tech. rept. url: https://www.cbs.nl/en-gb/figures/detail/83101ENG, Accessed on: 24-11-2021.

Wismans, Luc Johannes Josephus. 2012. *Towards sustainable dynamic traffic management.* Ph.D. thesis, University of Twente, Enschede, Netherlands.