Concepts for the integration of drivers’ decisions into freight transport modelling

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Abstract. Route planning and navigation are important strategic and tactical driving decisions in freight transport. On the one hand they are determined by the design and the determinants of the city's traffic system (e.g. average speed, traffic jam level etc.), on the other hand by the restrictions set by the receiver or shipper, e.g. time windows or service promises. Great attention has been devoted to research of these factors. However, the influence of the driver on route planning and navigation and its resulting economic effects within transport systems have hardly been examined so far. Driver characteristics depend on time-stable factors such as experience, age, gender and personality and are moderated by salient attributes such as fatigue, stress and state of health. These characteristics can influence strategic decisions of the driver, in the context of the given conditions, before and during a trip.

Findings regarding driver characteristics have the potential to enable more precise freight transport models. For this purpose, the present paper uses secondary data to outline the characteristics of strategic decisions taken by the driver while driving, to present a state of the art concept to integrate drivers’ decisions into freight transport modelling. The aim is to create a basis for increasing the quality and forecast reliability of freight transport models. Further, new incentives for traffic planning and control can be set and advantageous disposition decisions can be supported.

1 Motivation

In current freight transport modelling, the human drivers’ behaviour is not represented as actively affecting the delivery. Up to now, freight transport models assume, depending on the specifications of the shipper, that the logistics actor (e.g. freight forwarder, transport service provider) carries out and passes the logistics planning to the driver. In fact, the driver is modelled as an executive body without personal traits or skills. Thus, it seems obvious that the driver cannot affect the execution of the logistics planning. In practice however, the driver is granted degrees of freedom while the delivery, including e.g. the choice of route and customer sequence.

The aim of this paper is to investigate the relevance and applicability of methodological approaches to integrate drivers’ decisions in freight transport modelling.

2 Driver characteristics and strategic drivers decisions

The driver might change the logistics planning due to internal states (e.g. fatigue) or external factors (e.g. traffic density) before and during the trip. Effects on the drivers’ behaviour can be both cognitive and motivational. These factors can either reduce or increase available cognitive resources for the driving task. Furthermore, driving behaviour may be determined by the drivers’ personality traits. There is a plethora of models that describe driver behaviour in the context of driving manoeuvres i.e. lane change or car following [1]. Michon divides the driving task in three hierarchical levels of skill and vehicle control: (i) the vehicle control level, (ii) the manoeuvre level and (iii) the strategic level [2].

The strategic level is particularly relevant for modelling freight traffic and demand. Route planning and trip scheduling takes place. In addition, driver objectives, plans and decisions are made and modified in order to achieve them.

Decisions at the strategic level depend on the information available to the driver. In general, a decision should lead to the most positive outcome with regard to the decision objective [3]. In psychological research two decision scenarios are predominantly considered: (i) all relevant information is available or (ii) incomplete information is available for decision making. Within a scenario where all information is available, decision making can be seen as solving a deterministic optimisation problem with no time constraints [4]. The majority of decisions taken while driving is lacking the criterion of full information. For example, a driver does not know the exact deceleration i.e. in m/s^2 of a braking preceding vehicle nor the traffic density within the next hour on the route ahead. The decision of how hard to hit the brake pedal or which route to choose, is then made under information uncertainty. However, decisions under uncertainty cannot be solved within the scope of a deterministic optimisation problem.

The quality of the decision depends on the expertise of the driver in the driving task but also on the time available for decision making. As time is sparse while driving, the complexity of the decision-making process needs to be reduced. Short cuts, also known as heuristics, are processes that allow to solve a decision problem within a short time and ignore, in the best case, irrelevant information to solve the decision problem [4]. These heuristics are described as rules of thumb and are based on intuition and routines [5]. Expertise plays a crucial role in distinguishing between relevant and irrelevant information and enables an expert driver to consciously and unconsciously separate them in the decision-making process.

Heuristics require few cognitive resources (e.g. driving in a known environment). In contrast, complex decisions (e.g. driving in an unknown environment) raise cognitive resource demand. In addition, complex decisions result in increased mental fatigue, as cognitive resources are depleted [6]. A possible representation of heuristics are Fast Frugal Trees (FFT) [7, 4]. Fast Frugal Trees use action recommendations, that can offer a decision aid by asking a limited number i.e. three to four binary questions about relevant specific cues. FFTs can thus lead to an adequate decision regarding the decision objective within in a short time, despite or rather because of neglecting information.

Driver decisions are made in the context of dynamic traffic and evaluated with regard to the outcome of decision objectives e.g. short cuts in route selection. The dynamic decision making approach understands a decision as a cyclical (feedback) process, which depends mainly on recurring decisions and the quality evaluation of the decision [8]. Thus, decisions can be improved over time. In DDM expertise allows drivers to make better route choices than less experienced drivers. Crucial in skill acquisition is (i) how the quality of the decision is determined, (ii) when the quality criterion is retained or (iii) replaced by a new instance. In this approach, it is particularly relevant that past decisions are taken into account in the next cycle of the decision-making process.

3 Decisions in freight transport modelling

To integrate drivers' decisions in transport modelling, it is necessary to provide appropriate approaches to the transport models. Agent-based traffic models appear to be most promising. An agent-based traffic model consists of agents (objects), the system environment, and the description of the relation of the agents to the system environment as well as to other agents [9, 10]. Drivers can be modelled as agents. Agents have attributes with assigned properties and methods that enable the interaction with the environment and other agents. The following properties are often assigned to agents [10,11]: (i) Agents are independent and can be clearly (individually) identified as objects (self-containedness). (ii) Agents are not controlled centrally, but control themselves proactively according to their own goals (autonomy). (iii) Agents are able to interact with other agents (social ability) and (iv) agents perceive and react to the system environment (reactivity).

Five strategic driving decisions are implemented in traffic models. These decisions are: (i) where a trip is going (destination), (ii) when to depart or arrive, (iii) how long to stay at a stopping location, (iv) how to cover the distance (choice of transport mode) and (v) which route (route choice) to take [12, 13]. Below, we present methodological approaches that appear useful to implement human centered decision-making behaviour of agents in traffic models.

Discrete choice models: The strategic decisions mentioned above can be represented by discrete choice models. Discrete choice models calculate the probability that an agent will select a specific choice among a set of decisions [14, 15]. A utility-function calculates the benefit of a given decision. The decision with the greatest benefit (greatest utility) to the decision maker has the highest probability of being selected. The decision maker is thus considered as a utility maximizer within the model.

Logit and probit models: Logit and probit models belong to the group of discrete choice models. The logit model is a form of regression analysis (logistic regression). Regression analysis is used to estimate how likely an event will occur, represented by the odds of how likely an option will be selected given the option will not be selected [16, 17]. By using a different link function also probit models represent the choice between two options as likelihood similar to logit models (see e.g. [18]).

Bounded-Rationality Models: Bounded-rationality models depict agents as utility maximizers, which however, do not necessarily make rational decisions. The bounded rationality of agents is attributed to the fact that not all information for a decision is available, perceived and processed [19, 20]. These decision procedures are heuristics aiming at satisfactory results.

Beliefs-Desires-Intentions Models (BDI): BDI models are based on an algorithmic approach to model decision making. In BDI Models an agent has a set of beliefs, plans, events, actions and intentions. Additionally, agents can execute three selection functions to select an event, a plan or an intention [21]. The agent must choose a plan for execution that is a logical consequence of the agent's beliefs. The current plan is executed by the agent during the simulation until the plan is processed and a new plan is selected [21-23].

In contrast to the above models, a literature review showed that in current freight transport modelling, drivers do not make decisions that degrades model performance. An extensive literature analysis will be presented in the final paper: [24-38].

Only van Duin et al. developed a modelling approach in which an agent makes decisions locally [39]. Within the approach, a central route planning is implemented, that the agent 'truck', which can be equated with the truck driver, will use as a plan. During the trip, the agent makes the local decision at each junction as to which branch to take.

4 Conculsion

This paper presents a state of the art concept to integrate drivers' decisions into freight transport modelling. We showed that the driver is currently widely neglected in transport modelling. We however think that the driver is a key aspect to improve freight transport simulation by acknowledging the decisions and behaviour as a relevant factor. In order to close this research gap, we propose to further analyse current freight transport demand models and to test the above approaches of behaviour integration within microscopic freight transport modelling.

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