Dynamic Process Model of Mass Effects in Travel Demand Forecasting

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Extended Abstract for LATSIS 12

Traditional travel demand forecasting assumes perfectly-informed travellers, whereas it is not clear how travellers acquire such information about alternatives that they end up using and decide not to use, e.g. non-chosen modes. It seems likely that much of this information especially for unchosen modes could be from word-of-mouth, and may follow (and reinforce) the general negative or positive perceptions of a mode within an individual's social group. While interactions between household members are considered in activity-based approaches, we are more interested in the wider influences across social groups and households which we believe are not yet well represented in existing modelling approaches despite various recent literature confirming their importance for travel decisions (e.g. Weinberger and Goetzke (2011)).

It is rather the *negative* effects of mass transportation that are commonly evaluated. That is to say, the aggregate effects of individual mode, departure time and route decisions are routinely modelled through impact models to represent on-street congestion, public transport crowding, pollution, etc. These effects are negative in the sense that increased use of a mode will tend to decrease its attractiveness. Our interest, on the other hand, is for the potential for significant *positive* mass effects to exist, whereby increased use of a mode will generally increase its attractiveness for future travellers.

We imagine a situation such as the following: A transport planner might set up a scheme, such as car sharing and encourage its usage through communicative measures. This might then persuade some to initially join. Through the experience of these few others might be persuaded join. For minor services, such as car-sharing this might then allow improving the service through, for example, providing further vehicles at additional locations. The service might hence become more attractive to additional users, eventually creating a positive cyclic effect. In summary, initial investments and possibly communicative measures to a selected group will be the trigger for a desirable trend effect as envisaged by mobility management.

In this paper we describe a modelling approach for such mass effects inspired by literature from social physics, evolutionary game theory and marketing. For simplicity our model notation relates to a scenario assumption of choice between two lifestyles, for two population groups. That is, we refer to mobility lifestyles *c* and *t* and population groups λ and φ. Broadly *c* stands for car and *t* for transit, but one might more generally consider *c* as the prevailing unsustainable mode and *t* as the new sustainable mode. Similarly, λ stands for "leading" population group and φ for "following", but one might more generally interpret λ as innovators as in the Bass model or, i.e. those who are easier to experiment with new forms of mobility and are possibly convinced by persuasive policy measures. Followers are more likely to be influenced by the decisions of others and often make up the mass of the population. Our question is primarily to understand at what stage a large amount of followers will be likely to consider switching to the, by policy makers desired, mode *t*. The problem can be described with following notation:

A:{ λ, φ}:	Population groups, λ: leading, trendsetting group, φ: following group
Λ, Φ:	Size of population groups λ and φ respectively
L: {*t*,*c*}:	Set of possible mobility life styles, *t*: transit oriented, *c*: car oriented
N:	State of population
$n_i^\alpha \in$ **N**:	Number of persons in group α with mobility life style *i*

From this notation it follows that the state of the population is described by the set $\boldsymbol{N} = \{n_t^\lambda, n_c^\lambda, n_t^\varphi, n_c^\varphi\}$ and since

$$n_c^\lambda = \Lambda - n_t^\lambda \qquad (1)$$

$$n_c^\varphi = \Phi - n_t^\varphi \qquad (2)$$

the solution to this problem can be fully described with two unknown variables n_t^λ and n_t^φ. We are interested in the evolution of these variables over time.

We assume that each mobility lifestyle has its intrinsic, possibly population specific, utility ζ_i^α. Further, we consider that the utility of a mode, u_i^α, will be in two ways directly a function of n_i^α. Firstly, there are congestion effects meaning that the utility of lifestyle *i* decreases with the total number of people adopting this lifestyle. To reflect the negative external effects of cars one might expect that the utility of lifestyle *c* decreases faster with more users taking up this lifestyle compared to the decrease in utility of lifestyle *t* when more people take it up. For lifestyle *t*, in the contrary one might even consider positive long term "congestion" effects, considering that the service attractiveness of minor (uncongested) modes might increase if more users take it up due to, e.g. more demand responsive buses or more car sharing stations spreading throughout a city.

Finally, we consider the trend or conformity effects to measure the influence an individual from group α perceives by adapting the same mobility lifestyle as others from group β. In general one would expect the effect to be larger if α *and β* denote the same groups as found in the psychological literature on provincial descriptive social norms. Further, given our definition of one group as "leading" and the other as "following", we would expect the effect of group λ on group φ to be larger than vice versa.

In summary, considering all these effects leads to our general assumption on u_i^α as in Eq. (3) where the specific functional forms are to be specified. g_i^α specifies the congestion or service improvement effects due to the sum of people taking up lifestyle *I*; h_λ^α and h_φ^α specify the trend effects due to following people in group λ and φ respectively. Function f^α then combines the group specific, mode specific effects and considering the intrinsic utility ζ_i^α.

$$u_i^\alpha(n_i^\lambda, n_i^\varphi) = f^\alpha\left(\zeta_i^\alpha, g_i^\alpha\left(n_i^\lambda + n_i^\varphi\right), h_\lambda^\alpha\left(n_i^\lambda,\right), h_\varphi^\alpha\left(n_i^\varphi\right)\right) \tag{3}$$

In the full paper we will develop the transition probabilities and transition dynamics. We illustrate with a case study that despite lower intrinsic utility for the sustainable lifestyle, significant changes towards this lifestyle can be achieved by considering congestion, service improvements and mass effects. We further illustrate that mass effects can be positive or negative. Negative mass effects, such as the perception of the car as a status symbol might be difficult to be overcome and can make it difficult for new (attractive) modes to obtain significant market shares. It appears that the combination of mass effects together with service improvements can achieve the best results.

Key References

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