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SOCIAL VALUE ORIENTATION AND THE EFFICIENCY OF TRAFFIC NETWORKS

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ABSTRACT

Transport models include the mathematical and logical abstractions of real-world systems. It is common to describe the traffic system as a non-cooperative agents game, assuming travellers’ behaviour is selfish by nature (focus on optimizing outcomes for themselves, without considering much others’ benefits). In this paper, some basic concepts of pro-social behaviour are illustrated. Adding to the individual user’s utility function a component to represent social value, the user equilibrium is extended to a social equilibrium. The sensitivity of the social equilibrium to social values is investigated. Also introduced here is a dynamic travel-choice model of travel behaviour which considers social value orientation. The potential for incorporating social aspects in the development of transport modelling is demonstrated by a numeric example.

1. INTRODUCTION

Traffic network models are designed to emulate the behaviour of travellers in the traffic network over time and space and to predict changes in system performance, when influencing conditions are changed. Such models include the mathematical and logical abstractions of real-world systems implemented in computer software. In many of the applied models each traveller is formulated as an individual agent, making independent decisions about his or her desired use of the transport system (travel mode, route, departure time, etc.). Social aspects of travel behaviour (such as social value orientation) are commonly omitted from the formal modelling process, quite often treated as (unbiased) random errors or qualitative caveats. Travel behaviour research in recent years has tended to focus on normative models, which tend to represent the individual traveller as a homo economicus, a rational economic human being, rather than on descriptive models to represent and measure travel behaviour without making an explicit value judgment. A clear distinction between normative modelling and descriptive modelling of travel behaviour is not always made. As
stated by Gärling (1998), the behavioural assumptions in travel demand models are almost always made without reference to the existing theories in behavioural sciences. Many transport problems can be defined as social dilemmas. A social dilemma problem represents a situation in which (voluntary) contributions are needed to attain some common and shared social payoff, and where the rational choice of the individual is to not to cooperate. It is common to represent the performance of a traffic network as the aggregate behaviour of the individual agents, not taking into consideration the social interactions and the social values they may have towards each other. This approach is based on an implicit assumption that social aspects can be neglected.

Recently, there have been signs of increased interest in the study of social influence in the context of travel, mainly in activity-based modelling (see, for examples, Vovsha et al., 2003; Salvini and Miller, 2005; Arentze and Timmermans, 2006; Goulias and Henson, 2006). However, socio-psychological aspects of dynamic choice behaviour have not gained much attention from researchers of the more traditional travel behaviour models (such as equilibrium models, microsimulation, and discrete choice analysis). Understanding and modelling the behaviour of the individual traveller, influenced by his/her social values, may be considered to be a new territory in travel behaviour that has not been much explored. This paper presents an investigation of the effect of social value orientation on choice behaviour in a path-choice situation, simulating a social dilemma. The sensitivity of the traffic equilibrium to the travellers’ social value orientation is demonstrated, followed by a discussion on the importance of incorporating social value orientation into transport modelling.

2. SOCIAL VALUE ORIENTATION AND THE SOCIAL EQUILIBRIUM

In congested traffic networks, the optimal route choice for an individual depends on the congestion on alternative routes and on the route choices made by other individuals. Under System Optimum (SO) conditions traffic should be arranged in congested networks such that the total travel cost is minimised. This implies that each agent behaves cooperatively in choosing his/her own route to ensure the most efficient use of the whole system. However, in such networks, patterns of traffic flow may differ from the socially efficient state of system optimum, as individual travellers attempt to minimize their own travel cost without taking into consideration the effects of their actions on other travellers, thus without considering the system externalities.

A typical equilibrium of a traffic network with a finite number of non-cooperative agents (players) is the Nash non-cooperative optimum. It represents a situation where no agent can receive any benefit by changing his/her own route decision. When players are symmetric (i.e., they are identical in all respects and share the same origin and destination) and the number of players becomes infinitely large, the Nash equilibrium converges to the Wardrop equilibrium (Haurie and Marcotte, 1985).

Each network user non-cooperatively seeks to minimize his/her cost of transport. This leads to Wardrop's (1952) principle of route choice, that states that the journey times (or costs) in all routes actually used are equal and less than those which would be experienced by a single
vehicle on any unused route. The traffic flows that satisfy this principle are usually referred to as User Equilibrium (UE) flows, since each user chooses the route that is the best for him or herself. Specifically, a user-optimized equilibrium is reached when no user can decrease his/her route travel time (or cost) by unilaterally switching routes. This well-known equilibrium became accepted by transport modellers as a sound and simple behavioural principle to describe the spreading of trips over alternate routes due to congested conditions.

Every transport system may be described as a social system, composed of individuals who interact and influence one another’s behaviour. While in most of the transport applications, we are interested in studying the behaviour of the totalistic system as the prime focus, the tools used by transport modellers tend to focus on the behaviour of the individual traveller. The analysis of travel behaviour is typically disaggregated, meaning that common models represent the choice behaviour of individual decision-making entities, whether these are individual travellers or households. However, merely aggregating individuals' choices means that the functions and the characteristics of the social system are ignored. Attention should be given to interactions between individuals who are part of a social system, and to other social aspects of travel behaviour that may influence the system equilibrium and the system dynamics.

Assuming travellers behave in a completely non-cooperative and selfish way might be too extreme. The paradigm that selfish motives always underlie the choices travellers make may be questioned (Gärling, 1998). A certain level of collaboration, that may result from social interactions, information sharing and considering others’ utilities, may change the system equilibrium and the network’s overall dynamics. The importance of understanding the social aspects of travel-choice behaviour is not only relevant to the measurement and the prediction of such behaviour. It may also be important in terms of influencing and changing travel behaviour.

There is also a valuable line of intended enquiry in studying altruism, which is defined by behaviourists as “being costly acts that confer economic benefits on other individuals” (Fehr and Fischbacher, 2003). Many definitions of altruism also include what is often considered a critical component of such behaviour: that the behaviour must have some cost for the actor. According to Sorrentino and Rushton (1981, p. 427), altruism is “behavior directed toward the benefit of others at some cost to the self where no extrinsic or intrinsic benefit is the primary intent of the behavior”. Fehr and Fischbacher (2003) distinguish between reciprocal altruism, whereby people help in return for having been helped, and strong reciprocity. They define strong reciprocity as a combination of altruistic rewarding and altruistic punishment. Strong reciprocators bear the cost of rewarding cooperators or punishing defectors even it confers no personal benefit, whereas reciprocal altruists only reward or punish if this is in their long-term self-interest. Many behavioural scientists debate the existence of pure altruism in humans (Skinner 1978). There are alternative explanations to individuals’ pro-social behaviour and motivation to cooperate, rather than pure altruism. For example, where gains to the beneficiary not perceived to be meaningfully larger than the costs to the benefactor, cooperative players may not be regarded as altruistic.

This work looks at pro-social behaviour which is a broader term than altruism. It comprises helpful actions intended to benefit another person, which are not undertaken through professional obligation. Altruism is a narrower category of pro-social behaviour, in which the motivation for helping is, in addition, characterised by empathy and the ability to understand
the perspective of the help-recipient. Pro-social behaviour can be categorised as either egoistically motivated (helping someone in order, ultimately, to benefit oneself) or altruistically motivated (intended only to benefit the other person) (Bierhoff, 2001).

In their work on interdependence theory, Thibaut and Kelley (1978) propose that interdependent persons may find it mutually beneficial to perform a pro-social transformation, in which each person starts to take decisions on the basis of what benefits the other person, rather than him/herself. One of the factors determining whether or not such a transformation takes place is social value orientation (McClintock, 1972). Essentially, social value orientation determines one’s preference for a particular allocation of common resources between oneself and others, referred to as “self and other”. According to McClintock’s model, the importance a person attaches to outcomes for self may be used to categorize people to those having a pro-self value orientation who focus on optimizing outcomes for themselves, and to others with a pro-social value orientation who focus on optimizing outcomes for others. A distinction is made between prosocials and proselves is made in the study of social dilemmas (See, for examples, Van Vugt et al., 1995; Gärling, 1999).

Over the last decade, the study of social interactions, social value orientation and collaborative behaviour has attracted much research in behavioural sciences and economic decision-making (see a review in Soetevent, 2006). In research into social dilemmas it has been found that some people cooperate even when they are anonymous and unaware of others’ choices. These people (‘prosocials’) are assumed to have a pro-social value orientation (Liebrand and McClintock, 1988). It is possible to encourage people with a more individualistic social value orientation (‘proselfs’) to make choices that take into consideration the system negative externalities.

Structural interventions can alter the objective features of the decision situation by changing the incentive patterns associated with cooperation and non-cooperation (See, for example, Yamagishi, 1986). Providers and managers of transport systems have introduced structural interventions that include a change of the incentive patterns associated with cooperation and non-cooperation. Typical examples of such interventions may include changing the payoff structure (e.g. congestion charging), reward-punishment (e.g. incentives for public transport users, restriction on car parking), and situational change (e.g. residential or workplace relocation). Recently, there has also been increasing interest in the influence of psychological and social aspects on the behaviour of travellers. This so-called ‘softer’ side of transport policy is relatively new in the UK and Australia (see, for examples, Cairns et al., 2004 and Stopher, 2005). Such soft measures are aimed at influencing travellers’ attitudes and beliefs rather than making physical or economic changes in the transport system. Sunitiyoso et al. (2006) argued that the effectiveness of ‘soft’ measures may be enhanced if more consideration and emphasis is given to the support of social aspects of human behaviour. Goulia and Henson (2006) considered pro-social behaviour and altruism as a powerful determinant of travel behaviour, and as a motivator to use in changing travel behaviour. They provide two main reasons to study the potential of altruistic behaviour modelling in such a context: a) understand altruism as a value to use in motivating people to move toward the common good; and b) understand altruism expressed in specific activity and travel behaviours. They suggest that social interactions should be the core of activity-based approaches to travel demand forecasting.
Laboratory experiments simulating route-choice situations (Rapoport et al., 2006, 2008a, 2008b; Morgan et al., 2008) revealed that aggregated route choices and resulting travel times are significantly closer to the predictions of user equilibrium rather than to the predictions of system optimum. In all of the above works, participants were not familiar with each other, communication between participants during the experiment was forbidden and the participants were paid based on their individual performance. Morgan et al. (2008) did not provide participants with information on the choices of others. One may argue that these aspects of experimental design do not encourage participants to exhibit prosocial value orientation, and that there is not much reason to expect prosocial behaviour by the participants.

Other important factors that might influence the degree of prosocial value orientation may be the size and complexity of the transport network (e.g. the number of alternative routes), and the size of the social group an individual traveller is identified with. A small group of individuals is more likely to secure voluntary compliance than a larger group (Olson, 1971). Common traffic networks are quite large, and individual travellers may have only little social interactions with each other, neither do they have much ‘group identification’, thus might not identify themselves with the larger group (or society) values and interests. One may argue that due to the social characteristics of the traffic situations which travellers are faced with, it is unlikely that common users of the traffic network exhibit strong pro-social behaviour. Indeed, experimental work on route-choice (Rapoport et al., 2006, 2008a, 2008b; Morgan et al., 2008) does not provide any evidence of prosocial behaviour in small groups of participants, varying in size from 10 to 40.

The translation of social responsibility to economic behaviour can be done by adding the attitude toward the policy or the community to the utility function (See Train et al., 1987; Rabin, 1993). Following this concept, an $n$-agents system in which social values influence travel choice, is considered. Agent $i$’s social utility at time period $t$ is defined as follows:

$$U_i(x^t) = -k_{ii}t_i + \sum_{j \neq i}^{n} k_{ij}t_j$$

The first component of Eq.1 represents agent $i$’s individual utility, which is defined as the negative value of his travel time ($t_i$), weighted by the parameter $k_{ii}$. The weighted utilities of other agents, in the mind of agent $i$, are represented by the second component of Eq. 1, $k_{ij}' = \sum_{i \neq j}^{n} k_{ij}$. Each agent’s travel time, $t_i$, is a function of the choices made by all agents at time period $t$, $x^t$. Other externalities, related to the travel choices made by the network users, are not explicitly represented in Eq. 1; however, Eq. 1 (and mainly its second component) can be generalised in order to represent them as well.

For simplicity, it is assumed that other agents’ utilities are weighted the same, i.e.

$$k_{ij} = \frac{1-k_{ij}'}{n-1} \quad \forall j \neq i$$

Agent $i$’s social value is defined by the ratio

$$k_i = \frac{k_{ij}'}{k_{ii}}$$
Agents may be classified into types according to their social values \((k_i)\). A selfish agent, who does not consider others’ utilities at all, is represented by \(k_i=0\). A system in which \(k_i=0\), \(\forall i\) converges to the user equilibrium. \(k_i=1\) represents a high pro-social value orientation by agent \(i\), who weights his own utility the same as he/she weights others’ utilities. A system in which \(k_i=1\), \(\forall i\) (i.e., \(k_i=k_i'=0.5; \forall i\)) converges to the system optimum. \(k_i>1\) represents an altruistic behaviour by agent \(i\), where actions taken by him are done mainly in order to improve other agents’ utilities, without considering his own utility. A system in which \(\mathcal{A}\), \(k_i>1\) does not necessarily converge to the system optimum. The situations where \(k_i<0\) may be considered to be less realistic in a travel behaviour context; an agent with a negative \(k_i\) value aims to minimise his own utility, while an agent with a negative \(k_i\) value is interested in reducing others’ utilities (‘aggression’). However, in some contexts of travel behaviour (mainly car driving) we may find some evidence to users who fail to acknowledge the courtesy of others, aggressive driving, road rage, and even physical violence among travellers. The change in the utility of agent \(i\) at time \(t+1\), assuming he/she made a choice \(x_{it}\) at time \(t\), and other agents do not change the choices they made at time \(t\), is represented in Eq. 4.

\[
\Delta u_{it+1} | x_{it+1}, x_{it} = x_{jt}, \forall j \neq i \right) = -k_i A - k_i' B \tag{4}
\]

where \(A=(t_{it+1} - t_{jt}), B=\sum_{j \neq i} (t_{jt+1} - t_{jt}), \) and \(t_{jt}\) is the travel time of agent \(j\) at time period \(t\) \((t_{jt}\) is a function of the choice made by agent \(j\) at time period \(t\), \(x_{jt}\), and the choices made by other agents at time period \(t\), \(x'\)).

Assuming the system has converged to a social equilibrium state \((t \to \infty)\), the change in the utility of agent \(i\) at time \(t+1\) cannot be positive, regardless of the decision he/she makes at time \(t+1\), \(x_{it+1}\), thus

\[
-k_i A - k_i' B < 0 \quad \forall i, \forall x', t \to \infty \tag{5}
\]

Eqs. 4-5 are derived from the definition of agent \(i\)’s social utility function as defined in Eq. 1, and the generalisation of Wardrop’s principle.

There are two applications of Eq. 5: (i) observing travellers’ behaviour and the network performance, it is possible to estimate travellers’ social value \((k_i)\); and (ii) assigning different values to \(k_i\), different states of social equilibrium can be explored. This may be useful in the study of the effect of demand management measures, where structural and/or psychological interventions are introduced.

Combining the above applications (i) and (ii), it is provides a potential tool to evaluate the required change in travellers’ social values in order to change the social equilibrium to a different (more efficient) one.

The extreme cases of traffic equilibrium, system optimum \((k_i=1)\) and user equilibrium \((k_i=0)\), are studied much in the transport literature; however, other degrees of social value \((0<k_i<1)\) may lead to other social equilibria. This is demonstrated by the numeric example given in the next section.

3. NUMERICAL EXAMPLE

In this section, a simple path-choice numerical example, featuring Braess’ Paradox, is investigated in order to demonstrate how a measure of travellers’ social value orientation can be incorporated into modelling of multi-agents traffic systems. The concept of social user
equilibrium is illustrated in section 3.1 and the sensitivity of this equilibrium to travellers’ social value orientation is investigated. In section 3.2 group travel choice decisions are studied in the laboratory environment, featuring the same numerical example. A methodology to derive the social value from participants’ choices is demonstrated. Finally, a simulation model to represent the dynamics of social agents’ choices is developed in section 3.3 and its results are compared with the results of the static equilibrium model in section 3.1.

3.1. The Social Value User Equilibrium

In order to illustrate the traffic assignment process, and to demonstrate some of the concerns related to the choice of scale when representing a traffic network, the following numeric problem is considered.

Assume that the link volume-travel time functions are linear, and given by:

$$T_{ij} = \alpha_{ij} + \beta_{ij} f_{ij}$$  \hspace{1cm} (6)

where $T_{ij}$ is the travel time on link $ij$, $\alpha_{ij}$ is the free flow time on link $ij$, $\beta_{ij}$ is the delay parameter for link $ij$ (the increase in travel time per unit increase in the flow on link $ij$), and $f_{ij}$ is the flow on link $ij$.

Let us consider a simple network problem, presented in Figure 1. There are three possible paths to get from origin ‘a’ to destination ‘d’, and the total traffic, $Q$, is equal to the sum of traffic volumes on paths 1, 2 and 3 (represented by $F_1$, $F_2$, and $F_3$, accordingly).

$$Q = F_1 + F_2 + F_3$$  \hspace{1cm} (7)

where:

$$f_{ab} = F_1 + F_3; f_{bd} = F_1; f_{ac} = F_2; f_{cd} = F_2 + F_3; f_{bc} = F_3$$  \hspace{1cm} (8)

and the travel times on paths 1, 2 and 3 (represented by $T_1$, $T_2$, and $T_3$, accordingly) are:

$$T_1 = T_{ab} + T_{bd}; T_2 = T_{ac} + T_{cd}; T_3 = T_{av} + T_{bc} + T_{cd}$$  \hspace{1cm} (9)

The parameter values used in this numeric example are presented in Table 1.

Figure 1  The Traffic Network and Three Possible Paths
Following Wardrop’s principles, in a user equilibrium state, no user can decrease his/her route travel time by unilaterally switching routes. This condition may be represented by

\[ T_1 = T_2 = T_3 \quad (10) \]

Setting \( Q \) (the total volume) to 32, the user equilibrium solution for this 3-path network is \( F_1 = F_2 = 6; \ F_3 = 20 \) and the resulting travel time is \( T_1 = T_2 = T_3 = 22.4 \) minutes. The system optimum of the same network is \( F_1 = F_2 = 16; \ F_3 = 0 \), and the resulting travel time is \( T_1 = T_2 = 19.6 \) minutes. This illustrates the Braess’ Paradox (Braess, 1968): adding new capacity (such as an extra link) in a congested network does not necessarily reduce congestion and can even increase it. This situation happens because the users of the network do not face the true social cost of an action; in a situation where all travellers exhibit pro-social travel behaviour no traffic is assigned to path 3.

The user equilibrium and the system optimum are not the only possible equilibrium states, and other social equilibrium states may be present as well. 17 different equilibrium states are resulted by taking into consideration travellers’ social value orientation, and assigning different weights to \( k_i (0 \leq k_i \leq 1) \). The sensitivity of the system performance to travellers’ social value orientation was investigated by calculating the possible social equilibrium volumes. Figure 2 presents the proportion of path choices as a function of travellers’ social value \( (k_i) \).

![Figure 2](image-url)
The system efficiency of a social equilibrium as a function of travellers’ social value orientation is defined as follows:

\[
E(k_i) = 1 - \frac{n \sum_{j=1}^{n} tt_{j}^{k_i} - \min_{k_i} n \sum_{j=1}^{n} tt_{j}^{k_i}}{\max_{k_i} n \sum_{j=1}^{n} tt_{j}^{k_i} - \min_{k_i} n \sum_{j=1}^{n} tt_{j}^{k_i}}
\]

(11)

where \( n \sum_{j=1}^{n} tt_{j}^{k_i} \) is the total travel time at a social equilibrium resulting from assigning all agents with \( k_i \) as the social value, \( \min_{k_i} n \sum_{j=1}^{n} tt_{j}^{k_i} \) is the minimal travel time at the system optimum, resulting from assigning a value of 1 to \( k_i \), and \( \max_{k_i} n \sum_{j=1}^{n} tt_{j}^{k_i} \) is the maximal travel time at a social equilibrium (this value is not necessarily resulting by the user equilibrium). \( n \) is the number of agents (in this numerical example, \( n=32 \)).

For example, by assigning all agents with a social value \( k_i=0.1 \), the system efficiency of the resulting social equilibrium is 74%. The system efficiency as a function of travellers’ social value is presented in Figure 3.

![Figure 3](image_url)

**Figure 3** The System Efficiency as a function of the social value (\( k_i \))
(based on analysis of static equilibrium states)

Based on the above sensitivity analysis, several observations can be made: (i) the maximum efficiency (system equilibrium) can be achieved with a less than 1 social value (\( E=100\% \) for \( k_i \geq 0.58 \)); (ii) assigning \( k_i \) with a negative value, a static equilibrium which is worse than the user equilibrium becomes possible; this might be a less realistic situation in a travel behaviour
context; (iii) as can be seen from Figures 1 and 2, the social equilibrium is very sensitive to the social value in the range \(0 < k_i < 0.1\). Thus, making a small adjustment to travellers’ social value in the above range may make a noticeable change to the system efficiency. On the other hand, motivating agents with higher social values may not make much impact on the resulting social equilibrium and the system efficiency.

3.2. Experiment

Based on the numeric example described in section 3.1, a path-choice experiment was conducted in order to demonstrate how terms of social value orientation can be estimated and used.

32 undergraduate students from the Ben-Gurion University of the Negev, Israel took part in the experiment. The participants knew each other before the experiment. They had basic background in operational research, but have never been introduced before to concepts of network theory or concepts of equilibrium. The participants were introduced to the simple network problem shown in Figure 1, and were provided with the functions to calculate the different path travel times. On each trial, each participant was asked to choose one of the two alternative paths. The participants were given about 30 seconds to write down their choices. They were not allowed to discuss their choices with their colleagues or inform them of their decision. After all the participants made their choices, they were provided with the travel time on each of the paths. Following this information, they were asked to make another choice. This stage was repeated four times.

The average proportion of path 1, 2 and 3 choices during the experiment were \(P_1 = 32\%\), \(P_2 = 34\%\), \(P_3 = 35\%\) respectively. The resulting system efficiency is 74% (average value). The proportion of Path 3 choices is much lower than the choice proportion predicted by the user equilibrium (63%, see Figure 2). The experimental results do not provide evidence in support for the existence and significance of pro-social behaviour. But they do not necessarily support the opposite, but they are close to the predictions of user equilibrium. However, one should be careful in explaining the experimental results by the existence of pro-social values: it is rather likely that some of the deviation from the system optimum is due to confusion, inexperience with the network, and the small number of iterations. Due to the small scale of the experiment, these results do not provide clear evidence of the existence and the significance of pro-social values. Following the methodology described in Eqs. 4 and 5, the social value of travellers during the experiment is evaluated as \(k_i = 0.17\). Taking into account the small size of the group and correlated effects due to group identification, this can be considered to be a low social value.

A value of \(k_i = 0.17\) is far from representing any sign of pro-social behaviour. However, as been illustrated above, in order to have a maximum efficiency a social value of \(k_i = 0.58\) would be enough. Thus, a partial representation of the network externalities (in this example - \(\Delta k_i = 0.41\)) may be sufficient in order to have a strong effect on the social equilibrium and the overall efficiency of the network.

The experimental design neither supported direct cooperation, nor encouraged pro-social behaviour. However, the participants, who knew each other before the experiment took place, could have had some group identification and the social distance between group members...
may be smaller than in the overall population of the users of a typical network. This, together with the small group size, may have some effect on the revealed behaviour and the derived social value, which may assumed to be higher than a value derived from travellers’ behaviour in real-life situations. In future experiments of group travel behaviour, it may be important to control (but not necessarily reduce) as much as possible the endogenous and exogenous (contextual) interactions, as well as correlated effects, between subjects, due to the possibility that some of them may be familiar with each other, or have some group identification.

The participants in this experiment were provided with complete information about others’ choices and resulting travel time. In real-life scenarios information on the choices of other travellers and the travel time outcomes are quite limited, and travellers may be informed only about their own travel costs. In the presence of uncertainty, providing complete information does not necessarily lead to higher system efficiency, which can be explained by the bounded rationality of Bayesian-learning travellers (Avineri and Prashker, 2005). The dynamic processes of travellers’ behaviour in different information schemes may have a considerable effect on the aggregated route choices and the performance of the overall network. This limits the generalisability of the numeric example studied here.

### 3.3. Simulation Model of Agents with Social Value Orientation

Taking into consideration travellers’ social value orientation, as discussed in section 3.1 and described by Eqs. (1-5), a state of social equilibrium is assumed. Such equilibrium may not hold due to measurement errors, bounded rationality, dynamic fluctuations in aggregate choice or over-sensitivity of users to the alternative utility values. Thus, the aggregated behaviour of travellers with social values may not be converged to a social equilibrium. As an alternative to the equilibrium model presented in the previous sections, and in order to address perception errors and the dynamic process of learning and adaptation, we introduce a dynamic model of travellers’ choice with components of social value orientation.

Travellers’ choices are represented by the Multinomial Logit model; it implies that each probability to choose a route is non-negative and the sum of the probabilities of any route will be chosen is unity ($\sum_{k=1}^{m} p_k = 1$). Specifically, the probability that path $l$ will be chosen by agent $i$ at time period $t$ is:

$$P_{il}^t = \frac{e^{\lambda u_i(x^t|x_l^t) - \sum_{k=1}^{m} e^{\lambda u_i(x^t|x_k^t)}}}{\sum_{k=1}^{m} e^{\lambda u_i(x^t|x_k^t)}}$$

(12)

where $u_i(x^t)$ is agent $i$’s utility value of path $l$ at time period $t$, as defined in Eq. (1). $\lambda \geq 0$ is a free parameter that determines the “extremeness” of the choice probabilities and the sum is over $m$ route alternatives. Assigning $\lambda$ with a value of 0 represents an agent who is indifferent between choices and will have similar propensity to choose each of the alternative choices, while assigning $\lambda$ with a high value represents an agent who will very rarely choose an alternative which has low utility value.

The system efficiency of the network described in section 3.1 was estimated based on the aggregated behaviour of 32 agents simulated over a time period of 10 iterations. In order to demonstrate the sensitivity to social value ($k_i$) and the extremeness of choice probabilities ($\lambda$),
16 scenarios, each of them representing a different set of parameter values \((k_i\) and \(\lambda\)), were studied. The system efficiency as a function of these two parameters is represented in Figure 4. Also presented in this figure is the sensitivity of the social equilibrium, to the social value \((k_i)\), as defined in section 3.1.

As can be seen from Figure 4, the efficiency of the overall system is highly sensitive to the value of \(\lambda\); low value of \(\lambda\), reflecting high sensitivity of agent’s choice to experienced travel times on the previous time period, leads to much dynamic fluctuation between the alternative paths. Even with high social value, the pattern of aggregate choices for paths 1 and 2 is far from being stable.

![Figure 4 The System Efficiency as a function of the social value (k_i) and the extremeness of choice probabilities (lambda) (based on simulated results of dynamic choice behaviour and on analysis of static equilibrium states)](Figure4.png)

It is assumed that all agents adopt a strategy based on the decision rule described in Eq. 12: each agent makes his/her choice at time period \(t\) based on the assumption that other agents will repeat the choices they made at time \(t-1\). Since all agents make their choices at the same time, this strategy may lead to a ‘herd behaviour’, where agents avoid tactical decision making and follow rather simple rules, such as Thorndike’s law of effect (1898). This law states that good outcomes, associated with selecting a particular strategy, increase the probability that this strategy would be chosen again. Fluctuations, revealed in the simulation model (as well as in the experiment described in Section 3.2) may be explained by Thorndike’s law of effect or other reinforcement learning models; an overestimation of travellers’ propensity to choose the alternative which was more attractive in the recent turn. The low level of stability may be explained by these fluctuations. Observations of route choices in the laboratory environment revealed fluctuations in travellers’ choices (see for examples, Selten et al., 2004; Morgan et al., 2008). It has been argued in these works that the fluctuations about the mean are persistent, and that the user equilibrium provides good...
prediction of mean traffic flows. On the other hand, it has been shown by simulation studies that social learning in route choice situations and other situations that can described as “stochastic fictitious games” may lead to oscillating aggregated behaviour, where traffic volumes are not converged to a single equilibrium (Horowitz, 1984). Moreover, in a small group of network users, any small change of choices may generate high fluctuations in the group behaviour and may destabilise the equilibrium or convergence. ‘Overreaction’ may happen when too many travellers respond to the information producing oscillations at aggregate level or instability of choices at individual level and is a consequence of the fact that travellers’ have only limited ability to forecast the behaviour of others (Ben-Akiva et al., 1991).

Although the decision-making strategy represented in Eq. 12 was not validated by empirical research, and might be too simplistic, it may provide us with a possible explanation to the system efficiency revealed in the experiment. In a system where all agents have a social value orientation of zero, it is still possible to achieve an efficiency level higher than the one resulting from the user equilibrium. The aggregated choices of users who are motivated to maximize their individual utilities, without considering the system externalities, may deviate from user equilibrium simply because they fail to maximise outcomes for themselves.

In situations where travellers are provided with complete information on the travel-time functions and the choices previously made by other individuals, some travellers may adopt more sophisticated choice strategies. While such strategies may be possible in small-size groups of travellers, they are not expected in relatively large-size group of travellers (where \( n=32 \) in the example presented in this work may be considered to be a reasonably large group).

Assuming all travellers have the same social value (\( k_i=k_j \forall i,j \)) may be too simplistic. The heterogeneity of prosocial values in a social group may influence the dynamics of the individual agent behaviour and the overall behaviour of the system; the level of agents’ compliance and the social equilibrium the system is converged to might be very sensitive to the distribution of social value orientations among the network users.

4. SUMMARY AND CONCLUSIONS

The importance of social value orientation and its influence on travel behaviour, as a measure to analyse, predict and improve the performance of the overall system, was demonstrated in the numerical example presented in Section 3. First, it was argued that besides the extreme cases of user equilibrium (representing complete selfishness) and system optimum (representing pro-social behaviour), other states of social equilibrium, based on mid-values of social parameter values, may result as well. The social equilibrium model described in Section 3.1 provides us with one possible tool to analyse the performance of the overall system and its sensitivity to social value orientation. Using such models, policy makers can estimate the effectiveness of structural and psychological interventions to motivate a change in travel behaviour, and to better understand the reasons for the success or failure of such schemes.

The lack of existence of a pro-social value in the experiment described in section 3.2 is not surprising. Moreover, there is no reason to believe that in many common real-life situations travellers will exhibit pro-social values, unless demand management measures will be utilized
to address situations of transport social dilemmas. This can be done by influencing travellers’ social value orientation and incorporating structural approaches that offer material reward or punishment (such as congestion charging) as well as psychological approaches (‘soft measures’) to influence attitudes.

There is a lack of empirical evidence concerning social value orientation in a transport-related context, and there is a need for much more experimental work in order to investigate the existence, significance and influence of pro-social values on travellers’ behaviour. Incorporating social aspects such as social values orientation in the analysis and modelling of travel-choice behaviour may help in setting the perspective on the social system, and not only on the individual. Studying the changes in social value orientation after introducing a policy scheme that represents externalities may help us to understand how travellers’ behaviour changes over time, and how it can be influenced in an effective way. Further research may assess the degree to which beliefs and attitudes toward travel behaviour affect an individual’s propensity to take a pro-social travel decision, and the dynamics of this process.

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