



## Journal Article

# Energy laws in human travel behaviour

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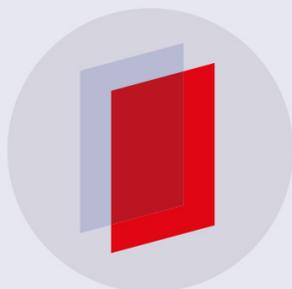
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## Energy laws in human travel behaviour

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**Abstract.** We show that energy concepts can contribute to the understanding of human travel behaviour. First, the average journey times for different modes of transport are inversely proportional to the energy consumption rates measured for the respective human physical activities. Second, when daily travel-time distributions for different modes of transport such as walking, cycling, bus or car travel are appropriately scaled, they turn out to have a universal functional relationship. This corresponds to a canonical-like energy distribution with exceptions for short trips, which can be theoretically explained. Combined, this points to a law of constant average energy consumption for the physical activity of daily travel. Applying these natural laws could help to improve long-term urban and transport planning.

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## 1. Introduction

During the last decade, physicists have discovered the significance of many methods from statistical physics and nonlinear dynamics for the description of traffic flows [1]–[3], including master and Fokker–Planck equations [4], molecular dynamics and cellular automata [5], gas kinetics and fluid dynamics [6], instability and phase diagrams [7], complex pattern formation [8], Korteweg–de Vries and Ginzburg–Landau equations [9], and invariants or universal constants of traffic flow [10]. The observed instability mechanisms, jamming, segregation, breakdown and clustering phenomena are now viewed as a paradigm for similar phenomena in granular and colloidal physics [3, 11, 12], in biology (social insects), medicine (evacuation, coagulation), logistics (instability of supply chains) and economics (business cycles, optimal production) [2, 3, 11, 13]. The success of traffic theory is partly based on the fact that it has delivered a quantitative theory of a system involving human behaviour.

Scientists have also tried to apply physical laws to other areas of transport. For example, they have transferred the law of gravity to fit migration rates and origin–destination matrices to the movements of persons or goods [14]. Moreover, in order to derive more appropriate mathematical relations for these, they have applied entropy principles [15, 16]. In fact, some of the most common decision models, such as the so-called multinomial logit model [17], can be derived from entropy principles [18]. At present the discussion on regularities in travel times is dominated by the concept of a constant travel-time budget [19]. It states that, on average, humans have travelled for about  $75 \text{ min day}^{-1}$  for many decades (or even centuries). This idea has been both supported and criticised over the years. The critique has focused on issues such as collective versus individual behaviour, day-to-day variations, explanatory methodology or theoretical and practical implications, since the conjecture of a constant travel-time budget has been used, for example, as the basis of most studies on induced traffic.

We will show that the concept of a constant travel-time budget is only consistent with empirical data if different modes of transport are not distinguished. It will turn out to be a special case of a more general law of a constant travel-*energy* budget, which is proposed in this paper. This energy-based travel-time concept is also consistent with entropy-based decision theories. In our study, we will first investigate the average travel times over many years separately for different modes of transport (see section 2). We will find large differences between the mode-specific travel times, but (considering the small sample size) they are relatively stable over 25–30 years, i.e. typical planning periods. Interestingly, the proportions of the mode-specific average travel times are inversely proportional to the energy consumption rates of the human body during the respective travel activities. This is first support for the idea that energy concepts may help us to understand human travel behaviour. In section 3, we will then scale the mode-specific travel time distributions by the average travel times. Within the statistical variation, the resulting distributions appear to be universal and, therefore, the universal scaled travel-time distribution can be considered to be a law of human travel behaviour. Apart from significant deviations for short trips, the curves are well consistent with a canonical distribution, which can be derived from energy and entropy concepts. The deviations for short trips are related to the Simonson effect in ergonomics and can also be explained by energy considerations (see section 4). After relating our energy law for human travel behaviour to previous approaches in section 5, we suggest in our outlook how it could be further tested in the future.

## 2. Constant travel time versus constant energy budgets

In our study, we have investigated the electronically available statistical data of the *UK National Travel Surveys* during the years 1972–98, which were carried out by the Social Survey Division of the Office of Population Census and Surveys [20]. The data were gathered on a nationwide scale. Until 1986, about 25 000 travellers were evaluated, and later about 8000 persons. For this reason, we are confronted with worse statistics than in experimental physics, where the sampling sizes are normally much larger. Nevertheless, certain features of the data become visible.

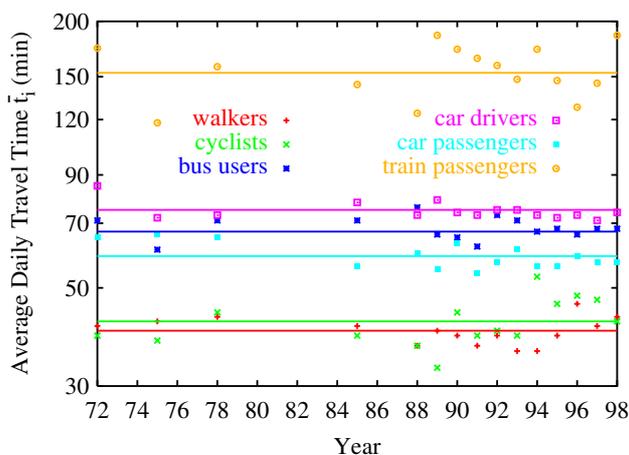
In terms of the data recording procedure, we have used the records of the so-called seventh day of a recording week (which does not necessarily mean a weekend day). On this particular day, short trips (<1 mile) were also recorded, whereas on the other six days only long walking trips (>1 mile) were observed. For this study, these separate data categories (of short and long walks) have been grouped together, and so were bus journeys in London and other places. Moreover, we have used the overall journey times, which are defined as the travel time plus the access, egress and waiting times, summed for each day. (Not only do we expect journey times to be more significant for human travel behaviour than travel times, they are probably also remembered and recorded more exactly.) We have focused on those days on which, apart from walking, only one mode of transport  $i$  has been used. (This is the case in 80% of all daily travel.)

When we distinguished the different daily modes of transport, we found that the average modal journey time  $\bar{t}_i$  per day and per person remained almost constant over the 27 years of observation (see figure 1). More specifically, the average journey times  $\bar{t}_i$  were 40 min during a day with walking ( $i = w$ ), without use of any other means of transport, 42 min for cyclists ( $i = c$ ), 67 min for bus users ( $i = b$ ), 75 min for car drivers ( $i = d$ ), 59 min for car passengers ( $i = p$ ), and 153 min for train passengers ( $i = t$ ). The 95% confidence intervals  $C_i$  for the slopes  $b_i$  of the regression curves were  $C_w = [-0.26; 0.16]$ ,  $C_c = [-0.09; 0.63]$ ,  $C_b = [-0.45; -0.02]$ ,  $C_d = [-0.576; -0.17]$ ,  $C_p = [-0.32; 0.28]$ , and  $C_t = [-1.27; 1.96]$ , i.e. the hypothesis of constant average travel times corresponding to slopes  $b_i = 0$  was predominantly compatible with the data for most modes over more than 25 years, i.e. typical horizons for transport and urban planning. From the analysis below, it will become evident why the car-related values seem to decrease slightly. We should, therefore, underline that the analysis in section 3 can also be applied to situations where the average travel times (apart from statistical variations) change over the years in a systematic way.

Note that the average journey times vary by a factor of up to 3.8 between different modes of transport. This questions the commonly believed hypothesis of a constant average travel-time budget of about 75 min a day [19]. Instead, each mode of transport has its own constant average travel-time budget, which calls for a new unifying law of human travel behaviour. Such a law exists, and it is the average energy consumed by travel activity, which is more or less a mode-independent constant. Here, we mean the energy consumption of the human body, not the energy consumption of a means of transport such as a car, bus or train.

To support this idea, let us study the values of the energy consumption  $p_i$  per unit time for certain activities obtained by ergonomic measurements of the related  $O_2$  consumption [23] (see table 1). The data suggest that the average daily journey times  $\bar{t}_i$  are inversely proportional to the energy consumption rates  $p_i$ , i.e.

$$p_i \approx \frac{\bar{E}}{\bar{t}_i}. \quad (1)$$



**Figure 1.** Average journey times on a logarithmic scale for different daily modes of transport over the course of the years (symbols). Within the statistical variation, the data are mainly compatible with constant fit curves (solid lines).

**Table 1.** Measured average values of energy consumption per unit time for different kinds of activities (after [23]).

Activity	Speed (km h <sup>-1</sup> )	Energy consumption (kJ min <sup>-1</sup> )
Sitting on a chair		1.5
Standing, relaxed		2.6
Standing, restless		6.7
Walking on even path	4	14.1
	5	18.0
Cycling on even path	12	14.7
Car, roads		4.2
Car, test drive		8.0 (5.9–12.6)
Car, in city, rush hour		13.4

With an estimated average travel-energy budget of  $\bar{E} \approx 615$  kJ per person and day, the energy consumption per unit time should amount to  $p_w = 15.4$  kJ min<sup>-1</sup> for walking,  $p_c = 14.6$  kJ min<sup>-1</sup> for cycling,  $p_b = 9.2$  kJ min<sup>-1</sup> for bus users,  $p_d = 8.2$  kJ min<sup>-1</sup> for car drivers,  $p_p = 10.4$  kJ min<sup>-1</sup> for car passengers and  $p_t = 4.0$  kJ min<sup>-1</sup> for train passengers. (The lower value for car drivers as compared to car passengers can be explained by the fact that car owners usually park their cars closer to their home or workplace, while car passengers will usually have longer walks to the meeting points (see below).)

Comparing these values with table 1, the energy consumption of 15.4 kJ min<sup>-1</sup> for walking corresponds to a realistic speed of 1.2 m s<sup>-1</sup> (on an even path and without carrying weight), the 14.6 kJ min<sup>-1</sup> are in accordance with a cycling speed of 12 km h<sup>-1</sup>, the 8.2 kJ min<sup>-1</sup> for car drivers fit the 8.0 kJ min<sup>-1</sup> of test drive data. The elasticity of the energy consumption during driving on clear roads (with 4.2 kJ min<sup>-1</sup>) and driving in rush hours (with 13.4 kJ min<sup>-1</sup>) can explain the apparent slight decrease in the average journey time over the years. As traffic conditions have

obviously become heavier during the last decade, driving under these conditions is also more stressful, which brings an increase in the energy expenditure. Hence, under the hypothesis of a constant energy expenditure, the journey times are expected to decrease. Similar interpretations can account for small changes in average travel times for other means of transport.

Finally, the energy consumption of bus, train and car passengers can be understood as weighted averages of the energy used in walking to and from the bus stop, train station or meeting point ( $15.4 \text{ kJ min}^{-1}$ ) and the energy used in some activity between restless standing ( $6.7 \text{ kJ min}^{-1}$ ) and sitting on a chair ( $1.5 \text{ kJ min}^{-1}$ ). Here, one should bear in mind that the actual values for standing and sitting in a moving means of transport are probably higher, as the body has to perform an additional balancing activity.

### 3. Derivation of a universal travel-energy distribution

When we scaled the  $t$ -axis of the modal travel-time distributions  $P_i(t) dt$  by the average journey times  $\bar{t}_i$ , we discovered that, within the statistical variation, the resulting distributions collapsed onto one single curve

$$P'(\tau_i) d\tau_i \approx N' \exp(-\alpha/\tau_i - \tau_i/\beta) d\tau_i \quad (2)$$

with  $\tau_i = t/\bar{t}_i$ , only two fit parameters  $\alpha$  and  $\beta$ , and the normalization constant  $N = N(\alpha, \beta)$  (see figure 2). This suggests a universal law [21] of human travel behaviour which quantitatively reflects both, variations of individual journey times and variations between individuals. Defining  $E_i = p_i t = \bar{E} \tau_i$ , this corresponds to a universal travel energy distribution

$$P(E_i) dE_i \approx N \exp[-\alpha \bar{E}/E_i - E_i/(\beta \bar{E})] dE_i \quad (3)$$

with  $N = N'/\bar{E}$ . While  $N$  is determined by the normalization condition

$$\int_0^{\infty} P(E_i) dE_i = 1, \quad (4)$$

the parameters  $\alpha$  and  $\beta$  must be consistent with the definition

$$\int_0^{\infty} E_i P(E_i) dE_i = \bar{E} \quad (5)$$

of the average energy. On the one hand, if  $\alpha$  is 0, corresponding to a canonical distribution, then  $\beta$  must be 1. On the other hand, because of condition (5),  $\beta$  has values different from 1, when  $\alpha$  is not 0.

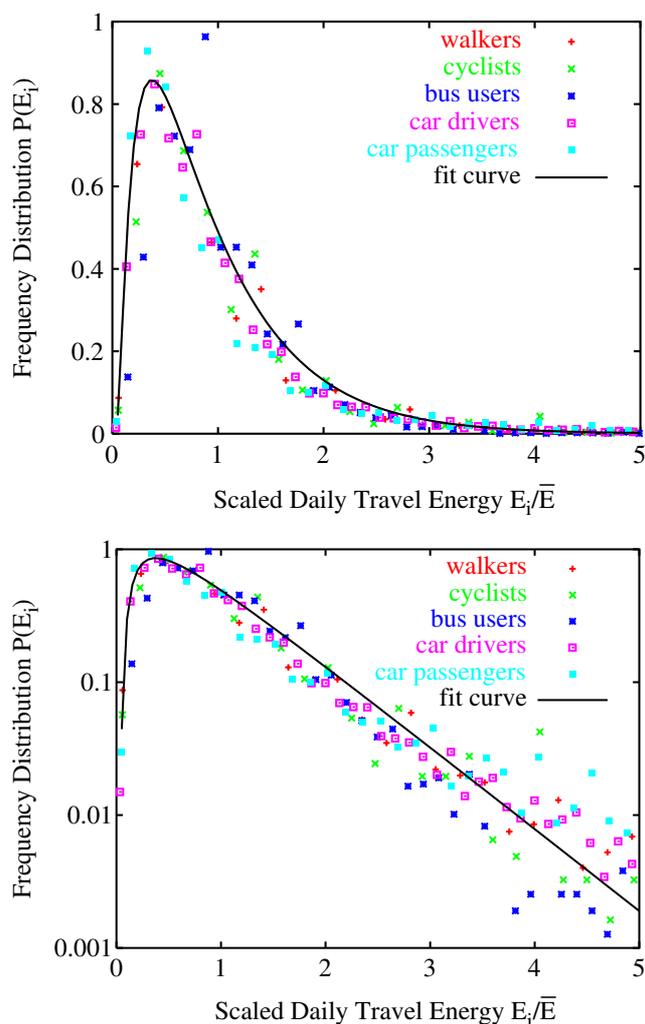
In the semilogarithmic representation

$$\ln P(E_i) = \ln N - \alpha \bar{E}/E_i - E_i/(\beta \bar{E}), \quad (6)$$

the term  $-\alpha \bar{E}/E_i$  is relevant only up to  $E_i/\bar{E} \approx 0.5$ , while the linear relationship  $\ln P(E_i) = \ln N - E_i/(\beta \bar{E})$  clearly dominates over a wide range of travel energies  $E_i$  (see figure 2). Although the different modes of transport could, of course, be fitted by separate parameter values, the hypothesis of identical values is supported by statistical tests. For example, the 95% confidence intervals for the values of  $\beta$  are  $\beta_w = [0.30; 0.74]$ ,  $\beta_b = [0.34; 0.95]$ ,  $\beta_c = [0.38; 0.71]$ ,  $\beta_p = [0.32; 0.71]$ , and  $\beta_b = [0.56; 1.10]$ , when we fit  $E_i/\bar{E}$  over  $\ln P(E_i)$  in the range  $1 \leq E_i/\bar{E} \leq 6$ .

We suggest the following interpretation: the dominating term

$$P(E_i) dE_i \propto \exp[-E_i/(\beta \bar{E})] dE_i \quad (7)$$



**Figure 2.** Scaled time-averaged travel-time distributions for different modes of transport in linear (top) and semilogarithmic representation (bottom). Within the statistical variation (and rounding errors for small frequencies, which are magnified in the semilogarithmic plot), the mode-specific data could all be fitted by a universal curve, the travel-energy distribution (3) with  $\alpha = 0.2$ ,  $\beta = 0.7$ , and normalization constant  $N(\alpha, \beta) = 2.5$ . Due to a lack of a sufficient number of data, it is not clear whether this finding is also supported by the railway data or whether the behaviour of train passenger follows constraints other than energy constraints. The few railway data were not significant because of their large scatter.

corresponds to the canonical energy distribution, while the term  $\exp(-\alpha \bar{E}/E_i)$  reflects the Simonson effect [22]. It describes the suppression of short trips, a surprising effect, which will have to be explained in section 4.

Based on entropy maximization, the canonical distribution may be interpreted as the most likely distribution, given that the average energy consumption  $\bar{E}$  per day by an ensemble of travellers is fixed for the area of investigation [24]. For the sake of completeness, we briefly

repeat the derivation of this well-known result for a general readership. We have to maximize the entropy function [24]

$$- \int dE_i P(E_i) \ln P(E_i) \quad (8)$$

under the constraints (4) and (5). This is equivalent to maximizing

$$- \int dE_i P(E_i) \ln P(E_i) + \lambda \left[ 1 - \int dE_i P(E_i) \right] + \mu \left[ \bar{E} - \int dE_i E_i P(E_i) \right] \quad (9)$$

and determining the Lagrange multipliers  $\lambda$ ,  $\mu$  so that (4) and (5) are fulfilled. Functional differentiation of (9) leads to the condition

$$- \ln P(E_i) - 1 - \lambda - \mu E_i = 0 \quad \text{or} \quad P(E_i) = e^{-1-\lambda-\mu E_i}. \quad (10)$$

The parameters  $\lambda$  and  $\mu$  are now specified in such a way that the constraints (4) and (5) are satisfied. The result for  $P(E_i)$  corresponds to the canonical distribution. It agrees well with the investigated data if only  $E_i/\bar{E} = t/\bar{t}_i > 0.5$ .

#### 4. Explanation of the Simonson effect for short trips

Let us now explain the prefactor  $\exp(-\alpha \bar{E}/E_i)$ . This reflects the fact that short trips are less likely to be undertaken, because it is not worthwhile spending an additional amount of energy, of the order  $\alpha \bar{E}$ , on the preparation for a trip. The quotient between the average energy spent on preparing for a trip and the trip itself is  $\alpha \approx 0.2$ . This value, by the way, agrees well with the threshold value of accepted detours in route choice behaviour [25].

We should note that the amount of data does not allow us to decide between this fit function and very similar ones such as

$$P(E_i) dE_i \approx N_* [1 - \exp(-\gamma E_i/\bar{E})] \exp[-E_i/(\beta \bar{E})] dE_i, \quad (11)$$

where  $\beta$  and  $\gamma$  are two fit parameters and  $N_*(\gamma, \beta)$  is a normalization constant (see figure 3). This function is not so suitable for semilogarithmic fitting, but it can be theoretically derived. For this, let us assume that the preparation for a trip requires an additional amount of energy  $E_0$ . For similar reasons as outlined in section 3, the most likely distribution of the preparation energy is

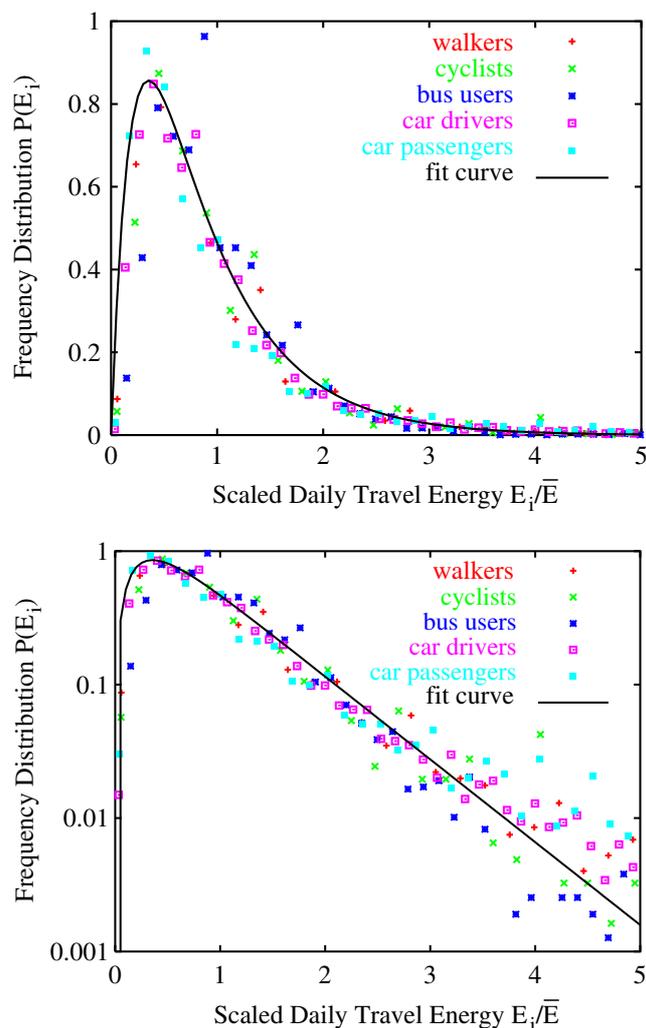
$$P''(E_0) dE_0 = N'' \exp[-E_0/\bar{E}_0] dE_0, \quad (12)$$

where  $N'' = 1/\bar{E}_0$ , and  $\bar{E}_0$  denotes the average energy required for trip preparation. The trip will not be started if this energy exceeds a certain proportion  $\epsilon$  of the energy  $E_i$  required for the trip itself. The probability of starting a trip requiring energy  $E_i$  is, then, given by

$$\int_0^{\epsilon E_i} dE_0 N'' \exp[-E_0/\bar{E}_0] = 1 - \exp(-\epsilon E_i/\bar{E}_0). \quad (13)$$

Comparing this with equation (11) establishes the relation  $\epsilon/\bar{E}_0 = \gamma/\bar{E}$ .

We underline that the interpretation of the approach (11) basically agrees with one of the simpler formulae (3). However, although this interpretation appears plausible, there is at present no strict proof for it. It could, for example, be that short trips are systematically underreported, or that there are just not enough destinations that can be reached with a small travel energy. However, our interpretation is supported by the observation that the distributions of the travel energies and scaled journey times essentially agree for different modes of transport at both high and low travel energies.



**Figure 3.** Alternative fit for the scaled time-averaged travel-energy distributions for different modes of transport in linear representation (top) and on a logarithmic scale (bottom). Within the statistical variation, the mode-specific data could all be fitted by the travel-time distribution (11) with the same value of  $\beta$  as in figure 2 (i.e.  $\beta = 0.7$ ),  $\gamma = 3.5$  and normalization constant  $N_*(\gamma, \beta) = 2$ .

## 5. Comparison with previous trip distribution models

In this study we have shown that empirical travel-time data support the concept of a constant daily travel-energy budget rather than a travel-time budget. Not only are the mode-dependent average journey times inversely proportional to the energy consumption related to the respective physical activities but the scaling to energy variables also leads to a universal travel-energy distribution, which can be theoretically supported. The distribution basically corresponds to a canonical one, which can be derived from entropy principles. However, we found fewer trips with small travel energies than expected according to the canonical distribution. This could be explained as an effect of the additional energy required for the preparation for a trip. If the latter exceeds a certain percentage of the energy required for the trip itself, the trip is unlikely to be undertaken.

In such cases another means of transport is possibly selected, or the trip may be combined with another trip.

Note that the canonical distribution is analogous to the multinomial logit model  $P_i^* \propto \exp(U_i)$  developed to describe the trip distribution as a function of some utility function  $U_i$  [15, 17, 18]. Therefore, the above theory not only gives an alternative, physical explanation for the applicability of the multinomial logit model but also allows us to extend and improve previous trip distribution models, which have focused on variables such as distances and travel costs [15, 17]. For this purpose, the mode-dependent energy consumption  $E_i$ , which is shown to be an essential variable of human travel behaviour, is to be taken into account as a (negative) cost term entering the utility function  $U_i$ .

The travel-energy concept also allows one to understand why it is difficult to establish an explanatory principle for all modes of transport based on *distance*. As travelled distance in transport is mode dependent, it cannot be regarded as an invariant measure. Travel costs, on the other hand, can be assumed to be a determinant for modal choice. In qualitative terms, this means for the above approach that a clear distinction can be given between trip distribution and *modal* choice, where the former determines the physical boundary conditions of daily trip making in which the latter takes place. As a consequence, both aspects of travel behaviour can be combined in a stringent and complementary way.

## 6. Summary and outlook

In our opinion, the significant progress by this study is the identification of a simple and universal law of human daily travel behaviour after many decades of fit models with multiple fit parameters. In contrast to utility functions of classical decision models, which are typically based on preferences, our model contains only physical variables such as journey times and energies, which are well measurable. It was, therefore, possible to critically evaluate our travel distribution model, which resulted in a canonical travel-energy distribution with a correction term for short trips. In contrast, decision models like the multinomial logit model or other trip distribution models are usually presupposed and used to determine unknown utilities, which are normally not measurable in an independent way. These models could, therefore, not be verified or falsified in a strict sense. Furthermore, it was very surprising to find that physical variables determine human travel behaviour in a fundamental way and that laws from equilibrium thermodynamics apply. Once again, this underlines the importance of physical concepts for the understanding of traffic and transport.

The main advantage and practical relevance of the behavioural law (3) is its expected long-term validity under changing conditions. It will, therefore, prove to be important for urban, transport and production planning: previous trip distribution models had to separately determine various parameter values for each mode of transport, which was related to large errors in the calibration of the model parameters and did not allow for a theoretical interpretation of travel behaviour. Compared to this, the discovered travel-energy law facilitates improved conclusions about trip distributions, modal splits and induced traffic [26] after the more reliable determination of fewer parameters, which are (apart from statistical variations) constant or systematically changing over typical planning horizons. The new concept also contributes to understanding interactions between the temporal evolution of settlement patterns and transport systems. Furthermore, it helps to assess the increase in the acceptability of public transport,

when the comfort of travel is improved, to predict the usage of new modes of transport and to estimate the potential market penetration of new travel-related products.

The authors are aware of the problems relating to the empirical data, which were characterized by a large scattering and were affected by errors in recording trips and related journey times. For example, travellers tended to round journey times to full 5 or 10 min units (so that these intervals were overrepresented in the data). However, at present there are no better data available. In some sense, the current situation in socio-physics is comparable with the early days of classical physics, where the data situation was also much poorer than today. But empirically justified principles such as the proposed travel-energy laws will certainly stimulate further research. If only a small fraction of the money spent on experiments in elementary particle physics was invested into measuring human behaviour, one could certainly make fast progress. We are now carrying out similar studies with travel-time data from other countries, but there are similar problems with the quality of the data. So, basically, one would have to spend considerably more money in measuring the data.

In order to further test the proposed travel-energy laws, the authors suggest the following supplementary investigations: first, one could study the travel-energy distribution of combined trips, i.e. trips using different means of transport. The total travel energy

$$E = \sum_i p_i t_i, \quad (14)$$

where  $t_i$  denotes the journey time spent with mode  $i$ , should also be distributed according to the law (3), if the combined trip does not require additional energy for its preparation compared to a one-mode trip (or long additional waiting times). Second, we are confident that the concept of a travel-energy budget can be generalized to a human energy concept. For example, we expect that blue-collar workers would tend to allocate a smaller energy share to travelling than white-collar workers. We also predict that elderly people would make shorter trips on average, because travelling is more exhausting for them. This could be investigated by distinguishing different groups (subpopulations) of travellers. These questions shall be addressed in future publications.

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