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# A microeconomic framework for integrated agent-based modelling of activity-travel patterns and energy consumption

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**Abstract**

The sophistication in the demand management approaches in both transport and energy sectors and their interaction call for modelling approaches that consider both sectors jointly. For agent-based microsimulation models of travel demand and energy consumption, this implies the necessity to ensure consistent representation of user behaviour with respect to mobility and energy consumption behaviours across the model components. Therefore this paper proposes a microeconomic framework, termed the HOT model (Home, Out-of-home, Travel) grounded in the goods-leisure paradigm, but extended to incorporate emerging activity-travel behaviour patterns and their energy consumption implications. We discuss how the model can be operationalised and embedded within agent-based frameworks with a case study using time use and energy consumption data from the UK.



*Keywords:* Energy; time allocation; microeconomic model; activity-travel behaviour

## 1. Introduction

The last decade has witnessed profound disruptions to the way people travel and conduct activities. These changes include increasing vehicle electrification, large-scale proliferation of ride- and vehicle-sharing services, vehicle automation, and a resurgence in popularity of active modes and micro-mobility services. In addition, remote activity participation, such as tele-working, online shopping, and social interactions, and activity participation in

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mobile contexts appears to have spread beyond highly-skilled segments of society with impacts on travel behaviour and activity scheduling [1, 2].

At the same time, transport has remained one of the largest drivers of energy consumption. Furthermore, the emerging activity-travel behaviour patterns have been associated with an unprecedented spatial and temporal flexibility in conducting activities, implying not only change in future energy demand profiles but also more volatility and possibly unpredictability. Strong interactions between energy consumption at home, at work, and through travelling, i.e. activity-travel behaviour therefore require a more comprehensive and joint consideration. The energy sector, particularly electrical energy, has also been shifting away from the 'predict and provide' approach, towards more advanced demand management strategies relying increasingly on more volatile renewable sources [3].

The energy sector demand management measures include demand-responsive pricing, deployment of smart meters, localised generation and storage, and energy micro-trading such as vehicle to grid (V2G) technologies. By their nature, their exact parameters as well as effectiveness may vary substantially across agents. Hence the simultaneous sophistication in the demand management approaches in both transport and energy sectors, and their ever closer interaction, call for modelling approaches that systematically look at both sectors together [4]. Typical integrated urban models, however, treat energy consumption of individuals as an exogenous variable, while considering activity and travel at a disaggregate spatio-temporal level thus forecasting the demand for resources based on a needs perspective (i.e. heating, lighting, mobility). Agent-based integrated urban microsimulation models have shown promising features to capture the interactions between transport and energy sectors [3, 5]. However, to date the links between the activity-travel and energy consumption choices have either been made to a limited extent, such as electric vehicle adoption or tele-commuting choices [6, 7], or made at an operational level, combining various models into systems of models [8, 9]. These model systems, however, lack an overarching time and resource utilisation theory that can link the consumption components.

Thus, the present paper brings together the two sets of choice considerations, i.e. those related to activity-travel behaviour and those related to energy consumption choices, within a microeconomic framework of individual time and resource allocation. This is predicated on the fact that both energy and mobility decisions fundamentally concern time and monetary budget allocations. We focus on developing a unifying framework that can accommodate existing modelling approaches with regards to use cases such as electrification of personal vehicles, flexible working schemes, mobility sharing services, vehicle automation and active travel modes (including micro-mobility). We discuss how the extended framework can trace pathways in which energy consumption interacts with mobility under various scenarios of energy pricing or available mobility options. Further, we demonstrate how the model can be operationalised to simulate agent behaviour and responses, using a dataset of activity-time use and energy consumption which can then be used to underpin any operational, agent-based model.

This extended toolkit allows systematic conceptualisation of the trade-offs faced by individuals operating under such circumstances, and hence is central to understanding and validating agent responses to various policy measures. Without this theoretical backbone, different operational models can lead to different kinds of demand response behaviours due to operational assumptions, rather than the underlying, behavioural ones. For example, the conventional operational practice sees income included as one of the covariates in models of agent behaviour. Yet such models would not typically consider reduction in the disposable income resulting from a particular activity and travel decision and the consequent impact on the consumption of the agent, or their other activity-travel behaviour decisions. Such considerations are key to better understand the implications of policies aimed at demand response. This issue has been a central problem with many of the agent-based microsimulation models of transport-land use.

## 2. Microeconomic Framework

The goods-leisure framework is a utility-maximisation microeconomic framework in which an individual derives utility from the consumption of goods and allocation of time to leisure, subject to budget and total time constraints. The constraints capture the trade-off between consumption and leisure, which translates into the time allocation decision between income-generating work and non-salaried leisure. In this framework, travel choice is modelled as a discrete decision concerning the mode of travel that incurs monetary and time costs. In the existing microeconomic models of time use, energy consumption and expenditure are included only implicitly in the budget constraint, which is too restrictive to accurately capture the interactions between transport and energy sectors.

In our framework, a utility-maximising individual seeks to allocate their work and leisure time between Home, Out-of-home and Travel contexts, i.e. the HOT model. In addition, the individual can select their generalised consumption level, as well as travel mode and schedule. The utility function to be maximised can be formalised as:

$$U(G, W_H, W_O, W_T, L_H, L_O, L_T, i, s) \quad \text{(Eq.1)}$$

subject to of the following constraints:

- total monetary budget constraint:

$$wW + M = G + c_i + F(W_H, L_H, s) \quad \text{(Eq.2)}$$

- total time budget constraint:

$$W_H + W_O + L_H + L_O + t_i = \tau \quad \text{(Eq.3)}$$

- travel time use constraint:

$$W_T + L_T = t_i \quad \text{(Eq.4)}$$

- allocation of work time between home, office and mobile (travel) locations, considering the possibly differing productivities at such locations:

$$\eta W_H + W_O + \zeta_i W_T = W \quad \text{(Eq.5)}$$

where *U(.)* is the direct utility function to be maximised and is a function of $W_H, W_O, W_T, L_H, L_O, L_T$, which are times allocated to Work or Leisure (non-work) at home, office, or while travelling, and the level of generalised consumption of goods (non-energy) is *G*. *M* is non-salary income and *w* is work salary per unit time, relative to the consumption goods price level, assumed to be exogenous. $\tau$ is the total time available in the reference frame. $c_i$ and $t_i$ are monetary travel cost and travel time by mode *i*, and *s* is the discrete activity schedule. $\eta$ and $\zeta_i$ are work productivity relative-to-office when working from home or travelling by mode *i*, respectively. *F(.)* is the energy expenditure function that relates duration of home activities and their schedule *s* to energy consumption and cost.

The particularly novel extension in this framework, to the best of our knowledge, is the energy expenditure function *F(.)*. It relates time allocations to home-based activities to energy cost, typically capturing the energy prices and energy consumption per-unit-time from activities, sometimes called *conversion factors* or *electricity footprints* [10]. The explicit specification allows us to incorporate into the time allocation arbitrarily complex, elaborate structures for energy pricing by time of day, electric vehicle charging or choice of fuel, including renewable ones. This achieves the purpose of integrated the modelling of activity-travel behaviour with energy consumption. This further enables us to reflect the emerging mobility and activity participation patterns and their interactions with the energy sector. The following are examples of how such emerging patterns could be captured in the model:

- *electric mobility*: reflected as a separate transport mode *i* with additional energy expenditure (vehicle charging) related to home-based activities. V2G technologies could result in a combination of positive and negative conversion factors especially when allowing temporal and spatial price differences, e.g. schedule-based pricing.
- *shared mobility services*: could be reflected as a separate transport mode *i* with a varying travel cost $c_i$ dependent on the time of day and with implications for travel time productivity $\zeta_i$.
- *vehicle automation*: allowing travel time to be used productively and enjoyably which is reflected in the explicit presence of work and leisure during travel time ($W_T$, $L_T$) and travel time productivity $\zeta_i$;
- *active travel modes*: could be reflected in lower (or null) monetary travel cost $c_i$ and relatively low travel time productivity $\zeta_i$ emphasising the more leisure-oriented and personal nature of the mode;
- *flexible working schemes*: reflected in the allocation of work time between home, office and travel locations ($W_H$, $W_O$, $W_T$) with potentially different relative productivities.

The examples above are not exhaustive, nor are definitive suggestions concerning how to capture the postulated phenomena. In particular, the framework is general enough to link and make use of the existing, and more specific models concerning transport and energy interactions.

## 3. Empirical Application

In order to understand the modelling implications of the framework above, it is possible to solve the optimisation (using substitution or Lagrangian approach) using first order conditions, leading to the following expression:

$$\frac{\partial U}{\partial G}\left(\frac{\partial F}{\partial L_H}+\frac{\partial F}{\partial W_H}\right)=\frac{\partial U}{\partial W_H}+\frac{\partial U}{\partial L_H}-2\frac{\partial U}{\partial L_O}+\eta\frac{\left(\frac{\partial U}{\partial L_T}-\frac{\partial U}{\partial W_T}\right)^2}{\frac{\partial U}{\partial L_O}-\frac{\partial U}{\partial W_O}} \quad \text{(Eq.6)}$$

Equation 6 can be interpreted as a combined response in the utility from additional allocation of a unit time to work and leisure. Assuming the following form of the utility function:

$$U(x)=\sum_{j=1}^{J}-\exp(\beta_j Z)\exp(-x_j) \qquad J=\{G,W_H,W_O,W_T,L_H,L_O,L_T\} \quad \text{(Eq.7)}$$

Where $x_j$ is the amount of consumption of a particular good or time allocated to an activity $j$ among the $J$ alternatives, $Z$ is the vector of covariates and $\beta_j$ are parameters to be estimated associated with the baseline marginal utility (also marginal utility at zero consumption). The associated marginal utilities have a convenient form that also reflects that they diminish with an increasing consumption of $x_j$:

$$\frac{\partial U}{\partial x_j}=\exp(\beta_j Z)\exp(-x_j) \quad \text{(Eq.8)}$$

Further assumptions are imposed to enable model operationalisation using the available datasets (described below):

- $\beta_G=0$ i.e. parameters associated with time allocations are normalized with respect to goods consumption;
- $\eta=1$, i.e. productivity at home is similar to office conditions;
- $\frac{\partial U}{\partial L_O}=\frac{\partial U}{\partial W_O}+1$ , i.e. marginal utility of office-work is a parallel shift of marginal utility of out-of-home leisure, always below it, meaning that individuals would always enjoy more out-of-home leisure to office work;
- $F=p_E\xi_{W_H}W_H+p_E\xi_{L_H}L_H$, where $p_E$ is energy price per kWh and $\xi_{W_H}$ and $\xi_{L_H}$are energy intensities of activities, i.e. consumption of electricity per unit time.

The assumptions above lead to the formulation of Eq.6 as a linear-in-parameters model:

$$p_E(\xi_{W_H}+\xi_{L_H})\exp(-G) \\ =\beta_0 Z+\beta_{W_H}Z\exp(-W_H)+\beta_{L_H}Z\exp(-L_H)-2\beta_{W_H}Z\exp(-L_O)+\beta_{LTWT}Z(\exp(-L_T)-\exp(-W_T))^2+\varepsilon \quad \text{(Eq.9)}$$

where $\beta_0$ is an additional term, under current formulation, that captures heterogeneity in energy intensity of domestic activities ($\xi_{W_H}+\xi_{L_H}$) while $\varepsilon$ is a normally distributed error term censored so as to ensure non-negativity of the LHS. The latter requirement warrants formulation of Eq.9 as a tobit model and estimation using the maximum likelihood approach. To demonstrate operationalisation in a real-world context, an innovative dataset from METER: UK household electricity and activity survey, is used [11]. Electricity readings and activity records were collected from UK households in 2016 along with detailed sociodemographic information and dwelling characteristics [10]. An electricity recorder was attached below the household's electricity meter to collect readings of electricity consumption for every minute. Activities were self reported via a dedicated app. Respondents could participate for several days, typically for 2 days. Table 1 presents a descriptive summary of the dataset used in our analysis.

For the energy consumption and expenditure sub-model, i.e. *F(.),* we chose the simple conversion factor, assuming fixed energy prices faced by individuals across the day. We calculated the electricity usage of each activity based on the start time and end time of the activity and the data from the electricity recorder. We are specifically interested in the energy consumption of home-based work and home-based leisure, as they have a direct impact on individuals' expenditure based on their time allocation. For this study, we grouped the original 100 activity types based on their location (home, office, travel), and work and non-work (leisure). For each activity, start time is recorded and we assumed the start time of the next activity to be the end time of the previous activity. The electricity readings were then averaged for specific activity categories to obtain values for $\xi_{W_H}$ and $\xi_{L_H}$. $p_e$ was assumed £0.14852 per kWh based on the Office of Gas and Electricity Markets data, the government regulator for the energy markets in the UK. In line with the 7% saving ratio observed in the UK, $G$ was estimated as 93% of weekly income (mid-interval of an income group used), scaled to the size of the available time use diary. Day of week variables were included based on whether the diary fell within those dates (hence multiple days could be reported).

Table 1 Descriptive summary of sample characteristics.

| **Continuous Variables** | | | | min | max | mean | SD | Parameter |
|---|---|---|---|---|---|---|---|---|
| Time allocated to *Work at home* (min) | | | | 0 | 1260 | 75.9 | 145.7 | $W_H$ |
| Time allocated to *Work at office* (min) | | | | 0 | 1358 | 142.0 | 213.2 | $W_O$ |
| Time allocated to *Work while traveling* (min) | | | | 0 | 1314 | 82.4 | 185.8 | $W_T$ |
| Time allocated to *Leisure at home* (min) | | | | 0 | 4091 | 1058.2 | 443.6 | $L_H$ |
| Time allocated to *Leisure at office* (min) | | | | 0 | 1565 | 134.0 | 192.5 | $L_O$ |
| Time allocated to *Leisure while traveling* (min) | | | | 0 | 1398 | 121.4 | 169.4 | $L_T$ |
| Energy consumption $W_H$ (Wh) | | | | 1.9 | 5070.5 | 897.6 | 688.5 | $\xi_{W_H}$ |
| Energy consumption $L_H$ (Wh) | | | | 6.1 | 2899.2 | 749.3 | 486.2 | $\xi_{L_H}$ |
| Goods consumption | | | | 1 | 8 | 2.2 | 0.7 | $G$ |
| Household size | | | | 0 | 6 | 2.9 | 1.2 | $Z$ |
| **Categorical Var.** | **Freq.** | **Categorical Var.** | **Freq.** | **Categorical Var.** | | | **Freq.** | |
| Age 8-19 | 15.0% | Employed | 69.6% | Day of week: Tuesday | | | 29.0% | |
| Age 20-34 | 16.5% | Student | 16.3% | Day of week: Wednesday | | | 36.6% | |
| Age 35-49 | 38.2% | Female | 52.5% | Day of week: Thursday | | | 19.7% | $Z$ |
| Age 50-70 | 24.7% | Work from home | 60.4% | Day of week: Saturday | | | 19.7% | |
| Age 70+ | 5.6% | Day of week: Monday | 30.0% | Day of week: Sunday | | | 19.2% | |

Model estimation involved finding parameters that maximise the likelihood function, while ensuring identifiability through setting several reference categories with fixed parameters. The observed consumption expenditure level is set as the reference given it is the only non-time-use argument in the utility maximisation problem. Table 2 presents the estimation results. The first observation is that only a handful of covariates were found to be statistically significant. The model turned out to be most effective in describing heterogeneity in preferences to work at home. Recalling from Eq.7 that a negative coefficient indicates higher utility, we observe that people who report being able to work from home at least one day per week are indeed also more likely to allocate time to it. Fridays and Saturdays are days when people find utility of working from home comparatively higher to other days of the week. This is intuitive as end of working week would be when people may find it more convenient to avoid the commute trip and provide smoother transition to discretionary activities. Lastly, people with larger household sizes report higher utility from working at home, reflecting a way to more easily reconcile work and home responsibilities.

Table 2 Model estimation results.

| $Z$ | $\beta_0$ | $\beta_{W_H}$ | $\beta_{L_H}$ | $\beta_{L_O}$ | $\beta_{L_T W_T}$ | $G$ (reference category) |
|---|---|---|---|---|---|---|
| Constant | -19.5905 | 95.8313*** | 72.4294 | 3.8400 | -15.3326 | - |
| Female | 26.7966*** | | . | . | . | - |
| Work from home | 26.7512 | -51.3043** | . | . | . | - |
| Household size | 14.8740** | -16.8697* | . | . | . | - |
| Day of week: Friday or Saturday | 42.2634* | -45.8992* | . | . | . | - |
| *Goodness of fit:* LL($\boldsymbol{\beta}^{\gamma}$=0) -1426 LL at convergence: -1393 | | | | | | |
| Significance: *** $p \le .01$ ** $p \le .05$ * $p \le .10$ | | | | | | |

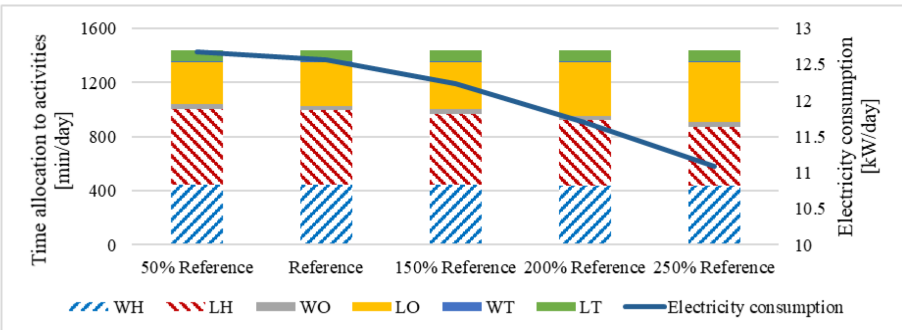


Fig. 1 An illustrative electricity demand response to variation in reference energy price (£0.14852 per kWh).

In terms of $\beta_0$ factors, which is a proxy for heterogeneity in energy intensity of domestic activities, we observe that female respondents would on average have highest intensities. Within the data we observe higher association between female respondents and domestic activities that are energy intensive, including cooking or baking. In addition, we observe larger households to also report more energy intensive activities. This results from an aggregate reporting of energy intensity. In other words, while activities are associated with energy consumption temporarily, parallel consumption of other household members would also be captured in the recording, thereby inflating it. Further modelling work is aimed at resolving this confounding problem. To demonstrate applicability of the model in simulating a response of an agent's activity-travel behaviour to energy policy, Figure 1 provides an example of the model used to produce optimal time allocations and the associated electricity consumption under various energy pricing scenarios. As expected, with an increase in price, an agent shifts their time away from (home-based) activities, for which they incur the cost of energy.

## 4. Conclusions

In response to the growing interaction between transport and energy systems, this paper extends a microeconomic time allocation framework grounded in the goods-leisure paradigm to incorporate emerging activity-travel behaviour patterns and their energy consumption implications. The proposed framework enables predictions of agents' responses to transport and energy policies, ensuring a consistent representation of the user behaviour within agent-based microsimulation models. The present study constitutes the first step towards expanding an agent-based travel demand model into allowing the more sophisticated energy consumption expenditure functions to appropriately reflect the smart and flexible energy pricing schemes. Future effort will seek to extend the current operationalisation beyond time allocations to also allow responses in the scheduling of activities and travel. Lastly, we seek to integrate the present contribution with an agent-based and activity-based microsimulation model system [14], to allow detailed representations of the demand side responses for a large-scale population of agents.

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