Using activity-based modeling to simulate urban resource demands at high spatial and temporal resolutions

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Keywords: urban metabolism, activity-based modeling, energy, cities, simulation

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Published in the Journal of Industrial Ecology (2012)
http://dx.doi.org/10.1111/j.1530-9290.2012.00486.x
Summary

Urban metabolism is an important technique for understanding the relationship between cities and the wider environment. Such analyses are typically performed at the scale of the whole city and using annual average data, a feature that is driven largely by restrictions in data availability. However in order to assess the resource implications of policy interventions and to design and operate efficient urban infrastructures such as energy systems, greater spatial and temporal resolutions are required in the underlying resource demand data. As this information is rarely available, we propose that these demand profiles might be simulated using activity-based modeling. This is a micro-simulation approach that calculates the activity schedules of individuals within the city and then converts this information into resource demands. The method is demonstrated by simulating electricity and natural gas demands in London and by examining how these non-transport energy demands might change in response to a shift in commuting patterns, for example, in response to a congestion charge or similar policy. The article concludes by discussing the strengths and weaknesses of the approach, as well as highlighting future research directions. Key challenges include the simulation of in-home activities, assessing the transferability of the complex data sets and models supporting such analyses, and determining which aspects of urban metabolism would benefit most from this technique.
**Introduction**

In the years since Wolman’s 1965 article popularizing the idea, urban metabolism has become a key tool for assessing the environmental impact of cities. Such analyses typically examine the exchanges of water, energy, materials, and wastes between a city and its hinterland. This can be seen in a recent review study by Kennedy et al. (2008), which highlights the method’s application in eight metropolitan regions spanning five continents. These descriptive studies are vital if a city is to understand its links with the natural environment and to identify and respond to environmental constraints appropriately.

As an analytical tool, urban metabolism faces several practical challenges. First, the resolution of these studies is often coarse with data typically collected for the whole city and measured on an annual or annual per capita basis (Kennedy et al. 2008). Even at this aggregate level, Decker et al. (2000) note that data on key sectors, such as energy and material fluxes, can be hard to find particularly in support of comparative analyses. A second issue is that measuring flows across urban boundaries neglects some of the key metabolic processes within the city, for example storage (e.g. water within aquifers, nutrients in waste dumps, materials in building stocks) (Kennedy et al. 2008) or local transportation (e.g. the distribution of water, energy vectors, and materials). Finally, an aggregate ecological view of urban metabolism neglects the motivation for these resource flows. Brunner (2008) sums up the issue nicely, noting that “the focus on material dimensions of cities does not mean that this aspect is the most important feature of a city. The decision to concentrate on materials is based on the fact that there are reliable metrics for the assessment of urban material flows and stocks and that materials and substances are crucial for the sustainability of a city in terms of functioning resource availability, and
environmental protection” (p. 11). He advocates that these flows should be interpreted within a framework of human-focused urban activities, namely “to clean”, “to nourish”, “to reside and work”, and “to transport and communicate” (Brunner et al. 1994).

These criticisms are particularly important when one considers that urban metabolism is dominated by anthropogenic flows (Brunner 2008), which in turn are facilitated by large infrastructure systems such as buildings, roads, pipe or wire networks. The efficiency of resource use is determined by the design and operation of these infrastructures, which are spatially-embedded within the city’s fabric. Temporal dimensions matter too, as infrastructure must be sized to cope with peak demands while overall operating costs may be guided largely by average conditions. This can be seen in the structure of regulatory price controls for natural monopolies in water and energy systems (e.g. Ofgem 2004; Ofwat 2011). Understanding the impact of new infrastructure technologies such as pervasive sensing, smart grids, and embedded generation, (e.g. Bahaj et al. 2007; Massoud Amin and Wollenberg 2005; TaKaDu 2011), climate (e.g. Donovan and Butry 2009; Miller et al. 2008), and energy-efficiency retrofits in buildings (Hamilton et al. 2010) also requires an appreciation of the spatial and temporal distribution of resource demands.

The distinction between aggregate urban metabolism data and the highly-resolved demand data necessary for efficient infrastructure design and operation presents a substantial research challenge. If, as noted above, researchers struggle to capture whole-city annual data for many key urban flows, how can they acquire demand data at higher spatial and temporal resolution necessary for detailed designs? In this article, we propose that activity-based modeling offers a solution, particularly for those resources like energy
whose infrastructures are highly dependent on spatial and temporal variations in supply and demand. This technique, which has evolved in the transportation and land use literature, facilitates micro-level simulation of individual activities within a city at temporal resolutions of approximately 5 minutes and spatial resolutions on the order of blocks or finer (<10 ha). Although interest in this topic has been growing, we are not aware of any implemented activity-based models for urban resource demand simulation within the industrial ecology field. Therefore in the remainder of this article, we will describe the technique and its origins before presenting a case study for London’s electricity and natural gas demands. We conclude by highlighting some outstanding research questions and assess how the technique might benefit the study of urban industrial ecology.

**What is activity-based modeling?**

Broadly speaking, activity-based modeling is a state-of-the-art technique in land-use and transportation (LUT) modeling wherein the unit of analysis is the activities that individuals, households, and firms perform during the day. In this section, we briefly describe the history and structure of a typical integrated LUT model system before highlighting how these models can be used to calculate urban resource consumption.

**Overview of integrated LUT modeling**

Integrated land-use and transportation models were traditionally developed as a means of estimating travel demand in response to land use changes and over the years they have evolved to become rich descriptors of the activity and travel patterns of all the agents in a study area including households and individuals, businesses, real-estate developers
and so on. The land use components of such integrated model systems describe medium to long-term urban processes such as household (re)location, work (re)location, real-estate development, business (re)location and automobile ownership, thus providing planners with a tool to forecast future land use layouts of urban areas. This is integrated with model components that predict the activity and travel patterns generated by the agents within the urban landscape. The transport flows created through these processes, in turn, feed back to the land use models guiding further real estate development, as well as business and household relocation in response to conditions on the transport networks. Such integrated land use-transport model systems thus attempt to produce reliable and policy-sensitive travel demand estimates by capturing the complex relationships between transport and land use in a system of descriptive models (for detailed reviews, see Miller et al. 2004; Wegener 1994, 2004).

The earliest land use-transport models were essentially static models, driven typically by gravity, entropy, or input-output based formulations (see, for example, Lowry 1964). These models were linked to a four-stage transport model through iterative feedback of network flows in the form of an accessibility index to estimate equilibrium patterns of land-use and transport (see, for instance, LILT, the Leeds Integrated Transport package by Mackett (1983), DRAM/EMPAL by Putman (1995), IMREL by Anderstig and Mattsson (1991), MUSSA by Martinez (1996)). Since these static models do not model market processes behaviorally and cannot realistically capture urban spatial processes, they are not very responsive to policy and scenario analyses and, from the perspective of urban resource demand modeling, these models provide no additional benefits over
simpler, aggregate demand estimation techniques (e.g. linear regression or down-scaling regional data).

The next generation of LUT models were the general spatial equilibrium models such as MEPLAN (Hunt and Simmonds 1993) and TRANUS (Barra 1989), which are typically also spatially aggregate models like the static models but with more closely integrated land-use and transport elements. The interactions between these elements are determined by input-output analysis or discrete choice models, and these interactions are used to derive the demand for transport. General spatial equilibrium model systems are based on random utility theory and theories of competitive markets, which treat land-use and transport systems endogenously and therefore capture the interactions between these systems more accurately. However in being spatially aggregate, these models are still not entirely behaviorally realistic. Nevertheless one of these models, TRANUS was one of the first LUT models used to analyze urban energy demand.

The third generation of LUT models are agent-based micro-simulation models, which combine the strengths of micro-simulation and the disaggregate modeling of behavior and land use processes (see, for example, DELTA by Simmonds (1999), ILUTE by Miller et al. (2004), UrbanSim by Waddell (2002), and PRISM by Alberti and Waddell (2000)). These are activity-based models with the individual (one person, household, firm, or any other agent in the urban system) as the unit of analysis and their formulation captures the interactions between land-use and transport systems to the greatest extent possible. The application of micro-simulation methods allows these models to apply probabilistic and econometric models at the level of the individual. In this sense they are distinctly different from the older school of LUT models, which were predominantly based...
on aggregate flows of people, goods and resources. Furthermore, focusing on individual agents facilitates highly disaggregated representations of time and space, with some of the models operating on a continuous (second by second) time scale with parcel-level spatial detail.¹

The flip side of such descriptively rich models is the quantity of data and computational time (effort) required to operationalize them. While some agent-based models rely on hypothesized rules to illustrate emergent properties and cope with limited data or computational ability (e.g. Schelling’s 1971 segregation model), modern activity-scheduling models such as TASHA (Miller and Roorda 2003) and ALBATROSS (Arentze et al. 2000) use a combination of econometric and rule-based agent-based simulation techniques, each parameterized from large observed data sets. However this effort is arguably worthwhile as once operational, such models are excellent test beds for a variety of policy, engineering, and technological solutions as they can effectively capture both the direct and indirect effects of the scenarios of interest.

*Calculating urban resource demands with LUT models*

Many operational land-use transport model systems are loosely integrated with transport air quality and energy assessment models that translate the predicted transport flows into pollutant and fuel consumption estimates (see, for instance, Wagner and Wegener 2007). In fact, as Wegener (1994) claims, these models are now being called integrated land use-transport and environment (LTE) model systems. For instance, we now have PROPOLIS (Lautso et al. 2004), which is an LUT model with energy and sustainability indicators; CEMUS (Bhat and Waller 2008) which is a very detailed model of individual
travel behavior and the energy and environmental implications thereof; ILUMASS (Strauch et al. 2005) which combines land use, transport and the environment; I-PLACE3S (Czachorski et al. 2008) which is not a full-fledged integrated urban model but rather a GIS-based land-use mapping/ scenario building platform. More detailed reviews of other currently operational urban models can be found in Wegener (1994), Wegener (2004) and Kazuaki (2006).

These models focus primarily on the resource implications of transportation processes, without accounting for other activities. For example, an activity-based model might generate a schedule like the one shown in figure 1. The LTE models discussed above would look primarily at the environmental implications of the transport episodes linking each activity. However each block of time also represents the presence of an individual within a specific part of the city, conducting a specific activity, for example the use of heat and power within the home. Therefore if we can characterize these activities based on the resources they consume, it should be possible to build a much more detailed picture of urban resource demands. The resulting activity-based model would then provide the necessary information to capture significant urban interactions and better predict changes in transport flows and fuel consumption resulting from changes in urban layouts, assess the resource consumption in buildings over space and time to reflect the activity patterns of the occupants, as well as capture the direct and indirect effects of policy interventions (e.g. resource pricing) on these schedules and resource flows.
Work in this area is evolving rapidly. For example, a collaborative team led by the Universidade de Coimbra under the MIT Portugal program is developing iTEAM or Integrated Transport and Energy Activity-based Model (Ghauche 2010, Almeida et al. 2009). As the name suggests, iTEAM is focused on urban form, transport and energy demands working up from behavior at the household/individual level and the form/organizational level. SynCity, being developed at Imperial College London (Keirstead et al. 2010; Sivakumar et al. 2010), is one of the very few urban energy model systems that integrates full-fledged and detailed supply and demand model components and forms the basis of the present article.

**Summary**

From the perspective of analyzing urban metabolism at high spatial and temporal resolutions, state-of-the-art integrated land use-transport models offer a behaviorally-realistic means of simulating energy consumption activities. These agent-based micro-simulation model systems therefore hold the potential to produce detailed resource demands that are not only spatially and temporally disaggregate but also are sensitive to a wide variety of scenarios, and are endogenous to the model. While the focus of this article is on the short-term factors such as where, when, and how people participate in activities, such models can also capture the effects of medium and long-term decisions made by
individuals and households with respect to residential and workplace location, auto-ownership, labor force participation and so on.

**Simulating London’s electricity and natural gas demands**

To demonstrate the modeling approach, we now simulate the demands for electricity and natural gas from the built environment (i.e. not transport) in London. These demands are typically required as a major input in energy system design models such as Keirstead et al. (2011), which seek to identify an optimal combination of fuels and energy conversion technologies subject to constraints on land availability, cost, pollutant emissions, and so on. Although we are simulating the demands for electricity and gas in the present article, such models typically require as input final energy service demands rather than raw fuel requirements as, for example, a number of possible energy technologies can be used to provide space heating. The model simulation can be broadly summarized as a three-step process, which will be described in greater detail below:

- Define the case study and collect input data
- Run the agent-activity model to generate activity schedules
- Convert activity schedules into resource demands

*Define case study and collect input data*

We wish to calculate the demands for electricity and gas in London so the first step is to decide how to represent the city’s geography. The activity scheduling model used here (TASHA, described below) uses discrete zones as typically found in a city’s transportation survey or transport planning model; in this case, the model in question is the London
Transportation Studies (LTS) model. It consists of 1285 zones representing major centers of travel demand although the physical area of each zone varies widely. For example, in central London, the average zone size is 2.2 hectares while some of the other zones represent whole regions (e.g. other parts of the UK, Europe, and the world). For the purpose of this study, we focus only on the 391 zones of Inner and Central London.

To calibrate our model, we rely upon energy demand data from the UK Department of Energy and Climate Change (DECC). This data is provided at the Middle Level Super Output Area (MLSOA) level, a geographical unit for UK statistics which represents a minimum of 5000 residents and 2000 households. The DECC data set provides 2008 demands for domestic and commercial gas and electricity consumption in each MLSOA zone (DECC 2008). These demands were then area-weighted to correspond to the LTS zones.

TASHA, the Travel Activity Scheduler for Household Agents, is an activity scheduling model designed originally at the University of Toronto (Miller and Roorda 2003, Roorda et al. 2008) and a copy of the model code was provided to the authors. As the model was developed for the Greater Toronto Area, we had to make some amendments before running the model for London. First, we divided TASHA’s inputs into three categories. Configuration parameters control the model’s running including details of where to store working files, thresholds for scheduling algorithms, and other constants; these values were left unchanged. The second set of inputs is the characteristics of activity behaviors in a given location, but without any specific geographic information. That is, these inputs describe discrete frequency distributions for major activity scheduling parameters such as the number of times an activity is performed per day, the likely start time of an activity, and the
likely duration of an activity for a given start time. For these inputs, we have assumed that travel behavior in Toronto is a good proxy for that in London. Finally, there are data that describe the geography of the case study in question, such as the number of travel zones, the activity and residential housing provision in each zone, and the physical network connections between them. This information was drawn from the LTS model representation of the 391 zones of Inner and Central London.

A final important piece of information is the population of agents for whom schedules will be generated. We created a synthetic population of approximately 65,000 agents (approximately 2.5% of the population in the study area) with distributions of major characteristics, such as age, gender, education level, occupation type, student status and so on drawn from observed distributions in Toronto.

*Generate activity schedules*

The TASHA model is described in detail in Roorda et al. (2008) and Miller and Roorda (2003). Briefly, the algorithm begins by representing the local geography, and characteristics of the simulated household and individuals. For each household and individuals within a household, the model then generates a schedule of “projects”. A project consists of a number of “episodes” and an overall classification so, for example, a “work” project might involve three episodes: a travel episode to go from home to the office, an activity episode in which the individual works at the office, and a final travel episode to return home in the evening. TASHA builds these schedules with a combination of distribution samples (for activity frequencies, start times, and durations) and a series of rules which ensure that activities are only generated for the correct individuals (e.g. a child...
cannot work). As these procedures may sometimes result in a schedule clash, TASHA contains a rule-based conflict resolution module to ensure that consistent non-overlapping schedules are created for all members of the household. Note that this scheduling process also selects the location at which an activity will be performed. This is done using multinomial discrete choice models, selecting from the zones specified in the input files. The major variables in these models are the distance from the agent's current location to the potential activity location and its “size”, for example, the number of jobs in that location.

**Convert schedules into resource demands**

As output, TASHA creates a file listing all of the episodes generated by the scheduler. Each episode is described by its start time, duration, activity type, location, and number of adults participating in that episode. It is this information that we use to estimate the resource demands.

There are at least two strategies by which one could estimate resource demands from this data. The preferred method is arguably to develop a process-based model of the resource demands. For example, one might hypothesize that each zone is characterized by a typical building type that will have some baseline level of demand as a function of external temperature. By varying the external temperature, we can therefore estimate the likely demands at different seasons of the year. Furthermore, visits by individuals to the building in order to perform an activity will result in an additional load. For example, a retail area may have very high electricity base loads during opening hours (due to display lighting and so on) but low marginal loads due to additional shoppers arriving at the store.
In contrast, an office building may have baseline loads associated with climate control, but each additional worker could contribute a distinct load of several hundred watts as they turn on their desk lamp, computer and so on. This approach could be built using models of building energy demands and simulated occupancy. The second option is to use a data-driven model in which a regression is performed to explain the observed annual average demands (from the DECC data source) as a function of the simulated activity patterns (e.g. total annual people-hours performing activity a in zone z). This is a simpler method but it has limitations and cannot respond to changes in temperature or time-dependent loads (e.g. the difference in a building’s base-load when it is open or closed).

For the purpose of this article, we wish to demonstrate how changes in the underlying drivers of activity generation can affect resource demands at high spatial and temporal resolution. Therefore, we use the second regression-based approach to create a simple model of how demands for electricity and gas vary in each zone for an annual average day. However as the activities simulated by TASHA represent out-of-home activities such as work and shopping, this model is unable to simulate the temporal variations in resource demand due to in-home activities.

Results

To demonstrate this approach, we have simulated the demands for electricity and gas throughout London under two scenarios: a business-as-usual situation representing the loads of an average day and a “peak-shifted” scenario which simulates the possible impacts of a shift in rush-hour commuting habits (referred to hereafter as Original and Shifted respectively). The Shifted scenario was prepared by modifying the start time...
distributions used by TASHA. This file contains a frequency distribution of the number of episodes of a given activity expected to start at a specified time. We first identified the “peak” periods, that is those time intervals which contained a number of episodes at least equal to 70% of the observed maximum in the distribution. Eighteen per cent of the episodes in these peak intervals were then re-allocated to time intervals representing a half-hour before and after the identified peak. These assumptions are based on changes in peak travel seen in London following the introduction of the congestion charge. Although the main observation was a 18% reduction in peak travel, some evidence of load shifting to the half-hour following the charging period was also seen (TfL 2004). An example of the resulting modified start time distribution is shown in figure 2.
Figure 2: Example of start time distributions for the Original baseline case and in a Shifted case, where 18% of episodes in peak intervals are moved to adjacent periods.

The TASHA model was then run with the Original set of start time distributions in order to produce the baseline level of activity within the city. The result of this model provides the necessary information to determine the resource demands associated with each activity by regressing against the observed demands from DECC. The formulation of the model is as follows:

\[ d_{t,a} = \beta_{tr} P_{a} + \sum_{z} \beta_{a,n} V_{az} \]
where $d_{r,z}$ is the observed annual average daily demand for resource $r$ in zone $z$, $P_z$ is the observed population of each zone $z$, $V_{a,z}$ is the number of minutes per day spent on activity $a$ in zone $z$, and $\beta_{r,a}$ are the regression coefficients for resource $r$. Separate models were fitted for the gas and electricity data using the nnls (non-negative least squares) R package to ensure that the coefficients of each activity are positive (Mullen and van Stokkum 2010; R Development Core Team 2011). This method was used instead of a normal linear regression since, a priori, we know that none of the activities considered by the model result in a decrease in electricity or gas demand. The resulting models, including a comparison with R’s standard lm regression model, are shown in table 1.
Table 1: Summary of regression models used to estimate resource demands from activity levels. Significance levels: *** < 0.001, ** < 0.01, * < 0.05, . < 0.1; significance estimates unavailable for the nnls coefficients. Methods: lm = R’s standard linear model function, nnls = non-negative least squares regression function provided by the nnls R package.

<table>
<thead>
<tr>
<th>Method</th>
<th>Electricity</th>
<th></th>
<th>Gas</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>lm</td>
<td>nnls</td>
<td>lm</td>
<td>nnls</td>
</tr>
<tr>
<td>Coefficients</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population</td>
<td>14.0***</td>
<td>13.2</td>
<td>42.8***</td>
<td>41.7</td>
</tr>
<tr>
<td>Primary work</td>
<td>-8.19*</td>
<td>0</td>
<td>-12.5</td>
<td>0</td>
</tr>
<tr>
<td>Secondary work</td>
<td>-336.</td>
<td>0</td>
<td>-10.8</td>
<td>0</td>
</tr>
<tr>
<td>Home-based business</td>
<td>177*</td>
<td>184</td>
<td>830.**</td>
<td>832</td>
</tr>
<tr>
<td>Work-based business</td>
<td>-63.9*</td>
<td>0</td>
<td>-71.8</td>
<td>0</td>
</tr>
<tr>
<td>Return home (lunch)</td>
<td>-1080**</td>
<td>0</td>
<td>-1130</td>
<td>0</td>
</tr>
<tr>
<td>Shopping (individual)</td>
<td>-0.804</td>
<td>0</td>
<td>40.9</td>
<td>16.1</td>
</tr>
<tr>
<td>Shopping (joint)</td>
<td>-5.57</td>
<td>0</td>
<td>-71.0</td>
<td>0</td>
</tr>
<tr>
<td>Other (individual)</td>
<td>55.5***</td>
<td>24.7</td>
<td>61.1*</td>
<td>26.7</td>
</tr>
<tr>
<td>Other (joint)</td>
<td>91.3**</td>
<td>50.8</td>
<td>88.2</td>
<td>32.2</td>
</tr>
<tr>
<td>School</td>
<td>28.1***</td>
<td>27.6</td>
<td>77.5***</td>
<td>76.5</td>
</tr>
</tbody>
</table>
| $r^2$                       | 0.642***    | 0.619***| 0.554***   | 0.559***
Figure 3 compares the spatial distribution of both the observed DECC demands and the simulated demands. As can be seen, the general pattern of high demands in central areas and lower demands in the periphery can be seen for both the electricity and gas figures. However, a large number of the simulated zones, particularly in the outlying areas, show higher loads than in the observed data. Since the maps aggregate the demands into four discrete bands (for improved legibility), a one-sample t-test was performed to see if the differences in each zone were significantly different from zero and the results showed no significant difference (for electricity, $t = 0.639$, $df = 390$, $p = 0.523$; for gas, $t = -0.0396$, $df = 390$, $p = 0.968$).
Figure 3: Maps showing observed and simulated baseline demands for electricity and gas. The figure also shows two zones of interest for further study, zone 1050 is a residential zone and zone 370 is a commercial zone.
The maps also highlight two zones for further examination: Southend South and Beckenham Hill (zone 1050), a primarily residential area in southeast London, and Belgravia North (zone 370), a commercial and mixed-use region in central London. As noted above, the regression model used to estimate the demands has no way of accounting for in-home variations in resource demand. We inspected the temporal profiles of electricity and gas demand for the residential zone and confirmed that, for both the baseline simulation and the case with shifted commuting patterns, the demands are constant.
A more promising result is the case of commercial demands in Belgravia North (figure 4). Here we can see demands for electricity and gas change throughout the day as citizens perform various out-of-home activities. We also observe a relatively constant base load during the night, which can be interpreted as the sum of (constant) domestic loads and commercial base-loads for this zone. Each demand curve shows differences between the Original data set and that driven by the Shifted commuting pattern. A follow-up analysis found that although the total demand was very similar in both cases (0.66% higher for total electricity demand, 0.67% lower for total gas demand) there were notable variations at any given time. For electricity, it was found that between 00:00 and 00:30 demands were 71% higher than in the original case; however from 21:00 to 21:15, demands were 54% lower. Similarly with gas demands, an increase of 29% was seen from 00:00 to 00:30 but savings of 43% were observed between 21:00 and 21:15. When periods of maximum demand were considered, we found that the peak demand was slightly higher and occurred earlier for electricity in the Shifted case, versus the Original case, and was lower but also earlier for peak gas demands (see table 2).
Figure 4: Electricity and gas demand profiles for a commercial zone (Belgravia North, zone 370), before and after the shifting of non-residential activity start times.
Table 2: Timing and magnitude of simulated peak resource demands in a commercial zone within London, before and after the shifting of non-residential activity start times.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Original</th>
<th>Shifted</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Electricity</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Peak demand (kW)</td>
<td>192</td>
<td>201</td>
</tr>
<tr>
<td>Time of peak</td>
<td>13:20</td>
<td>12:15</td>
</tr>
<tr>
<td><strong>Gas</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Peak demand (kW)</td>
<td>489</td>
<td>453</td>
</tr>
<tr>
<td>Time of peak</td>
<td>13:20</td>
<td>12:15</td>
</tr>
</tbody>
</table>

Research challenges

In this section we review the results in order to assess the suitability of activity-based modeling for the simulation of high-resolution spatial and temporal variations in urban resource demand.

Overall the method was able to simulate the demands for electricity and gas demands at higher resolutions than typically used in urban metabolism studies. At a spatial scale, the model used 391 zones to represent Inner and Central London with the smallest area representing 2.2 hectares and the generated profiles calculated at 5 minute intervals. This resolution enabled the examination of the consequences of a shift in travel patterns on resource demands and generates the kind of resource demand profiles required by both operational and planning models for urban energy systems (e.g. Girardin et al. 2010;
Keirstead et al. in press; Weber and Shah 2011). Such applications represent an improvement on aggregate urban metabolism studies and open the way to a better understand of in-city resource consumption patterns.

However it remains to be seen for which aspects of urban metabolism this method might be most useful. For the energy infrastructures considered here, variations in demand at high spatial and temporal resolutions are significant because the system must balance supply and demand in near real-time in order to maintain acceptable levels of service (particularly with electricity networks). Other aspects of urban metabolism, such as wastes, material flows, or atmospheric releases, may not need this level of detail owing to service requirements and the design of the related infrastructure (e.g. municipal solid waste collection does not need to be instantaneous because it is possible to store these wastes locally for some time). Similarly the method does not directly resolve some of the methodological concerns raised earlier, such as an improved understanding of metabolic processes within a city including local resource storage and transportation. The role of activity-based simulation in urban metabolism studies should therefore be considered on a resource-by-resource basis.

The results also highlighted several areas for further work. The first is a need for improved techniques for translating urban activity and travel patterns into associated resource demands. In the present analysis, we have used a simple regression framework which enabled us to calibrate the model effectively to observed demand data but lacks responsiveness to many important variables. For example, the regression model has no temperature variable and therefore would not be able to capture seasonal variations in resource demand (particularly important for understanding space conditioning.
requirements). This suggests that a process-based model, as discussed by Yamaguchi et al. (2007), is needed. As they note for the case of commercial buildings, bottom-up simulations of demands for heating, cooling, hot water, and electricity can complement more aggregate statistical analyses and enable modelers to assess changes in demand under a wider range of scenarios.

A related issue is the observed lack of variation in the domestic zone demand profiles, since the regression model used here had no parameters to capture in-home activity and associated resource demands. In the case of energy systems, a number of alternative approaches exist which rely primarily on detailed simulation (e.g. Firth et al. 2008; Shimoda et al. 2007; Swan and Ugursal 2009; Tanimoto and Hagishima 2010). The result is a model which is sensitive to the variations of domestic energy consumption at much higher resolutions, down to the level of a refrigerator's compressor switching on and off, but the difficulty is that such simulations require substantial amounts of input data: on building fabric, individual behavior, appliance ownership and so on. The travel surveys used to build activity-scheduling models, like the TASHA model used here, do not gather this data. This suggests that from the perspective of the model developer, a modular approach should be adopted. This would enable users to easily switch between detailed process models and aggregate statistical models depending on the available data for any given case study.

One of the main research challenges is therefore data availability and transferability. Activity-based models require substantial amounts of input data, even before the difficulties of converting activity patterns to resource demands. As discussed above, we have used a combination of London and Toronto data for this case study as not all of the
required data were available for London. As large cities in OECD nations, the differences between London and Toronto are perhaps acceptable for the present analysis as we have primarily carried across assumptions about the temporal distribution of activities, their start times and durations. But in the coming decades, urbanization will occur primarily in the developing world (UN 2008) and it is not yet clear to what extent techniques premised on massive data sets will be applicable in these environments. Other researchers in the area of activity-based modeling have suggested that alternative data sources, such as mobile telephony records or internet surveys, may provide some assistance in this matter (Ghauche 2010, Almeida et al. 2009). It is clear however that, given the investment necessary to build these models, it would be beneficial to the community if the opportunities and limitations of transferring such models from one city to another were well understood.

Finally, while this article has focused on the potential advantages of activity-based modeling for urban metabolism studies, the general method described here may also be of interest to others in the industrial ecology community. Specifically the core of this technique, that is the generation of detailed schedules of individual behavior, may be a valuable resource for those attempting to study new more efficient modes of service provision. For example, an earlier study in this journal compared the life-cycle impacts of DVD rentals from traditional and e-commerce providers (Sivaraman et al. 2008). Key components of this assessment include the building energy consumption of the retail store, the transportation energy needed to deliver or collect the DVD, and the electricity needed to play the disc. A detailed model of activity patterns, particularly in-home activities, would enable such assessments to capture environmental impacts more accurately as, for
example, the carbon intensity of electricity varies significantly throughout the day (e.g. in the UK, see Hawkes 2010). These new service models also highlight the importance of further research into the links between the short-term activity patterns discussed here, and the medium and long-term changes in urban land use that can be assessed by LUT models.

Conclusion

Urban metabolism studies are vital for local authorities seeking to improve the environmental performance of their cities. To date, these assessments have been conducted primarily at an annual time-scale and for the city as a whole. For some resources, this granularity may be sufficient. However for other resources, particularly energy resources, those seeking to design the infrastructure systems that mediate between urban service provision and resource consumption will require greater detail on the spatial and temporal variation of demands. This article has demonstrated how activity-based modeling can be used to simulate such demands at temporal resolutions of 5 minutes and spatial resolutions of approximately 2 hectares. The resulting model enables users to assess the resource consequences of new policy options, such as altering travel patterns, but this relies on effective models to convert between activity patterns and resource demands. The regression-based approach illustrated here has the advantage of simplicity but it fails to capture in-home activity patterns. We therefore believe that further research in this area will begin to incorporate more sophisticated process-based models of building energy consumption, as well as evaluating the challenges of implementing such data-intensive models in a wider range of cities.
Acknowledgments

The financial support of BP via the Urban Energy Systems project at Imperial College London (www.imperial.ac.uk/urbanenergysystems) is gratefully acknowledged. We would also like to thank Eric Miller and his group at the University of Toronto for providing us with a copy of the TASHA model code, and the helpful comments of three anonymous reviewers.

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References


Ofgem 2004. What is a price control?


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1 A land parcel is an area of land that is uniquely defined for ownership or land use purposes. A parcel is therefore a fundamental cadastral unit: a piece of land which can be owned, sold, and developed