Simulating Household Waste Management Behaviour


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Abstract

The paper reports the outcome of research to demonstrate the proof of concept for simulating individual, collective and interactive household waste management behaviours to provide a tool for efficient integrated waste management planning. The developed model simulates whole communities as distributions of individual households engaged in managing their own domestic waste, through home composting or recycling activities. The research addresses the personal hierarchical ordering of these activities, choices for participation and the factors affecting the waste diversion levels to each of the available outlets. These choices are driven by the underlying attitudes of the community residents, linked in part to socio-demographic factors but also containing a large random, or stochastic, element. Structures for modelling the stochastic variations are developed. The social elements of the simulation are used as control parameters determining the waste material flows through the household which provide a process simulation, or material balance, across the household. The developed models enable the investigation of possible management interventions to increase overall performance. Behavioural responses to other external stimuli can also be simulated. Model application to the simulation of environmental impacts from recycling are discussed briefly. The paper concludes with examples drawn from model validation trials on kerbside newspaper recycling schemes.

Keywords:
Artificial societies, Composting, Environmental impact, Material balance, Recycling, Stochastic modelling, Waste management

Introduction

1.1

In the UK, diversion of materials from the domestic waste stream still relies on the combined voluntary behaviours of individual householders. The waste management professional is now being charged with increasing these flows, at an economic cost and with net environmental benefit. The management objectives lie in optimising the provision of facilitating infrastructure, and in maximising the utility of this infrastructure through stimulating and sustaining high levels of voluntary action. Such objectives are difficult to achieve, especially within the fiscal constraints imposed and with a view to achieving the best practicable environmental option (BPEO) which, in most cases, is still undefined. The problem firstly centres on achieving the best possible deployment and spatial location of facilities, to minimise the economic and environmental costs of servicing whilst maximising the ensuing social benefits and acceptability. Secondly, people must be educated, encouraged or induced to use those facilities to their maximum potential, and in an environmentally responsible manner. Effective management of the system as a whole demands an understanding of the individual attitudes, beliefs and perceptions of all individuals serviced by scheme, and of
the local, personal and managed circumstances that they face. All individuals are, of course, different and will hold different assemblages of motivations, expectations and behaviours for their individual management of their household waste. These individuals are the fundamental units within the system. Any diagnosis of performance at the system level is, in theory, traceable back down the cause-effect chain, ultimately to the discrete actions of the separate individuals. The point of action of any management intervention is also on the individual. System response to this intervention is determined by the aggregated effect from all affected individuals.

1.2 This paper describes:

1. the development of a model of artificial communities of individual households that simulates their observed and measured household waste management behaviours, together with the factors that influence or induce that behaviour;
2. the testing of the model against measured time series data;
3. model application to, and initial results from, predicting the effect of interventions on household waste management behaviours.

The model is aimed at providing decision support for local and regional waste management planning.

1.3 This 'bottom-up' approach to support waste management provides new, enlarged perspectives compared to the more traditional 'top-down', e.g. systems approach (e.g. Leach et al. 1997). Potentially it can provide superior resolution and greater depth of understanding of the complex factors and interactions involved. A pilot 'bottom-up' simulation model for kerbside recycling of newspaper was developed and validated by Tucker et al. (1998a, 1998b), from which it was considered that a simulation of the totality of waste management behaviours within a community might be feasible. To set up this full societal simulation within the integrated waste management framework requires the development of new simulation structures to account for (i) the logical choices made by individual households in their preference and patronage of waste management schemes, and (ii) individual performances in using those schemes. The research presented in this paper details the conceptual and mathematical framework that has been developed to meet these objectives. It describes how the various technical, psychological, economic and environmental factors can be simultaneously modelled within the overall methodology.

1.4 The developed simulation is based on artificial societies, of given demographics. Each society comprises an assemblage of individual households who are allowed to behave individually, or respond coherently to stimuli such as management interventions, or to interact with each other through normative influences. The antecedents to behaviour are the underlying attitudes and perceptions of the individuals. Behaviour is expressed as a material balance of waste flows through the household. With this formulation, therefore, the social simulation might be considered as controlling a process simulation.

1.5 Detailed commentary on empirical studies into recycling behaviour have been given elsewhere (Tucker et al., 1997, 1998c, 1998d; 1999a, 1999b). These studies, together with the psychological studies cited in the text, provide the basis for the generalisation to the wider range of waste management applications addressed in this paper.

Model representations of household behaviour

Basic Premises

Household Waste Flux

2.1 The household waste stream can be pictured as a flux of material flowing through the household. Individual choices on how to manage that flux may be represented by nodes on that flowstream (figure 1). Each node is
formulated as a mathematical model of a given activity. If a household participates in that activity (e.g. recycling), there is a resultant is a diversion of part of the household's waste flux from their main waste stream. Such a representation is analogous to the process flowsheet or flowline, conventionally used to simulate separation stages in process engineering plant.

2.2

The diversion of flux categories initially places material in various recepticals, such as the kerbside recycling container (or containers if more than one is provided), the transfer bag or box for taking to the drop-off site or the kitchen bucket for compostibles. These containers are then discharged at intervals, when times are appropriate, into the appropriate aggregated unit: the collection lorry, drop-off bank or compost bin. The combined flux into these aggregated units provides an aggregation of the individual weights and compositional analyses. The aggregation process can, of course, be continued and flowlines extended to cover downstream processes as well, such as material recovery facilities (MRFs), dirty MRFs, and ultimately to the reprocessing plant itself. This can ultimately provide for a seamless integration of household activities through local authority operations to the downstream re-processor (figure 2 and Tucker and Lewis, 1993).
2.3

The household material flux can be formulated as a vector of individual material categories. In the UK, the prime waste classification is generally based on 11 major categories: Paper, glass, dense plastic, plastic film, ferrous metal, non-ferrous metal, textiles, putrescibles, non-combustibles, combustibles and 'fines' (a catch-all term for a mixed classification of small-sized material). (e.g. DoE, 1994). A more-detailed 33 category sub-classification has also been developed. In the current work, a mapping onto these classifications has been preserved, although for convenience, some aggregations and minor adjustments have been made. The 'working' material flux classification is shown in Table 1. Household material flux is quantified in the unit of kilograms per week.

Table 1: Material Flux Classification

<table>
<thead>
<tr>
<th>Prime Category</th>
<th>Sub-categories</th>
</tr>
</thead>
<tbody>
<tr>
<td>Paper</td>
<td>Newspaper, magazines, junk mail, catalogues, other paper, card</td>
</tr>
<tr>
<td>Glass</td>
<td>Green bottles, amber bottles, clear bottles, jars, other glass</td>
</tr>
<tr>
<td>Plastic</td>
<td>Beverage bottles, other dense plastic, carrier bags, other film</td>
</tr>
<tr>
<td>Metal</td>
<td>Ferrous cans, other ferrous, aluminium cans, aluminium foil, other</td>
</tr>
<tr>
<td>Organics</td>
<td>Kitchen veg., other kitchen, garden soft, garden woody, other*</td>
</tr>
<tr>
<td>Textiles</td>
<td>Second hand clothes/bedding, clean rags, other</td>
</tr>
<tr>
<td>Combustibles</td>
<td>n/a</td>
</tr>
<tr>
<td>Non-combustibles</td>
<td>n/a</td>
</tr>
</tbody>
</table>

* e.g. trees, diseased material not normally home composted

2.4

To effect the flowsheet simulation, it is necessary to sequence the available waste management activities through specifying the logical ordering for the separation nodes. Householders may formulate their own preferred hierarchies, though in general these tend to follow the conventional wisdom of reduce, re-use then recycle. Within those broad categories, local sub-orders will also be determined, such as the preference for
one recycling scheme over another. These sub-orders are considered in more detail later. The assumed 'broad' model order of composting followed by kerbside collection then by drop-off recycling is considered to be the most logical and valid assumption for most households (figure 1).

**Household Attributes**

2.5

The individual nodes on the 'process flowsheet' are described by unit-process models, one model for each generic scheme type. In conventional engineering, the unit-process nodes are designed to represent individual processes such as a reaction vessel, comminution device or separation device. The effect at each node depends on the physical device operating conditions, which may be represented by a set of model parameters. In the household, the operating conditions become the fundamental motivations, attitudes and perceptions of the householder.

2.6

Many psychological studies have attempted to identify correlations between specific attitudes and barriers and specific household waste management behaviours such as recycling (Jones, 1990; Boldero, 1995; Goldenhar and Connell, 1993; Taylor and Todd, 1995; McCarty and Shrum, 1994; Jackson et al., 1993), and composting (Taylor and Todd, 1995). Other approaches have opted to use demographic parameters and proxy variables to account for behaviour (e.g. Rufford, 1984; Aspinwall, 1991; MEL, 1996 - waste generation; Ellen, 1994; Reschovsky and Stone, 1994, Tucker et al., 1997 - recycling). Such studies have all achieved partial success, that is, they have been able to explain some of the observed variation, though few have been able to explain the major part of the variation. The unexplained component has been attributed to an inherent randomness by MEL (1996), though MEL also identified that this random assemblage of behaviours began to look more structured when expressed in terms of a behavioural distribution.

2.7

Measured waste generation rates appear to be quite well fitted by log-normal distributions (MEL, 1996; Leech, 1995) whilst Tucker et al. (1998a) showed that scaled beta distributions can provide good fits to recycling recovery data. Whilst there is no a-priori reason for preference of any specific distribution, beta distributions appear to be flexible enough to fit most observed distributions of waste generation, recycling recoveries and measured attitudes and barriers as well (Tucker, 1999a). The current work continues to use the beta distribution. The researches of MEL (1996) and Tucker et al. (1998a) indicate that the means of these distributions can be modelled as functions of specific socio-demographic proxy variables, i.e. means tend to change in a fairly systematic way with demographic category (figure 3). This concept mirrors many empirical observations that there are identifiable differences amongst different demographic groups, though these differences can be small compared with the natural variation within any given group.
2.8 In the simulation model each antecedent attitude distribution, \( p(Y) \) is formulated in terms of a generic shape function based on the beta distribution together with a scale factor based on the demographic descriptors. 

\[
P(\gamma) \propto \left( \frac{X}{\Pi S} \right)^m \left( 1 - \frac{X}{\Pi S} \right)^n
\]

where \( S \) are the socio-demographic descriptors and \( x \) represents the scale unit (Kg. or strength of attitude etc.). \( m \) and \( n \) are fixed model parameters, estimated from observational or survey data (Tucker et al., 1998c, 1998d, 1999a), or set through empirical adjustment.

2.9 It is difficult, however, to identify a comprehensive and mutually independent set of socio-demographic descriptors from the literature. Age, education, social class, housing type, tenure, household size and presence of children have all been claimed to have some bearing on waste management behaviour (see e.g. MEL, 1996; Rufford, 1984; Tucker et al., 1998a). The current study opts for housing type, stage in family life-cycle, household size and car ownership as the major predictor variables. Housing type is correlated to income and social class, whilst family life cycle stage (Rufford, 1984) encompasses the age and children dependencies. Despite this simplification, these broad descriptors still remain partially correlated. For example single persons and young couples may be more likely to reside in flats than would larger families. The residual correlations, however, do not appear to be detrimental to the overall simulation results.

2.10 Given the assumption that 'generic' distributions can be identified for each predictor variable for large populations, small population characteristics can be generated by random (Monte Carlo) sampling of the large sample distribution. In the current model, each household attribute is determined stochastically this way, independently for each specified neighbourhood within the community.

2.11 The attribute set for each household comprises a core set of these identified 'psychological' variables, i.e. their attitudes and perceptions. In addition householders are also allocated 'place' attributes, such as area of residence, street, distance to drop-off site etc. These attributes can be considered to affect the 'place' dependencies also considered important in determining recycling behaviour (Coggins, 1994). A third class of attributes are additionally introduced to account for the interaction of the householders with the specific waste...
management schemes. These variables include 'have compost bin' for home composting, and 'scheme appeal' for recycling sites. The full 'working' list of attributes is given in table 2.

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Demographics</strong></td>
<td></td>
</tr>
<tr>
<td>Housing type</td>
<td></td>
</tr>
<tr>
<td>Family Life Cycle</td>
<td></td>
</tr>
<tr>
<td>Family Size</td>
<td></td>
</tr>
<tr>
<td>Car Ownership</td>
<td></td>
</tr>
<tr>
<td><strong>Attitudes/Barriers</strong></td>
<td></td>
</tr>
<tr>
<td>Pro-recycling attitude</td>
<td>A Strength of pro-recycling attitudes</td>
</tr>
<tr>
<td>General recycling barriers</td>
<td>C Strength of general recycling barriers faced or perceived</td>
</tr>
<tr>
<td>Norms</td>
<td>N Susceptibility to normative pressures</td>
</tr>
<tr>
<td>Threshold weight</td>
<td>W0(j) Minimum perceived weight worthwhile recycling</td>
</tr>
<tr>
<td>Threshold weight</td>
<td>W1 Storage capacity of household</td>
</tr>
<tr>
<td>Save decision 1</td>
<td>D1 To accumulate material until W0 is reached - or to discard</td>
</tr>
<tr>
<td>Save decision 2</td>
<td>D2 With adverse PD: to save for favourable PD - or to discard</td>
</tr>
<tr>
<td>Awareness</td>
<td>AS(j) Knowledge that the scheme exists</td>
</tr>
<tr>
<td>Lifestyle</td>
<td>LF Frequency of lifestyle events negating intention to recycle</td>
</tr>
<tr>
<td>Ignorance</td>
<td>I(k) Misperceptions of types of material accepted by scheme</td>
</tr>
<tr>
<td>Forgetfulness</td>
<td>F(k) Frequency of forgetting to recycle individual items</td>
</tr>
<tr>
<td>Distaste</td>
<td>DT(k) Deliberate choice not to divert some items</td>
</tr>
<tr>
<td>Resilience to setback</td>
<td>R Susceptibility to change behaviour with adverse experience</td>
</tr>
<tr>
<td>Intervention susceptibility</td>
<td>X Susceptibility to respond to external stimuli</td>
</tr>
<tr>
<td>Pro-composting attitude</td>
<td>A' Strength of pro-composting attitudes</td>
</tr>
<tr>
<td>Composting barriers</td>
<td>C' Strength of general composting barriers faced or perceived</td>
</tr>
<tr>
<td>Composting proficiency</td>
<td>P Expertise in producing home compost</td>
</tr>
<tr>
<td><strong>Behavioural Control</strong></td>
<td></td>
</tr>
<tr>
<td>Scheme appeal</td>
<td>SA(j) Scheme specific appeal or scheme specific barriers</td>
</tr>
<tr>
<td>Personal difficulty</td>
<td>PD Frequency of events stopping intended participation</td>
</tr>
<tr>
<td>Have bin</td>
<td>HB Ownership of a compost bin</td>
</tr>
<tr>
<td><strong>Place Variables</strong></td>
<td></td>
</tr>
<tr>
<td>Neighbourhood</td>
<td></td>
</tr>
<tr>
<td>Street</td>
<td></td>
</tr>
<tr>
<td><strong>Waste Generation</strong></td>
<td></td>
</tr>
<tr>
<td>Waste arisings</td>
<td>W'(k) Average weekly arisings of waste material k</td>
</tr>
</tbody>
</table>

* for each site j and each material k if indicated
Spatial aggregation

2.12 The prime functional unit of population in the model is considered to be the ‘neighbourhood’. The definition of ‘neighbourhood’ is left very loose, though might be taken to be a contiguous group of households, separated from other neighbourhoods by physical barriers such as railways, main roads, green space, or by a step-change in housing type. Neighbourhoods are not necessarily of mono-housing type. They can equally comprise areas of co-mingled housing. In the model, the neighbourhood is considered to define a natural boundary to the diffusion of inter-neighbour normative influence. Typically a neighbourhood might define a group of 500-1000 households (or 2 to 5 Enumeration Districts).

2.13 Socio-demographic input to the model (when simulating real communities) can be drawn from the small area census statistics. The allocation of the individual family types and household sizes to the various household types, however, is not given explicitly in the census data. It is possible, however, to construct estimates of the necessary data from the recorded univariate distributions; using an iterative proportional fitting method (e.g. Fienberg, 1970). The model randomly distributes this reconstructed demographic profile into ‘pseudo-streets’ of uniform housing type. The resultant assemblage of pseudo-streets comprises the model neighbourhood. Whole towns, communities or districts may be aggregated from these individual neighbourhoods.

2.14 In the model, the provision of individual waste management schemes are specified separately for each neighbourhood, allowing for example pilot kerbside collection trials to be modelled for different parts of the community. Drop-off provision is also related to the neighbourhood. Mini-recycling centres, for example, are essentially neighbourhood-based with little, if any, patronage expected from outside that neighbourhood. Civic amenity sites and supermarket sites, by contrast service a wider range of neighbourhoods.

2.15 Overall waste management performances are aggregated street-by-street, area-by-area or for the whole community.

Time Dependencies

Discrete events resulting from external influences

2.16 Individual, street, neighbourhood and community recycling performances are not in steady state, though they often portray a reasonable degree of stability over the longer term (Boldero, 1995; Pieters, 1989). Longer-term performance changes have been observed to occur, often as a deterioration in participation in diversion activities, sometimes referred to as ‘recycling fatigue’ (Coggins, 1994). In the model, such changes can be linked to a drift in one or more of the determining attitudes. For example, the ‘novelty’ of a new scheme can wear out, decreasing its scheme appeal. One of the major factors that can reduce participation is the occurrence of ‘catastrophic’ or ‘perceived catastrophic’ events. In this catastrophic event is defined as an event that can lead to an irreversible step change in attitudes. For example, the loss or theft of the recycling container has been observed to switch off behaviours for some (Tucker, 1999a), as have overflowing drop-off banks or a lack of success in home composting. Other individuals however may seek to overcome such difficulties by seeking a replacement recycling container, retrying the drop-off scheme at a later date or having another attempt at composting. Discrimination between the two groups is modelled through the household attribute ‘resilience to set-backs’. On experiencing a catastrophe with a given scheme, the model triggers a reduction in scheme appeal for those who are not resilient.

Normative influences

2.17 Another factor that has been postulated to change with time is the individual’s susceptibility to respond to local normative pressures. Normative influences for kerbside recycling are assumed to act at the street level through the visual stimulus of seeing others set out. A high local behavioural norm has been considered to
stimulate new participations from susceptible individuals (Salimando, 1987; Everett and Peirce, 1992) or to stimulate more frequent use of the scheme by participants who are already active (Tucker, 1999b). Such influences are postulated to diminish as the recycling scheme matures (Taylor and Todd, 1995). Werner et al. (1995) and others argue that prolonged experience in a recycling scheme may serve to stabilise behaviours that were originally externally induced, with new reasons being internalised to justify those behaviours. It might be construed therefore, that a prolonged exposure to local normative pressures could catalyse increases in pro-recycling attitudes amongst susceptible individuals. In the model, the normative influence on a given individual is given by that individual's normative susceptibility compounded with the strength of the ambient local norm. Positive normative influence compounds with pro-recycling attitudes, strengthening the motivation to participate. Each normatively-induced participation is modelled as producing a small incremental increase in pro-recycling attitude. After many events, the pro-recycling attitude alone becomes sufficient motivation.

2.18 Householders might also revise some of their attitudes following social dialogue with neighbours or friends. The model assumes random interactions at the neighbourhood level. Pairs of households are randomly chosen. Each household's attitudes are allowed to converge a random distance towards consensus, where consensus is the midpoint of the household's attitudes after weighting by their respective normative susceptibilities. So, for example, if the second household had double the normative susceptibility of the first, the consensus point would be one third the distance on the attitude scale from the first household towards the second. Households with normative susceptibilities below a threshold value are assumed not to change their attitudes at all. Eventual convergence to a mono-behavioural pattern, is avoided through invoking natural household mobility. That is, new residents bring fresh attribute profiles into the community. This is modelled by resetting individual household attribute sets at random intervals around their given mean length of tenure.

2.19 Interactions at the community level are handled in the same way as at the neighbourhood level. The only difference is in their assumed mechanisms for meeting. At this level it seems reasonable that households will communicate through some type of common activity such as, for example, school events or pensioners' lunch clubs. The model handles these type of interactions by checking each selected pair for shared demographics. In the current model implementation, pairs are allowed to interact if, and only if, they share at least one demographic attribute.

**Planned and unplanned interventions**

2.20 As well as the above long-term changes affecting discrete households, some changes can act more coherently across the community, or parts thereof. These changes might result from planned interventions by the scheme operator or relate to external events such as occasional media coverage of waste management issues. These events are modelled in terms of their contact area and level of contact. Contact area may relate to individual demographic sections. For example schools programmes will reach families with children, radio broadcasts might preferentially reach young adults, leaflet drops will be area-bound, etc. Contact levels follow from these exposures but are tempered by the susceptibility of the contacted individuals to take notice. In the model, each event is considered to cause a directional shift in one or more attitudes consistently across the contacted segment. The degree by which an individual's attitudes are shifted is scaled by that individual's susceptibility to intervention. Modelling interventions is discussed further later in the paper.

**Lifestyle factors**

2.21 In addition to the longer-term changes, there are often quite dramatic shorter-term, reversible, performance fluctuations in household waste management schemes. Every recycling scheme operator is well aware that participation levels and weight recoveries will vary significantly from week to week. Within the model conceptualisation, this implies that some of the basic household attributes also have natural time dependences. Some of these time dependencies can be quite explicit. Personal difficulties in participating at a given recycling event might fluctuate according to factors such as illness and adverse weather conditions, whilst other life-style factors such as holidays and absences from home can temporarily switch off the
intention to participate on a given week. Forgetfulness to divert material into the recycling bag or compost bucket can also be variable according to the immediate pressures and priorities of the householder. In the model, individual householders are ascribed a given propensity to forget and an average frequency of experiencing difficulties. Week by week fluctuations are modelled through invoking random variations around these means.

**Volume and weight perceptions**

2.22

Other manifestations of time-varying behaviours can be linked to individual perceptions of the weights worthwhile to recycle or compost (Tucker, 1998a, 1998c, 1999b). Assumptions can be made that a householder will have a minimum weight perception, usually expressed in the metric 'bags' or 'boxes' of material or fractions thereof - say half a bag-full. Some householders may actually have a zero minimum weight threshold and are quite happy to recycle just one or two items each time opportunity permits.

Minimum weight thresholds might be established from given instructions "do not set out your recycling box until it is full", or through mimicking the behaviours of others. When normative pressures to behave are high, minimum weight considerations may be relaxed in order, simply, to be seen to participate (Tucker, 1999b). The minimum weight concept, coupled with consumption or waste generation rates, establishes a natural recycling frequency for the household. Summation of these individual frequencies leads to either an increase in the variability in aggregated participation (when the frequencies are not in phase) or to more systematic trends when individual frequencies come into phase. If a household fails to achieve their minimum weight in a given period, that householder is faced with the decision either (i) to continue to accumulate material until the minimum is achieved or (ii) to discard the material outside the scheme, often but not necessarily into the dustbin. Similar decisions are also taken when personal difficulties are encountered. These decision points are modelled in terms of the 'save it' or 'bin it' attributes allocated to the household. In terms of the household flux representation, the discarded material is simply returned to the household waste flux stream. Paper not recycled because of difficulties in a kerbside collection, for example, then becomes available for consideration for possible drop-off recycling prior to it being consigned to the bin.

2.23

As well as a low weight threshold, householders can have a high weight threshold, which describes the maximum weight that the householder is prepared to store in their household (Wang et al., 1997), linked to individual household storage capacities. Reaching the high weight threshold can trigger one of two consequences. Excess material might be reconsigned to the waste flux stream or, for drop-off recycling, a special recycling trip could be triggered.

**Model Structures and Rules**

2.24

The basic structure developed above provides for diversion of material out of the household waste stream though application of scheme specific models relating to each possible diversion path. These models are controlled by the specific collection of individual attributes held by each household. The general structure of the models can now be defined.

2.25

Each diversion activity can be expanded into the individual components affecting the overall decision; each component having a separate effect on one or more aspects of the material flux diversion. These sub-decisions can be assigned their own logical order represented as a sub-network of flowpaths and nodes within the overall simulation. The model kerbside recycling sub-network is given by way of example in figure 4.
At each node within the sub-network, the material flux vector is considered to contain components that are wanted by the scheme (e.g. glass bottles and jars for a bottle bank), unwanted components of the same material type such as other glass and unwanted items of different material types, e.g. plastic bottles. Each unit process model firstly determines whether or not a given household will actually use a given scheme. Secondly it determines how much of the available wanted material is diverted by that scheme, or conversely what degree of 'leakage' is expected. Thirdly, the model establishes how much unwanted material or contamination, is introduced to the scheme. These model mechanisms are described below:

## Scheme Participation Rules

The prime consideration for each unit process is whether or not a given household participates in that scheme. Most previous modelling studies of participation have sought to correlate the hypothesised antecedent factors
such as attitudes, norms and values with recycling or composing behaviours (e.g. Jones, 1990; Boldero, 1995; Goldenhar and Connell 1993; Taylor and Todd 1995; McCarty and Shrum, 1994; Jackson et al. 1993). Such models were generally based on univariate or multivariate statistical methods applied to categorical data. In developing the models, the hypothesised constructs were assumed to link sequentially according to an assumed model structure; the significance of each possible linkage then being tested statistically. A simpler and alternative approach was provided by the postulated ABC model of Guagnano et al. (1995). This model applied the simple inequality: If Attitudes > Constraints then Behaviour. Tucker et al. (1998a) argued that a more complete formulation would be: If Attitudes + Norms > Constraints then 'Intention to behave'. In effect, this provides a hybrid approach utilising the practical concepts of the ABC model with the established psychological concepts of Azjen's theory of planned behaviour (Azjen 1985). The theory of planned behaviour has been shown by Taylor and Todd (1995), amongst others, to be a reasonable predictor of participation for both recycling and composting activities. It should be borne in mind, however, that the theory of planned behaviour should not necessarily be taken as the definitive model for participation. Other models, such as Schwartz's (1997) altruism model have also shown some success.

2.28

To utilise the above inequality in numerical simulations, attitudes, norms and constraints need to be expressed on a numerical scale against a common metric. In the empirical determinations of these parameters, they are normally derived on a Likert scale in terms of the strength of agreement that a given attitude is held, or that a given barrier is faced. Two assumptions are necessary in order to map these data onto a numerical scale:

1. that the strength of agreement expresses the relative contribution of that factor to the motivation for behavioural intention;
2. that the Likert scale values may be mapped directly onto an interval scale (based on arbitrary units of motivation).

2.29

The relative significances of attitudes, barriers and norms respectively can be inferred from structural equation modelling with weighted least squares estimation (e.g. Taylor and Todd, 1995) and/or by empirical tuning of the scaling parameters against measured performance data. It is recognised that the approach is far from robust, though has been adopted as a simple expedient until more reliable and practical methodologies for attitude quantification are established.

2.30

The current model formulation provides a further development of the hybrid model of Tucker et al. (1998a). Clearly, within any behavioural model, it is not possible to identify each and every individual component that contributes to pro-behavioural attitudes, nor all the possible barriers and perceptions which can act as constraints. Nevertheless, previous research has consistently identified some specific features, which may be individually included. Other attitudes may be bundled. For example, pro-recycling or pro-composting attitudes can encompass factors such as environmental concern, dislike of waste and on occasions might include economic drivers as well (e.g. Tucker, 1999a). Specifically-identified barriers include the perception of the minimum weight to make recycling worthwhile and life-style irregularities (e.g. Tucker et al., 1998a). Other barriers relating to handling, storage difficulties and time and effort might be bundled into a general recycling barrier. Further antecedents to behaviour include any specific facilitating conditions (such as having a compost bin or, indeed, having a garden) and also self-efficacy, which might for example include the self-belief that one has the proficiency to make good compost. In the theory of planned behaviour, a favourable combination of these, together with social and personal norms, determines the intention to behave. Perceived behavioural control (facilitating conditions plus self-efficacy) then moderates whether that intention is converted into behaviour. In the waste management model, this moderating role is determined by the personal difficulty attribute.

2.31

In developing the model structure, it has proven expedient to combine certain specific attitudes and certain specific barriers together into a composite scheme specific variable, 'scheme appeal'. Positive factors influencing scheme appeal might accrue, for instance, for charity-run schemes, or because of attractiveness and helpful staffing at drop-off sites or the ease of access and parking. Co-location with supermarket facilities or in high street or village shopping centres can also add to scheme appeal. Conversely, distances from the household, lack of multi-material recycling provision or poor maintenance can discriminate against some
The theft of one's kerbside recycling container or fouling of that container by dogs (Tucker, 1999a) might reduce the appeal of the kerbside scheme, though does not necessarily weaken the general recycling attitude of the householder.

2.32 The developed participation model structure is shown in figure 5 and detailed below as a set of rules. The nomenclature follows that presented in table 2.

1. If AS is false, the intention to behave (BI) is false.
2. Lifestyle constraints, at a mean frequency of LF inhibit premeditated intent.
   If rand < 1/LF then BI is false (where rand is a random number between 0 and 1)
3. If the balance A + SA + (j * N) - C is positive then BI is true.
   j describes the local behavioural norm;
4. If BI is true, then participation (B) is false if available weight (W') is less than a threshold weight, W0, unless there is an over-riding social pressure (j * N) to participate.
5. If BI is true and W' < W0, material will be saved if D1 is true and discarded if D1 is false.
6. If BI is true and W' = W0, participation will be true unless a personal difficulty occurs.
7. Personal difficulty constraints, at a mean frequency of PD inhibit premeditated intent. If rand < 1/PD then B is false. If false, material will be saved if D2 is true and discarded if D2 is false.

Leakage Rules

2.33 Once it is determined that an individual householder will participate in a given scheme, it becomes necessary to determine how much of the available material is diverted. Tucker et al. (1998a, 1998c) identified two major controlling attitudes: ignorance and forgetfulness. Subsequently, a third controlling factor, 'distaste', has also been identified. It should be noted, however, that these descriptive labels should not be taken literally. They simply define three generic modes of leakage of which the label descriptor is an example. These mechanisms act on both the wanted and unwanted components of material flux. They are defined in the model in terms of trigger values at which behaviours change and a sliding scale for the level of that behavioural change.

Figure 5. Scheme Participation Model
2.34 For example, an 'ignorance that material is wanted' trigger can be defined as the threshold level of personal ignorance above which the whole category of wanted material is not recycled. Different trigger levels are set for individual materials to discriminate materials generally believed to be wanted (e.g. newspapers in a newspaper recycling scheme) from those where more general doubt exists (e.g. junk mail to that scheme). Default trigger levels have been estimated from analyses of questionnaire surveys of recycling participants (Tucker et al., 1998d). The complementary trigger 'ignorance that material is unwanted' defines the level of ignorance at which participants might commit unwanted materials like cardboard to a newspaper collection scheme.

2.35 Forgetfulness is modelled on a sliding scale from zero to one hundred percent forgetfulness. Randomness is built in to account for the underlying variability of this attribute. The converse of forgetting to contribute wanted material is the propensity to contribute unwanted material by accident. In the model, this is assumed to be by entrainment of unwanted material as a percentage of the wanted flux flow. For instance, a person recycling a high number of plastic drinks bottles is more likely to contaminate the product with a larger number of plastic bags than is a person recycling just one or two bottles.

2.36 The third control is distaste. This is effectively a combination of the forgetfulness and ignorance effects, and acts solely on the wanted flux stream. The distaste trigger provides a threshold level above which those with a high level of distaste deliberately choose not to divert the whole of a given material category. Below this trigger level, there is a sliding scale for the proportion of that category that the householder chooses not to recycle. For example, some householders can find it distasteful (or have other valid arguments) for not washing out food tins to enable their clean recycling. Other householders may have no objection to preparing tins that contained human foodstuffs, but might reject doing the same for pet-food tins. Distaste also accounts for events such as dealing with broken bottles or positive discrimination against recycling contaminated material, e.g. newspaper that might have been re-used to mop up oil spillage then returned in a contaminated state into the main household waste flux stream. The rules for the leakage controls are given below:

1. If $I > ITW(k)$, then consumed material of type $k$ is discarded. $ITW(k)$ is the ignorance trigger that material of type $k$ is wanted by the scheme.
2. If $I > ITU(k)$, then consumed material of type $k$ is contributed. $ITU(k)$ is the ignorance trigger that material of type $k$ is unwanted by the scheme.
3. A fraction $y$ of each wanted material $k$ is discarded through forgetfulness. $y = \text{rnd} \times F(k)$
4. A fraction $c$ of each unwanted material $k$ is introduced by accident. $c$ is proportional to $\text{rnd} \times F(k) \times W'$ where $W'$ is the total weight of all other materials contributed.
5. If $DT > DTT(k)$ then wanted material $k$ is discarded though distaste. $DTT(k)$ is the distaste trigger threshold for material $k$.
6. If $DT < DTT(k)$ then a fraction $l$ of wanted material $k$ is discarded through distaste. $l = \text{rnd} \times D(k) / DTT(k)$

Rules governing recycling scheme choice

2.37 Whilst the assumed household waste management hierarchy resolves many of the dilemmas relating to the ordering of individual actions, some conflicts still remain. In this respect, it has been necessary to develop a protocol to establish precedences (i) amongst specific kerbside provisions, if more than one is active within a neighbourhood and (ii) to determine which of the drop-of schemes accessible to a neighbourhood may be frequented by any given individual. The kerbside ordering is usually academic rather than of practical significance as multiple schemes rarely target the same material. For example there could be a green waste collection and a paper collection running in a neighbourhood but not normally two green waste schemes. Occasionally, however, a short-term charity collection (say of paper) may run in an area where newspapers are routinely collected. The consumer ranking of drop-off schemes, however, is more relevant. For instance, if a number of drop-off sites in the community provide paper collection facilities, the individual must choose which site to frequent. When questioned, individuals usually reduced their response to one of three main determining factors: nearness, convenience (or co-location with other amenities), or the provision of multi-
material recycling opportunities (Spiers et al., 1999). Minor expressed preferences also included attractiveness, ease of access or parking and links with charity associations. Within the model, the individual preferences are bundled into a composite index 'scheme-appeal', SA. Scheme appeal is modelled for each site j as the sum of four components: the general appeal of the site (GA), its multi-material provision (MM), its convenience (V) to household i and its distance (D) from household i. GA accounts for all the minor preferences.

\[ SA_{(i,j)} = GA(j) + c_1(i) \times MM(j) + c_2(i) \times D(i,j) + c_3(i) \times V(i,j) \]

2.38

The coefficients \(c_1(i), c_2(i), c_3(i)\) relate the relative importance of each of the factors MM, D, and V to household i. The fundamental data to help set the above variables has been developed through surveying recyclers at a number of recycling sites (Spiers et al., 1999). Like all other model parameters, the coefficients \(c_{1,2,3}(i)\) are determined by random sampling from distributions of generic shape, scaled by demographic factors (notably in this case car ownership).

2.39

Ideally, proximity information would be derived ideally by integrating the model with a geographical information system (GIS). However, a simpler and more workable expedient has been developed here. In the simplified approach, the user specifies the housing density for each neighbourhood and the distances \(D(j)\) from the neighbourhood centroid (which is assumed to lie at \(x=0, y=0\)) to each drop-off site j. The x, y co-ordinates of the drop-off sites are assigned within the model as \(D(j) \sin Q, D(j) \cos Q\) where \(Q\) is set randomly within the range 0 to \(\frac{\pi}{2}\). The housing density together with the number of houses specified for that neighbourhood determines its area, NA. Pseudo-street centroids are randomly assigned to spatial locations \(x(s), y(s)\) across the neighbourhood (i.e. in the region bounded by

\[-\frac{\sqrt{NA}}{2} < x < +\frac{\sqrt{NA}}{2}, -\frac{\sqrt{NA}}{2} < y < +\frac{\sqrt{NA}}{2}\]

2.40

The street distances to recycling centres \(D(s,j)\) are then determined from simple geometry:

\[ D(s,j) = \sqrt{[(\Delta \sin \theta - z(s))^2 + (\Delta \cos \theta - y(s))^2]} \]

2.41

In the model, the recycler is assumed to visit sites in strict order of scheme appeal, to a maximum of two site visits per week. Surveys show that few recyclers admit more than two visits per week, and most claim to remain fairly loyal to just one or two preferred sites (Spiers et al., 1999). Short-term fluctuations affecting scheme appeal are assumed not to be significant, though can be modelled, if required, by adding an extra random term into the expression for SA. Step changes is site loyalty, however, may occur through adverse experiences such as encountering overflowing bins at the site, or (as happened in 1998 in some Scottish communities) withdrawal of paper recycling facilities from some of the multi-material sites. Such events can be modelled as interventions (see later).

2.42

A second consideration affecting the modelling of visits to drop-off sites relates to the frequencies of visits. For supermarket sites or mini-recycling centres, it can be assumed that a visit frequency of once per week can be taken as the norm, e.g. co-inciding with the weekly shopping trip. Recycling activity, however, might not take place on every visit due to individual minimum volume considerations or personal difficulties. Visits to civic amenity sites tend to occur less frequently than visits to supermarket sites (Spiers et al., 1999) but could be associated with journeys passing close by the site as well as trips to use the general waste disposal facilities provided there. The model of civic amenity site usage must account for the lower frequency of visits to these sites. This can be modelled explicitly as a distribution of respective individual visit frequencies (analogous to modelling personal difficulty frequency) or implicitly modelled by setting higher minimum weight thresholds, \(W_0\), for those sites. (Higher weights per visit are generally recorded for civic amenity compared with supermarket sites (Spiers et al., 1999). The current model implementation adopts the second alternative.
2.43 The waste generation model is set up using a similar methodology to that used for setting the individual attitudes and other attributes. A mean waste arisings per household and waste composition are specified for each neighbourhood. Such data can usually be estimated from spot measurements undertaken by local authorities (if available) or by taking values from national data compilations (e.g. DoE, 1994). The model assumes a beta distribution of generation rates for each material category amongst the individual households, the scaling of these distributions again varying according to the demographics of the household. The quantification of appropriate scaling factors is progressively becoming better defined through a number of research studies (e.g. MEL, 1996, DoE, 1994, Jones et al, 1998a). Waste generations, like the other behaviours in the model, are not in steady state and might contain both longer-term (seasonal) dependencies as well as having short-term (week-by-week) fluctuations. Again data to quantify these variation is accruing from a number of investigation (e.g. Aspinwall, 1991 - waste generation) and (Jones et al., 1998b, weekly variations). Where these data are sufficient, sub-models can be constructed to predict the likely time dependencies, otherwise null relationships can be assumed for the model.

2.44 It must be borne in mind, however, that waste generation statistics are usually only known, or can be reasonably estimated, for wastes that end up in the domestic solid waste stream. Export of materials out of the household solid waste stream are less well quantified. For example, drinks cans that may be purchased during the household shopping expedition may be consumed and discarded at work ending up in a commercial or industrial waste stream. Newspapers may be used for fire lighting and magazines passed on to other households (Tucker et al., 1998d). A considerable proportion of green waste arisings may already be composted or just left to naturally decay in the garden. Normally the fate of such 'exports' remains outside the boundary of the household waste management model, the fluxes never entering the main household waste stream. Events may occur, however, that actually cause these materials to enter the household waste stream, say an intervention, to encourage recycling cans elsewhere. Modelling of such events is simply just another case of modelling the time dependencies of the relevant attribute, i.e. through discrete events or as a planned or unplanned coherent perturbation, as described above. In this case, however, the affected attribute is the material specific waste generation rate, rather than a specific attitude or perception.

Modelling Interventions

2.45 One major application of the waste management model is the prediction of the effect of interventions on household waste management behaviour. That is how might deliberate actions by the scheme operators impact on the overall scheme performance? Such interventions are also just special cases of time dependent changes affecting one or more of the household attributes. Interventions might be typified by a characteristic profile (figure 6), where attitudes (or other attributes) are induced to rise as the intervention takes effect, remain at elevated values through the duration of the intervention, the progressively decay once the intervention is withdrawn. The decay might leave a residual effect, which may or may not be higher than the pre-intervention value. This conceptual model of interventions is consistent with the, albeit small, documented evidence gained from controlled experimentation (see Schultz et al., 1995; Porter et al., 1995, for reviews). Whilst some indications of the strengths and longevities of specific interventions can be gleaned from the published literature, a full catalogue of effects still remains far from realisation. Most interventions applied in practice have been insufficiently monitored or documented to allow their cause-effect or cost-benefit to be adequately quantified. Further controlled experimentation is considered essential in order to compile this relevant information. Eventually, a library of intervention profiles may become available and can be built into the model. At this point in time, however, assumptions still need to be made as to how each intervention might affect each attribute. In this respect, it is quite easy to formulate conceptually reasonable hypotheses over these possible cause-effects. A general information campaign, for example, can be considered (and modelled) as perturbing the ignorance attribute and as switching on scheme awareness. Inducement or reward for recycling provides a boost to the general recycling attribute and/or the specific scheme appeal. Missed kerbside collections produce a spike in the personal difficulty attribute and might adversely affect the scheme appeal for the affected household, according to the strength of their resilience attribute. Promotional activities to encourage households to home compost can increase the pro-composting
attribute and activate the 'have bin' attribute according to the strength of the promotion and the cost of the bin. Specific promotions using say school contacts as a focus for bin distribution provides clear a socio-demographic focus and a well-identified boundary to the contact area of the intervention. Contact area can be specified, in the model, either by neighbourhood or by demographic sector.

Simulation Results And Validation Against Measured Time Series Data

3.1 Five example simulations are presented. All are drawn from studies of kerbside newspaper recycling schemes, for which extensive validation studies have been undertaken.

Simulation studies

Model calibration

3.2 In deploying the model, estimates need to be made for each of the household attributes given in table 2. Definitive solutions are not yet possible, as the data on which they could be based are still far from sufficient or comprehensive enough in coverage. Nevertheless, working distributions for most of the parameters can be hypothesised from the data that is available. The data sources used to set the these parameters were as follows:

3.3 The mean waste generation rates and waste compositions of the communities studied were estimated from the statistics compiled under the National Household Waste Analysis Programme (DoE, 1994) The per-household waste distributions were set according to distributions reported by Leach (1995) and MEL (1996). The material partition coefficients (i.e. the leakage parameters) were derived from the authors' own analysis of a number of recycling schemes within the UK (Tucker et al., 1998d). Lifestyle and personal difficulty frequencies were inferred from disparities between monitored participation frequencies and the age spans of material contributed (Tucker et al., 1998c). The forms of the probability distributions describing attitudes and barriers were inferred from questionnaire surveys of recyclers and non-recyclers (Tucker et al., 1999a). The weight thresholds were based on the survey data of Tucker et al. (1997b) and the 'save decision' parameters set according to the professional opinions of a number of scheme operators. The socio-demographic profiles of the communities studied were derived from small area census statistics.

3.4 The above model parameterisation does not yet allow for absolute predictions to be made at an un-monitored site, though can predict relative behaviours within that site. Inter-community variability has not been fully explained and remains an ongoing research issue. Numerical accuracies can be enhanced through model calibration against measured scheme performance data, usually weight recovery data (which is often the only
performance parameter which is regularly monitored). In the simulations presented below, calibrations were effected by empirical adjustment of a single model parameter, the general recycling barrier strength.

Results

3.5

The examples reported here focus on predicting scheme participations. Two specific performance indicators have been modelled:

1. the scheme set-out rate which is defined as the percentage of generators, who are serviced by the scheme, who put out recyclables on a given collection day, and
2. the participation rate which is defined as the percentage of serviced generators that put out recyclables at least once in a given 4 week period.

3.6

The first example (figure 7) simulates the short-term time dependency of weekly participation for a 2000 household sample in the Fylde, Lancashire over the first eight collections of the scheme. In producing these model results, two interventions were simulated. The first intervention occurred at the scheme start up itself (collection 1). The prior information given to participants and the novelty aspect associated with the new scheme were modelled as producing a short term increase in the pro-recycling attitude that acted coherently across the community. The second intervention occurred at collection 5. From that collection onwards, the operators changed their collection route without warning, now servicing the flats in the early morning rather than in the afternoon as previously. Some residents had not set out at collection time. This effect was modelled as a short term increase in the personal difficulty attribute of the flat dwellers.

![Graph of Type B](image1)

![Graph of Type E](image2)

**Figure 7.** Simulated and measured weekly participations (P = semi-detached, small detached, E = flats)

3.7

The second example (figure 8) simulates the differences between two distinct neighbourhoods within the 2000 household sample. These observations commenced 4 months after scheme start up. Neighbourhood I is of homogeneous semi-detached and small detached housing, whilst in neighbourhood II this type of housing...
is co-mingled with local authority properties including the flats. The observational data reveals possible coherences in behaviour between the two different housing types in neighbourhood 2 that are not mirrored in neighbourhood I. This effect was simulated through allowing households to interact within their own respective neighbourhood. The applied rule generated a convergence of the attitudes amongst the separate housing types in neighbourhood II, with the type B properties there behaving more like their type C neighbours than like their type B counterparts in the adjacent neighbourhood. The two to three collection periodicity in the data is hypothesized to arise because of local normative influences, which force some coherency into the phase of individual participations. In the simulation, an initial high set-out event triggers extra set-outs from those, who have not reached their minimum weight threshold, to discharge ahead of time. This reduces the amount of material saved and carried over to the subsequent subsequent collection, and depresses that collection's set-out rate. By the following collection, more recyclers achieve their minimum weight threshold and another high set-out occurs. This again triggers other recyclers, who have not reached their minimum weight threshold, to discharge. And so the cycle continues.

![Measured](image1)

![Simulated](image2)

Figure 8 (a,b): Simulation of Intra-Neighbourhood Social Influence

E= Semi-detached; slum-detached; C=Local authority

3.8

The third example (figure 9) follows the same community through two years of scheme operation. The simulation invokes a cumulative random series of adverse events causing irreversible step-changes in the general recycling barrier attribute. The overall effects are tempered by intra-neighbourhood interactions and household mobility effects. These events simulate the gradual longer-term drop-off in participation, or 'recycling fatigue' (Coggins, 1994) which is relatively common in recycling schemes.
The fourth example (table 3) follows the scheme through a management intervention that was introduced 27 months after scheme commencement. At this time, the collection frequency was changed from once every 2 weeks to once every four weeks. Measured results refer to observations taken two months prior to the intervention and three months subsequent to the intervention respectively. The simulations report mean values for the performance indicators, averaged over a 32 week simulation run spanning the intervention.

**Table 3: Simulation of Collection Frequency Change**

<table>
<thead>
<tr>
<th>SCENARIO</th>
<th>2 Week Measured</th>
<th>2 Week Simulated</th>
<th>4 Week Measured</th>
<th>4 Week Simulated</th>
</tr>
</thead>
<tbody>
<tr>
<td>Set-out rate (%)</td>
<td>35.0</td>
<td>35.3</td>
<td>44.8</td>
<td>44.1</td>
</tr>
<tr>
<td>Participation rate (%)</td>
<td>48.5</td>
<td>48.4</td>
<td>44.8</td>
<td>44.1</td>
</tr>
<tr>
<td>8-week participation (%)</td>
<td><em>Not measured</em></td>
<td>55.7</td>
<td>54.0</td>
<td>55.8</td>
</tr>
</tbody>
</table>

The per-collection set out rate increases as a result of the intervention because the set-outs of 4-weekly recyclers have been forced into phase. Overall participation (approximated by the percentage who participate at least once every 8 weeks), however, appears unaffected. The drop in the standard participation rate performance indicator, which is based on a four week accounting period, happens in the simulation because of the effects of lifestyle and personal difficulty factors. Those who miss a collection because of such factors will discharge their material at the next collection. With two-weekly collections, this delayed set out may well fall in the same 4-weekly accounting period as the missed collection, so the 4-week participation statistic is not compromised. With collections once every four weeks, the missed collections always fall in the next accounting period and thus always compromise the four week participation statistic.

The fifth example (figure 10) is drawn from a simulation of a community in South Ayrshire, Scotland. It demonstrates how individual street participations can be matched by the pseudo-street predictions of the model. The simulation was initially calibrated to fit the performance of the whole community. In the model run, the simulation generated nine pseudo-streets of type B housing. (In reality the type B neighbourhood comprised 11 streets.) Model and real streets' results were paired through picking out (by eye) those with the closest profiles. It is noted that five of the pairs (shown on the left hand side of the figure) display quite reasonable agreement.
Evaluation of Simulations

3.12

In evaluating the above simulations, it should be remembered that the models used are stochastic in nature and will produce slightly different predictions each time the model is run. The magnitude of the variability between repeat simulations increases as the level of aggregation decreases, i.e. as the size of the community becomes smaller. This is a direct consequence of the random sampling of the attribute distributions that are used to set up the community profile. The extent of this variability is illustrated in figure 11. These simulations were based on a small neighbourhood of 320 type B houses within the South Ayrshire community. The time-averaged set out rates and the standard deviations in these set-out rates are given in tables 4 and 5 for all housing type segments represented within the community.
Table 4: Mean Per-Collection Set Out Rate (%)

<table>
<thead>
<tr>
<th>House Type</th>
<th>Measured</th>
<th>Run 1</th>
<th>Run 2</th>
<th>Run 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>B (Semi and small detached)</td>
<td>29.9</td>
<td>32.0</td>
<td>28.4</td>
<td>30.3</td>
</tr>
<tr>
<td>C (Local authority)</td>
<td>18.9</td>
<td>22.1</td>
<td>21.1</td>
<td>21.7</td>
</tr>
<tr>
<td>D (Terraced)</td>
<td>12.5</td>
<td>13.5</td>
<td>14.2</td>
<td>15.1</td>
</tr>
<tr>
<td>All</td>
<td>19.7</td>
<td>21.7</td>
<td>21.3</td>
<td>21.6</td>
</tr>
</tbody>
</table>

Table 5: Standard Deviation in Per-Collection Set Out Rate (%)

<table>
<thead>
<tr>
<th>House Type</th>
<th>Measured</th>
<th>Run 1</th>
<th>Run 2</th>
<th>Run 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>B (Semi and small detached)</td>
<td>5.4</td>
<td>2.6</td>
<td>2.6</td>
<td>3.1</td>
</tr>
<tr>
<td>C (Local authority)</td>
<td>3.6</td>
<td>1.3</td>
<td>1.1</td>
<td>1.8</td>
</tr>
<tr>
<td>D (Terraced)</td>
<td>1.9</td>
<td>0.8</td>
<td>1.0</td>
<td>1.1</td>
</tr>
<tr>
<td>All</td>
<td>3.1</td>
<td>1.0</td>
<td>0.8</td>
<td>1.4</td>
</tr>
</tbody>
</table>

3.13

Whilst all runs of the model had a tendency to slightly overestimate the per collection set outs, this is not considered unreasonable as the methodology by which set-outs are measured can be prone to underestimate true set-outs by up to 5% (relative). This can be due to the observer failing to spot all the bags that are set out (Tucker et al., 1997). The standard deviations of the temporal set out data, however, are consistently lower in the simulated results. Thus whilst the model has accounted for a significant part of the observed variability, it has not yet accounted for the whole variation. These simulations were undertaken without invoking any random discrete events or any random external events. On introducing such events, the standard deviations in the simulated results can be increased to match the observed levels. However, although the scale of the temporal fluctuations can be modelled, it is not always possible to predict the correct phase of the variations, unless an initial triggering event is locatable in time.

3.14

Whilst there is no a-priori expectation that any model street should have any direct association within any
real street, predicted model street variations often appeared very similar to specific real streets. In the model run illustrated in figure 10, five out of eleven real streets could be approximately matched in the simulation. Experience has shown that typically some 30-40 % of streets may be reasonably matched in any given simulation run, and that a reasonable pair to every real street can be generated, normally, within three or four model runs.

Summary And Discussion

4.1 The research has demonstrated the feasibility of developing a simulation model of integrated household waste management across an artificial community. This community can be set up with the socio-demographic characteristics of a real community to enable waste management planning applications to be simulated at local level. The simulation has been made possible through the development of new model structures which represent individual household waste management options as a sequence of activities; the sequences being set according to the personal hierarchies of preference. Each activity diverts material out of the main household waste stream, and is represented by a separate unit-process model. Each unit-process model is configured as a decision tree controlling a flow network of individual household waste fluxes. Decisions are rule-based with individual psychological characteristics as their controlling variables. Those individual psychological characteristics form one part of the attribute set held by each household within the community. Attributes are assumed to form well-structured distributions over large populations, and have identifiable socio-demographic dependencies. Temporal variability is explicitly built into some variables and rules, to account for natural (and reversible) short-term behavioural fluctuations. Longer-term behavioural change is modelled by allowing systematic changes to attribute values. These changes can be triggered by events, rationalised through personal evaluation of outcomes, shaped by normative influences, or manipulated through management interventions. The design and evaluation of intervention strategies is one of the key applications for the simulation.

4.2 In the simulation, social factors are used to control physical flow simulations, integrating aspects of an agent-based social simulation with aspects of process engineering simulation. This approach enables a simultaneous prediction of participations in each waste management activity with predictions of the weights of material recovered and of the recovered compositions. Previous waste management models have predicted participation (as referenced earlier) or weight recovery (e.g. Saltzman et al., 1993; Jones and Porteous 1996; Lake et al., 1996) but never both. Most previous models provide a steady-state time averaged solution and do not allow for the simulation of interventions or behavioural evolution. The new model is unique also in that it can provide solutions at a number of spatial levels, from streets, through neighbourhoods to whole communities or districts. This structure provides an implicit traceability between individual attitudes and overall community performance, and vice versa, enabling full diagnostics and market segmentation analyses to be undertaken.

4.3 The discussions presented so far have highlighted the modelling of the 'technical' waste management performance indicators, linked to participation and weight recovery respectively. The model additionally provides a framework for determining the environmental burdens, that arise from the various waste management options. For example, the extra transport emissions generated through householders' trips to the recycling banks are accessible from the model. Distances travelled are known as are weights deposited. Multiplying the 'journey efficiency' parameter (km. extra travelled per Tonne deposited) by the appropriate emissions, or energy, factors (e.g. gm. CO₂ / km, MJ / km etc.) provides estimates of the environmental burdens (see Powell et al., 1996, Spiers et al., 1999 for fuller discussion). The extra distance travelled relates primarily to those making special trips to recycle, for instance those not combining recycling with other activities, such as a shopping expedition or a general trip to the dump. Typical proportions of special recyclers at various types of site have been quantified in questionnaire surveys (MEL, 1989; Spiers et al., 1999). The proportion of special recyclers is also predicted directly by the simulation. Adding the burdens caused by the operators' vehicles servicing the schemes then enables the totality of environmental burdens to be estimated. These data now open up the possibility of simulating and optimising the combined technical, social and environmental performance of integrated waste management provision throughout the whole community.
4.4

The results of a number of simulation studies have been discussed. The means and standard deviations of the observed and simulated data have been shown to differ. However, the difference in means is justified in terms of the inherent downwards bias of observed set out and participation rates. The difference in standard deviations might well be due to sources of variability that are yet to be fully incorporated in the model. Examples of planned and unplanned scheme interventions have been simulated and shown to be able to provide plausible model explanations of the observed behavioural changes. A more extensive validation of the effect of interventions awaits the results of controlled scientific monitoring of a wider range of management interventions. Such research will shortly be undertaken by the authors of this paper.

4.5

This paper has addressed and concentrated on the development of the structure and mathematical framework for an integrated household waste management model. Although parts of the model still remain to be validated, the authors believe that the research has demonstrated the proof of concept that artificial societies of individual households can demonstrate similar characteristics to actual communities in their waste management behaviours. At the current stage of development, individuals within the model perform planned behaviours that are determined by the mix of attitudes individually held. These attitudes can change as the result of external stimuli or through social interactions. Explicit cognitive processes are not included and, indeed, may not be warranted if the premise of planned behaviour strictly holds across the whole domain. It is considered, however, that the home composting activity may be an area where more explicit cognitive processes might be introduced, for example to stimulate compost heap management, the evaluation of outcomes after producing compost, increasing proficiency through experience or through seeking help and advice. These issues are being researched.

4.6

The size of the simulation that can be undertaken with the new model is only limited (effectively) by the available computer RAM. The authors have successfully run simulations for communities of up to 30,000 households.

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http://jasss.soc.surrey.ac.uk/2/3/3.html 24 25/08/2014


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