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ACCOUNTING FOR SPATIAL AND TEMPORAL VARIABILITIES IN HOUSEHOLD RECYCLING SCHEMES: A SIMULATION APPROACH*

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ABSTRACT

Household waste recycling performances can vary markedly between communities, spatially within communities, and with time. These variations, which arise as a consequence of the wide variability of behaviors of the residents, are simulated through a stochastic model of recycling. The model assumes random variabilities in individual attitudes, beliefs, and perceptions, then applies decision-based rules in order to predict resulting behaviors. This approach is shown to be capable of accounting for a large part of the observed short-scale performance fluctuations. The residual variations have been explained through socio-demographic differences between population segments. The modeling methodology is explained in detail and the rule-based presented in full. A curbside newspaper recycling scheme is simulated, with results that reasonably fit observed behaviors. Applications to recycling scheme management and potential future developments are discussed.

INTRODUCTION

The performances of voluntary curbside household waste recycling systems can vary markedly between the different locations in which the schemes operate. Comparative studies have identified performance differences between individual cities in the United Kingdom [e.g., 1, 2]; the United States [e.g., 3-5] and elsewhere. Spatial differences in recycling scheme performance also occur within communities as well as between communities. Marked differences are frequently observed for all levels of spatial aggregation: between adjacent neighborhoods [6-8], or adjacent blocks [9], or adjacent streets [7, 8], or adjacent apartment

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buildings [10], or between different floors of apartment buildings [11]. Temporal variations in recycling scheme performance are also well known to scheme operators. Long-term decreases in participation rates have been attributed variously to "recycling fatigue" [12], reversion to older habits [13], or changes in population [12]. Step changes in performance can occur as the result of interventions such as scheme promotion, education campaigns, and the offer of reward [14, 15]. Shorter-term performance fluctuations also occur, for example variations around ± 4 percent in per-collection set out rates have been reported for curbside newspaper collection schemes in the United Kingdom [8]. These fluctuations are thought to occur as an aggregated effect of the different frequencies of participation of the serviced households [8]. This has been linked to differences in individual consumption levels, different perceptions of the minimum weights worthwhile to recycle, and irregularities in personal lifestyle [16].

Previous research into recycling behavior has attempted to delineate which specific attitudes, beliefs, barriers, or pressures form the main determinants of that behavior. It has been found that specific environmental attitudes such as saving landfill space, litter reduction etc. may be important [e.g., 17, 18] though, in general, negative attitudes concerning the effort required [19, 20], lack of storage space [21-23], lack of time [21], and perceived effectiveness of action [23, 24] appear to be stronger determinants. It is also argued [e.g., 25-27] that local social (normative) influences can be important factors determining why some localities develop strong recycling behaviors and why other localities recycle very little. There is, however, poor consensus on the relative roles of each of the above factors. Identified models of recycling behavior differ significantly between researchers [e.g., 20, 23, 28-31].

Other lines of research have attempted to explain recycling behavior through surrogate variables, notably population demographics. The fundamental premise behind this is that specific demographic segments of the community may be more likely to hold certain attitudes, form specific social norms, and possibly face some commonality in the barriers faced. The main socio-demographic factors thought to influence recycling behavior include age [21, 32-35], income [19, 21, 36-39], educational level [35, 36, 39, 40], the presence and ages of children in the household [41], and living in single-family, as opposed to multi-family, dwellings [19, 32, 33]. The identified dependencies, however, were usually quite weak.

A prototype model of recycling behavior, based on two demographic variables: "housing type" and "stage in family life-cycle" was developed by the author of this article [42, 43]. The basic premise was that the average underlying attitudes varied in a systematic way among these demographic groupings although the distribution of individual attitudes within any given grouping could vary widely. The model was formulated as a material balance of the flow paths of recyclable materials through the household. Partition coefficients were used to calculate the diversion of material out of the recycling stream. The partition coefficients were expressed as distributed "attitude" variables whose means were determined by the demographics. The variance and skewness of the respective distributions were assumed to be independent of demographic factors and were established from empirical measurements. The model was tested against measured performance data from a curbside newspaper recycling scheme in North West England and demonstrated (qualitative) potential in simulating spatial variations in performance between neighborhoods and also between streets within those neighborhoods. The current article reports on further developments of this model and introduces new features that have been enabled through its reformulation as an agent-based rather than a process-based simulation. More fully quantitative validation studies are now presented. The article also presents examples of further aspects of recycling performance that can now be simulated.

MODEL FORMALIZATION

The revised model assumptions are summarized as follows: All households serviced by a recycling scheme are represented as individual objects within the model. Each of these household objects holds as set of attributes that refer to its attitude and belief structures, consumption behavior, regularity of lifestyle, and its response or susceptibility to external pressures. The values of each of the attributes are assumed to vary over the sample population and, given a large enough sample population, would conform to reasonably well-defined frequency distributions. These large-sample frequency distributions are assumed to vary in a consistent and predictable manner between certain specific demographic segments of the population. Each demographic segment of the measured community is considered to be a random sub-sample of its respective large-sample population with its attributes being randomly sub-sampled from the posited overall frequency distribution. In the model, the demographic classification has been based on a two-dimensional matrix of housing type and stage in the family life-cycle (Table 1) which encapsulate the main class and age dependencies thought to be significant (see discussion above). The concept of family life cycle variable originates and has found value in work on predicting household waste generation rates [44]. The demographic classification matrix, itself, is generated from the separate distributions of each variable over the community using an iterative proportional fitting method [45].

Each household object is assigned, in the model, to a neighborhood of given housing type within the model community and then assigned to a street unit within that neighborhood. Housing type, family type, and street designation complete the attribute set for the household. The full attribute set used in the model, based on the determinants discussed above, is listed in Table 2. In the model, attitudes and barriers are treated as composite variables. Individual attitudes and barriers are not separately identified.

Individual household behaviors are then modeled through applying a set of rules to the individual circumstances defined by the attribute set. This rule set is

Table 1. Demographic Variables Used in Model

Housing Type		Family Life Cycle	
B	Suburban semi & small detached	1	Young adults/no children
C	Local authority & ex-l.a. houses	2	Families/young children
D	Older terraced housing	3	Families/older children
E	Multiple household dwellings	4	Mature/children left home
F	Poorer neighborhoods	5	Retired
J	Larger detached & exclusive estates		
I	More affluent apartments		

Table 2. Attribute Set
(The index k designates a sub-set of attributes for each material type accepted by the scheme)

Attribute		Description
Attitudes	**A**	Strength of pro-recycling attitudes
Barriers	**C**	Strength of barriers faced or of perceived barriers
Norms	**N**	Susceptibility to normative pressures
Competing attitude	**CA(k)**	Strength of attitudes favoring other outlets or reuse
Awareness	**SA**	Knowledge that the scheme exists
Ignorance	**I(k)**	Misperceptions of types of material accepted by scheme
Forgetfulness	**F(k)**	Frequency of forgetting to recycle individual items
Threshold weight	**W0**	Minimum perceived weight worthwhile recycling
Consumption	**W(k)**	Weights of recyclable materials consumed
Lifestyle	**LF**	Frequency of lifestyle events negating intention to recycle
Personal difficulty	**PD**	Frequency of events stopping intended participation
Save decision 1	**D1**	To accumulate material until W0 is reached—or to discard
Save decision 2	**D2**	With adverse PD: to save for favorable PD—or to discard
Response to change	**R**	Susceptibility to change behavior with external conditions
Housing type	**Htype**	
Family type	**Ftype**	
Street unit	**Stype**	

applied at each recycling opportunity, which can be a curbside collection event or, for drop-off schemes, a weekly interval. In the rules, the term "discarded" means disposed off to another outlet. This outlet is not necessarily the household dustbin but could be another recycling scheme, reuse of material or passing it to a non-household waste stream. The base rule set is given as follows:

Rules

1. If the household is not aware of the scheme, **SA** is false and all consumed material is discarded. Participation is false;
2. If lifestyle conditions inhibit premediated intent then participation is false. Inhibitory conditions are set to occur randomly with a long term average frequency of **LF**; (Rules 2, 6, and 9 provide an approximate representation of the theory of planned behavior [46].)
3. If **I(k)** is true (the household is ignorant that material **k** can be recycled through the scheme) then all consumed material of type **k** is discarded;
4. A fraction of each material **k** is discarded proportional to the strength of competing attitudes, **CA(k)** towards other outlets for the material;
5. A fraction of ψ of each material **k** is discarded through forgetfulness. ψ is modeled as a random variable with a long term average proportional to **F(k)**;
6. If the balance **A** + (φ ***N**) - **C** is positive then there is an intention to behave (**BI**). φ describes the local behavioral norm; (Rules 2, 6, and 9 provide an approximate representation of the theory of planned behavior [46]. The rule extends the A-B-C model of recycling behavior [47] through the addition of norms.)
7. If **BI** is true, then participation will be false if available weight (**W′**) is less than a threshold weight, **W0**, unless their is an over-riding social pressure (φ * N) to participate; (The concept of a minimum threshold weight is a consequence of "Perceived consumer effectiveness" [23, 24] and has been acknowledged in self-reported recycling behaviors [48].)
   W′ = Σ**W(k)** plus previously stored material (**W″**) minus 'leakages' due to **CA(k)**, **I(k)** and **F(k)**;
8. If **BI** is true and **W′** < **W0**, material will be saved if **D1** is true and discarded if **D1** is false; (D1 is also linked to perceived consumer effectiveness [23, 24].)
9. If **BI** is true and **W′** > = **W0**, participation will be true if 'personal difficulty' conditions allow. Unfavorable conditions are set to occur randomly with a long term frequency of **PD**; (Rules 2, 6, and 9 provide an approximate representation of the theory of planned behavior [46].)
10. If **PD** is unfavorable, material will be saved if **D2** is true and discarded if **D2** is false;

These base rules provide a quasi steady-state model of individual recycling performance taking irregularities of lifestyle into account. They are thought sufficient to model the micro-scale fluctuations in performance. Such rules, however, can not provide a description of the behavioral changes, either resulting from external pressures on the individual or from internalized changes in belief. Neither can they account for macro-scale variations. Additional rules and procedures need to be included in order to model such events.

One source of external pressure is normative influence. This can arise both through direct social interaction or indirectly from observation of others' behaviors. This second route is more significant for curbside schemes because, in these schemes, visibilities of behaviors are high. It is assumed in the model that if neighbor's behaviors exceed or fall below given trigger values, the household might be pressured to conform to the majority behavior [27, 49]. The sphere of social influence in the model is assumed to be the street unit. Rules concerning normative influence have been formulated as follows:

11. If the number of neighbors participating in a given collection (= **Set out**) is greater than the high trigger level (reckoned to be around 35% of households participating) then the local behavioral norm is positive. Its descriptor φ is given a positive value, rising from 0 at the trigger level to a value of 1 at very high participations. (Based on the work in references [27, 49].)
12. If **Set out** is below the trigger level (around 10%) then the pressure is not to participate. φ is set to a negative value between 0 and -1, proportional to **Set out**. Between the two triggers, φ is set to 0; (Based on the work in references [27, 49].)
13. Activated norms are assumed to effect (i) the next recycling opportunity (a pre-meditated response) and (ii) the current recycling event (opportunistic response). The opportunistic response is considered to cause a re-evaluation of the intention to behave [rule 6] and to override any minimum weight perceptions [rule 7] according to the strength of (φ * **N**);

Similar considerations are used to model the gaining of an awareness of the scheme. If a sufficiently high visual stimulus is provided and the individual concerned is also receptive to such stimuli then that individual becomes aware. The model rule becomes:

14. If (**Set out** * **N**) > trigger then **SA** is true;

Procedures

Other external influences of concern tend to affect larger segments of the community than just an individual household, i.e., they are macro-scale phenomena. Such influences can be modeled by a procedure that perturbs the values of the relevant household attribute (or attributes) for every house in the affected neighborhood or street unit. The types of influence that are modeled in this way include:

(i) Missed collections and public holidays—modeled as an increase in personal difficulty;
(ii) Procedural information campaigns—modeled as a decrease in ignorance;
(iii) Provision of feedback or reminders—modeled as an decrease in forgetfulness and/or an increase in attitudes;
(iv) Change in collection time—modeled as a change in personal difficulty and barriers;
(v) Incentive based interventions—modeled as an increase in attitudes;

Many other examples could be cited, and they could easily be interpreted in the same way.

Each influence, if it occurs, will occur at some given date, will have its own duration and might leave a residual effect after it ceases to operate. A generalized structure has been developed to model such effects (Figure 1).

Its application is as follows (taking an attitude-based intervention as the example): The attitude of household i in street j on week t is given by:

$$\textbf{Attitude(i)} = \textbf{A(i)} + \Sigma\delta\textbf{A}\ \text{(t,j)}$$

where **A(i)** is the baseline attitude and **ΣδA** (t,j) is the sum of all induced attitude changes that are effective or remain effective at week t.

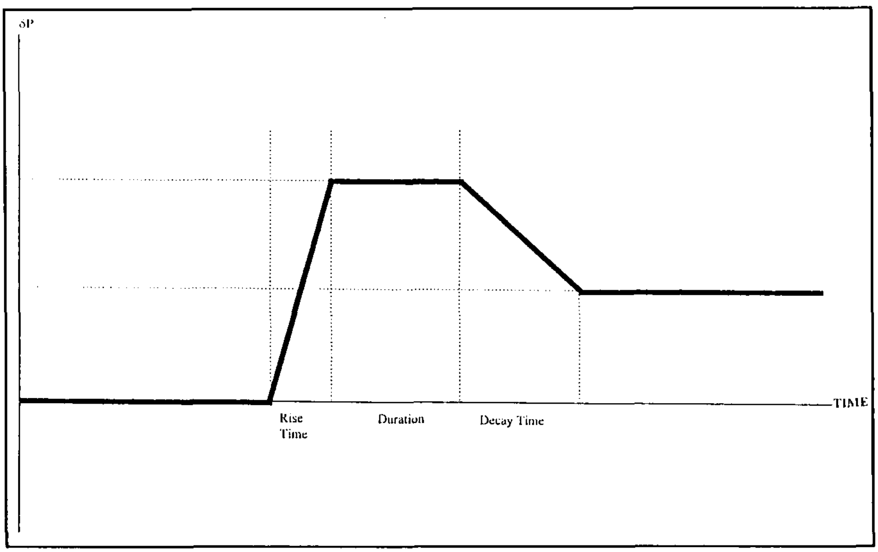

Figure 1. Modeled time dependence (δP) in a household attribute (P).

It should also be noted that seasonal variations in consumption levels can also be modeled through the same generic procedure.

MODEL CALIBRATION

Calibration of the model comprises the specification of the frequency distributions for each attribute variable including their dependencies on the identified socio-demographic explanatory variables. Definitive solutions are not possible, as the data on which they could be based are still far from sufficient or comprehensive enough in coverage. Nevertheless, working distributions can be hypothesized from the data that is available, and these can be tuned empirically, as necessary, through regression of model output onto measured performance data. The data for the initial estimates used in the model were gained as follows. These estimates have been made specifically, in this instance, for curbside recycling of newspapers.

Material specific consumption distributions were estimated from a combination of sources; (i) waste generation distributions measured in the West Midlands of England [50], (ii) measured distributions of material recycled in four communities in Scotland and North England [16] and self reported consumptions in two communities in Scotland [48]. Measured distributions are positively skewed for all materials. Consumed weights tend to increase with affluence of housing type for most paper components, particularly magazines. In contrast catalogue consumptions are highest in the less affluent households [16, 48].

Leakage rates and proportions of "leakers" were estimated from studies in Scotland, North England, the West Midlands, Sheffield, and Luton [16, 48, 51-53]. These results were correlated with self-reported admissions of forgetfulness, ignorance, and competing attitudes [48] and partitioned accordingly. Leakage of newspapers is highly skewed toward low weights [48, 51-52] while magazine leakage is higher and more normally distributed [48]. Leakage is also correlated with family type, higher losses being associated with the earlier stages in the family lifecycle [48].

Losses from lifestyle factors were estimated by comparing the measured age spans of material recycled against the independently monitored time since that household last participated [16]. Whole weeks of missing material can be attributed to lifestyle irregularities. Lifestyle frequencies from one in five weeks up to one in twenty-six weeks or more have been observed [16].

Distributions of the minimum weights thought worthwhile to recycle have only been specifically investigated for drop-off recyclers [48] though some parallel inferences have been made for curbside schemes [16]. The data suggest that recycling container size may be the prime metric upon which minimum weights are perceived. The highest weight thresholds appear to be associated with the most affluent single family housing types with the lowest are held by residents of multi-family dwellings [16].

The distributions of attitudes, barriers, and susceptibilities to influence are more difficult to quantify. Results of an unpublished questionnaire survey by the author has shown that the distribution of pro-recycling attitudes may be highly skewed toward strong attitudes for both recyclers and non-recyclers alike while the distribution of barriers faced would appear to be more normally distributed across these populations. Attitudes were found to strengthen slightly and barriers to decrease slightly with advancing stage in the family lifecycle. The relative strengths of attitudes and barriers could not be determined and must be set empirically. Inferences on normative susceptibilities were obtained through questioning residents of a community in Scotland. Thirty percent admitted to being encouraged by their neighbors recycling while 60 percent admitted noticing how many of their neighbors had set out on collection day [48].

SIMULATION RESULTS

In this section, the simulation results are presented alongside measured recycling performance data. The measured data were obtained mainly from a performance monitoring study of a curbside newspaper collection scheme operating in South Ayrshire in South West Scotland. Household participations were measured over four consecutive collections during June and July 1997 and for three further collections in September and October that year. The collections were made fortnightly. A weight and compositional analysis of the material set out was undertaken for a sub-sample of 100 households during the first collection in August. The whole collection round comprised 1660 households of 55 percent type C, 26 percent type D, and 19 percent type B according to the definitions in Table 1.

Because of the random factors involved in the modeling, each model run produces different results. Normally when using random process simulations it is customary to average the results of many runs in order to derive the likely means [e.g., 54]. However, in this case, the random fluctuations are of as much interest as the mean and any averaging would destroy these data. As such, results are quoted for individual runs. There will inevitably be bias according to which runs are selected for presentation, though this bias has been minimized by comparing results over three runs. The only deliberate bias in the presentation of results has been to adjust to the best fitting phase of the temporal variation. This is done for clarity of presentation. It should be borne in mind that the model can not normally predict this phase.

Participation Data

The results are presented in the form of the standard performance indicators recognized by professionals in the field. The model adopts the definitions proposed by ERRA [55]:

$$\text{Set out Rate} = \frac{\text{Number of generators putting out on collection day}}{\text{Number of generators served by the program on that day}}$$

$$\text{Participation Rate} = \frac{\text{Number of generators participating at least once in a four week period}}{\text{Number of generators served by the program in a four week period}}$$

It has been recognized, however, that a four-week accounting period for participation rate does not always provide a good indicator of overall participation in a scheme [e.g., 9] and an eight-week participation rate has been proposed as a better indicator of true participation [9].

The results (Figures 2 through 5, Table 3) demonstrate that the simulations give rise to temporal fluctuations in participation that appear similar to those occurring in the real scheme. The magnitude of the fluctuations, and the errors in model fit, both decrease as the level of aggregation increases: in time, i.e., from fortnightly through four-week to eight-week accounting periods, and in space from a small neighborhood sample to a whole community sample. Even at the lowest level of aggregation (i.e., per-collection set out of type B properties; Figure 3), the approximations still remain acceptable. While these runs of the model all had a tendency to slightly overestimate the per collection set outs (Table 4), this is not considered unreasonable as the measured data is considered to err toward underestimation because of missed observations [9]. Of more note, however, is that the standard deviations in the temporal set out data are consistently lower in the simulated results (Table 5). It would appear, therefore, that

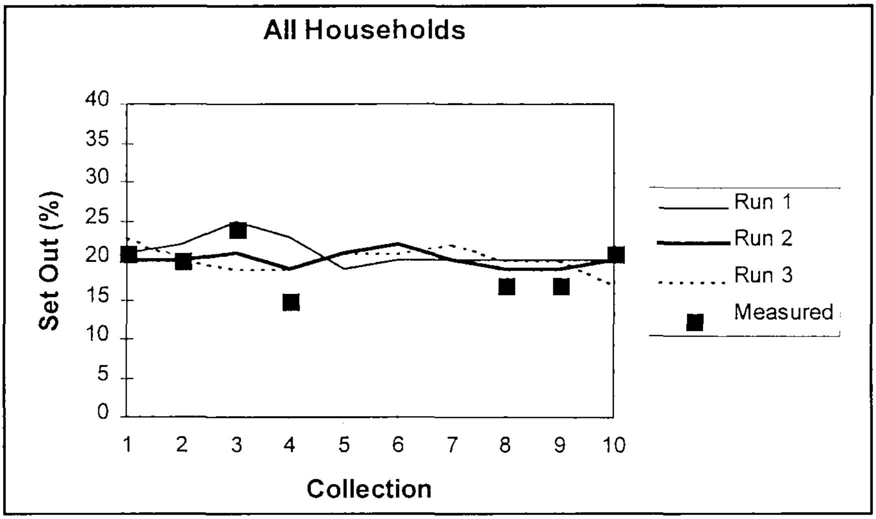

Figure 2. Per-collection set out rates.

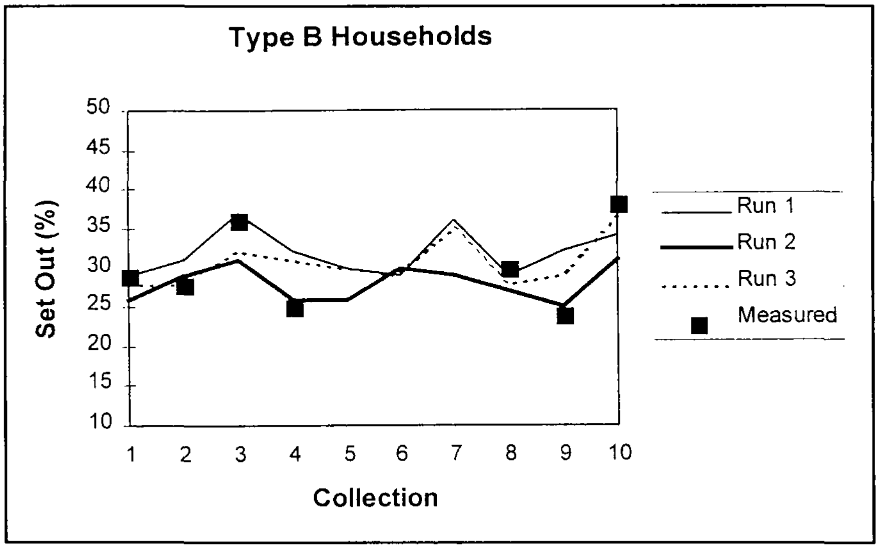

Figure 3. Per-collection set out rates (semi-detached and small detached houses).

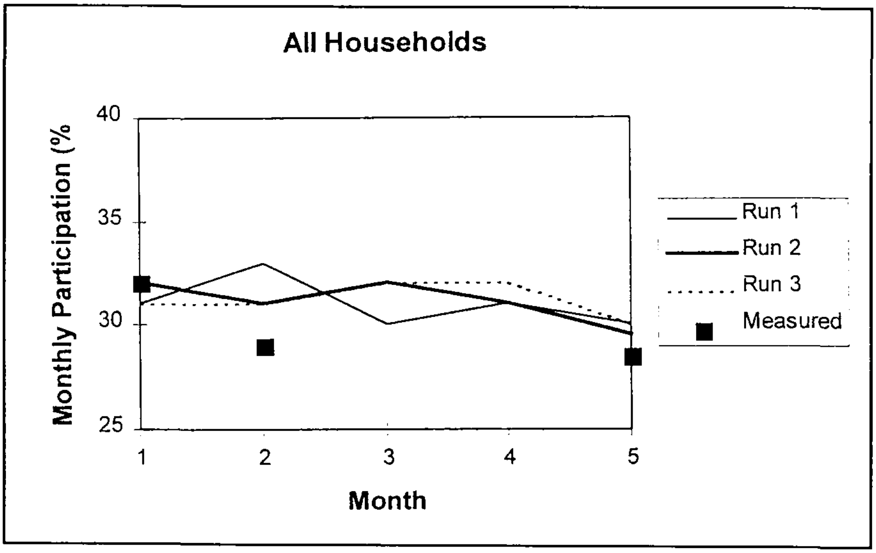

Figure 4. Four-week participation rates.

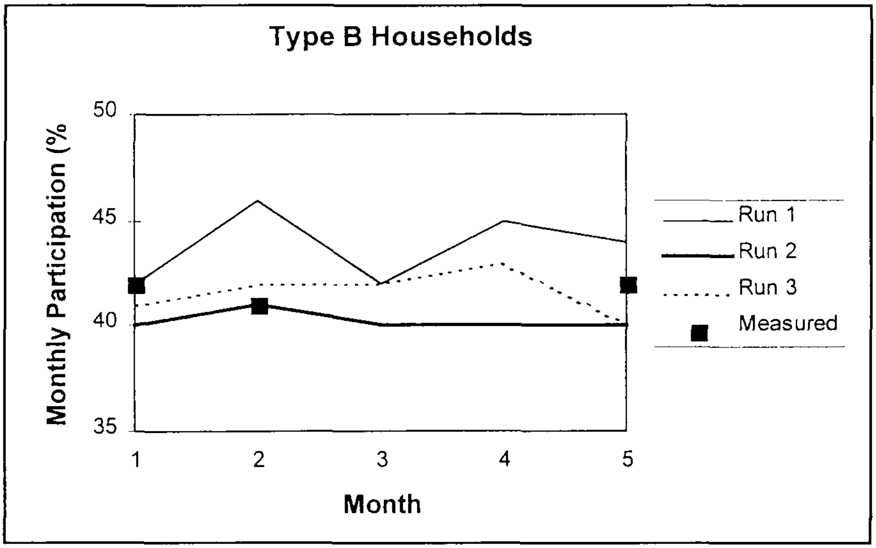

Figure 5. Four-week participation rates (semi-detached and small detached houses).

Table 3. Percentage of Participants Setting Out at Least Once per Eight Weeks (Months 1 and 2)

House Type	Measured	Run 1	Run 2	Run 3
B	52	52	49	49
C	41	38	40	39
D	32	25	34	28
All	41	38	39	39

Table 4. Mean Per-Collection Set Out Rate (%)

House Type	Measured	Run 1	Run 2	Run 3
B	29.9	32.0	28.4	30.3
C	18.9	22.1	21.1	21.7
D	12.5	13.5	14.2	15.1
All	19.7	21.7	21.3	21.6

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

House Type	Measured	Run 1	Run 2	Run 3
B	5.4	2.6	2.6	3.1
C	3.6	1.3	1.1	1.8
D	1.9	0.8	1.0	1.1
All	3.1	1.0	0.8	1.4

while the model has accounted for a significant part of the observed fluctuations, it has not yet accounted for the whole variation.

The tendency to under-predict the extent of some of the natural variation in the performance indicators may be due, in part, to a more coherent element of behavior occurring within individual population units than has so far been assumed. Such coherences can be modeled using the macro-scale perturbation approach that has been described earlier in this article. For example, in the case study above, the first part of the monitoring study coincided with the school holiday. Absences from home (modeled by lifestyle factor LF) are more likely to be concentrated in this period for households with children. Introducing seasonal variabilities in LF as a macro-scale perturbation provides a new simulation (Figure 6, Table 6) which accounts for substantially more of the observed variation, though does not necessarily produce a better fit to individual data points.

Weight Recovery

In addition to the above participation data, the model provides predictions of weight recovery data. The model fits to the measured per-household weight recoveries are shown in Figures 7 and 8. The standard deviations in the predicted overall weight recoveries and in the predicted recoveries of individual components are both slightly lower than those actually observed (Table 7), although, again, much of the observed variation has been accounted for. The residual discrepancy is largest for the magazine fraction. Magazine recoveries are subject to a rather more erratic accumulate—discharge cycle than are newspapers (which tend to have a more steady state flow through the household). Accumulate—discharge effects can give rise to a significant component of variation. This component is not yet included in the model.

Street-Level Variations

As well as the neighborhood average effects, the model can also provide finer-scale output through partitioning the neighborhood into individual street units. In the model, this is done randomly, with no a priori association made between any model street and any real street. The number of model streets

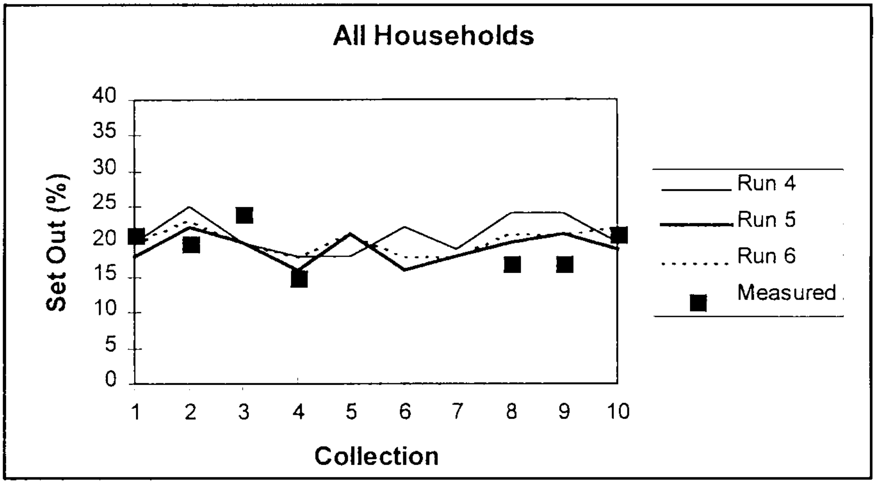

Figure 6. Per-collection set out rates including simulated holiday period.

Table 6. Standard Deviation in Per-Collection Set Out Rate (%) Including Simulated Holiday Period

House Type	Measured	Run 4	Run 5	Run 6
B	5.4	5.0	4.9	3.7
C	3.6	2.8	2.0	1.9
D	1.9	1.4	1.4	1.3
All	3.1	2.3	1.7	1.4

assigned to a neighborhood may differ from the number of real streets located there.

The predicted spatial distribution of monthly participation rates, per street unit, reveals the same overall distribution as the rates actually observed (Figure 9). Mean street participations disaggregated according to the dominant housing type are also consistent in overall trend between model and reality, though with a tendency to slightly over-predict participations for the type C and D streets (Table 8). This discrepancy arises largely because of a small number of streets having zero participants were not foreseen by the model. The same discrepancy also contributes to a tighter spread of participation rates being predicted than are actually observed (Table 9). The temporal range of within-street variation also shows good qualitative agreement between model and reality, though again with the

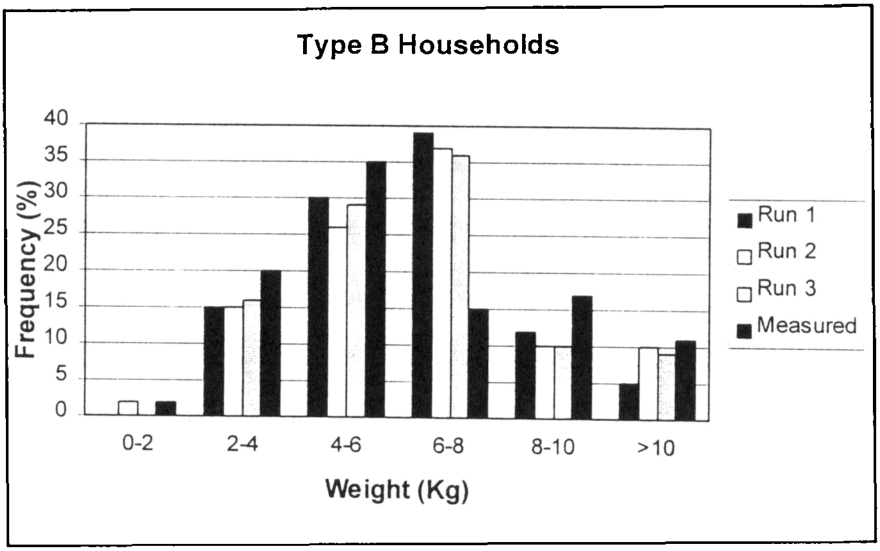

Figure 7. Distribution of total weights of material set out by participating households (Collection 5).

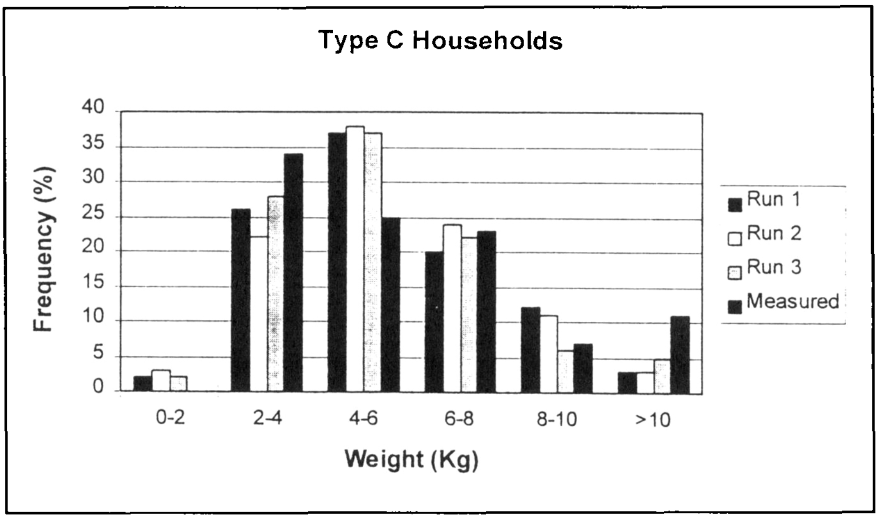

Figure 8. Distribution of total weights of material set out by participating households (Collection 5).

Table 7. Standard Deviations in Per-Household Weight Recoveries

House Type	Material	Measured (Kg)	Run 1 (Kg)	Run 2 (Kg)	Run 3 (Kg)
B	All	3.59	2.34	3.41	2.34
	Newspaper	2.76	1.93	2.97	2.09
	Magazines	0.97	0.48	0.55	0.53
C	All	2.84	2.35	2.27	2.41
	Newspaper	2.50	2.08	1.97	2.18
	Magazines	0.67	0.42	0.43	0.39

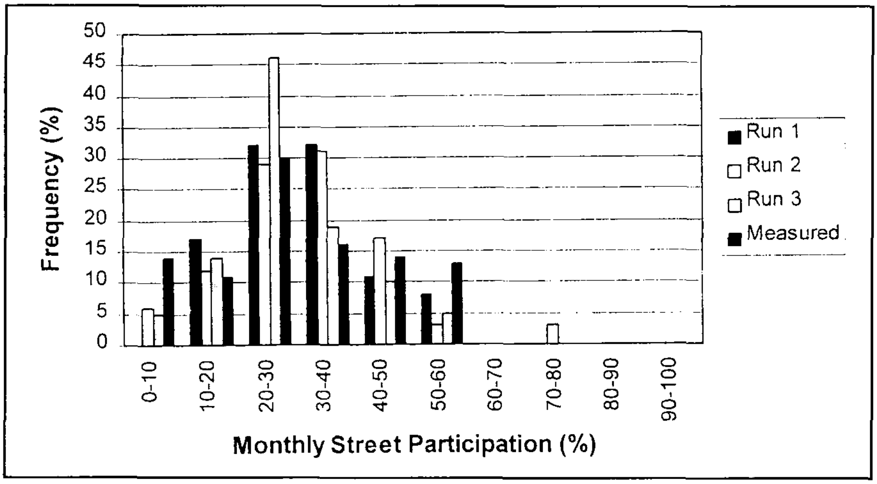

Figure 9. Distribution of four-week participation rates per street unit (Month 2).

Table 8. Mean Monthly Participation per Street Unit (Month 2)

House Type	Measured	Run 1	Run 2	Run 3
B	41.6	43.7	40.2	42.3
C	25.2	31.1	32.9	27.2
D	17.7	24.3	23.0	19.0
All	27.6	31.9	31.7	28.5

Table 9. Standard Deviation in Mean Monthly Street Participation (Month 2)

House Type	Measured	Run 1	Run 2	Run 3
B	17.1	10.7	5.2	9.6
C	13.5	9.3	12.7	8.2
D	11.7	5.4	10.1	7.9
All	16.4	10.8	12.4	11.6

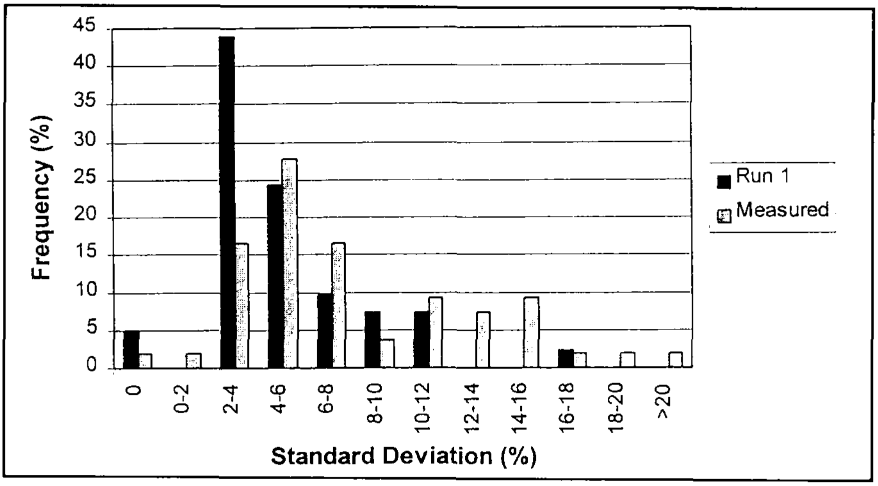

Figure 10. Distribution of standard deviations in the temporal variations in participation rates per street unit (Month 2).

same tendency to slightly under-predict the full extent of the natural variations (Figure 10).

It is additionally noted that, while 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. Such similarities are illustrated in Figure 11. In the model run selected, nine pseudo-streets were assigned to the type B neighborhood. In reality this neighborhood comprised eleven 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. Experience has further shown that a reasonable pair to every real street can be generated, normally, within three or four model runs.

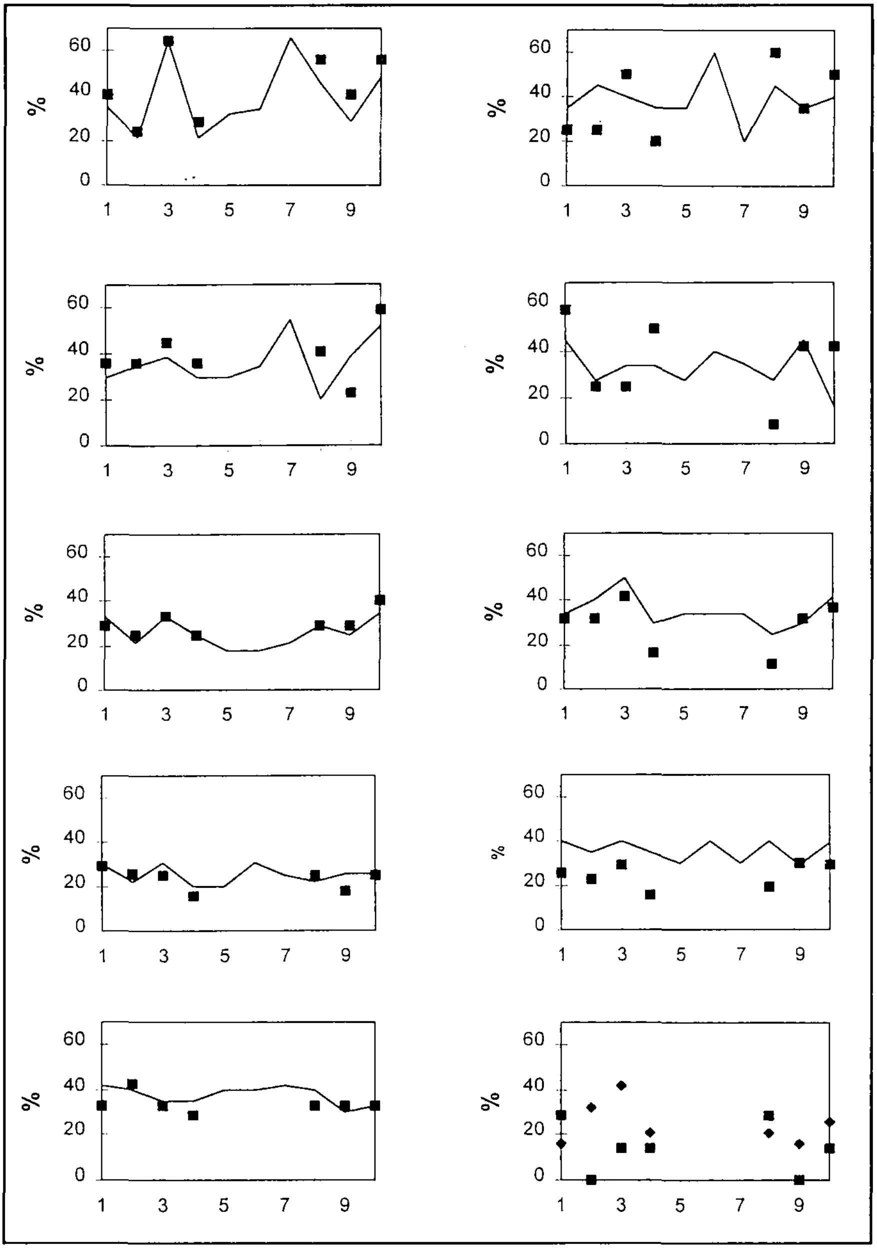

Figure 11. Best fitting pairs of model and real streets (Run 1). Results refer to per-collection set out rates. The two unpaired real streets are shown in the last figure.

Other Features

Illustrations of other aspects of observed behaviors that can be predicted by the model are given in Figures 12 and 13. Figure 12 shows the simulated results of a build up of awareness in the early stages of a (hypothetical) new scheme, for which pre-scheme promotions were weak.

Figure 13 provides a demonstration of a possible neighborhood-wide normative interaction. Results refer to a scheme operating in North West England. Within this scheme, two distinct and spatially separated neighborhoods can be identified. Neighborhood I is a homogeneous area of semi-detached bungalows (type B). Neighborhood II consists of co-mingled type B properties among local authority and ex-local authority housing (type C) and flats. Observations (Figure 13a) reveal possible coherences in behavior between the two different housing types in neighborhood II that are not mirrored in neighborhood I. There also appears to be a rather weaker differential in behavior between the types B and C properties when they are co-mingled compared to when they are more spatially separated (see also Table 4). The only identified perturbation was a change in the order of collection at collection 3. Previously the neighborhood I was serviced first, early in the morning. From collection 3 onwards, neighborhood II was serviced first. This was modeled by introducing small and opposite step changes in personal difficulty between the two neighborhoods. Agent interactions were then introduced to simulate normative pressures within the two neighborhoods,

Figure 12. Simulated build up in participation through increasing awareness (hypothetical community).

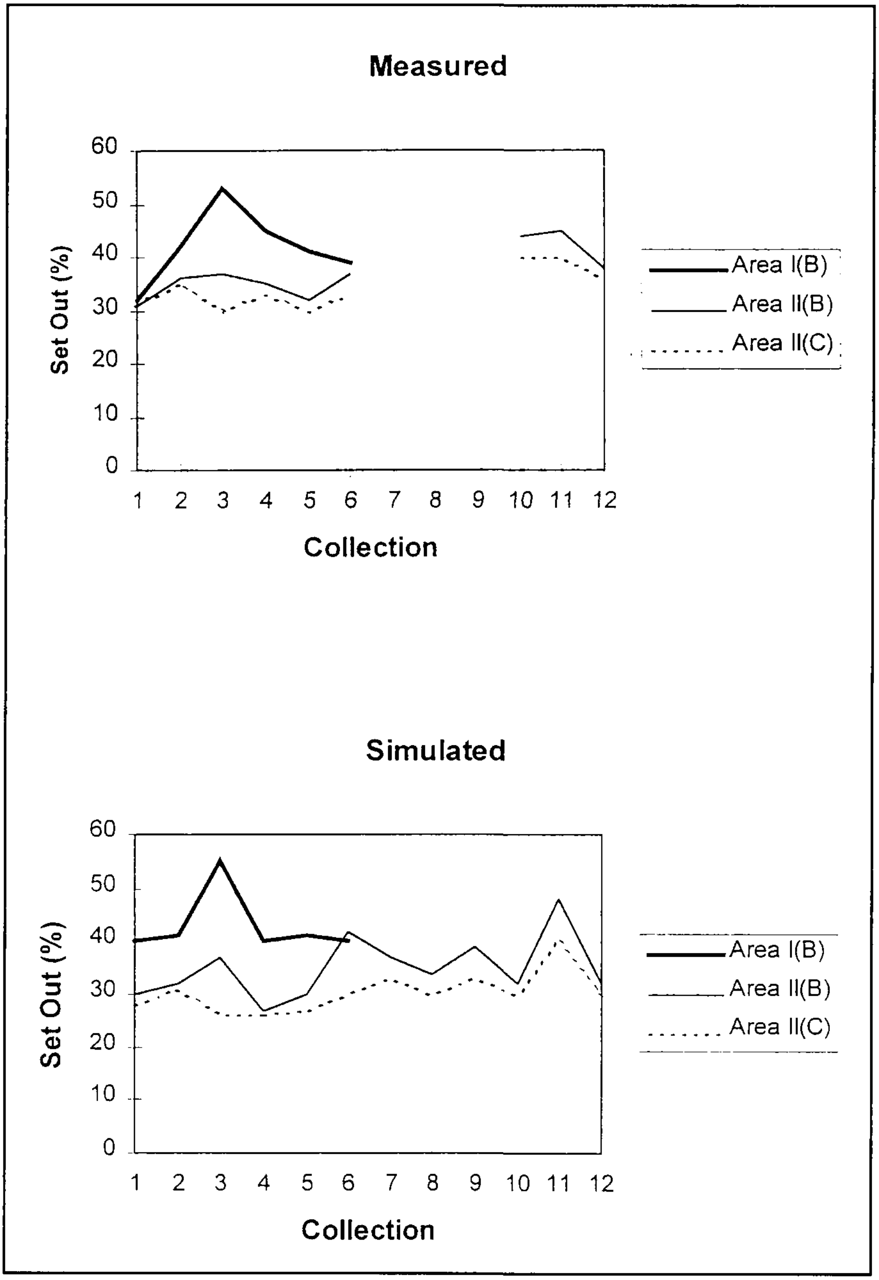

Figure 13(a,b). Simulation of intra-neighborhood social influence.

the premise being that agents would only interact with agents in the same neighborhood. The applied rule generated an erosion of the differential between the attitudes and perceived barriers of the interacting agents. The simulation results, presented in Figure 13b show good qualitative agreement with the observed behaviors.

SUMMARY AND FUTURE POTENTIAL

Previous research into the prediction of recycling behavior has produced equivocal results. It is conjectured here that some of the noted discrepancies among these earlier studies can be attributed to different random elements operating among the populations studied. In small populations the relative contribution of these random elements increases. The model presented here explicitly considers this randomness, building up individual profiles of attitudes, barriers, and perceptions by random sampling from the postulated large sample distributions of these attributes. It is postulated that variations between the large sample distributions may be accounted for through socio-demographic explanatory variables. In this research, two demographic variables: housing type and stage in family life-cycle were chosen as the prime descriptors. These have shown considerable promise in accounting for systematic differences between populations. This has substantial implications towards enabling practical predictions of community recycling performance. Socio-demographic profiles of the community are readily available from national or local-authority held statistics. Statistics on the attitudes and beliefs of the residents are not. Input data for a practical model must be easy to obtain.

The modeling approach has demonstrated that it can simulate much of the spatial and temporal fluctuations in recycling performances, at each of the different levels of aggregation of interest to authorities and to scheme operators. It is recognized that the achieved closeness of fit was better for some performance indicators than it was for others, though it is considered that overall better fit should be possible with more extensive calibration. It must be emphasized, however, that predictions of all performance indicators were made simultaneously. The model thus provides operators with a total description of scheme performance. Previously models were limited to predicting just participation [e.g., 20, 23, 28-31] or weight recovery [e.g., 56-58] but not both.

The current model showed a tendency to under-predict the extent of natural variation in the respective performance indicators when it was based solely on random distributions of individual attitudes and perceptions. This discrepancy was thought to arise because a more coherent element of behavior was also occurring within the individual population units. It is believed that such coherences could occur either through local normative pressures or as the result of shared experiences, such as a change in the recycling system itself. When the causes of such coherences can be established, they can be modeled using a macro-scale perturbation approach. Normative influence can additionally be modeled through applying rules that seek to represent possible changes in individual attitudes and perceptions when such individuals interact.

It is especially noted that the model predicted the existence, scale, and possibly also the frequency of the temporal variations in street performance for a significant proportion of individual streets within the community. While there is no a priori expectation that any model street should have any direct association within any real street, it may be that the matched real behaviors could arise from a similar profile of underlying attitudes and perceptions as those assigned to the model streets. Analysis of the appropriate paired model street might thus provide an insight into the causes of behavior occurring in the real street. If such an association can be made, the model will then provide a powerful tool toward identifying behavioral weaknesses and would provide for a structured market segmentation of those weaknesses. This would enable corrective interventions to be designed and deployed more effectively. It must be said, however, that definite associations between model-assigned attributes and actually-held attributes have not yet been made, and remains a topic for future research. More generally, the simulation method provides a tool for testing theories where direct examination is impractical. Within the recycling literature, the cause-effect links to recycling behaviors are more often hypothesized than proven and, in any event, are never easily measured. The model proposed here shows that the model implementation of certain of these hypotheses can give good fits to aspects of recycling behavior that can actually be measured (with confidence). As stated ". . . we may then tentatively accept the theory—as implemented in the model—as a pragmatically useful tool for making predictions, until a more accurate or simpler tool can be found" [59].

The research model developed here has concentrated on accounting for the detail of the temporal and spatial fluctuations in recycling performance. Previous models have centered on attempting to explain a mean recycling performance. We believe that by gaining a better understanding of the details, a better understanding of the whole will emerge. Put another way, the model has been successful in accounting for some of the variation that has hitherto been considered unexplained. It is, of course, still possible to improve the simulation through developing and validating better rule sets that implement further or more-refined hypotheses.

One such direction that has not been tackled to date is to simulate a long term decay in recycling behavior. This could, for example, be hypothesized to result from a cumulation of discrete events with a given event (say the non-return, theft or dog-fouling of the curbside recycling container [48]) producing a negative step change in a single individual's attitude or perceptions of the recycling scheme.

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