Exploring Heuristics Underlying Pedestrian Shopping Decision Processes

An application of gene expression programming

Wei Zhu and Harry Timmermans
Eindhoven University of Technology

Keywords: GEPAT, Decision process, Bounded rationality, Satisficing heuristic, Utility maximization, Model comparison

Abstract: Most analytical pedestrian behavior researches use utility-maximizing models and have paid less attention to models based on alternative behavioral theories such as bounded rationality. Consequently, there is a lack of deeper explorations into the decision processes of pedestrians. This lack of such alternative models may also be the result of inappropriate methods to estimate such models. For this reason, the paper first introduces a modeling platform GEPAT which has the GEPAT which has the ability to estimate parallel functions using a multi-gene-sectional chromosome structure and to facilitate building models using processors emulating simple decision mechanisms. The going-home decision of pedestrians in Wang Fujing Street is taken as an example to illustrate the use of GEPAT. The most important conclusion from a comparison of the MNL, hard cut-off, soft cut-off and hybrid model is that the satisficing heuristic fits better to the problem structure, at least in this case, than the utility-maximizing rule does. This example also shows the flexibility of GEPAT as a modeling toolbox and the power of estimating complex models.

1. INTRODUCTION

Mathematical modeling represents a way of understanding pedestrian behavior in shopping environments and supporting urban planning by predicting pedestrian behavior under alternative plans. Earlier research used gravity models to explain aggregate pedestrian movement patterns. Examples are Borgers and Timmermans (1985, 1986), Hagishima, Mitsuyoshi, et al. (1987) and Berry, Epstein, et al. (1988). Since the 1990s,

Jos P. van Leeuwen and Harry J.P. Timmermans (eds.), Innovations in Design & Decision Support Systems in Architecture and Urban Planning, 121-136.

the focus of this research tradition has shifted to the microscopic, individual level. The emergence of discrete choice models (DCM) in the 1970s is one of those major reasons that lead to this shift. Many research projects have been carried out using DCM to explore the decision mechanisms of pedestrians by assuming that the pedestrian make choices among alternative shopping places.

Another major reason for the shift in focus to microscopic models is the development of computer technology. The agent-based modeling technique, a hot topic recently, largely inherits the idea of object-oriented programming (OOP). Some agent-based computer simulation systems are available (e.g., Dijkstra and Timmermans, 2000, Haklay and O'Sullivan, 2001, Kerridge, Hine and Wigan, 2001) to mimic pedestrian behavior and support planning.

A good design and decision support system for retail planning relies heavily on reliable models of pedestrian behavior that are embedded in these systems. In turn, the reliability largely depends on the appropriateness of the assumed decision processes, which lead to behavior, and how this is represented by the model. Appropriateness here means the closeness between the decision mechanisms represented by the model and the real decision processes. Although many models have been suggested, the exploration of underlying decision processes is still scant. Simulation techniques are useful to construct very sophisticated decision diagrams, however, they are still unable to identify the behavioral rules underlying behavior. Although the DCM is based on a theory of human behavior and has proven its applicability in a variety of domains, the appropriateness to its behavioral underpinnings in the context of pedestrian movement has largely gone untested. One potential problem is that the assumed decision process may be too simple. According to Bettman (1979), the decision process of consumers should be composed of several inter-related information processing nodes, such as attention, evaluation, decision, learning, just to mention a few key ones. Another potential problem is that the assumed mechanisms may be too complicated, in the sense that pedestrians are assumed to have perfect knowledge of all choice options, and choose the option with the highest utility.

In contrast to such fully rational models, more realistic models might be built based on the bounded rationality theory proposed by H. A. Simon in 1947, who argued that heuristics are crucial in making fast, frugal, and good enough decisions (Todd, 1999, Todd and Gigerenzer, 2003). Different professions have formulated different definitions of heuristics. In the context of this study, we mean simple decision rules such as ignorance-based decision, one-reason decision, elimination heuristics and satisficing heuristics (Todd, 1999). Since the boundary between simplicity and complexity is vague, we only have intuitive belief that mental activities searching for information, using limited information and applying non-compensatory rules are simpler than those getting full information and applying compensatory rules. Such belief is partly supported by Gigerenzer, Todd and ABC Research Group (1999) whose experimental outcomes showed the superiority of simple models over complex models. However, a similar comparison, especially based on real-world behavioral data, has not yet been carried out in the context of pedestrian behavior.

The aim of the present study therefore is to conduct such a comparison. Before the results of this comparison are described in the third section, we will introduce, in the second section, a modeling platform—GEPAT which we developed to construct, calibrate and compare behavioral models. The fourth section will discuss the implications of these results for model building and concludes the paper.

2. GEPAT

2.1 Why GEPAT?

GEPAT is the acronym of Gene Expression Programming as an Adaptive Toolbox. It is a computer program for constructing and calibrating models. The core algorithm is gene expression programming (GEP, Candida Ferreira, 2001), one kind of genetic algorithm (GA). Linear regression models, general linear models, multinomial logit models (MNL), and other classical non-linear models can now be calibrated using different software such as SAS and SPSS. However, when the degrees of non-linearity, discontinuity and non-differentiability of the model function increase, it is difficult or even impossible for these software packages to calibrate the model. Genetic algorithms have been proven to perform satisfactory in solving such problem numerically. Because behavioral models could be very complicated, using GA may have some advantages.

In the case of pedestrian decision research, one usually only observes the behavioral outcome while the decision process remains hidden. It is very well possible that different decision processes could generate the same behavioral outcome (Todd and Gigerenzer, 2003). Thus, comparing different models may be less arbitrary than relying on a single model. GEPAT facilitates such a modeling process with building blocks, representing simple information processing nodes. It becomes much easier to manipulate and reuse these building blocks to specify models than to repeatedly write specific codes for every single model.

2.2 Features of GEPAT

2.2.1 Get Simultaneous Solutions

In GEP, a target function is derived from a code sequence which is composed of numbers, variables and operators. The code is transformed, mated with other codes to give offspring. Usually, the structure of the code is similar to Figure 1. The fundamental element of this structure is the *condon* where operators and operands are randomly generated and stored. Several numbers of codons compose the *gene*, the basic element forming functions after being translated. Both the length (the number of codons) and the number of the genes can be extended to include more information and create more complex functions. Among the genes, a space is designated for the *link function* to work together. All of these elements compose the *chromosome*. After the evolutionary process, the best chromosome with the highest fitness value is preserved and returns the target function.

When a decision process is a system composed of several information processing nodes, one function may well not be enough to represent the whole system. Calibrating model with parallel, inter-related functions is inevitable, which is impossible for the single chromosome structure in GEP. We extended this structure. In GEPAT, an additional element, *gene-section*, is designed (Figure 2). The gene-section is just the chromosome in GEP and the chromosome here is the composition of gene-sections. Each gene-section is an individual function block.

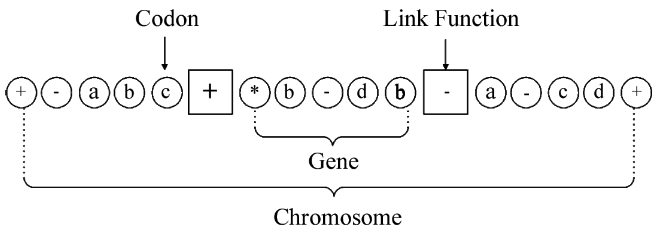

Figure 1. Chromosome structure in GEP.

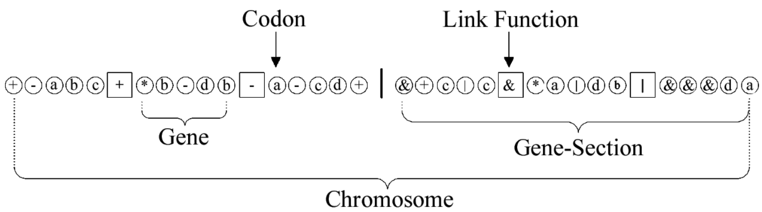

Figure 2. Chromosome structure in GEPAT.

This structure brings more flexibility. First, each gene-section can have its own length according to the complexity of the target function. Second, each gene-section can be assigned a specific type of function (e.g. arithmetic or logical) according to the nature of the task we want it to solve. Third, the gene-sections can communicate with each other with predictions and by-products of the function. This is the most important feature for modeling decision processes where information flows are frequently exchanged among mental operators. With this structure, getting simultaneous solutions for parallel functions becomes viable. In addition, when there is no priori model specification, GEPAT is capable of generating the model automatically. It is also efficient in searching the parameter space when the model is strictly defined.

2.2.2 Test Different Models

By organizing simple building blocks, called *processors*, models with different specifications and complexity can be tested. Each processor has input and output interfaces to receive information from and send information to other processors. For example, *satisficer* represents satisficing heuristics, that is the decision maker acts when the value of an option is over the threshold (cutoff); *maximizer* represents the decision rule choosing the option with maximum (minimum) utility; *memorizer* represents the function of memory and stores information for later use; *updater* cooperates with memorizer to update information when necessary; *collector* collects pieces of information and send them out as a whole when needed; *evaluator* evaluates the chromosome by fitness value and records the best chromosome in the generation; etc..

Figure 3 illustrates an example workflow of GEPAT. It starts from the data source transferring data to the receivers. If the model needs memorized information, the data is first transferred to the memorizer, then to the gene-sections. If the model is run for the first time, an initial generation of chromosomes is randomly generated. Usually, each gene-section corresponds to a processor about whose decision mechanisms we care most. In this example, gene-section1 corresponds to a maximizer so that in the end we can get a function telling how the pedestrian trades off factors and chooses the option. The gene-section2 corresponds to a satisficer. It can extract some judgement thresholds by using logical functions. After the information being transferred and modified in other processors, the evaluator evaluates each chromosome. If this is not the end of the iteration, the chromosomes are modified by gene operations according their fitness values. If the iteration ends, GEPAT outputs the results including the best chromosomes and their corresponding functions. Manipulating GEPAT is no more difficult than drawing such a flowchart. Each building block is represented by a visual element. By linking them and setting parameters properly, we can test many complex schemes of pedestrian shopping decision process.

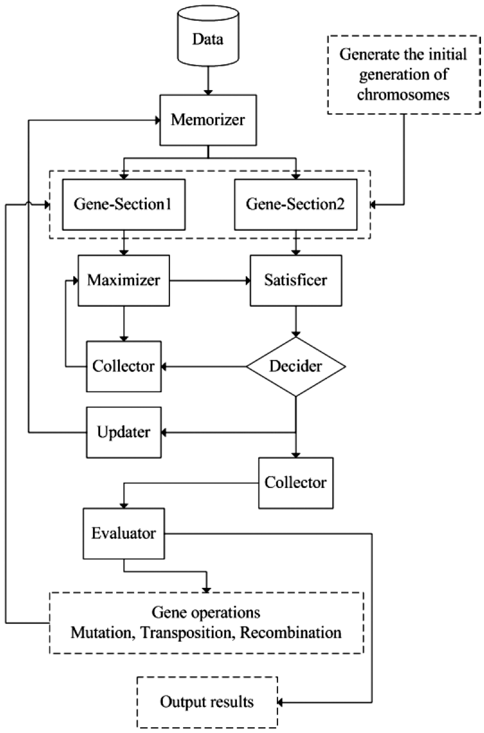

Figure 3. Sample workflow of GEPAT.

3. MODEL COMPARISON

The going-home decision of the pedestrian is taken as an example for the model comparison. The pedestrian shopping decision process can be differentiated into several stages. We assume that before the pedestrian patronizes a store, he/she must decide whether to go home/stop shopping. Building the appropriate model for this decision stage is important, especially for supporting plans based on number of patronages, because it influences the number of pedestrians who continue shopping.

3.1 Data

The data is collected from a survey carried out in Wang Fujing Street, the major shopping street in Beijing, China. The major section of this linear street where most retail stores are located is about 1,200 m long of which 534 m is the pedestrian street (Figure 4). Twenty undergraduate students administrated the survey on May 17th (Monday) and 22nd (Sunday), 2004. On 9 survey spots evenly distributed along the street from 11:00 to 20:00, they randomly asked pedestrians who completed their shopping trip to fill out a questionnaire. The surveyor recorded, based on the respondent's recall, every spatial point (entry/exit point and store) where he/she stopped since he/she entered the survey area. The activity type, expenditure, start and end time of the shopping trip were recorded sequentially in detail. The sample consists of 760 valid respondents of which 275 (36.2%) participated on May 17th and 485 (63.8%) on May 22nd.

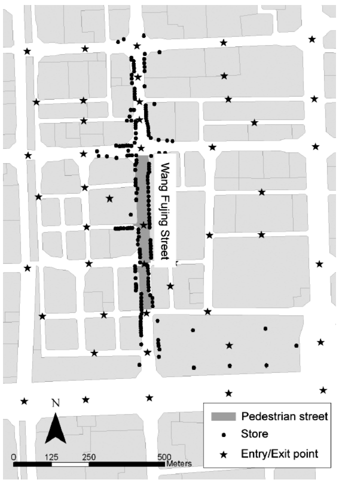

Figure 4. Survey Area.

The percentage of male respondents is 54%, implying that female respondents represent 46%. The sample was categorized into three age groups, young (16-29), middle-aged (30-49) and old (>=50). Their percentages are 53%, 34% and 13% respectively. A total of 689 records with complete multi-stop information were selected for calibrating the model. Each stop in every record is treated as an independent decision process. But we excluded the first stop, that is, the first visit of the pedestrian after entering the shopping street, from the data set, because the decision of not going home is certain. Finally, 2,741 observations were used in the model comparison.

3.2 Model Specifications

The pedestrian may decide to go home for many reasons. The survey also asked the respondents their major reasons for ending the shopping trip (Figure 5). Thirty-five percent of the respondents answered that they had fulfilled their purposes. Tiredness is the second most frequently given answer, representing 30% of the respondents. These two reasons and the fourth largest reason, planned places visited (14%), represent 80% of the respondents. It suggests that a satisficing heuristic could be the major decision mechanism of most pedestrians in Wang Fujing Street in deciding to go home.

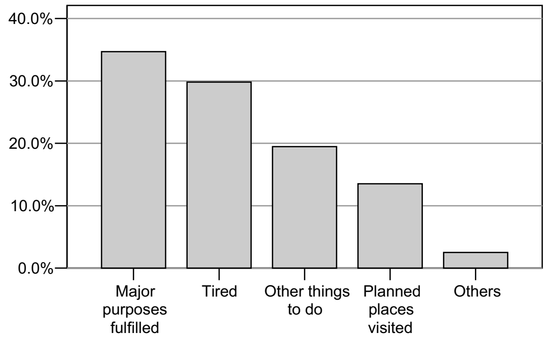

Figure 5. Reasons for going home.

However, these factors are very difficult to measure. We do not know the pedestrian's purpose, the degree of his/her tiredness or visit plans. Time is a substitute factor. The more time a pedestrian spends on shopping, the more likely he/she has fulfilled the purposes, becomes tired, or visited planned places. Time itself may also be a reason. The third largest reason (20%), other things to do, implies more or less that there is a cut-off time after which the pedestrian stops shopping.

We only recorded the start time and the end time of pedestrians' shopping activities because of the difficulty for the respondents to remember the exact time of performing every activity. An estimation technique was used to estimate in-between real time. Based on the known spatial points of the activities, the estimation was carried out using a simple distance/speed equation in the grid space. The shortest path rule was adopted. Two kinds of real time were used in the model: relative time and absolute time, both in minutes. Relative time refers to the time elapsed since the pedestrian started the shopping trip. Absolute time refers to the time difference between the current activity time spot and the 0:00 base.

We compare the rational utility-maximizing model with the bounded rational heuristic models. The former is represented by the classical MNL and the latter is represented by cut-off models adopting the satisficing heuristic.

3.2.1 MNL

In the MNL framework, we assume two choice options for pedestrian's decision making, shopping and going home. Their observable utilities are specified as,

$$\begin{aligned} V_s &= \beta_1 * RT + \beta_2 * AT \\ V_h &= \beta_3 \end{aligned} \tag{1}$$

where V_s is the utility of shopping which is the sum of relative time (*RT*) and absolute time (*AT*) weighted by their parameters, β_1 and β_2, respectively. It is hypothesized that the utility of shopping should decrease as time increases, so these two parameters should be negative. We set the linear combination of factors in this utility function for the convenience of the standard estimation procedure in SAS, although the true function may take any other forms, but this specification is enough to explore the general relationship between time and going-home decision in this study. The utility of going home, V_h, is represented by the single parameter β_3 whose sign is not hypothesized. Then the probability of going home is,

$$P_h = \frac{\exp(V_h)}{\exp(V_s) + \exp(V_h)} \tag{2}$$

MNL is a classical rational model which assumes that the utility is calculated as the weighted sum of all explanatory variables by the decision maker. However, the pedestrian may not necessarily use both *RT* and *AT* for decision. Another unrealistic point is that it adopts the compensatory rule which states that a smaller value in one variable can be (at least partially be) compensated by higher values of one or more other variables, so that, for example, even when the absolute time is very late (e.g., the stores are going to close at 22:00), the pedestrian could still decide to shop if he arrives at the shopping street at exactly this time as long as the utility from *RT* is large enough than that from *AT*.

3.2.2 Hard Cut-off Model

In the hard cut-off model, we use cut-offs for factors and avoid using compensated utilities. We hypothesize two cut-offs, a higher cut-off and a lower cut-off, for *RT* and *AT* (Figure 6). The higher cut-off is set as a physical or psychological limit of the pedestrian: once this cut-off has been passed, a pedestrian must go home. For example, it may be related to tiredness and the pedestrian does not have more energy to shop. In contrast, the lower cut-off is the threshold that must be reached by a pedestrian to continue shopping. It may mean that the pedestrian has not fulfilled the purposes or he/she has more time to spend on shopping when the values of factors are below these lower cut-offs. Unlike the MNL which assumes that all factors are considered simultaneously in the decision, the hard cut-off model includes a three-step information search and judgment procedure.

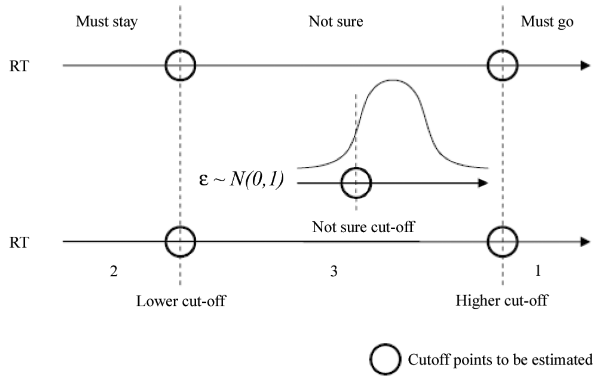

Figure 6. Hard cut-off model.

Step 1: The pedestrian thinks first whether either the value of *RT* or *AT* is above the respective higher cut-off. If it is true, he/she will go home. That is,

$$P_h = 1, \text{ if } RT \geq HC_{RT} \text{ or } AT \geq HC_{AT} \tag{3}$$

where HC_{RT} is the higher cut-off for *RT*, HC_{AT} is the higher cut-off for *AT*.

Step 2: If neither *RT* nor *AT* is above its higher cut-off, the pedestrian checks whether either *RT* or *AT* is below the respective lower cut-offs, RT_{LC} and AT_{LC}. If it is true, he/she will continue shopping. That is,

$$P_h = 0, \text{ if } RT < LC_{RT} \text{ or } AT < LC_{AT} \tag{4}$$

Note that, within the above two steps, the probability of going home either equals 0 or 1, because the cut-offs are hard.

Step 3: If neither *RT* nor *AT* is below its lower cut-off, we assume that the pedestrian is in the *Not-Sure* state. That is, his/her decision cannot be made on these two factors, but on the unobserved factor ε which we assume to be standard normally distributed which can be observed from many other social phenomenon. Another cut-off C_{NS} is hypothesized for ε. If ε is larger than C_{NS}, the pedestrian will go home; otherwise he/she will continue shopping. That is,

$$P_{hNS} = 1, \text{ if } \varepsilon \geq C_{NS} \tag{5}$$

$$P_{hNS} = 0\text{, if } \varepsilon < C_{NS}$$

Rewriting equation 5 into probabilities, we get

$$P_{hNS} = 1 - F_{NS}(C_{NS})\text{, if } (RT \geq LC_{RT} \text{ and } RT < HC_{RT}) \text{ and } (AT \geq LC_{AT} \text{ and } AT < HC_{AT}) \tag{6}$$

where $F_{NS}()$ is the cumulative density function of the standard normal distribution.

To sum up, there are five parameters to be estimated in the hard cut-off model, LC_{RT}, HC_{RT}, LC_{AT}, HC_{AT} and C_{NS}. Because C_{NS} is a constant, estimating it is same as estimating the probability of going home when the pedestrian is in the not-sure state, P_{hNS}.

3.2.3 Soft Cut-off Model

The cut-offs in the hard cut-off model are assumed to be constant for every observation of every pedestrian. In reality, this is unrealistic because pedestrians have different habits, purposes, schedules, and/or taste variations. These factors may cause cut-offs to differ among pedestrians or shopping stages of the same pedestrian. Incorporating heterogeneities into the model specification usually makes a model more general and may improve its performance.

We make the hard cut-offs soft by assuming that cut-offs are iid normally distributed across observations. For example, the lower cut-off of RT is assumed to be normally distributed with mean LCM_{RT} and standard deviation $LCSD_{RT}$. The cumulative density function is $F_{LCRT}()_0$, that is,

$LC_{RT} \sim N(LCM_{RT}, LCSD_{RT}), F_{LCRT}()_0$ where the 0 at the lower right corner means that the distribution is left-truncated at 0 because the time cannot be less than 0.

For the same reason,

$$HC_{RT} \sim N(HCM_{RT}, HCSD_{RT}), F_{HCRT}()_0$$

$$LC_{AT} \sim N(LCM_{AT}, LCSD_{AT}), F_{LCAT}()_0$$

$$HC_{AT} \sim N(HCM_{AT}, HCSD_{AT}), F_{HCAT}()_0$$

$$C_{NS} \sim N(CM_{NS}, CSD_{NS}), F_{CNS}()$$

For RT, the probability of the variable larger than the lower cut-off is,

$$P(RT \geq LC_{RT}) = F_{LCRT}(RT)_0 \tag{7}$$

The pedestrian must go home if RT is larger than the lower cut-off and the higher cut-off simultaneously. The probability is,

$$P_{MGRT} = F_{LCRT}(RT)_0 * F_{HCRT}(RT)_0 \tag{8}$$

The pedestrian must stay if RT is less than the lower cutoff and the higher cutoff simultaneously. The probability is,

$$P_{MSRT} = (1 - F_{LCRT}(RT)_0) * (1 - F_{HCRT}(RT)_0) \tag{9}$$

The pedestrian is not sure to go or stay if *RT* is larger than the lower cutoff and less than the higher cutoff. The probability is,

$$P_{NSRT} = 1 - P_{MGRT} - P_{MSRT} \tag{10}$$

For the same reason, probabilities for *AT* are,

$$P_{MGAT} = F_{LCAT}(AT)_0 * F_{HCAT}(AT)_0 \tag{11}$$

$$P_{MSAT} = (1 - F_{LCAT}(AT)_0) * (1 - F_{HCAT}(AT)_0) \tag{12}$$

$$P_{NSAT} = 1 - P_{MGAT} - P_{MSAT} \tag{13}$$

We still assume $\varepsilon \sim N(0,1)$ when the pedestrian is in the not-sure state. This time because the C_{NS} is not constant, the probability of going home depends on the joint distribution of the two variables, assuming their independence. That is,

$$P_{hNS} = P(\varepsilon \geq C_{NS}) = P(C_{NS} - \varepsilon \leq 0) = F_{NS}(0) \tag{14}$$

where $F_{NS}()$ is the cumulative density function of the normal distribution $N(CM_{NS} - 0, \sqrt{CSD_{NS}{}^2 + 1})$.

The logic of the soft cut-off model is the same as the hard cut-off model. With the above probabilities, the probability of a pedestrian going home is,

$$P_h = P_{MGRT} + P_{MGAT} - P_{MGRT} * P_{MGAT} + P_{NSRT} * P_{NSAT} * P_{hNS} \tag{15}$$

For the same reason as the hard cut-off model, the estimation of CM_{NS} and CSD_{NS} can be substituted by the estimation of the single probability P_{hNS}. Thus, in the soft cut-off model, a total of 9 parameters are to be estimated.

3.2.4 Hybrid Model

The pedestrian might also decide in such a way that simple rules are used first; if simple rules cannot help to decide, more complex rules will be applied. Similar arguments have been made by Bettman (1979) and Grether and Wilde (1984). The hybrid model incorporates both the cut-off model and the utility-maximizing model. It is specified as the soft cut-off model with the only difference in the not-sure probability, P_{hNS}. In the hybrid model, P_{hNS} is not constant but derived from,

$$\beta_3 - \beta_1 * RT - \beta_2 * AT + \varepsilon \geq 0 \tag{16}$$

where β_1, β_2, and β_3 are parameters with the same meanings as in MNL. ε is a random factor assumed to be standard normally distributed, so that,

$$P_{hNS} = 1 - F_{\varepsilon}(\beta_1 * RT + \beta_2 * AT - \beta_3) \tag{17}$$

The probability now is dependent on the trade-off between the utility of going home and the utility of shopping. In total, eleven parameters are to be estimated in the hybrid model.

3.3 Results and Comparison

The MNL model is calibrated with SAS and cut-off models are calibrated with GEPAT, as the parameter finder, using a hill-climbing algorithm as the local search method to complement GEP as the global search method. The results are shown in Table 1. Three statistics are used for model comparison. All the models are calibrated based on the maximum likelihood (ML). Akaike's Information Criteria (AIC) is calculated as the comprehensive index of goodness-of-fit against model complexity. Each model is simulated 20 times, drawing random numbers when necessary, to give the average percentage of correct hits as another statistic for the comparison.

Table 1. Results of model calibrations.

	MNL		Hard Cut-off		Soft Cut-off		Hybrid	
	P	Value	P	Value	P	Value	P	Value
	β_1	−0.007	LC_{RT}	29.797	LCM_{RT}	132.048	LCM_{RT}	0.000
	β_2	−0.008	HC_{RT}	674.966	$LCSD_{RT}$	83.976	$LCSD_{RT}$	327.290
	β_3	−10.501	LC_{AT}	809.840	HCM_{RT}	676.000	HCM_{RT}	676.992
	-	-	HC_{AT}	1313.169	$HCSD_{RT}$	0.010	$HCSD_{RT}$	0.010
	-	-	P_{hNS}	0.308	LCM_{AT}	927.851	LCM_{AT}	916.544
	-	-	-	-	$LCSD_{AT}$	87.422	$LCSD_{AT}$	85.820
	-	-	-	-	HCM_{AT}	1305.591	HCM_{AT}	1377.659
	-	-	-	-	$HCSD_{AT}$	104.161	$HCSD_{AT}$	230.719
	-	-	-	-	P_{hNS}	0.752	β_1	-0.047
	-	-	-	-	-	-	β_2	0.000
	-	-	-	-	-	-	β_3	-3.502
ML	−1121.200		−1381.830		−1070.599		-1077.843	
AIC	2248.400		2773.660		2159.199		2177.687	
Sim	0.546		0.656		0.743		0.744	

The parameters of MNL are estimated as expected. Its ML is only higher than that of the hard cut-off model. The parameters of the hard cut-off model could be interpreted as follows. The lower cut-off for RT is about 30 min, suggesting that all the pedestrians shop for at least half an hour. However, this cut-off could be too small for the whole sample because the model is too clear-cut to allow any mis-prediction which will lead to a very low ML. The same problem could also apply to the lower cut-off for AT, which is about 13:30. For this reason, only 19.1% of the sample can be explained by the lower cut-offs, although completely right, while the shopping behavior actually represents 74.7% of the sample. The effectiveness of the higher cut-offs is weak for that only 0.6% of the sample can be predicted as going home. The remaining 80.3% of the sample is explained by the random variable where the going-home probability under the not-sure state is 0.308. The hardness of the specification of the hard cut-off model makes its ML the least among all models.

The introduction of heterogeneity into the soft cut-off model clearly raises the ML, which is the highest. The means of the lower cut-offs increase (about 132 min for RT and 15:20 for AT), compared to the ones in the hard cut-off model, and their standard deviations are also reasonable. This directly leads to the increase in shopping behavior within the sample and the increasing probability of going-home in the not-sure state. However, the means of the lower cut-offs are similar to those in the hard cut-off model and their effects remain weak. Because the higher cut-off for AT is still large, about 22:00, its standard deviation can only enclose limited number of observations.

The ML of the hybrid model is slightly lower than that of the soft cut-off model, but the mean of the lower cut-off drastically changes to 0 with a large standard deviation, others remain similar. This means that, on average, the utility-maximizing part substitutes some of the predictability of *RT*. However, this substitution effect is more competitive rather than complementary so that it detriments the overall ML a little bit.

The same conclusions can be drawn based on the AIC-statistic. Although the soft cut-off model has more complexity (the number of parameters), its AIC is still the best (lowest). In contrast, the more complexity in the hybrid model brings a lower ML and AIC, probably implying that the utility-maximizing part is just mis-specified. As for the simulation statistic, an interesting question exists between the MNL model and the hard cut-off model, where the latter simulates behavior much better than the former, inversing the relationship represented by ML and AIC. This raises the question on how to judge the goodness of a model with conflicting goodness-of-fit statistics. A deeper exploration into the properties of the model is required and we only give a first explanation here. The MNL model may be performing better in terms of the ML-statistic because of its better averaging ability to enclose more variance, just like using a big round shape (the model) to wrap an irregular shape (the data). But because the hardness of the hard cut-off model (just like a slim ellipse shape) limits its flexibility, it tries to wrap the most significant feature of the irregular shape (may be the most frequently happening event in the data) while ignores other parts. The more variability of the MNL implies more uncertainty during simulation while the hard cut-off model hits the most important data effectively by predicting more certainly with modest variability. In this sense, we argue that the hard cut-off model fits better to the problem structure of the going-home decision.

4. CONCLUSION

Most analytical pedestrian behavior research has used utility-maximizing models and paid less attention to models of other behavioral theories such as bounded rationality, which may lead to a deficiency in deeper explorations into the decision processes of pedestrians. Such deficiency could also be a result of inappropriate methods to estimate the model. For this reason, the paper first introduces the modeling platform GEPAT with the ability to estimate parallel functions using a multi-gene-sectional chromosome structure and to facilitate building models using processors emulating simple decision mechanisms.

The going-home decision of the pedestrians in Wang Fujing Street is taken as an example to illustrate the use of GEPAT. The major conclusion derived from the model comparison is: (1) the satisficing heuristic fits better to the going-home decision than the utility-maximizing rule, suggesting the bounded rational behavior of pedestrians; (2) pedestrian behavior is heterogeneous; introducing heterogeneity into the model specification is appropriate and effective; (3) lower cut-offs, as the baseline of decision, are much more important than high cut-offs, reinforcing the hypothesis that pedestrians are satisficers.

This example has also shown the flexibility of GEPAT as a modeling toolbox and the power of estimating complex models. Because that GEPAT uses numerical estimation algorithm, it causes a common problem of unawareness of the user whether the estimator reaches the global optimum. In this case, although we tried the estimation procedure for each model several times and got similar results, but usually not the same, it still cannot guarantee the global optimum. Such procedure costs intensive computation resource and time. Improving the estimation efficiency of GEPAT will be the major task of our next step, with other additional functionalities such as a parameter sensitivity test.

5. REFERENCES

Berry, B. J. L., B. J. Epstein, A. Ghosh, et al. 1988, *Market Centers and Retail Location: Theory and Applications*, Prentice-Hall, London.

Bettman, J. R., 1979, *An Information Processing Theory of Consumer Choice*, Addison-Wesley Publish Company, Reading.

Borgers, A. and H. Timmermans, 1985, "A Model of Pedestrian Route Choice and Demand for Retail Facilities within Inner-City Shopping Areas", *Geographical Analysis*, **18**(2): 115-128.

Borgers, A., and H. J. P. Timmermans, 1986, "City Centre Entry Points, Store Location Patterns and Pedestrian Route Choice Behavior: a Microlevel Simulation Model" *Socio-Economic Planning Science*, **20**(1): 25-31.

Dijkstra, J. and H. Timmermans, 2002, “Towards a Multi-agent Model for Visualizing Simulated User Behavior to Support the Assessment of Design Performance”, *Automation in Construction*, **11**: 135-145.

Ferreira, C., 2001, “Gene Expression Programming: A New Adaptive Algorithm for Solving Problems”, *Complex Systems*, **13**(2): 87-129.

Gigerenzer, G., P. M. Todd and ABC Research Group, 1999, *Simple Heuristics that Make us Smart*, Oxford University Press, New York.

Grether, D., and L. Wilde, 1984, “An Analysis of Conjunctive Choice: Theory and Experiments”, *Journal of Consumer Research*, **1984**(10): 373-385.

Hagishima, S., K. Mitsuyoshi, and S. Kurose, 1987, “Estimation of Pedestrian Shopping Trips in a Neighborhood by using a Spatial Interaction Model”, *Environment and Planning A*, **19**(9): 1139-1152.

Haklay, M., and D. O‘Sullivan, 2001, “‘So go downtown’: Simulating Pedestrian Movement in Town Centers”, *Environment and Planning B*, **28**(3): 343-359.

Kerridge, J., J. Hine, and M. Wigan, 2001, “Agent-Based Modeling of Pedestrian Movements: The Questions that Need to be Asked and Answered” *Environment and Planning B,* **28**(3): 327-341.

Todd, P. M., 1999, “Simple Inference Heuristics versus Complex Decision Machines”, *Minds and Machines*, **9**(4): 461-477.

Todd, P. M., and G. Gigerenzer, 2003, “Bounding Rationality to the World,” *Journal of Economic Psychology*, **24**(2): 143-165.