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DECISIONAL PROCESSING ON PARKING BEHAVIOR IN ENTROPIC SETTINGS

Moreno Ferrarese
University of Trento, Department of Economics and Management, Trento, Italy
e-mail: moreno.ferrarese@unitn.it, moreno.ferrarese@gmail.com

Abstract: *This paper surveys the most recent advances in the context of decisional processing with focusing on the parking behavior in entropic settings, including the measures and the necessary mechanisms for the interaction of the actors-players, and their connection to decisional processing theory.*
The aim of this article is to provide a critical review of the most fashionable models and methods in parking lot financial design: the first class of methods covers the approach of analysis with the random entropic model; the second class of methods is the decisional processing through rational choice models as rational individual evaluations. Both techniques are described in detail in sections; we illustrate them using the well-known and easy multimodal problem approach and then we present the advanced applications. Thus, it is possible to identify all strong and weak points of the models and to compare them for a best feasible solution for parking lot economic and financial design.
Taking into account a close equivalence between the aggregate methods of entropy maximization and disaggregated microeconomic method of discrete choice models, based on random utility theory, we try to provide a critical approach of it through the rational choice models and to underline the possible benefit of it for the problem decision.

Key words: *urban parking lot, discrete choice models, decision making models.*

1. Introduction

Entropy, as a fashionable design philosophy for infrastructure in urban areas, which analyzes the interaction between the components of an Ecosystem, has been, in the recent past, a robust design environment at low cost.

Moreover, what it has been found by scholars, who have dealt with, was the demonstration of a close equivalence between the entropy maximization of microeconomic approach to discrete choice models based on random utility theory. These theories are based on observed choices, made by individuals, introducing the concept of perceived usefulness as utility (expressed in the form of probability of choice) for individuals subdivided into social classes.

This article evolves from entropic theories to address the use of discrete choice models for the design and management of urban parking lots in entropic asset, based on a design activity which was realized in Italy as the Corrubio Square parking lot design (Verona, 2015).

2. Modelling approach: parking analysis with models

2.1. General description

What differentiates the class of models of discrete choice from the sequential or direct demand models is the different pattern of data set that is used to represent the demand for mobility and parking. The behavioral models as the unit of observation and analysis of parking lot behavior, take on the individuals or families rather than flows that are carried from one area to another one, e.g. described by the O/D matrixes (Galatioto, F. & Huang, Y. & Parry, T. &, Bird, R. & Bell, M., 2015).

In the behavioral or disaggregated models we paid attention on the process of choice that each individual-consumer performs in an attempt to maximize its net benefits (Spiegler, R., 2015).

The real object of the theory of discrete choice models is the "random utility" theory or "aleatory utility" theory: these models differ from the aggregate models because they are based on observed choices made by individuals. Through the discrete choice models we study the choices of the individuals in a discrete basket of alternatives, with the assumption that the utility functions are somewhat variable on the population of individuals and that, therefore, appear to be subject to some random element that takes into account the incompletion of entropic information, or, even, the aspects essential for the decision-makers neglected by the analysts (Daganzo, C., 2014; Hoyos, D. & Mariel, P. & Hess, S., 2015). For this category of discrete choice models the probability that an individual chooses a certain option is a function of its socio-economic characteristics and of its attractiveness/desirability relative to the chosen option compared to the alternative options (Finnis, J., 2011), according to the well-known concept of *utility* (Oppenheimer, D. M. & Kelso, E., 2015; Ferrarese, M., 2016), or, more commonly, what an individual tries to maximize in order to meet it.

In these models the utility, which derives from an individual-consumer in choosing an option *k* among n^{th} possible options, is expressed in the form of probability of choice.

The behavioral patterns, in comparison to the aggregate models, present some important advantages (Bollen, K.A 2014):

- the disaggregated models are probability models and, this fact, allows us to transfer only probabilistic calculation as the estimation process;
- the coefficients of the explanatory variables provide a direct interpretation of the direct marginal utility (they reflect the relative importance of each attribute), as the utility function allows us to combine more fully the different attributes in contrast to what happens in the aggregate models for the generalized cost functions;
- each observation corresponds to each individually accomplished choice, while, in the aggregate models, each observation is based on multiple individual observations. The use of individual data allows to exploit a greater variability in the observations compared to what we might get from the zonal division of the territory and, also, it allows us to insert a wider range of explanatory variables (behavioral and attitudinal, social and economic, financial, etc.) in the functions of choice and to build more detailed segmentation of individuals with data sets more easily available (Axhausen, K. W. & Kowald, M., 2015);
- the behavioral models are more stable in time and space as they are based on the analysis of individual behavior.

According to Ben Akiva and Lerman (Ben-Akiva, M. E. & Lerman, S. R., 1985) the individual decision-maker, assuming a rational behavior, opts for the selection that would supply him, as one considers, with the maximum utility among all the available behaviors (Avineri, E. & Ben-Elia, E., 2015; Nuzzolo, A. & Crisalli, U. & Comi, A., & Rosati, L., 2015), so that the probability to choose the alternative *i* is equal to the probability that the utility of the alternative *i*, U_{in} is greater than any other possible utility associated with alternative *choice set*, i.e.:

$$P\left(i|C_{ni}\right)=Pr\left(U_{in}\geq U_{jn}\right);\forall J\in C_n \tag{1}$$

The maximizable utility is defined by two components: a deterministic component representing the average behavior of the individual decision-maker and a stochastic component representing the unobserved factors (Swait, J. D., 2011; Huang, Y.& Smith, B. & Olaru, D. & Taplin, J., 2015; Chen, W. Q.& Graedel, T. E., 2012)

If U_{in} is the utility of a certain alternative for the individual *n*, then the random utility is expressed as:

$$U_{in}=V_{in}+\varepsilon_{in} \tag{2}$$

where:

– V_{in} is the deterministic component of the utility, the same for individuals, which is a function of only observable attributes of alternative *i*;

– ε_{in} is the stochastic component different for each individual and for each alternative of a randomized choice.

The randomized element, introduced in the function of utility (Ferguson, T. S., 2014), describes the specific deviation of each individual from the average assessment V_i. The causes of the deviations may be as follows: measurement errors on the variables due to the analyst, omission of variables or attributes and important idiosyncrasies of the individual (Cohen, J. & Cohen, P. & West, S. G. & Aiken, L. S., 2013; Bollen, K. A., 2014). As it has been stated, it is not the determination of the maximum of the utility function, which will be taken into consideration, but its probability distribution.

If we take into account the dichotomous case as a choice between two alternatives, also called *binary* *choice model*, the probability of choosing alternative *i* is expressed as (Dong, Y. & Lewbel, A., 2015):

$$P(i) = Pr\left(U_{in} \geq U_{jn}\right) \tag{3}$$

while, for the alternative *j*:

$$P(j) = Pr\left(U_{in} \leq U_{jn}\right) = 1 - P_n(i) \tag{4}$$

and then, for the alternative *i* we'll have:

$$\begin{aligned} P_n(i) &= Pr\left(U_{in} \geq U_{jn}\right) = Pr\left(V_{in} + \varepsilon_{in} \geq V_{jn} + \varepsilon_{jn}\right) \\ &= Pr\left(\varepsilon_{in} - \varepsilon_{jn} \geq V_{in} - V_{jn}\right) \end{aligned} \tag{5}$$

The individual does not decide on the basis of absolute values but on the differences among his assessments *V*. The probability of choice is given only by the difference between the evaluation values *V* and the values of ε (Fazio, R. H. & Pietri, E. S. & Rocklage, M. D. & Shook, N. J,. 2015).

Furthermore, we note that two components of the equation, the deterministic and the stochastic one, are not independent of each other, but they follow the appropriate distributions of ε. The choice models differ from each other for the distribution of the difference of the errors $\varepsilon_n = (\varepsilon_{in} - \varepsilon_{jn})$ (Bifulco, G.N., 1993; Wu, H. & Browne, M. W., 2015; Lebo, M. J. & Weber, C., 2015).

In case of multiple alternatives, if *C* is the set of all possible alternatives, and with C_n we indicate a subset of *C* and with $j_n < j$ we indicate the number of possible choices; then, the probability that the i^{th} element C_n is chosen from n^{th} individual-decision-maker is expressed as:

$$P_n(i) = Pr\left(U_{in} \geq U_{jn}\right); \forall J \in C_n \tag{6}$$

which will become, substituting the evaluation:

$$P_n(i) = Pr\left(V_{in} + \varepsilon_{in} \geq V_{jn} + \varepsilon_{jn}\right); \forall J \in C_n, j \neq i \tag{7}$$

The fundamental equation of all random utility models, assuming a certain distribution of the random and known terms of *V*, is used to calculate the probability with which each alternative will be chosen. The following subject models are based on random utility theory, as well known: systematic utility and attributes, invariant models in calibration, Multinomial Logit, Hierarchical Logit, Probit and Monte Carlo method.

2.2. Analysis through multinomial logit

As a close equivalence between the aggregate of entropic maximization and disaggregated microeconomic approach of the multinomial *Logit model* (Nijkamp, P. & Reggiani, A., 1988; Kruglanski, A. W. & Chernikova, M. & Kopetz, C., 2015), in a very close connection with the microeconomic and collective behavioral theories, is established, so we observe the existence of dynamic relationships in the area of parking lot choice between tariff and time, according to the same *utility theory*.

This determinates the exact proportion of the parking population which select the alternatives through its behavioral economic approach (Bradley M. & Kroes, E. & Hinloopen E., 1993; Mirabi, V. & Fadihe, Z. A., 2015).

The class of random utility models, that in recent years has seen more favors in the econometric literature - for its simple and cheap use - is the *Logit Model* family (GLM-class of generalized linear models to which the Probit and the Loglinear model belong) expressed as (de Grange, L. & González, F. & Vargas, I. & Muñoz, J. C., 2013):

$$P_{ij}^h = \frac{T_{ij}^h}{T_{ij}} = \frac{e^{-\left(\beta C_{ij}^h\right)}}{\sum_k e^{-\left(\beta C_{ij}^k\right)}} \tag{8}$$

where:

K = 1,2,.. M [M = modal cut] being estimated with:

- P_{ij}^h the fraction of displacements *T* between the zones *i* and *j* that took place with the mode *h*.
- C_{ij}^h a composite function of the characteristics related to the displacement with the same form of displacement *h* between the zones *i* and *j* (site staging/parking area).
- *k* is referred to a generic way of displacement among the *m* alternative ways considered until the parking stalls.

The Logit model presents important properties, among which (in particular with reference to the bi-modal model) we define the following conditions:

– it determines the generation of an *S-curve*, widening of the difference between C_1 and C_2, or of a competitive range of a modality as to another, as for the empirical curves said *diversion curves* (Oppenheimer & Kelso, 2015);

– it generates, for equal characteristics, the distribution of displacements which takes place between the two ways in equal parts ($C_1 = C_2$);
– if the competitive characteristics of the mode of displacement 1 tend to be significantly lower than that of the displacement mode 2, alternatively all individuals tend to move on the latter, in which case P_{ij}^2 tends to 1.

As noted previously, the various models of choice (Choice Models) are derived from different assumptions that are made about the distribution of errors, namely, the stochastic part of the utility function. We have already shown that the most simple, and at the same time, used model is the discrete choice Logit (Train, K., 2002).

This model, however, has some limitations. In reality, there are often omitted many variables in the systematic part because the use of a high number of attributes may lead individuals to choose among alternatives too complicated to evaluate and consequently the distribution of ε depends from the joint distribution of variables omitted.

It should be noted that it is not of limitations that exclude the use of this model in the analysis of the data collected. In fact, one must always consider the context in which you want to operate as what appear limits could become "strong points" of this model. Train (Train, K., ibid.) shows that occur in internal three types:

- the change in taste (Taste Variation): the logit model assumes homogeneity in tastes as outlined by Ben-Akiva and Lerman (ibidem). In reality we know that tastes vary from person to person because everyone can receive from a particular attribute or a different level "satisfaction". With the Logit it can be observed only tastes that vary in a deterministic way, i.e. those caught by the analysis of the observed variables (whether they are the variables of the experiment or those that characterize individuals). The Logit doesn't capture those tastes that are not expressed in the observed variables or are simply random. For example, two individuals who have the same education and training and receive the same income might make different choices that reflect their way of thinking and living. This limit of Logit becomes a real problem if the analyst expects that there may be some tastes that vary depending on variables not observed or just in a purely random;
- the independence of irrelevant alternatives - IIA (Substitution Patterns): the IIA is an assumption restrictive part of the logit model and indicates that the ratio of the probability of selection is independent of the presence or absence of other alternative choices. This limit may not always be seen as something negative (Train, K., ibidem, pp. 52-53);
- the repeated choices (Panel Date): this happens, for example, in an experiment of choices (Stated Preferences) where the individuals are asked to perform several experiments of choice so as to collect for each one much more data. Every choice situation becomes, therefore, an observation of the dataset.

Considering the limits which we have previously exposed, we could opt to estimate in each case a Logit model and further highlight empirically with the difference that there may be an extension of this model, e.g. which it maybe uses a Mixed Logit model.

2.3. The economic scenario for the realization of an artifact parking in entropic setting

In consistency with theories of rational human behavior (Neth, H. & Gigerenzer, G., 2015), as well as the advantages offered in terms of more realistic modelling by this model form, there have all been known for some time. Although few studies have applied tree Logit models, however, applications have been restricted by practical and theoretical difficulties in the estimation of these models, in particular with the sequential estimation that has normally been necessary (Bajari, P. & Nekipelov, D. & Ryan, S. P. & Yang, M., 2015). The study of parking design and management, through the use of socio-graphic techniques, allows a more accurate determination of the experimental parameters which enable choice of the model to minimize the uncertainty of the data that will define the management revenue (Woo, J. Y. & Bae, S. M. & Park, S. C., 2005).

In fact, the problem of the choice of a Logit multidimensional equation to design an artifact parking always depends on the market demand structure (Cantarella, G. E. & de Luca, S. & Di Gangi, M. & Di Pace, R., 2015) and on its elasticity (or on elasticity of demand at general service levels) and, in general, it depends on the market shape in which the parking lot is to be inserted.

When designing, it is distinguished between the situation "without project approach" (sometimes monopolistic, or quasi-monopolistic – when it exists a partial illegal use) and "with project approach" (in monopolistic competition or in market competition), for which the choice of the Logit multidimensional equation falls between the situation of absence of parking and the presence of an artifact.

The problem can be treated in terms of economic theory - working on consumer habits - of monopoly and competition, putting the situation "without project approach" as a "natural monopoly" of public parking lot, and "with project approach" as a situation of (semi) competitive market - to simplify - with elasticity of demand to price.

In the case of monopoly (Fig. 1), charging a price above marginal cost, the monopolist (public administration of parking stalls in natural monopoly), prevents the realization of some exchanges that would be beneficial from a social point of view, because there are consumers who would be willing to pay more the marginal cost (and hence would be convenient for both the public monopolist and for the consumer) but not a price equal to the price of monopoly.

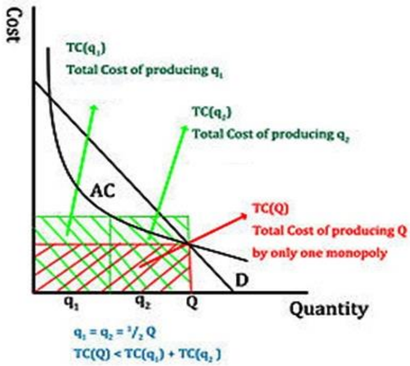

Fig. 1. A graphical explanation of the inefficiencies of having several competitors in a naturally monopolistic market (freely reduced from Campanella, 1977)

The problem of the public natural monopoly is not about the fact that part of the consumer surplus is moved into the hands of the public monopolist: the real problem comes from the fact that the public monopolist - for parking stalls - enlarge its share of the profit practicing a higher price to marginal cost, that is called (Figure 1) "loss of efficiency".

If there are two bidders of parking services, the one public surface in non-differentiated stalls set time, and one i.e. within an underground differentiated car parking with private management, we have a situation of monopolistic competition (Figures 2-3).

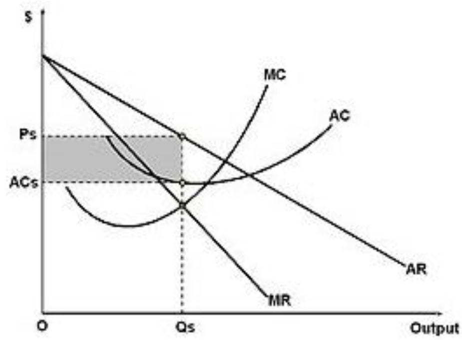

Figure 2. Monopolistic competition. Short-run equilibrium

Short-run equilibrium of the enterprise under monopolistic competition. The parking enterprise maximizes its profits and produces a quantity where the enterprise's marginal revenue (MR) is equal to its marginal cost (MC). The parking enterprise is able to collect a price based on the average revenue (AR) curve. The difference between the parking enterprise's average revenue and average cost, multiplied by the quantity sold (Qs), gives the total profit. (freely reduced from Campanella, 1977).

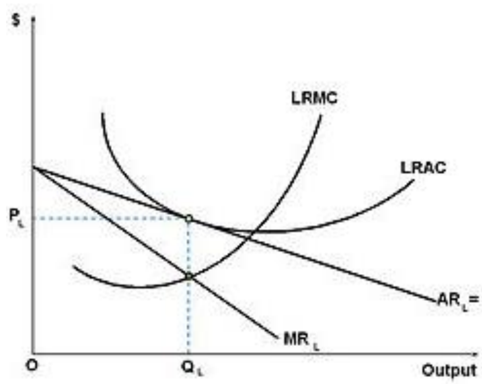

Figure 3. Monopolistic competition. Long-run equilibrium

Long-run equilibrium of the parking enterprise under monopolistic competition. The parking enterprise still produces where marginal cost and marginal revenue are equal; however, the demand curve (and AR) has shifted as other enterprise entered the market and increased competition. The enterprise no longer sells its parking services above average cost and can no longer claim an economic profit (freely reduced from Campanella, 1977).

We note (from Figures 2-3, Tab.1) that there are two sources of inefficiency in the Monopolistic Competition-MC market structure for parking lot design and management: the first source of inefficiency of the parking enterprise is when it charges a price that exceeds marginal costs at its optimum output, i.e. when the MC enterprise maximizes profits (where marginal revenue is equal to marginal cost). Since the MC demand curve is downward sloping, this means that the parking enterprise will be charging a price exceeding marginal costs.
An MC parking enterprise, that will operate at a point where demand or price equals average cost, it will possess a monopoly power when it maximizes the profit level of production: in this case, there will be a net loss of consumer and producer surplus.

3. Discussion: the use of the decisional processing vs. Random discrete choice

In the previous section we have shown how the utility theory, where individual choice is randomized, impulsive, constrained and adopted by imitation, is applied in random discrete choice models in entropic environment (for the design and management of the parking lot in urban area), presents few economical limits for design. An explanation can be given because it does not preventively keep in counting (in phase of demand analysis, or BCA and D.C.F. design) of the incomes of a (public/private) enterprise through the revenues in monopolistic competition scenario, to be obtained from the purchase of slots on parking stalls from consumers. These consumers, indeed, manifest individual decisions rather than make indistinct collective (for class) choices.
For this reasons, the analyses of the individuals' behavior is better to be processed through stochastic rather than deterministic inferential methodologies within the *rational choice theory* (Stigler, G. J. & Becker, G. S., 1977). These own individual decisions, studied through *generalization for inductive inference*, make the business income for the public/private enterprise.
In this case, the social aggregate behavior weighs up the sum of own choices made by individuals, i.e. each individual in society, makes its choice based on its own preferences and the constraints.
Furthermore, in microeconomic models, rationality, when there are self-interested preferences of individual, is an assumption of the specific behavior of individuals: this is a mode of thought and action identifying problems directly working towards their solution. The individual will undertake any action that is optimally to achieve the own desired ends in any situation. Moreover, the choice of ends being given when rationality is seeking the most cost-effective means to achieve a specific goal also without worthiness. If it prescribes only ultimate goals we, particularly, speak of *instrumental rationality*, which is a tool necessary to reach the goals regardless of whether the goals are right or wrong.

Table 1. Example of market structure comparison for parking lot

Market structure comparison for parking lot								
	Number of parking enterprises	**Market power**	**Elasticity of demand**	**Parking service differentiation**	**Excess profits**	**Efficiency**	**Profit maximization condition**	**Pricing power**
Perfect Competition	Infinite	None	Perfectly elastic	None	No	Yes	P=MR=MC	Price taker
Monopolistic competition	Many	Low	Highly elastic (long run)	High	Yes/No (Short/Long)	No	MR=MC	Price setter
Monopoly	One	High	Relatively inelastic	Absolute	Yes	No	MR=MC	Price setter

The second source of inefficiency is when the MC parking enterprise operates with excess of capacity e.g. when MC enterprise's profit maximizing output is less than the output associated with minimum average cost.

An MC enterprise's demand curve is downward sloping: thus, in the long run the demand curve will be tangential to the long run average cost curve at a point to the left of its minimum. The result is excess capacity (Perloff, J., 2008, pp. 483–484).

Thus, if rationality is concerning with critically evaluating actions, instrumental rationality is focusing rather than its own 'whys', on the 'hows' of an action and for these reasons, rational choice theory, for an essential level, uses the narrowest definition of rationality, as under-represented features:

a) evaluative;
b) goal-oriented;
c) consistent on time and choice situations.

Rational choice theory entails that an individual has preferences among the available choice alternatives (the ranking between two alternatives involves no uncertainty), in terms of available information or probabilities of events: when acting, it operates according to benefit-cost potential preferences as real-valued utility functions, and economic decision making becomes only a problem of maximizing this real-valued utility function subject to constraints, i.e. payoff, income, access. This allows to state which option it prefers and assumes to lead to a complete and transitive decision, in choosing the self-determined best set of action such "what to do?" or a set of objects such "what to choose or buy".

Then as individual outcomes can be evaluated in terms of individual costs and benefits, a rational individual chooses the set of exhaustive and exclusive actions and outcomes in a partial ordering ranking that provides the maximum benefit/cost ratio, i.e., the maximum benefit divided by cost, to arrive at action that maximizes personal relative advantages.

The available alternatives are expressed as a set of objects, or as a set of *j* exhaustive and exclusive instrumental actions for obtaining a particular outcome as maximal element, such as:

$$A = \{a_1, ..., a_i, ..., a_j\} \tag{9}$$

when:

- discounting future payoffs identifying and weighing each alternative are arising through alternatives across time;
- limitations of individuals - as the cost that these impose or cognitive gives - arise to theories of bounded rationality.

The individual sets, at least, two alternatives that can be:

- Strictly preferenced, as equally preferred: when $|a_1| \equiv |a_2|$;
- Weakly preferenced, as alternative (or it is indifferent): when $|a_1| \rangle |a_2|$
- Indifferently preferenced, when: $|a_1| \neq |a_2|$

This way to proceed presents many advantages. First of all it provides a solid theory that makes empirical predictions with a relatively poor model in which we describe the agent's objectives and constraints. In the second case, the optimization theory is a well-known field developed from maths' development. Thus, this approach that is generally strikingly and rational tractable, become compared to other approaches to choice models.

All these limits are provided by the indicated objectives of operating income, both in the design under the project financing in the DCF analysis, than under management of the same parking lot, from their income statement. It becomes, therefore, necessary to explore the factors of individual decision which allow, by summation of the individual decision, a collective habitual behavior, which will be introduced, eventually, in discrete choice models as it is the Logit model for entropic multidimensional analysis, that takes into regard the territorial impact.

All the decisional processing models are based on assumptions only of steady rational behavior of the individual through computational decision models.

In this case, the individual choice can be interpreted as the result of a steady decision-making process formulated in a sequence of steps, ranging from the definition of the decision problem to the final choice.

The elements that characterize processes of individual evaluations, are principally under described:

A. *Comparison procedures*, on which the choice of a purchase of parking service is based as:

1) Compensatory action based by:

1.1) Additive or linear rule:

$$V_A = \sum_{i=1}^{n} b_{Ai}\, e_i \qquad (10)$$

with: A = parameter characteristic; b = choice parameter; e = i^{th} elasticity.

1.2) Sum of the differences:

$$\sum_{i=1}^{n} [b_{Ai} - b_{Bi}] > 0 \qquad (11)$$

with: b = choises parameters; A, B = features parameters.

1.3) Majority of positive dimensions, where:
- we note an evaluating alternatives to couples;
- we note an evaluating of each attribute and the choosing of the service that is the best for the greatest number of attributes.

1.4) Frequency of the good or bad characteristics, where:
- critical levels are established according to which an attribute may be "good" or "bad”;
- we count positive and negative characteristics and we choose the service with the best balance.

1.5) Homogeneous weight: a particular case of the addition rule, in which the importance weights are equal.

1.6) The matrix unfolds with (Tab. 2):

Table 2. Table matrixes of evaluations - example

PARKING SERVICE	IMPORTANCE	VALUTATIONS (1 - 5)					
Caracteristic 1	0.30	5	3	3	4	2	5
Caracteristic 2	0.15	2	3	4	3	5	3
Caracteristic 3	0.25	2	4	3	4	5	2
Caracteristic 4	0.10	1	5	5	5	1	2
Caracteristic 5	0.20	3	3	3	4	4	3

Evaluation: A, B, C, D, E, F, items to be evaluated according to the scale of Likert.
Importance: range [0.00: 1.00].

2) Non compensatory action based by:

2.1) Conjunctive rule, where:
- we establish a minimum acceptable level for each attribute;
- we choose the service that meets (in > or =) that level for all attributes.

2.2) Disjunctive rule, where:
- we establish a minimum acceptable level for each attribute;
- we choose the service that meets (in > or =) that level for at least one attribute.

2.3) Satisfactory level rule, where:
- we establishes a minimum acceptable level for each attribute;
- we choose the first service that rises above that level for all attributes with:
  - Cognitive consequences of such trust, mental loyalty, loyalty;
  - Behavioral consequences of such repurchase, positive word of mouth, resistance to change, willingness to pay premium price, collaboration.

2.4) Lexicographical rule:
- we choose the service with the highest rating on the most important attribute;
- if two or more services have the same assessment, we compare the feedback on the second most important attribute.

2.5) Elimination by aspects rule, where:
- we establish a minimum acceptable level for each attribute;
- we choose the service that meets (in > or =), the most important attribute level;
- if they remain more alternatives we consider the second most important attribute.

B. *Heuristics (cues*): as the valuations: rules of choice, mental "shortcuts" that reduce the cognitive effort as availability, representativeness, anchoring and adjustment - heuristics of judgment.

C. *“Effects of context”* as *compromise* (identifying conditions where adding an option surrounded by two other options would gain choice share relative to that predicted by value maximization) and *attraction* (adding an asymmetrically-dominated third option to a binary choice increases the likelihood of choosing the asymmetrically-dominating option).

D. *Decisions under uncertainty*: as the Prospect theory.

E. *Alternatives*: if in theory there is a universe full of alternatives for each decision-making process generally known to the decision-maker it is presented a subset of possible choices called the choice set.

F. *Attributes of alternatives*: that qualify quantitatively and/or qualitatively the attractiveness of alternatives

G. *Rules of Decision*: that describe the mechanism by which we opt for an alternative over another and each way allowing to arrive to a single choice

Rules of Decision (G) are classified into nine categories:

1) *Prevalence/Dominance*: when an alternative is winning if it dominates the other in terms of attributes and, in any case, it is not worse than the others.

2) *Fulfilment/satisfaction*: when all those alternatives, that do not exceed by at least one attribute a satisfaction threshold - defined a priori - in accordance with the expectations of the decision maker, are excluded.

3) *Lexicography*: when it is so called a scale of increasing importance of the attributes of the decision maker.

4) *Utilities*: when the attractions of the attributes are expressed by a vector of values and the "utility" of the alternative due to a scalar, namely, the definition of a function that expresses the usefulness of an alternative in relation to the attributes associated with it. The utility is a measure, in this context, that the decision maker tends to maximize in its process of choice. Depending on the scope of this function it will be defined in a specific way so that it can be maximized in the case of profit or minimized in the case of cost .

5) *Compromise-off*: when consumers tend to prefer the alternative that represents a compromise rather than an alternative extreme.

6) *Loss aversion* in formula:

$$\left| f(x) \right| \langle \left| f(-x) \right| \tag{12}$$

- When the benefit of a gain is less, in absolute value, at the sacrifice, of a loss.

7) *Segregation of earnings* in formula:

$$f(c) < f(a) + f(b) \tag{13}$$

with: a < b < c and: a + b = c

- Segregation of earnings: it is greater than the benefit of a loss.

8) Integration of losses in formula*:*

$$f(-c) < f(-a) + f(-b) \tag{14}$$

with: -a > -b > -c and (-a) + (-b) = -c

9) The *effect of framing*: where – substantially - identical data placed in different conceptual frameworks produce different decision outcomes.

4. The use of a multidimensional logit model in decisional processing setting

In the problem that we are examining, we do not presume that the consumer prefers the nearest parking with the shortest path, because, sometimes, longer paths leading to parking lots equipped can offer some perceived benefits over bearable actual costs.

The probability that a parking lot is chosen by the consumer depends on a set of factors, and it increases with the level of service offered, and it decreases on account of the greater transfer time associated. The role of the factor impedance is to compose, in a mathematical way, the probability which decreases the choice of a displacement to reach a parking lot with increasing time.

In the logit model the punctual impedance factor I between i and j through h is usually set equal to an exponential function inverse to the displacement time in the form:

$$I_{ij}^{h} = e^{-\beta\, t_{ij}^{h}} \tag{15}$$

From equation (8), in order to calculate the fill rate demand F between i and j that points to the path h, we have:

$$F_{ij}^{h} = F_{ij} \left(\frac{I_{ij}^{h} \ \omega_h}{\sum_h I_{ij}^{h} \ \omega_h} \right) \tag{16}$$

where:

- F_{ij} is the fill rate demand between i and j
- F_{ij}^{h} is the fill rate demand between i and j through h
- ω_h is the perceived and desired service level of parking lot

in which I_{ij}^h is given by equation (15), with $\sum_h F_{ij}^h = F_{ij}$ as the constraint complied of $\sum_h I_{ij}^h\ \omega_h$ for which the sum of the demand flows that reaches the parking lots, allocated among the various paths, should be equal to the total flows between *i* and *j*.
Assuming that the rate of demand that will point to the free parking lot rather than the parking lot artifact is the difference of the displacement times *z* between the two walking paths 1 and 2, putting:

$$q = \frac{F_{ij}^1}{F_{ij}} \tag{17}$$

as a rate relative to the path 1, it will be $1-q$ the rate of demand relative to the walking path 2.
Substituting the equation (17) into equation (16), after some steps we obtain the equation:

$$q(z) = \left(\frac{\omega_1}{\omega_1 + \omega_2 \cdot e^{-\beta \cdot (z)}} = \frac{\omega_1}{\omega_1 + \omega_2 \cdot e^{-\beta \cdot \left(t^2 - t^1\right)}} \right) \tag{18}$$

where:

– $z = t^2 - t^1$ it represents the difference in travel time between the two parking lots,

with:

- ω_1 as the parking service tariff/price of surface area recognized as the most convenient for the consumer, such as the surface infrastructure of the parking closest to residential users actually chosen by cars (also in terms of illegal or elusive parking);
- ω_2 that represents the parking service tariff/price, consisting of parking stalls provided in the artifact parking;
- $e^{-\beta*(t_2 - t_1)}$ represents the virtual impedant factor, usually set equal to an inverse exponential function to the time required to reach the manufact (usually on foot);
- $-\beta*(t_2 - t_1)$ represents the actual time of displacement (taken per first minute) on foot between the choice of parking - alternatively - closer, less constrained (t^1) and farthest (t^2) - made by the consumer; the parking equipped is perceived as better in terms of comfort, flexibility and more constrained, although much safer and less polluting, but more expensive;
- β represents a parameter relative to decisional processing setting variables such as perceived by the consumer.

According to Stigler and Becker (Stigler, G. J. & Becker, G. S., 1977), the rational choice theory appears as the theory that presents fewer weak points than the random discrete choice, and it manifests a better versatility of application, as it is easily adaptable to the DCF analysis or BCA analysis, which are mandatory in the case of design through the "Environmental Impact Assessment-EIA" or under the project financing.
Among the many ratios of financial calculations that are used in the analysis DCF, as well as in the BCA analysis, which are used to evaluate the feasibility of a project, such as a parking lot equipped, the index benefits divided by costs is certainly the best known and more used for.
Then, we put $\beta = \left[C/B\right]$ as share percentage coefficient with the following ratios:

- C = Cost of share percentage evaluated in "opportunity cost" or "shadow price";
- B = Benefit of share percentage evaluated in "opportunity cost" or "shadow price";

In the case of the parking artifact, the classic multinomial logit equation (18) is transformed in an equation that includes the decisional processing .
Thus, starting from (18) in the situation of absence of parking and the presence of an artifact (with monopolistic competition), using the decisional B/C processing setting, the (19) it is expressed as:

$$q(z) = \frac{\omega_1}{\omega_1 + \dfrac{\omega_2}{e^{\beta \cdot (t_2 - t_1)}}} = \frac{\omega_1}{\omega_1 + \dfrac{\omega_2}{e^{[C/B] \cdot (t_2 - t_1)}}} \tag{19}$$

ω_1 – is the omega-1 constant

ω_2 – is the omega-2 constant

With exact form (© 2015 Wolfram Alpha LLC computational knowledge engine):

$$\frac{\left(\sqrt{3} - i\right) e^{\frac{C(t2-t1)}{B}}}{\left(\sqrt{3} - i\right) e^{\frac{C(t2-t1)}{B}} - 2i} \tag{20}$$

And limit:

$$\lim_{B\to\pm\infty} \frac{\omega_1}{\omega_1 + \frac{\omega_2}{e^{\frac{C(-t1+t2)}{B}}}} = \frac{\omega_1}{\omega_1+\omega_2} \approx 0.5 + 0.288675i \quad (21)$$

The function, according to Abramowitz & Stegun (1972) is:

$$\begin{aligned} &\text{periodic in } C \text{ with period } \frac{2iB\pi}{t1-t2} \\ &\text{periodic in } t1 \text{ with period } \frac{2iB\pi}{C} \\ &\text{periodic in } t2 \text{ with period } -\frac{2iB\pi}{C} \end{aligned} \quad (22)$$

with derivative:

$$\frac{\partial}{\partial B}\left(\frac{\omega_1}{\omega_1 + \frac{\omega_2}{e^{\frac{C(t2-t1)}{B}}}}\right) = \frac{C\omega_1\omega_2(t1-t2)e^{\frac{C(t2-t1)}{B}}}{B^2\left(\omega_1 e^{\frac{C(t2-t1)}{B}} + \omega_2\right)^2} \quad (23)$$

with the Laurent series expansion for B=∞:

$$\frac{\omega_1}{\omega_1+\omega_2} + \frac{C\omega_1\omega_2(t2-t1)}{B\left(\omega_1+\omega_2\right)^2} - \frac{C^2\omega_1(\omega_1-\omega_2)\omega_2(t1-t2)^2}{2B^2\left(\omega_1+\omega_2\right)^3} - \frac{C^3\omega_1\omega_2(\omega_1^2-4\omega_1\omega_2+\omega_2^2)(t1-t2)^3}{6B^3\left(\omega_1+\omega_2\right)^4} + O\left(\left(\frac{1}{B}\right)^4\right) \quad (24)$$

From (18) and (19), when $z = t^2 - t^1 = 0$, the distribution of quotas q (z) is not 50%, as an unequal distribution depends on the level of access and the quality of the parking lot.
For all representations of ($t_2 - t_1$)= walking time we have $t_2 - t_1 = 0$ if $t_2 = t_1$ i.e. when transfer times are the same then the decision is made for only the cost/benefit ratio of parking service perceived by the rational decision-maker.
The value 50% for $q(z)$ is the hurdle-rate, the iso-cost to shadow prices equivalent, in the case where the timing for the choice is equivalent. In this case, all the perceived costs are equivalent.
Thus, if:

- q (z) < 50% the consumer's choice falls into the parking lot of regulated manufact;
- q (z) > 50% the consumer's choice falls into the free parking.

5. Concluding remarks

The study of the choices of the individuals in a discrete basket of alternatives appears to identify the incompletion of entropic information, even if the collective behavior is extended to the estimated probability of choice for homogeneous groups of individuals with the same characteristics.
Thus, it is supposed that because of the practical and theoretical difficulties in the estimation, in particular with the necessary applications of the sequential estimation, the approach with the random entropic choise models have been restricted.
As to the approach of analysis with the rational model, the study of parking design and management through the use of socio-graphic techniques allows, indeed, to make the accurate determination of the experimental parameters in order to minimize the uncertainty of the data that will define the management revenue.
In fact, the random utility theory does not keep in counting of the incomes of a (public/private) enterprise, even if the revenues in monopolistic competition scenario depends on both external factors and internal factors, i.e. from the purchase of slots on parking stalls from consumers. These consumers, indeed, manifest individual decisions rather than make indistinct collective (for class) choices. Thus, the social aggregate behavior weighs up the sum of own choices made by individuals, e.g. using computational techniques through focus group surveys.
So, we have demonstrated that, among the rational choice theories, as decisional processing, the simple benefit/cost ratio, is an individual rational choose set of exhaustive and exclusive actions and outcomes in a partial ordering ranking, in order to arrive at action that maximizes personal relative advantages, i.e. the maximum benefit/cost ratio for individual, and to be more suitable for the application in the Logit multinomial equation in entropic environment.
We have shown how the shape of the market depends on the rational choices of the consumer.
Even in case of the choice of urban parking we must take in account these individual rational choices, which tend to maximize rather than the “benefits minus costs” difference, the benefit/cost ratio.
Finally, the shape of the market depends, apart from the enterprises’ profitability, also on choices made in an entropic environment, especially with regard to the (market) positioning of urban parking.

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