Dealing With Increased Complexity in Conjoint Experiments: Background and Overview of Alternate Approaches

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Abstract. This paper serves as background information for the TRB workshop on stated preference modelling. The main argument of the paper is that the development of stated preference and choice models has witnessed increased complexity, which in turn has led to higher respondent burden. The paper discusses some examples of such increased complexity and some potential solutions to reduce respondent burden. Because some of these developments and solutions are discussed in more detail in other workshop papers, the level of detail in this paper depends on the specific topic. Those topics that are not discussed in the workshops receive slightly more attention.

Keywords: Stated preference and choice analysis, respondent burden, portfolio analysis, context effects, hierarchical information integration, pairwise conjoint analysis, uniform designs, optimal designs

1. Introduction

Conjoint analysis, typically called stated preference analysis in transportation research, has been developed in the mid 1970s first to estimate preference functions and later to model choice behaviour. The method can be traced back to different theoretical frameworks, which have in common the notion that individuals combine their judgement about the attributes making up a multi-attribute choice alternative according to some integration rule to arrive at an overall utility or preference. In the beginning, the focus of much of this research concerned the nature of the integration function. Krantz (1964) and Luce and Tukey (1964) were the first to consider the problem of decomposing some overall utility measurement into scale values for the attribute levels, given some type of composition rule. This measurement problem is known as the ‘conjoint measurement problem’ because it concerns simultaneously scaling the independent and dependent variables such that a composition rule or measurement model preserves the manifest preference order relationship in the data as closely as possible. Because their focus was on identifying the conditions that lead to a particular measurement model (additive vs. multiplicative), this approach became known as axiomatic conjoint analysis. Similarly, information integration theory (Anderson, 1970) was concerned with testing alternative models of how individuals integrate their values of attributes into an overall value judgement, using experimental designs. Interest was primarily focused on examining the functional forms underlying the value scale as different forms either support additive or multiplicative integration rules or some hybrid form.

In the mid 1970, different groups in marketing (Green), geography (Louviere) and urban planning (Timmermans) started experimenting with estimating these functions, shifting the focus from theory testing to model development. Their work was partly a reaction to previous, mainly attitudinal and compositional evaluation models in marketing and spatial interaction models in geography and urban planning. Especially in these spatial sciences, the development of conjoint analysis was strongly influenced by the discussion to what extent observed or revealed behaviour reflected underlying preferences. The argument here was that many spatial choice markets are not in equilibrium and that consumers are often faced with unavailable choice options. Moreover, many spatial attributes show very strong correlations and/or limited variance. It was felt that under such circumstances, preferences/utilities could not be validly derived directly from observed behaviour. Numerical simulations (Veldhuisen and Timmermans, 1981) supported this argument. It was shown that utility functions could not be validly uncovered when applied to different spatial configurations. Conjoint analysis allowed researchers to control the covariance structure of their data. The use of orthogonal fractional designs implied that the main effects of attributes could be estimated in an unbiased manner, not confounding main effects with any other effects.

Although conjoint analysis was used originally for measuring preferences, the approach was also used for simulating choices. To that effect, some choice rule was assumed and linked to derived preferences to simulate choices and market shares. Highest preference and Luce choice axiom were examples of such approaches. For some time, also the exploded logit model was popular. It involved generating choices and choice sets from rank data and then estimating a logit model. All these approaches were however ad hoc in the sense that the validity of the assumed choice rule could not be empirically tested. This changed, making all these ad hoc approaches obsolete, when Louviere and Woodward (1983) developed experimental design strategies that allowed one to test and estimate preference functions and choice rules simultaneously, Much of the research was based on the IIA-choice models. At this stage, the core of conjoint preference and choice modelling as it is applied currently in transportation research was well developed. In the next section, we will discuss how the methodology was further enhanced to deal with increased complexity. Increased complexity often led to increased respondent burden. Hence, we will also discuss alternatives of dealing with such respondent burden.

2. Increasing complexity

The tendency of increased complexity was related to several developments, which we will briefly introduce and discuss below. On the one hand, increased complexity was related to the desire or need to include more attributes in the models. On the other hand, it was triggered by the desire to relax some potentially limiting assumptions underlying commonly used IIA-models and to expand the approach to different choice problems and formulating context-dependent choice problems.

More attributes

Early work was based on a limited number of attributes. For example, the very first studies only manipulated 3 attributes to test for alternative combination rules. Even in the late 1970s, more than 10 attributes were very rare indeed. However, it was realised that in some choice situations, the number of potentially relevant attributes may be very high. Arbitrarily limiting the number of attributes varied in the experiment would likely lead to confounding of effects and therefore to misleading conclusions as the effect of particular attributes will likely appear to more be significant than they really are, should the proper attributes have been included in the experiment. Examples are residential choice and shopping center decisions which likely involve many influential attributes. In case of residential choice decisions, the literature suggests that several attributes related to respectively the house, the physical neighbourhood, the social composition of the neighbourhood and distances to various facilities influence the residential choice decision. Numbers of attributes in the order of 40-50 are to be expected.

It goes without saying that if the number of attributes or the number of attribute levels increases or both, the number of attribute profiles to be judged becomes too demanding for an individual respondent to complete. Consequently, several approaches have been suggested to reduce respondent burden.

Context dependence

Most stated preference models have implicitly or explicitly assumed that preferences are independent of context. However, in reality the choice of transport mode may depend on weather conditions, (e.g. Molin and Timmermans, 2007), and mode choice may depend on other modes that are available in one’s choice set (e.g. Molin, et al, 2007). Hence, the *decision context* may affect the decision-making process in various ways. Oppewal and Timmermans (1991) distinguished the following factors. First, the *composition* of the choice set may influence the evaluation of an alternative. This may be either because (a) the size of the choice set brings consumers to use noncompensatory decision heuristics to screen and eliminate alternatives, (b) some alternatives are perceived as being more similar and therefore more substitutable, or (c) the framing or presentation format of the choice task leads consumers to attribute-wise processing of information. Such effects would violate the assumption of Independence of Irrelevant Alternatives (IIA), which underlies the multinomial logit (MNL) model, typically used in stated choice analysis, which states that the utility of a choice alternative is independent of the existence and attributes of all other alternatives in one's choice set. There have been many attempts to derive tractable models that relax this assumption. A review of such models can be found in Timmermans and Golledge (1990).

Second, preference or utility functions can only be assumed to be valid under a limited set of circumstances. This is because variables that describe the *background* of the choice situation may differentially affect the evaluations of the alternatives. For example, people's evaluations of housing attributes might be conditional upon factors such as mortgage costs and tax levels. Likewise, firms' investment strategies will be influenced by interest levels, economic prospects and strategic planning of competitors, and choice of transportation mode will likely be dependent on trip purpose. Most applications do not explicitly account for such background effects in the specification of the utility function. Either one assumes that the model is independent of context and the model is applied directly to different conditions, or a new model is estimated for each condition separately.

One approach to modelling such context effects is to include constants and attributes of other available alternatives in the utility function, as first applied by McFadden, Train, and Tye (1977) who called this extended model the Universal Logit model. Their approach was meant as a test of the IIA assumption, but later it was realized this specification could serve as a model in its own right. Such additional terms, called *cross effects*, represent corrections on the utilities as predicted by the standard IIA-type model, to account for the composition effects. Significant cross effects indicate violations of the IIA property. For example, a negative cross effect indicates that the utility, and hence the market share, of an alternative is lower than predicted by the IIA model. Likewise a positive cross effect would indicate that an alternative's utility is underestimated by the IIA model and should be corrected upward. In the latter case, this could lead to a violation of regularity. The utility function can also be extended with terms that represent the effects of background variables on utility.

Conventional preference and choice experiments typically manipulate only the attributes of choice alternatives. Background variables that affect the utilities of alternatives are specified in the task instructions but never vary as part of the experiment. One could, nonetheless, easily treat the background variables as additional factors in the factorial design to create treatments that vary the hypothetical background. Such an approach could thus employ the same design principles that underlie standard conjoint choice experiments. There is, however, one exception: whereas in standard experiments the main focus is often on the main effects of the attributes, in stated background experiments all effects have to be specified as interactions with alternative specific constants and/or as interactions with alternative specific variables. This is necessary because if some background variable were specified as a generic effect, the variable's effect on each of the alternatives would be equal and cancel out.

Therefore, the designs with only main effects, which are often used in standard experiments, are not sufficient, and larger designs have to be used that permit the independent estimation of these types of interactions. Such larger designs can easily be constructed by nesting a standard design that varies the attributes of alternatives under a design that specifies the levels of the background variables.

Design strategies for experiments that allow the estimation of composition effects are a little more complicated than those for experiments that assume IIA, but essentially the same principles can be applied. A common strategy is to choice sets of varying size according to a 2^N design to vary the availability of alternatives in an orthogonal way or to construct an orthogonal fraction of a 2^N design plus its foldover (Anderson and Wiley, 1992). Regardless of the specific approach taken, the inclusion of context effects tends to increase the size and complexity of the experimental designs and therefore increase respondent burden.

Portfolio choice

Existing applications of stated preference and choice models in transportation research typically estimate utility functions and choice models for choice alternatives described in terms of a set of alternatives. The experimental task is to select from each choice set the most preferred choice alternative. This *single* choice task however does only represent one type of choice problem. Another choice problem class problem has become known as portfolio choice problem, which can be defined as the problem of choosing a *combination* of choice alternatives as a function of the attributes of the choice alternatives, and possibly some contextual variables. The composition of the chosen set of alternatives may have a specific effect on the probability of choosing particular combinations of choice alternatives. Examples would be combined destination-transport mode choice, task allocation, composition of activity agendas, and time allocation. These problems have in common that the utility of each choice alternative is not invariant, but in part depends on the presence or absence and attribute values of the other alternatives in a choice set.

Portfolio models can be estimated by designing experiments which allow the estimation of own and cross effects. Generally, a 2^N main effects plan and its foldover will provide an availability design that allows one to estimate a portfolio model. Respondents are requested to respond to the design by using any of the following response formats: (i) unconstrained choice of portfolio; (ii) pick 1 from each choice set; (iii) pick precisely *n* from each choice set of size; (iv) pick *n* of *N*, or (v) pick up to a maximum of *n*. Further details are discussed in the workshop contribution of Wiley and Timmermans (2008).

3. Approaches to reduce respondent burden and information overload

The developments briefly discussed above have in common an increased complexity of the designs. This may be reflected in (a combination) of using more attributes, more attributes values and more attribute profiles. It may result in the problem of information overload, leading to increasing respondent demand. A larger number of attribute levels and attribute profiles implies that the time to complete the experimental task will increase. Consequently, respondents may become tired or bored, or loose concentration, resulting in less reliable responses. In contrast, a larger number of attributes means that every attribute profile contains more information, implying that respondents require to spend more mental effort in understanding and appreciating the description of the choice alternatives, capture significant differences between profiles and maintain consistency. It may result in simplifying strategies in that only a subset of variables is taken into account. The extent to which this leads to invalid results depends on the relative importance of ignored attributes and the properties of the design that is used.

Conjoint analysis knows two different ways of combining attribute information and experimental design. Originally, researchers applied the so-called trade-off approach, which involved combining all attribute levels of *pairs* of attributes, and asking respondents to provide some value judgment for each resulting combination of attribute levels. Alternatively, and this has become the dominant approach over the years, the so-called full profile approach was used. This approach requires respondents to provide some measure of his overall utility or preference for a set of choice alternatives, described in terms of levels of *all* attributes. The main advantage of the full profile approach is that the descriptions of the choice alternatives are realistic. However, when the number of attributes is large, individuals might encounter difficulties, in providing accurate preference judgments. Because of this information overload problem individuals might simply ignore the less important attributes in providing their judgments. On the other hand, the trade-off approach also has some obvious problems. For example, the way in which the attribute combinations are presented may bias an individual's responses and cause some attributes to be over-valued. In addition, the judgment task becomes rather unrealistic and individuals may be unclear as to what should be assumed about the attributes that are not considered in a specific trade-off table. Moreover, Johnson (1974) has pointed at a tendency for individuals to adopt patternized types of responses. Evidently, the results obtained under such circumstances will not be valid. Finally and most importantly, the trade-off approach assumes that the trade-offs are independent of the attributes that are not considered. If, however, interactions exist inaccurate utility estimates will be obtained.

Information overload and respondent burden may thus be caused by (i) a large number of attribute levels, and/or (ii) a large number of attributes, and/or (iii) a large number of profiles. In the following sections, we discussed some approaches that have been suggested to avoid these situations.

Large number of attribute levels

Dealing with a large number of attribute levels may be the easiest. If one can assume that the utility function is linear, only two levels for each attribute are required, and this would dramatically reduce the total number of profiles that are generated. However, a linear utility may not always be very realistic, or sometimes the attribute is inherently categorical. Another way of limiting the number of profiles is to avoid more than 4 attribute levels and combinations of attribute levels across attributes that have a high common denominator.

Large number of attributes

PARTIAL INCOMPLETE BLOCK DESIGNS

Several approaches have been suggested to reduce the information overload problem that arises as a result of a large number of selected attributes. One approach involves the use of balanced incomplete block designs to vary the attributes shown to respondents. This approach will lead to a smaller number of attributes in each hypothetical choice alternative presentation, reducing information overload, but one should realize that it increases the total number of profiles and hence may be more demanding in that respondents have to make more judgements. If the number of attributes is a perfect square, partially balanced incomplete block designs can be used.

HIERARCHICAL INFORMATION INTEGRATION (HII)

Another, more theoretically based approach, is hierarchical information integration, originally suggested by Louviere (1984) for stated preference task, and later extended by Timmermans (1989, see also Louviere and Timmermans, 1990) for stated choice tasks. This approach assumes that when faced with a complex choice task, individuals will first group the set of influential attributes into higher order constructs, evaluate the attributes making up a higher order decision construct separately and finally combine their evaluations of the higher order constructs into some overall utility. The experimental approach follows this idea very closely. In HII the respondent's evaluation and decision-making process is framed in a hierarchical structure to help the respondent in handling a large number of attributes. The hierarchical structure is researcher-defined, but can be based on empirical data (see Bos, et al. 2004), and maps the large number of attributes onto a smaller number of perceptual dimensions, or as they are typically called, decision constructs. Each decision construct summarizes a particular subset of attributes. For example, in residential choice, attributes are commonly grouped into housing attributes, attributes of the neighborhood, and attributes related to relative location/accessibility. In the first step of this approach, separate designs are constructed for each decision construct, systematically varying the attributes that are assumed to pertain to the decision construct of interest. Respondents typically evaluate the corresponding attribute profiles on some rating scale. To avoid respondent burden, respondent typically evaluate one or two decision constructs. Next, to arrive at an overall utility function, a so-called bridging experiment is designed. The factors varied in this design are potential evaluation scores for each decision construct. In a preference task, respondents are invited to provide an overall summary rating of the resulting profiles, consisting of rating scores of each decision construct. In case of a choice experiment, a choice task is constructed and respondents are invited to choose the attribute profile they like best.

Thus, HII is an approach that reduces both the information overload problem and respondent burden. Information overload is reduced by grouping the attributes. Respondent burden is reduced because the number of profiles that needs to be evaluated is smaller. However, the bridging experiment may be somewhat arbitrary.

INTEGRATED CHOICE EXPERIMENTS

To avoid this potential problem, Oppewal, Louviere and Timmermans (1994) proposed the use of integrated designs (HII-I). In HII-I there is no separate bridging design. Instead, the experimental designs for each decision construct do not only vary the corresponding attributes but also include summary evaluation scores of all remaining decision constructs. This design strategy avoids the use of a bridging experiment, and allows respondents to judge attributes pertaining to a particular decision construct against evaluation scores for the other attributes. The most interesting characteristic of the approach however is that the assumed grouping of attributes into decision constructs can be explicitly tested.

The inclusion of summary evaluations of the other decision constructs may imply that the number of profiles to be evaluated increases, and in addition respondents do receive more information. Moreover, the number of attributes in each profile also increases. In that sense, this approach may be more demanding than traditional HII. However, this approach guarantees that the profiles give the respondent information about all the dimensions that are relevant to the decision problem. Though this leads to an increase in the size of the profiles, this procedure is assumed to avoid that respondents too easily make biasing inferences about missing information. More details about Hierarchical Information Integration and Integrated Choice Experiments can be found in the workshop contribution of Molin and Timmermans (2008).

PAIRWISE CONJOINT ANALYSIS

To avoid respondent burden, in most applications of HII, the various designs required to estimate the preference or choice model of interest are typically distributed across the sample, implying that a particular respondent will never consider all attributes varied in the complete set of designs Although the approaches discussed above reduce task complexity and/or information overload, respondents still have to process many attributes. Moreover, the fact that they do not consider all attributes may be viewed as problematic in the sense that one implicitly assumes the sample is homogeneous and that evaluations of decision constructs are mutually independent. Finally, these approaches all require respondents to develop a mental representation of the attribute values which may be quite different from their experience. In principle, respondents may not have had any previous experience with any of the attribute levels and there is certainly no attempt to construct experimental situations that are as close as possible to the current situation of the respondent It may imply that the reliability and validity of their responses is at stake. To avoid these potential limitations, Wang, Oppewal and Timmermans (2000) suggested another approach, which they called pairwise conjoint analysis.

The quintessence of the pairwise conjoint approach is straightforward. Similar to the conventional fractional factorial design strategy, attribute profiles and choice alternatives are constructed by combining attribute levels. However, instead of using all selected attributes to construct a choice alternative, the pairwise strategy uses only *one pair of attributes plus a base alternative (typically the current situation)*. If we take a closer look at this design strategy, it turns out that the total number of profiles consists of three subsets. The first subset consists of those profiles in which both attributes are at their base level. These profiles are identical and hence collapse into one unique profile that is the current or base situation. The second subset consists of profiles in which one attribute is at its base level, whilst the other attribute is not. Only some of these are unique, the rest are duplicates. Finally, in the third subset of profiles, none of the attributes is at its base level. There is no duplicate in this subset, all these profiles are unique. Overall, this means that the total number of unique pairs of attributes is less than all possible pairs. If we compare this approach to a fractional factorial design more attribute profiles will be generated. However, the information load to respondents is much less demanding because profiles have only two attributes different from their base levels. Therefore, the pairwise design has the advantage of reducing information load.

The profiles generated by the pairwise design can next be used to construct choice sets or to generate hypothetical choice contexts similar to the fractional factorial design strategy. To estimate preference or choice models efficiently, one should select profiles in which orthogonality is preserved and attribute levels are balanced. There are at least two ways of selecting such profiles in the pairwise approach. In the first way one may use profiles of the subset in which none of the attributes is at its base level. Although all main effects and two-way interactions can be estimated, the disadvantage of this approach is that the part-worth utility of the base levels cannot be estimated because the profiles used do not include the base level. Consequently, the impact of the other attribute levels can only be assessed relative to each other, not relative to the base level.

To overcome this disadvantage, one may also select a fraction of attribute pairs (in the extreme case, one may select all possible pairs), and use all possible combinations of attribute levels. There are two important principles in selecting the pairs of attributes. First, one should select those pairs in which there are possible interactions between the two attributes in the pairs. Secondly, one should ensure that each attribute appears the same number of times, so that orthogonality in the profiles is preserved. The latter is especially important if one assumes that a non-IIA model drives the response data and the choice process under investigation. If one assumes the multinomial logit model to be correct, randomized choice sets may be constructed, although one should realize that some efficiency is lost.

Large number of profiles

The majority of stated preference and choice models have relied on orthogonal fractional factorial designs. More recently other types of designs have been introduced. Two such approaches will be discussed in this workshop: D-optimal designs and uniform designs. In general, these designs will lead to a smaller number of profiles or choice sets, reducing respondent demand.

D-OPTIMAL/EFFICIENT DESIGNS

Traditionally, virtually all designs used in stated preference and choice analysis were orthogonal fractional factorial designs. The objective is to construct designs such that the attribute levels are uncorrelated. The statistical efficiency of this design strategy was never questioned. More recently, the interest has shifted to designs that maximize the amount of information obtained from a design. The key note here is to use a design that allows more efficient estimates using the same number of choice sets as in orthogonal designs or the use of a smaller number of choice sets to obtain equally efficient estimates. In that sense, such design can be used to reduce respondent burden.

A property of such designs is that effect estimates are correlated. Which design principle (orthogonality or efficiency) should be preferred appears a matter of personal taste, but also depends on the application and goal of the analysis. A detailed discussion goes beyond the scope of the present paper. Several criteria have been suggested, but a maximization of the determinant of the variance-covariance matrix, known as D-optimality or efficiency, seems to have generated most interest. In practice, the inverse of this measure is usually calculated and produces a design with the smallest possible errors around the estimated parameters. This optimality criterion results in minimizing the generalized variance of the parameter estimates for a pre-specified model.

Optimal designs are model-dependent, implying that the results are directly dependent on the ensuing design, data, and analysis is dependent on the correctness of the assumed model. For example, if the responses from a particular process are actually being drawn from a cubic model and the analyst assumes a linear model and uses the corresponding optimal design to generate data and perform the data analysis, then the final conclusions will be flawed and invalid. All optimal designs need a model; without a model, the optimal design-generation methodology cannot be used, and general design principles must be reverted to. The other potential caveat is that the optimal design depends on a set of candidate points, supplied by the researcher. One should also be aware that algorithms to find the optimal design vary considerably between software packages and that there is no guarantee that the generated design is indeed optimal. Further details can be found in the workshop contribution of Rose and Bliemer (2008).

UNIFORM DESIGNS

Uniform designs have also been suggested to reduce the number of profiles or choice sets that are estimated. The essence of uniform design is to find a particular number of attribute profiles that are uniformly scattered in attribute space. The outcome depends on the measure of uniformity. In the context of the present paper, it is important that the number of attribute profiles or choice sets is much smaller than those generated by orthogonal fractional factorial designs, especially if the model includes interaction effects, or high, uneven number of attribute levels. It therefore considerably reduces respondent burden. It does however not provide a solution to the problem of information overload.

Optimal experimental designs produce efficient estimators assuming that the true form of the model is known. Uniform designs, in contrast, have been introduced as robust experimental designs that guard against inaccurate estimates caused by model misspecification. Under some conditions, however, uniform designs are D-optimal; on another set of conditions, they make also be (close to) orthogonal. Uniform designs find the attribute profiles by uniformly scattering these points across the domain space such as to maximize some of uniformity. Further details are provided in the workshop contribution of Wang and Li (2008).

Conclusions and discussion

The argument underlying this paper has been that progress in stated preference and choice modeling to deal with problems of increasing complexity has fundamentally increased respondent burden, both in terms of task complexity in the sense of larger experiments and information overload in the sense of more information provided in each profile description or choice set. While such progress allows researchers to estimate more complex choice models, increased respondent burden may imply that the validity and reliability of these models may become an issue. A second component of this paper therefore has been to briefly discuss some approaches that have been proposed to reduce respondent burden.

This overview has shown that most of these approaches address one source of respondent burden. They either tend to reduce the number of profiles or choice sets, or they tend to reduce the information overload problem. However, it virtually always means that a reduction of respondent burden comes at some costs in the sense that some limiting assumption is always made or implied. In that sense, the design of stated choice and preference experiments continues to require specific skills and professionalism. Researchers should be aware of all potential pitfalls and limitations and then design the experiment according to their needs, considering efficiency, respondent burden, and model specification and estimation issues.

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