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Abstract

In this paper we attempt to study the conjoint analysis (CA) method combined with the response surface methodology (RSM) tools, more precisely statistical models and optimization theory. As regards the service/product, this can be revised by considering the current situation (status quo) if it is just under production; alternatively, for a new service/product, the presented method only considers the baseline variables of the user/customer. With this spirit, changements related to the standard CA are performed in order to collect data about the current situation of the service/product and about the baseline variables related to the user/customer. RSM is applied in order to achieve the best optimal solution, equivalent to, in this case, the best hypothetical preference of the respondent; furthermore, the final optimal score for a variable may be explained for its importance in reaching the best profile when the judgement of the respondent about the current situation (status quo) is considered.
Keywords: Response Surface Methodology, optimization, conjoint analysis, status quo, optimal solution.

1 Introduction

Standard conjoint analysis is a multi-attribute quantitative method useful to study the evaluation of a consumer/user about a new product/service. In literature many authors (see for example Alvarez-Farizo et alt. (2002)), have studied and applied this method; the main theoretical problems are faced by Green et alt. (1990) about statistical models and by Moore (1980), related to the insertion of baseline variables related to the respondent. Therefore the proposal is based on the conjoint analysis jointly with a status quo evaluation. In literature, Hartman et alt. (1991), introduces an alternative named "status quo" which indicates the present situation or the actual state of art.
The aim of the present study is the proposal of a modified CA considering both the

*This paper is a joint work of the authors. Nevertheless, Berni took care of sections no.s 2 and 3; Rivello took care of section no. 4; sections no.s 1 and 5 are in common.

collecting data method and the subsequent analysis. Furthermore, it is relevant to point out the modified structured data, through a new questionnaire, in order to collect information about the baseline variables of the respondent, the quantitative data about the current situation (status quo), and the proper CA analysis by means of the planning of an experimental design. The subsequent statistical analysis is performed applying the RSM theory by considering the quantitative judgement of each respondent for each profile with respect to the assessed score about the status quo, according to the information obtained by the personnel data. The final result is achieved carrying out an optimization procedure on the estimated models, defining an objective function in order to reach the optimal solution for the revised (or new) service/product.
The remainder of the paper is organized as follows. Section 2 illustrates the methodology; our proposal is explained and discussed in section 3; in section 4 the case study, the questionnaire, data and results are displayed. Concluding remarks are outlined in section 5.

2 Theory

In this section the fundamental elements of conjoint analysis and RSM are outlined, note that for basic CA we mean the CA technique usually applied.

2.1 The basic Conjoint Analysis

The CA is a method (for details see Green et alt., 1990) based on global utilities formulated by a user/customer on a set of alternatives or profiles in order to evaluate the preferences of the future customer related to a new product or service. It allows to decompose the global judgement according to each single utility value for each factor (variable or attribute) influencing the service/product. The main specific aspect of this technique is the similarity among the statistical analysis procedure and the decisional process of the consumer (or user); in fact each hypothetical profile of the new product (service) is evaluated by formulating only one score, without expressing the single preference on each characteristic of the product (service), which is characterized through the factors involved in the study.
The main statistical tools applied for the basic CA are: the concepts of the experimental design (Box et alt., 1978) and the analysis of variance, but not exclusively. In literature, the applied statistical models have received great attention, considering that a specific model corresponds to a well-defined response variable (rating, ranking or binary), for details see: Chapman et alt. (1982); Elrod et alt. (1992).
As regards the experimental design, the fractional factorial designs are mainly used, with a high Resolution, (R=III or R=IV), in order to reduce the number of alternatives or preferences.
In general, the statistical model involves the judgements on each profile as response variable, while the factors are the dependent variables.
In the following, the CA will be explained by considering our proposal.

2.2 The general response surface model

We briefly describe some elements of the RSM theory relevant for this paper. For more details see Khuri et alt. (1987), Myers et alt. (1995). Note that we focus our attention on the statistical models and optimization in the RSM; the fundamental basis on experimental design are, however, indirectly introduced through the experimental planning for the CA.

In general, we define the set of variable, which influence the measurement process: $[x_1, .., x_j, .., x_k]$; and the set of noise variables: $[z_1, .., z_l, .., z_h]$. Following the theory previously outlined in the introduction, the general model can be written as:

$$Y_t(x, z) = \beta_0 + x^{'}\beta + x^{'}Bx + z^{'}\delta + z^{'}\Delta z + x^{'}\Lambda z + \epsilon_t \quad t = 1, .., N \tag{1}$$

where x is the vector of the main variables, z is the vector of the noise variables; β, B, δ, Δ, and Λ are vectors and matrices of the model parameters, ϵ_t is the random error which is assumed Normally distributed with zero mean and variance equal to σ. Λ is a $[k\text{x}h]$ matrix which plays an important role since it contains the parameters of the interaction effects between the noise and the main variables.

In general, a noise variable may be defined as a qualitative or quantitative variable which is also controllable and measurable. In the technological context, a noise effect which has these characteristics is introduced in the experimental design in order to reduce the pure experimental error and to set the internal variables which control the process variability. Furthermore, the final aim is to find the experimental run which is the most insensitive to noise, through the first order interaction effect between the noise and the internal variables.

3 Our proposal

In our study the proposal is based on the application of RSM through the general model (1) in order to set the best preference for a sample of respondents by evaluating both the quantitative judgements about the full profiles and the judgements about the current situation. Furthermore, the quantitative response variable Y is formed through the scores expressed by the N respondents in a metric scale $[0, 100]$ on each hypothetical profile. Therefore, in general, if n are the profiles, the observations are $N\text{x}n$.

The set of variables x, defined previously, is the set of independent variables related to the quantitative judgments on the current situation (status quo); note that the set x is the same by considering either the factors involved in the experimental design (profiles) and the factors influencing the status quo.

In addition, we estimate the model (1) including the information about the respondent, through the baseline variables considered as noise variables just because they introduce a subjective component in their expressed judgement.

Therefore, the prospective evaluation of the new or revised product/service is obtained by computing the optimal hypothetical solution through the experienced status quo. Note that, as explained in the following, the estimated model is subsequently optimized in

order to set the best preference on the basis of the factors and judgments involved.
A further issue about the baseline variables must be outlined. In this proposal we suggest and compare two analyses which differently include the individual information. In the first analysis, baseline variables are included in the model (1) as explained before; if a baseline variable is qualitative, as the gender, this must be considered both in the estimation of the model and in the optimization step, carrying out an optimal surface for each level of the qualitative variable. Nevertheless, this proposal is compared with the consideration of the building of the a-priori strata according to the baseline level variables. In this case, the response surface model (1) does not include the set of variables z which are used to built the strata.
The comparison is not trivial, just because in the first case we may estimate the interaction effects xxz which may add useful information to obtain the full optimal solution; in the second case, where the problem of a qualitative baseline variable is not relevant, the stratification allows to carry out the optimization process within every a-priori stratum.

3.1 Statistical models and optimization

As said in the previous section, our aim is the optimization of the estimated models according to the status quo situation, where each respondent expresses his/her satisfaction about each factor, and about each profile of the experimental design, specifically planned for the conjoint analysis. The expressed rate for each conjoint profile is considered as the response or dependent variable (formulated on a continuous scale); for example, a vote expressed according to the metric scale [0,100] may lead to a valid evaluation of the response as a continuous variable. Therefore, in general, the optimal target score may be defined as the maximum value of the metric scale; in the above example this is equal to 100. Note that the best solution is given by the higher score, close to the maximum value, achieved by each factor in the optimization procedure, considering those factors which are significant in the fitted surface.
Two optimization measures are defined for the optimization process; the first measure is very simple and it is formulated considering the quadratic deviation of the estimated surface $\hat{Y}$ from the maximum score τ. Therefore the formula at minimizing is the following:

$$F_1 = (\hat{Y}(x, z) - \tau)^2 \tag{2}$$

The second optimization measure is defined considering the approaching of $E(\hat{Y})$ to the maximum score; with this spirit we perform the minimization of the variance of $\hat{Y}$ jointly with the approaching to the ideal maximum score. The formula is:

$$minF_2 = var\hat{Y}(x, z) = E((\hat{Y} - E(\hat{Y}))^2 \tag{3}$$

according to the following decomposition of the Mean Square Error (MSE):

$$MSE = E(\hat{Y} - E(\hat{Y}))^2 + (\tau - E(\hat{Y}))^2 \tag{4}$$

$$B(\tau) = (\tau - E(\hat{Y})^2 \tag{5}$$

where the (5) explains the adjustment of the expected score value to the target score, assumed equal to the maximum value.

A further issue is about the computation of $E(\hat{Y})$; this component of the F_2 objective function must be calculated considering the expected values of each effect included in the estimated model.

The optimization procedure, carried out by SAS and proc NLP, is preferably computed using non coded data, just because we are not in a technological context (for further details see Berni et alt., 2006). Note that, as to optimization, the final result expresses the score for each factor involved in the model taking care of the individual judgements about the same factors related to the current situation. Furthermore, the final optimal score for a variable may be explained as the importance/utility of that variable in order to reach the best profile when considering the judgement of the respondent about the current situation (status quo).

3.2 An ad hoc questionnaire

As mentioned previously, the proposal may be carried out through a specific defined procedure of collecting data, called "questionnaire" even though in this case the word "questionnaire" is used to summarized data about the product/service and it is not an organized set of questions. The questionnaire ad hoc here defined is composed by three sections, corresponding to the three different types of structured data.

3.2.1 Baseline variables

In general, there are some aspects we wish to examine and which may have an influence on the expressed judgement of the respondent. We refer to those aspects related to social and demographic characteristics such as gender, age, educational level, income, job status. In fact, there are sensible reasons to believe that such features affect the final results. The way to introduce and to use this information may be carried out by considering the proposal explained in section 3, where two solutions are suggested.
The first way is the insertion of the baseline variables into the statistical model, considering these variables as noise variables; the second one takes into account the stratification of the sample in, say k sub-samples, according to the combinations of the baseline variables involved, and, subsequently, a model for each stratum is applied. The results could help the researcher in order to exploit a more complete knowledge of the reality and to improve the predictive power when the optimization procedure is performed.
In addition, a second reason is the belief that each group could have a different status quo point; this implies, in the estimated corresponding model, a different level of the intercept value, which may be viewed as a different average starting level.
Note that when planning this first section, it is preferable that each baseline variable has a low number of categories, in order to reduce the possible number of strata.

3.2.2 Status Quo

In literature, many researchers provide studies about status quo evaluation towards commodities considering even a price variable. Samuelson et alt.(1988) found that the current situation is positively evaluated by the agent over alternatives (status quo bias). This could be related to the indecisiveness or to people's "fear" about a new kind of product: between the actual, known position and a new proposal, people prefer the first. This is a limitation of a complete rationality in choosing between alternatives: the consumer doesn't maximize his/her utility and gives an over importance to the status quo point (Hartman et al. 1991).

In this paper we refer to the status quo situation as the current situation of the service/product, which must be revised. This situation is evaluated by each respondent (customer or consumer) by expressing a judgement towards some features of the good or service we would like to study. This step can be performed in several ways; in our proposal the best choice is the judgment expressed through a metric scale, the same applied in the CA phase.
In this second section of the questionnaire, the respondent is called to give his/her judgement about his/her overall satisfaction about the current situation and the related degree of "importance at the improvement", based on an inverted scale. In addition, for every attribute involved in the CA step and relevant for the product/service, the respondent must give his/her vote, always in the same scale.

3.2.3 The conjoint analysis step

The third and last section is devoted to the performing the basic CA; as explained in section 2, the fundamental element is the planning of an experimental design and the choice of which factors must be included in it. Nevertheless, in our proposal, this last choice, even though relevant, may be supported by the available a-priori information on the current product/service.
In this work we do not explain the strategy for a good experimental planning, for further details see Box et alt. (1978); however, we wish to point out the relevance of choosing the best Resolution criteria according to the number of factors involved and the interaction effects, if they must be estimated. In addition, the number of level for each factor is preferably low; the best choice is undoubtedly to use a fractional factorial with all factors at two levels, even though a simple technique for a fractional factorial at mixed-levels may also be found in Montgomery (1991).
Note that in our proposal the interaction effect has more relevance with respect the application of the basic CA just because our user/consumer also expresses his/her vote on each single factor; while, when performing the basic CA, the respondent gives his/her judgement only on each full profile.

4 An Empirical Example

In this section our proposal (section 3) is illustrated by an application to real data. Data are described in the first section; the application is shown in sections 4.2 and 4.3; baseline variables are inserted in the estimated models as noise variables (sec.4.2), or, alternatively, they are used to set the a priori strata (sec. 4.3). In every section, model estimates and optimization results are shown.

Table 1: Variable and levels

Variables	-1	1
cb	basic subjects with less theoretical deepening	basic subjects with much theoretical deepening
pl	practice and laboratory as compulsory part of characteristic courses	practice and laboratory only as two distinct courses
ie	one intermediate exam	no intermediate exam
me	oral test with practice	written and oral test
prof	a general degree course in order to continue studies	a more specifical degree course, in order to seek a job

4.1 Data

The main aim is the evaluation of an interdisciplinary degree course of the University of Florence.
As regards the survey, a questionnaire, following the instructions of section 3, is planned and submitted to a sample of $N = 46$ students of the II-nd and III-rd year. The questionnaire is articulated on three parts according to the three different sets of information:(i) baseline variables; (ii) judgements about status quo; (iii) the specific planned experimental design for the basic CA.
Every judgement is expressed on the metric scale $[0, 100]$. The first set of variables is related to the social and demographical data for each student: gender, age, exam average, enrolment status, job status.
In the second part the "status quo" is analyzed according to the specific factors and to three overall scores; we choose five attributes: contents of the basic subjects (cb); practice/laboratory (pl); intermediate examination (ie); exam modalities (me); professional subjects for the future job ($prof$). In addition, three judgements are requested in this section: the overall satisfaction about the degree course, the overall satisfaction about the five factors explained previously and, based on an inverted scale, the degree of importance at improving the degree course.
The third part contains the conjoint study planning through a fractional factorial design 2_R^{5-1} with 16 runs; therefore the full data-set is formed by 736 observations. Obviously, the attributes in the conjoint analysis are the same analyzed in the second part (ii); the

factors levels are showed in table 1.
Furthermore, in the following application, we consider as noise variable the job status of the student (*job*), identified also by case (*i*) working, and case (*ii*) non-working (or by with/without job).

4.2 Models and optimization results; baseline variables as noise variables

As mentioned before, the general model (1) may be estimated considering information about each single respondent. In this example the job status of the student (working; non-working) is considered. Note that this is a qualitative factor. The estimated response surface model is shown in the (6):

$$\begin{aligned} \hat{y}_t = -281.1940484 + cb * (2.3268809) + el * (-1.5397267) + \\ me * (3.0518247) + cb * el * (-0.0091306) + me^2 * (0.0245513) + \\ pi * (4.0353549) + prof * (0.3583258) + cb * pi * (0.0232320) + \\ cb * me * (-0.0466223) + cb * prof * (0.0100306) + el * pi * (-0.0250025) + \\ el * me * (0.0667522) + el * prof * (-0.0167123) + pi^2 * (0.0047992) + \\ me * pi * (-0.0796769) + pi * prof * (0.0190236) + me * prof * (-0.0205509) + \\ cb * job * (-2.6907077) + me * job * (0.2382367) + prof * job * (3.5191637) + \\ pi * job * (-1.0433555) + job * (-44.5289760) + e_t \end{aligned} \quad (6)$$

Estimates with standard error and p-values are displayed in table 2. Note that all the variables are significant, but *prof*, which has a non significant p-value. However, this main effect must be inserted given that it is relevant when considering the interaction effects of *prof* with the other variables, and, above all, with the *ie* variable. In addition, a highly significant p-value results for the interaction effect of *prof* jointly with the noise variable *job*. The same results are observed when considering *ie* and *cb*. The optimization procedure is performed applying the two measures (2) and (3) defined in section (3). The optimization results are described also considering diagnostic results such as: the objective function value (of), the infinity norm of the gradient ($\|x\|_\infty$), the determinant of the Hessian matrix ($|H|$). We have also checked the max-step, i.e. a specified limit for the step length of the line search algorithm, during the first n iterations.
In this first example two surfaces must be optimized, according to the two levels of the baseline variable: working and non-working. The results are shown in tables 3-4; tables 3 and 4 are related to the results about the measure (2) and the measure (3), respectively. We must point out that in this case, even though convergency is always reached and diagnostic results are quite satisfactory, the starting diagnostic results are not perfect. The reason of this problem may be leaded to the kind of data, so different with respect to technological data, where the experimental trials are usually conducted with high

accuracy.
As to this consideration, we must remark that a non controllable variability due to the respondent is implicitly inserted in our data. In fact, in this context, the optimization measure (3) is more relevant with respect to the (2) just because the computation of $E(\hat{Y})$ takes care of non orthogonal data and of the moments values. This is also confirmed when selecting the best fitted models; in this context, including or not a model term may be very relevant for the following optimization procedure.
As to the optimization measure (3) the best solution considers *cb* and *ie* (table 4) as relevant factors for the non-working students. The factor *ie* is included in the final solution also for the working students. The scores are very high for case (ii) : 84.9 and 99.9, respectively. The scores for the optimization measure (2) show very low values for all variables involved, but *ie* and $prof$ in case (ii), table (3). This may be viewed as a higher interest of non-working students versus professional learning. As to case (i),(table 3 and 4), *cb* and *ie* variables are relevant; however, in table 3, scores are low for both variables, 26.8 and 34.5 respectively; while, considering the measure (3), *ie* and *cb* achieve higher scores (42.0 and 56.8, respectively). These solutions allow us to hypothesize a greater consideration of the professional subjects by the non-working student in comparison with the one who works. The optimal solution obtained through the measure (3) confirms the importance of *cb*, *ie*, *prof*, which reach high scores, above all *ie* and *cb*, confirming the results obtained applying the (2) and the previous considerations about the relevance of computing $E(\hat{Y})$.

4.3 Models and optimization results; baseline variables in order to set a-priori strata

The response surface models, (7) and (8), fitted within each stratum of the job status, are shown in tables 5 and 6; in this context we have two models, one for each level of the baseline variable.

$$\hat{y}_t = -161.3623597 + cb * (-0.6099043) + pl * (7.4554833) + prof * 0.8322904 + pl^2 * (-0.0659864) + e_t \tag{7}$$

$$\hat{y}_t = 40.87917248 + cb * (0.98167124) + prof * (-0.48634975) + cb * prof * (0.02351825) + cb^2 * (-0.01658105) + prof^2 * (-0.01039676) + e_t \tag{8}$$

The results about the working students are shown in table 5; *prof*, *cb* and *pl* are significant. The estimated model related to the non-working students (table 6) allows us to confirm a large interest towards *cb* and *prof*. Furthermore, *prof* is a common relevant variable within each stratum; *pl* is relevant when considering the working students, while *cb* is more relevant for the students without a job, which express a great interest towards the basic courses in conjunction with more professional tools.
As regards the optimal results, (tables 7-8), the diagnostic measures are always good, even

though the results obtained through the (3) have a high objective function value; this can be explained considering the order of magnitude, or intensity, of our data. In fact the values of $|H|$ are very good. As to the working students, the optimization measures (2) and (3) confirm the previous consideration, with *pl* and *prof* as factors with the highest scores. Within non-working students, *prof* is confirmed as relevant variable together with *cb*, confirming the propensity of the non-working student towards studying. In this case, the *prof* score is lower with respect to the *cb* value and with respect to its corresponding score, achieved within the other stratum, where *prof* gains the maximum value.
These results are very satisfactory also considering the meaning of the final optimal score for a variable, which may be explained as the utility of that variable in order to reach the best profile when considering the current situation (status quo).

5 Concluding Remarks

In this paper RSM is combined with CA in order to reach the best theoretical profile by considering the status quo situation. In addition, qualitative variable related to the respondent are involved in our proposal in order to evaluate the subjective component for each respondent when he/she expresses his/her judgements.
The baseline variables are inserted as noise variables or are used for building a-priori strata.
The proposal is also evaluated through an empirical example and the results are quite satisfactory, as to the estimated response surface models and the optimization results. The insertion of the categorical variable job status as noise variable leads to interesting results, just because it allows the evaluation of the hypothetical scores for the significant factors together with the inclusion of the information about this structural variable.
Nevertheless, we wish point out that this is a first attempt of combining the two methodologies and further improvements could be introduced, above all when considering the optimization measures suggested.

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Table 2: Model estimates; job status as noise variable

Parameter	Estimate	Stand Error	t Value	p-value
Intercept	-281.1940484	47.863	-5.87	<0.0001
cb	2.3268809	0.751	3.10	0.0020
pl	-1.5397267	0.705	-2.18	0.0293
me	3.0518247	0.843	3.62	0.0003
ie	4.0353549	0.667	6.05	<0.0001
prof	0.3583258	1.069	0.34	0.7375
job	-44.5289760	24.862	-1.79	0.0737
cb*pl	-0.0091306	0.004	-2.23	0.0262
cb*ie	0.0232320	0.005	4.43	<0.0001
cb*me	-0.0466223	0.011	-4.17	<0.0001
cb*prof	0.0100306	0.008	1.30	0.1958
cb*job	-2.6907077	0.359	-7.49	<0.0001
pl*ie	-0.0250025	0.004	-5.76	<0.0001
pl*me	0.0667522	0.012	5.41	<0.0001
pl*prof	-0.0167123	0.006	-2.99	0.0029
me^2	0.0245513	0.007	3.76	0.0002
me*ie	-0.0796769	0.011	-7.02	<0.0001
me*prof	-0.0205509	0.011	-1.91	0.0565
me*job	0.2382367	0.154	1.54	0.1232
ie^2	0.0047992	0.004	1.31	0.1909
ie*prof	0.0190236	0.005	3.76	0.0002
ie*job	-1.0433555	0.218	-4.79	<0.0001
prof*job	3.5191637	0.430	8.18	<0.0001

Table 3: Optimization by measure (2). Job status as noise variable

Results	measure(2); case (i)	measure(2); case (ii)
Best score	cb=26.76; pl=0; me=0; ie=34.50; prof=0	cb=7.01; el=2.00; me=4.00; ie=46.09; prof=59.471427
o.f.	$5.0e-27$	$2.0e-28$
$\|x\|_\infty$	$8.6e-13$	$1.3e-13$
$\|H\|$	$< 10e-8$	$< 10e-8$

Table 4: Optimization by measure (3). Job status as noise variable

Results	measure(3); case (i)	measure(3); case (ii)
Best score	cb=42.04; pl=0; me=0; ie=56.85; prof=0	cb=84.98 pl=0; me=0.06; ie=99.99; prof=22.10
o.f.	$3.2e-27$	$3.2e-25$
$\|x\|_\infty$	7.5e-13	$1.0e-11$
$\|H\|$	$< 10e-8$	$< 10e-8$

Table 5: Model estimates; case (i) working students

Parameter	Estimate	Stand Error	t Value	p-value
Intercept	-161.3623597	31.370	-5.14	<0.0001
cb	-0.6099043	0.232	-2.62	0.0097
pl	7.4554833	1.304	5.72	<0.0001
prof	0.8322904	0.145	5.73	<0.0001
pl^2	-0.0659864	0.011	-5.98	<0.0001

Table 6: Model estimates; case (ii) non-working students

Parameter	Estimate	Stand Error	t Value	p-value
Intercept	40.87917248	15.233	2.68	0.0075
cb	0.98167124	0.362	2.71	0.0069
prop	-0.48634975	0.345	-1.41	0.1587
cb*prof	0.02351825	0.004	5.94	<0.0001
cb^2	-0.01658105	0.003	-4.92	<0.0001
$prof^2$	-0.01039676	0.003	-4.02	<0.0001

Table 7: Optimization by measure (2). Job status as stratification variable

Results	measure(2); case (i)	measure(2); case (ii)
Best score	cb=0.129066; pl=73.566046; prof=84.212416	cb=65.770543; prof=50.999462
o.f.	8.1e-28	1.5e4
$\|x\|_\infty$	1.3e-13	2.1e-14
$\|H\|$	$< 10e-8$	8.4e-1

Table 8: Optimization by measure (3). Job status as stratification variable

Results	measure(3); case (i)	measure(3); case (ii)
Best score	cb=5.70E-17; pl=56.49; prof=100.00	cb=65.77; prof=51.00
o.f.	2.7e4	3.4e2
$\|x\|_\infty$	2.1e-9	3.6e-15
$\|H\|$	$< 10e-8$	1.9e-2