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THE NONSTANDARD ALGORITHM FOR CONSTRUCTING EFFICIENT CONJOINT EXPERIMENTAL DESIGNS

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Abstract: Conjoint analysis is a research technique for measuring consumer preferences, and it is a method for simulating consumers' possible reactions to changes in current products or newly introduced products into an existing competitive market. One of the most critical steps in Conjoint analysis application is experimental designs construction. The purpose of an experimental design is to give a rough overall idea as to the shape of the experimental response surface, while only requiring a relatively small number of runs. These designs are expected to be orthogonal and balanced in an ideal case. In practice, though, it is hard to construct optimal designs and thus constructing of near optimal and efficient designs is carried out.

There are several ways to quantify the relative efficiency of experimental designs. The choice of measure will determine which types of experimental designs are favoured as well as the algorithms for choosing efficient designs. In this paper it is proposed the algorithm which combines one standard and one non-standard optimality criteria. The computational experiments were made, and results of comparison with algorithm implemented in commercial package SPSS confirm the efficiency of the proposed algorithm.

Keywords: Conjoint analysis, experimental design, efficiency, optimality criteria, algorithm, MCON software.

1. INTRODUCTION

Attractiveness of the preference measuring techniques and its usage in practice has been rapidly increased in the last few years. The practical significance of these techniques derives from their widespread use for new product or concept development

and valuation studies in such diverse areas as marketing, transport and financial services etc. In marketing research, for example, preference measuring techniques may provide an answer to questions as to which product will be successful or which attributes of a product drive the purchase decision and may thus serve as a valuable aid for managerial decision. One method that has become particularly popular in this context is Conjoint analysis.

Conjoint analysis is a decomposition method which assumes that product/services can "break-down" into their attributive components and which implies the study of joint effects of products' variety attributes on their preference.

In Conjoint analysis, respondents have to evaluate a set of alternatives that are represented by factorial combinations of the levels of certain attributes. In traditional Conjoint approach, the alternatives have to be rank ordered or rated on some graded scale. It is assumed that these preference judgments are based on the overall utility values of the considered profile's levels. These unknown parameters are then estimated from the data. If the data consists of ranking techniques from linear programming, non–metric versions of ANOVA can be used. Metric conjoint analysis comprises variants of conjoint analyses that use rating scales. Here, the utility values are usually estimated by the least squares procedures. Because of the metric response format and the linear relationship between preference judgments and attributes it is especially this type of conjoint analysis that can be readily applied to the optimal design theory techniques.

The quality of statistical analysis heavily depends on the alternatives presented in the experimental design. An experimental design is a plan for running an experiment. Experiments are performed to study the effects of the factor levels on the dependent variable. The factors of an experimental design are variables that have two or more fixed values or levels of the factors. In Conjoint analysis, the factors are the attributes of the hypothetical products or services, and the response is either preference or choice.

Using all combinations of attribute levels, i.e. a full factorial design, the number of evaluations required from every respondent soon becomes prohibitively large along with the number of attributes and/or levels increased. To deal with this problem, the application of formal experimental designs was suggested. Green (1974) as well as Green et al. (1978) proposed the use of orthogonal arrays, incomplete block designs and fractional factorial designs of different resolutions to reduce the number of evaluations to be performed. In this reduction process the goodness of the reduced designs is especially important. This goodness is named efficiency.

There are several ways to quantify the relative efficiency of experimental designs. The choice of measure will determine which types of experimental designs are favoured as well as the algorithms for choosing efficient designs. This paper proposes algorithm which combines two types of efficiency measures to constructing experimental designs.

The paper is organized as follows. Section 2 illustrates some of the fundamental concepts in Conjoint experimental design including standard factorial designs, as well as fractional factorial designs, orthogonal arrays and nonorthogonal designs. Design terminology introduces while design efficiency explains. Some standard algorithms for constructing efficient experimental designs are presented too. In Section 3 it is proposed the new algorithm which combines one standard and one non-standard optimality criteria for constructing efficient experimental designs. Finally, results of comparing algorithm efficiency with the efficiency of algorithm implemented in SPSS are presented in Section

4. The computational experiments confirm the efficiency of proposed new algorithm. In Section 5 conclusions are given.

2. CONJOINT EXPERIMENTAL DESIGN

The design of experiments is a fundamental part of Conjoint analysis. Experimental designs are used to construct the hypothetical products or services. A simple experimental design is the full-factorial design, which consists of all possible combinations of the factors levels. These combinations in Conjoint analysis are referred as profiles or concepts. For example, with five factors, two at two levels and three at three levels (denoted as $2^2 3^3$), there are 108 possible combinations. In a full-factorial design, all main effects, two-way interactions, and higher-order interactions are estimable and uncorrelated. The problem with a full-factorial design is that it is, for more practical situations, too cost-prohibitive and tedious to have subjects rate in all possible combinations. For this reason, researchers often use fractional-factorial designs, which have fewer runs than full-factorial designs. The basic difficulty is how to construct such fractional-factorial design which can provide worth data. In order to obtain valuable and reliable data, two basic principles must be taken into account: orthogonality and balance.

A design is orthogonal if all effects can be estimated independently from all other effects, and it is balanced when each level occurs equally often within each factor, which means the intercept is orthogonal to each effect. In ideal case experimental design is orthogonal and balanced, hence optimal [7]. This is the case in full-factorial designs.

However, orthogonal designs are available for only a relatively small number of very specific problems. They may not be available from the following reasons [6]:

When an orthogonal design is not available, nonorthogonal designs must be used. The measure of experimental design's quality is referred as "efficiency". In efficient experimental designs both variance and covariance of estimated parameters are minimal. Some orthogonal designs are not always more efficient than the other orthogonal or nonorthogonal designs.

Before the design is used, it must be coded [3]. One standard coding is the binary or dummy variable or (1, 0) coding. Another standard coding is effects or deviations from means or (1, 0,-1) coding. However, for evaluating design efficiency, an orthogonal coding is the most appropriate. This is because standard no orthogonal coding such as effects or binary is generally correlated, even for orthogonal designs. One of the standard ways to orthogonally coding data is Chakravarty's coding [3]. The other method is called the Helmert's procedure [11].

2.1. Optimality Criteria

Efficiencies are measures of design goodness. An optimality criterion is a single number that summarizes how good a design is, and it is maximized or minimized by an optimal design. In order to generate an efficient design, specific methodology was developed. Efficient designs can be efficient for one criterion and less efficient for another one. There are some standard criteria for measuring efficiency of experimental design in Conjoint analysis [7]. Two general types are: *information-based* criteria and *distance-based* criteria.

Consider the linear model where consumers provide utility scores, y_j, for each profile:

$$y_j = \alpha + \beta_1 x_{1j} + \beta_2 x_{2j} + \ldots + \beta_m x_{mj} + \varepsilon_j \quad (1)$$

for $j = \{1,...,n\}$, where x_{ij} are independent variables. In matrix notation equation (1) can be written as $\mathbf{y} = \alpha + \beta\mathbf{X} + \boldsymbol{e}$. Let $\mathbf{X}$ is the orthogonally coded design matrix of independent variables. The information-based criteria such as D- and A-optimality are both related to the information matrix $\mathbf{X'X}$ for the design. This matrix is important because it is proportional to the inverse of the variance-covariance matrix for the least-squares estimates of the linear parameters of the model. Roughly, a good design should "minimize" the variance $(\mathbf{X'X})^{-1}$, which is the same as "maximizing" the information $\mathbf{X'X}$. D- and A-efficiency are different ways of saying how large $(\mathbf{X'X})$ or $(\mathbf{X'X})^{-1}$ are.

For the distance-based criteria, the candidates are viewed as comprising a point cloud in *p*-dimensional Euclidean space, where *p* is the number of parameters in the model. The goal is to choose a subset of this cloud that "covers" the whole cloud as uniformly as possible or that is as broadly "spread" as possible.

D-optimality is based on the determinant of the information matrix for the design, which is the same as the reciprocal of the determinant of the variance-covariance matrix for the least-squares estimates of the linear parameters of the model.

$$(\mathbf{X'X}) = 1/|(\mathbf{X'X})^{-1}| \quad (2)$$

The determinant is thus a general measure of the size of $(\mathbf{X'X})^{-1}$. D-optimality is the most common criterion for computer-generated optimal designs.

A-optimality is based on the sum of the variances of the estimated parameters for the model, which is the same as the sum of the diagonal elements, or trace, of $(\mathbf{X'X})^{-1}$. Like the determinant, the A-optimality criterion is a general measure of the size of $(\mathbf{X'X})^{-1}$.

For both criteria, if a balanced and orthogonal design exists, then it has optimum efficiency; conversely, the more efficient a design is, the more it tends toward balance and orthogonality. Assuming an orthogonally coded $\mathbf{X}$:

- A design is balanced and orthogonal when $(\mathbf{X'X})^{-1}$ is diagonal.
- A design is orthogonal when the sub matrix of $(\mathbf{X'X})^{-1}$, excluding the row and column for the intercept, is diagonal; there may be off-diagonal nonzero for the intercept.
- A design is balanced when all off-diagonal elements in the intercept row and column are zero.
- As efficiency increases, the absolute values of the diagonal elements get smaller.

For appropriate coded matrix $\mathbf{X}$, measures of efficiency can be scaled to bi in interval 0 to 100. For Helmert's coded data (matrix) it is more appropriate to use A optimality criterion:

$$A-eff = 100 \times \frac{1}{N_D \cdot \mathrm{tr}(\mathbf{X}'\mathbf{X})^{-1} / p} \tag{3}$$

When data are coded by Chakravarty's procedure, it is more appropriate to use D optimality criterion:

$$D-eff = 100 \times \frac{1}{N_D \mid (\mathbf{X}'\mathbf{X})^{-1} \mid^{1/p}} \tag{4}$$

In the equations (3) and (4), p is number of parameters in model. The total number of parameters to be estimated is given by the formula: *total number of levels – number of attributes* + 1. N_D is number of runs (profiles) in fractional factorial design specified by the user. It is suggested, when possible, including between two to three times the numbers of runs as parameters estimated. However, design efficiency is not the only reason for including two to three times as many runs as parameters to be estimated. All real-world respondents answer conjoint questions with some degree of error, so those observations beyond the minimum required to permit utility estimation are needed to refine and stabilize utility estimates.

These optimality criteria measure the goodness of the design relative to hypothetical orthogonal designs that may be far from possible, so they are not useful as absolute measures of design efficiency. Instead, they should be used relatively, to compare one design to another for the same situation. Efficiencies that are not near 100 may be perfectly satisfactory.

2.2. Come Standard Algorithms for Constructing Efficient Conjoint Designs

As mentioned above, finding exact optimal designs is hard. Finding exact optimal designs in general requires solving a large nonlinear mixed integer programming problem, as the number of feasible designs explodes rapidly as the number of factors and levels increases. But we live in the real world, and we don't need absolute best design, but the one that is good enough. This is where approximation algorithms come in.

One of most simple algorithms for generating information-efficient designs is Dykstra's (1971) sequential search method [6]. The method starts with an empty design and adds candidate points so that the chosen efficiency criterion is maximized at each step. This algorithm is fast, but it is not very reliable in finding a globally optimal design. Also, it always finds the same design.

A typical approximation algorithm seeks to locate a good solution by the following sequential process [12]:

1. Choose initial feasible solution (random/greedy)
2. Modify solution slightly (random/greedy)
3. Repeat 2. until finished, then report best solution seen

Random methods modify the current solution in some random way, and this change is accepted or rejected via some decision routine. Even worse solutions may be accepted under certain decision routines. Simulated annealing is an example of a random approximation algorithm.

Greedy methods modify the current solution in a way that improves the score; as they are seeking to improve every iteration score for of the process they are frequently referred to as hill climbing algorithms.

One large class of pure greedy algorithms for generating efficient designs is the exchange algorithms. Exchange algorithms hill climb by adding new design points and removing the existing design points to improve the objective. There are both Rank-1 and Rank-2 exchange algorithms, and these classifications are based on how the algorithm changes the points in the current candidate design matrix [12]:

Rank-1: Choose points to add and delete sequentially (Wynn, DETMAX)

Rank-2: Choose points to add and delete simultaneously (Fedorov, modified Fedorov, *k*-exchange, *kl*-exchange)

Although the Mitchell and Miller (1970) simple exchange algorithm is slower than Dykstra's, it is a more reliable method. It improves the initial design by adding a candidate point and then deleting one of the design points, stopping when the chosen criterion ceases to improve. The DETMAX algorithm of Mitchell (1974) generalizes the simple exchange method. Instead of following each addition of a point by a deletion, the algorithm makes excursions in which the size of the design may vary. These algorithms add and delete points one at a time.

The next two algorithms add and delete points simultaneously, and for this reason they are usually more reliable for finding the truly optimal design; but because each step involves a search over all possible pairs of candidate and design points, they generally run much slowly. The Fedorov (1972) algorithm simultaneously adds one candidate point and deletes one design point. Cook and Nachtsheim (1980) define a modified Fedorov algorithm that finds the best candidate point to switch with each design point. The resulting procedure is generally as efficient as the simple Fedorov algorithm in finding the optimal design, but it is up to twice as fast.

The standard philosophy in approximation algorithms is that many small steps are generally better than fewer but larger steps. This is precisely the idea behind the coordinate-exchange algorithm, which follows the procedure:

1. Choose *k* least critical points
2. Examine each point for the best coordinate to exchange
3. Make this best coordinate exchange.

The coordinate exchange algorithm of Meyer and Nachtsheim (1995) does not use a candidate set [13]. Instead it refines an initial design by exchanging each level with every other possible level, keeping those exchanges that increase efficiency. In effect, this method uses a virtual candidate set that consists of all possible runs, even when the full-factorial candidate set is too large to generate and store.

Some researchers have proposed nonstandard algorithms and criteria for constructing efficient experimental design [6]. Steckel, DeSarbo, and Mahajan (SDM) (1991) proposed using computer-generated experimental designs for conjoint analysis in order to exclude unacceptable combinations from the design. They considered a nonstandard measure of design goodness based on the determinant of the (*m*-factor × *m*-factor) correlation matrix (|**R**|) instead of the customary determinant of the (*p*-parameter × *p*-parameter) variance matrix $(\mathbf{X}'\mathbf{X})^{-1}$. The SDM approach represents each factor by a single column rather than as a set of coded indicator variables.

3. THE PROPOSED ALGORITHM

The basic idea behind the algorithm proposed here is to generate random initial design and than remove and add points simultaneously in order to obtain more efficient design. The algorithm has the following features:

1. The variables (attribute levels) may be numeric or symbolic.
2. The number of runs is specified arbitrary by the user.
3. The user has control over how much effort is expended by the algorithm, and can if desired monitor the progress of the search. It is not necessary to specify initial points for the search.
4. The algorithm combines two measures of design goodness: A-efficiency and P-value.

Optimality criterion A-efficiency we discussed earlier. There are at least two reasons for using P-value as the second optimality criterion. First, it enables faster convergence to the optimal solution. Second, it is observed that two designs with the same A-efficiency can be differentially balanced. Thus, this criterion serves to choose a better balanced one.

P-value presents the return of F probability distribution. That is probability that there are not significant differences between the variances of columns in coded matrix **X**. In other words, P-value can be used to determine whether parameters in orthogonally coded matrix **X** have different degrees of diversity. P can take any value in interval [0,1]. Low values of P indicate that design has great unbalanced attribute levels. This value will be low even if some of attributes have perfect balanced levels, while some other have extreme unbalanced levels. By improving of balance in sense of quantity and homogeneity, the P-value is also increased. If P-value is equal to one, it can mean either all levels are completely balanced or there are unbalanced levels which are consistently distributed.

The algorithm is based on the following: The solution will be accepted (change will be made) only if it is equally good or better then the existing one, considering the least one of the criteria. The underlying rationality is: Existence of unbalance has an impact on efficiency but still serves as guideline to detect the list of appropriate and inappropriate candidates while enabling convergence to the better solution (design).

The algorithm proceeds as follows:

Step 0 (Initialization):
Specify the number of iterations (NI) and number of runs (profiles) N_d
Set A efficiency to zero, $A_i = 0,$ and set $i = 0$
Step 1 (Generation of initial solution**):**
Randomly generate initial solution $\mathbf{X}_0$ ($N_d \times p$ matrix)
Step 2 (Calculation of initial solution efficiency)
Calculate A_i, F_i, P_i for initial matrix $\mathbf{X}_0$
Step 3 (Estimation of initial solution efficiency)
IF $A_0 = 100$ and $P = 1$ design $\mathbf{X}_0$ is optimal. GO TO Step 5.
ELSE set i =1. Go to Step 4

Step 4: (Iterative procedure for finding better solution)

a) Detect the worse balanced column in matrix $\mathbf{X}_i$ (i.e. column with high value of absolute sum of elements)
b) Generate the list of candidate rows for excluding from existing (current) design (LE). Good candidates are those which levels affect on existing of unbalance
c) Generate the list of candidate rows for adding to the design (LA). Good candidates are those rows that can improve balance of design
d) Choose randomly one row from LE list and remove from the design. IF list LE is empty, GO TO Step 4a.
e) Choose randomly one row from LA list and add to the design. One candidate can be considered once in the current iteration. IF list LA is empty, GO TO Step 4a.
f) Solve A_i and P_i
g) IF $A_i \geq A_{i-1}$ or $P_i \geq P_{i-1}$ make exchange. Current solution (design) is matrix $\mathbf{X}_i$. GO TO Step 4h. ELSE GO TO Step 4e.
h) IF i = NI or IF $A_i = 100$ and $P = 1$, GO TO Step 5. ELSE Set $i = i + 1$, GO TO Step 4

Step 5: Efficient experimental design is current matrix $\mathbf{X}_i$. END**.**

Since the initial design has been generated randomly, each time we start the procedure, different design for the same date will be obtained. If the procedure will repeat several times, the best suitable solution (design) can be chosen.

4. COMPUTATIONAL EXPERIMENTS

The algorithm proposed in previous section was implemented in Visual Basic Application as the procedure for experimental design constructing, in the software named MCON. This software consists of:

1. Form for data input (attributes and attribute levels defining)
2. Module for orthogonal data coding according to Helmert's procedure.
3. Procedure for experimental designs construction.
4. Procedure for solving part-worths of attributes' levels and attributes' importance.
5. Module for market simulation.

The power of the proposed algorithm and MCON software was tested on numerous examples. Using A-optimality and attribute levels' balance criteria, the efficiency of constructed designs ware compared with efficiency of the designs constructed by SPSS Conjoint algorithm.

The following examples present some of the results.

Example 1. Let us consider an example with five attributes with 3, 4, 3, 2, and 2 levels respectively. Here full-factorial design consists of 144 profiles (3x4x3x2x2=144). Saturated design consists of 10 profiles ((3+4+3+2+2)–5+1=10), while recommended

number of profiles in design is between 15 and 30. The features of designs constructed by proposed algorithm as well as of those constructed by SPSS algorithm are shown in Table 1.

Table 1: Experimental results for Example 1

Number of profiles	F critical	SPSS			MCON		
		A	F	P	A	F	P
12	2.0333				85.0155	0	1
14	2.0185				82.5527	0.0490	0.99994
15	2.0126				86.0423	0.0545	0.09999
16	2.0076	91.7611	0.52500	0.83607	89.0611	0.0117	0.99999
					88.3294	0.0406	0.99999
18	1.9990				92.7027	0.0268	0.99999
					88.4320	0.1068	0.99893
20	1.9929				89.7209	0.0346	0.99998
24	1.9833				92.0730	0.1296	0.99999
					90.2650	0	1
25	1.9814	89.6047	0.50625	0.85094	94.4193	0.0001	1
					90.0875	0.2065	1
32	1.9717	91.7611	1.08500	0.37365	94.0762	0.0171	0.99999
					92.7915	0.0061	0.99999

The first column in the Table 1 shows the number of profiles in experimental design arbitrarily chosen. The second column contains F-critical values for designs with various numbers of profiles. This value serves for testing hypothesis of variance diversity. Column A shows values of the designs' A-efficiency. Column F indicates existence of unbalance in design. When this value is equal to zero, the design is completely balanced. Column P-value indicates uniformity of unbalance in experimental design. If this value is near to 1 it means that the design is uniformly balanced.

As it can be seen from Table 1, MCON software has constructed high efficient and well-balanced designs, no matter whether the dimensions of design are specified. Efficiency of all of constructed designs is greater than 82%, while for some of them (designs with 18 and 24 profiles) have reached A-efficiency greater than 90%. In all of these designs, very low and uniformly distributed unbalance of attribute levels exists (F is close to 0 and P value is close to 1). Especially, design with 12 profiles is completely balanced with high efficiency (85%), while completely balanced design with 24 profiles reaches efficiency greater than 90%.

Most efficient design, constructed by MCON software consists of 25 profiles. A-efficiency of this design is equal to 94.42% and design has only one unbalanced level.

In other hand, SPSS has constructed only the designs with specific number of profiles (16, 25 and 32). These designs are high A-efficient but tend to be highly unbalanced.

Furthermore, highly efficient designs constructed by SPSS are those with 16 and 32 profiles. Their A-efficiency is 91.76%, but both of them are extremely unbalanced. Moreover, only the 16-profiles design constructed by SPSS is more A-efficient than that

one constructed by MCON. Actually, for 25 and 32-profile designs, MCON was constructing more efficient and better balanced designs.

Example 2: Let us now consider somewhat larger five attributes example with 2, 2, 3, 4, and 4 levels respectively. Here full-factorial design consists of 192 profiles; saturated design consists of 11 profiles, while recommended number of profiles is between 20 and 33. Results of comparisons of SPSS designs with MCON designs are given in Table 2.

Table 2: Experimental results for Example 2

Number of profiles	F critical	SPSS			MCON		
		A	F	P	A	F	P
12	1.9660				72.0015	0.03718	0.99999
16	1.9428	96.1538	0.25424	0.98526	84.4061	0.00713	1
					81.0580	0.00891	1
24	1.9207				91.3267	0.01090	1
					88.7010	0	1
25	1.9190	87.7639	0.82474	0.59388	91.2385	0.00028	1
28	1.9146				93.1203	0.00418	1
					89.1572	0.00418	1
32	1.9101	96.1538	0.52542	0.85587	93.8371	0.00458	1
					92.5821	0.00366	1
36	1.9066				94.1552	0	1

Again, MCON software has constructed high efficient and well-balanced designs, no matter the dimensions of design are, while SPSS had constructed only the designs with specific number of profiles.

Efficiencies of all of the designs constructed by MCON software, except of design with 12 profiles, are greater than 84%, while for most of them have reached A-efficiency greater than 90%. Highly efficient designs constructed by MCON software is 36-profiles design. Its A-efficiency is equal to 94.15%, and it is completely balanced. 24-profiles design is completely balanced, too, but its A-efficiency is somewhat less (88.7%).

Highly efficient designs constructed by SPSS are again those with 16 and 32 profiles. Their A-efficiency is 96.15%, but both are more unbalanced than the designs constructed by MCON software. Particularly, MCON software was construct well-balanced 25-profiles design with efficiency equal to 91.24% (against the efficiency of design constructed by SPSS which is equal to 87.7%).

According the experimental results presented above, following conclusions can be derived:

SPSS Conjoint can construct only the designs with specific number of profiles, but often in practice there is a need for various dimensions of designs. This weakness of SPSS procedure is result of orthogonal design nature. Another effect of using ovly orthogonality as criteria for constructing experimental design in SPSS procedure is that these designs are often extremely unbalanced.

Proposed Algorithm can construct the high efficient and well-balanced designs with arbitrary number of profiles. Constructed designs are always better balanced and in many

cases has higher A-efficiency than designs constructed by SPSS. This is results of using additional optimality criteria, P-value.

6. CONCLUSION

Conjoint analysis has been widely used method for measuring customer preferences since 1970s. This method is based on the idea that customers' decisions depend on all tangible and intangible product features.

One of the fundamental steps in performing Conjoint analysis is the construction of experimental designs. These designs are expected to be orthogonal and balanced in an ideal case. In practice, though, it is hard to construct optimal designs and thus constructing of near optimal and efficient designs is carried out. Efficient designs are typically nonorthogonal; however they are efficient in the sense that the variances and covariances of the parameter estimates are minimized.

There are several ways to quantify the relative efficiency of experimental designs. The choice of measure will determine which types of experimental designs are favoured as well as the algorithms for choosing efficient designs. In this paper we have presented some standard optimality criteria for measuring design efficiency, as well as some widely used algorithms for constructing such efficient designs. These algorithms are typically approximate and can be random or greedy, sequential or simultaneous.

We have proposed a simultaneous algorithm which combines two optimality criteria: standard criterion named by A-efficiency, and nonstandard criterion, P-value in ANOVA. The algorithm was implemented in Visual Basic application, as the procedure in MCON software. The computational experiments were made and results are compared with results of SPSS procedure. The obtained results confirm the proposed algorithm effectiveness. The results show that it is very useful to use two optimality criteria to find efficient experimental design. The designs obtained by the proposed algorithm are not just highly efficient but they are also well-balanced.

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