Paper

# Supporting telecommunication product sales by conjoint analysis

Piotr Rzepakowski

**Abstract—Conjoint analysis is widely used as a marketing research technique to study consumers' product preferences and simulate customer choices. It is used in designing new products, changing or repositioning existing products, evaluating the effect of price on purchase intent, and simulating market share. In this work the possibility of conjoint analysis usage in telecommunication filed is analyzed. It is used to find optimal products which could be recommended to telecommunication customers. First, a decision problem is defined. Next, the conjoint analysis method and its connections with ANOVA as well as regression techniques are presented. After that, different utility functions that represent preferences for voice, SMS, MMS and other net services usage are formulated and compared. Parameters of the proposed conjoint measures are determined by regression methods running on behavioral data, represented by artificially generated call data records. Finally, users are split in homogenous groups by segmentation techniques applied to net service utilities derived from conjoint analysis. Within those groups statistical analyses are performed to create product recommendations. The results have shown that conjoint analysis can be successfully applied by telecommunication operators in the customer preference identification process. However, further analysis should be done on real data, other data sources for customer preference identification should be explored as well.**

***Keywords— decision analysis, multiple criteria analysis, utility theory, preference measurement, conjoint analysis, consumer behavior, purchase intent, marketing, marketing tools.***

## 1. Introduction

Selling is a practical implementation of strategies derived from marketing. One of them is loyalty management approach that is commonly used by telecommunication companies. Usually, loyalty programs are organized for but to remain competitive on deregulated market, other tasks like product recommendation should be done to maximize customer satisfaction. People who are satisfied with product usage are also loyal, since they do not need to change product supplier.

There is a permanent price reduction of telecommunication services and new products are launched so often that customers are not able to analyze all possibilities regularly and find the best products for themselves. Therefore, methods for preference identification should be developed to support telecommunication operator consultants with tools for products and services recommendation. In this work we have used conjoint analysis (CA) method to identify preferences of telecommunication customers. Contrary to the original method, instead of making a questionnaire, behavioral data were used to find real preferences not declared ones.

The paper is organized as follows. In Section 2, the basic requirements and customer preferences are reviewed. In Section 3, the optimization problem is explained and methods for problem solving are introduced. Also some assumptions are made to decrease the complexity of the problem. In Section 4, conjoint analysis process is described: the preference function is proposed and the statistical model for preference identification is created. Results are shown in Section 5 and conclusions are made in Section 6.

## 2. Preliminaries

### *2.1. Loyalty*

Deregulation brought new competition that forces telecommunication companies as well as other retailers to implement new sale strategies. Boston Consulting Group indicates ten quality drivers [2] that should be addressed to remain competitive:

- call center,
- complaint management,
- customer communication,
- offer development,
- branding,
- sales channels,
- customer understanding,
- loyalty,
- e-utility.

Good practices where divided into three stages: “mastering the basics”, “rising the bar” and “changing the game”. At the beginning “mastering the basics stage” the first four dimensions are most important. At the second stage offer development, branding and sales channels are essential. However, in deregulated, full competitive markets deep customer understanding, loyalty and e-utility must be addressed to have a real chance in the competition.

The role of loyalty is increasing owing to wide range of benefits. Loyal customer:

- provides positive advertising through his recommendations to family and friends,
- is more receptive to cross-selling,
- provides company with feedback,
- tends to be more profitable.

### *2.2. Customer preferences*

Because customer's loyalty depends on the satisfaction he gets from product and service usage, delivered goods should not only be of good quality but also should be well suited to user requirements. That leads marketing departments to research activity for identification and anticipation of clients' needs. Research results are used to design new products and deliver attractive goods to consumers. Attractive products are those which have sufficient functionality and acceptable price. Therefore, products of lower price and suited to user needs should be recommended. Paradoxically, telecommunication companies should take care about customers recommending cheapest products of that which are functionally acceptable. Customers should be sure that they do not pay extra money for not used additional features.

Two customer preference groups can be distinguished: real preferences and declared ones. Real preferences can be derived directly from information about bought products, services and product usage. However, that information tells us only about past preferences and is limited to existing products functionality. Declared wishes gathered from questionnaires, contrary to real preferences, give additional information about future needs and are not restricted to existing product functionality but do not have to correspond to real ones. Differences in declared and real requirements are caused by uncertainty of results obtained from questionnaires but also by limited information represented in behavioral data. To analyze preferences entirely both real and declared preferences should be considered. Additionally, preferences can also be derived indirectly from demographic, geographic and socioeconomic data connected with user behavior or declared needs. Nevertheless, in this article we restrict analysis to real preferences obtained from behavioral data.

### *2.3. Telecommunication products*

Telecommunication customers pay for net services (voice, short message service (SMS), multimedia messaging service (MMS) and general packet radio service (GPRS)) usage. However, price for services is dissimilar for them. Cheaper services are for users who declare to use services in fixed period or in minimum amount. For example, people who signed contracts have cheaper calls then the others. Cost can be also reduced by additional packages valid for a short period or other products that can be used only in specific time. For example, there are usually accessible packages that reduce call price after working hours or in the weekends. Those additional packages will be called further telecommunication products.

Products are provisioned at the end user level or at the account level. End user is associated with the account and is rated for service usage in the way defined by tariff plan he has. Some products are allowed at discount prices if there were bought other services or products. Moreover, more then one user can be associated with the account. Therefore, if products are installed at the account level they can be used by many users. For all users pays owner of the account who is called customer. Furthermore, there are additional businesses constraints that make some products unavailable at various tariff plans and some products are switched off which means that new installations cannot be made any more.

That is a big challenge for customers to be on time with all promotions and to find the most fitted products for all users on the account. That task requires identification of users' needs and solving a complex optimization problem.

### *2.4. Conjoint analysis*

In this article, usage of conjoint analysis technique is proposed for customers' preference identification. CA is well known in marketing research field and is commonly used to identify consumer preferences from a questionnaire data. It provides preferences in compact form as parameters of the utility function a priori defined by an analyst. CA allows determining relative preference structure that can be easily used to compare clients, make segmentation and profiling. When all of the attributes are nominal, the metric conjoint analysis is a simple main-effect analysis of variance (ANOVA) with some specialized output. The ANOVA problem can be solved using regression techniques what is shown in Section 4.

## 3. Service costs optimization problem

The task is to find optimal set of products individually for each user. Usually a telecommunication operator has dozen million users and more then one hundred products in an offer. Because business constrains complicate the problem some assumptions are made to simplify it.

### *3.1. Business constraints*

Three main groups of business constraints can be distinguished:

1. Tariff plan constraints:
   - user can change the tariff plan he has to a higher one then the one he signed in the contract;
   - old tariffs cannot be used any more.
2. Product constraints:
   - some old products cannot be sold any more;
   - only a few additional products are allowed within particular tariff plan;
   - usage of some products excludes usage of others;

- in some tariff plans users have to choose the demanded quantity of products;
- value of some packages can be defined individually;
- products can be defined on end user level as well as at the account level.

3. Product usage constraints:
   - data are accessible monthly;
   - some users do not make enough connections monthly to analyze the data;
   - users are charged in billing cycles that start on different days of month;
   - to have all information about connections for new users there is a need to analyze at least two months of data;
   - some products can be activated with a delay, for example from the customer billing cycle date.

### 3.2. Assumptions

To simplify the problem optimal products for the end user in his actual tariff plan will be found. Instead of optimal set of products, ranking lists of them will be made using only two months history of outgoing calls.

1. There would only be analyzed services within current users' tariff plans. Changes of tariff plans are not under consideration in this work. Tariff plans can be also treated as other services but to do so additional business knowledge about configuration constraints is required.
2. There would be created recommendation lists of services at the end user level. Also services that cannot be sold any more would be recommended. If some of them cannot be sold or are not allowed in current user tariff plan they will be removed later after creation of the ranking. The removal of services depends only on business constraints and is not taken into consideration in this work.
3. Data from two months will be analyzed and users who make less then 50 calls will be removed, since there is no need to sell them additional products.
4. Only outgoing calls will be analyzed because products reduce only those costs.

### 3.3. Optimization problem

**Indicies:**

$s$ – end user,

$p$ – product,

$a$ – attribute.

**Parameters:**

$S$ – finite and nonempty set of end users,

$P$ – finite and nonempty set of products,

$P_s$ – finite set of products that are available for users,

$D_s$ – finite and nonempty set of call data records (CDR) from one billing cycle of customers,

$A$ – finite and nonempty set of CDR attributes,

$V = \cup_{a \in A} V_a$, $V_a$ is a set of values of attribute $a$, called the domain of $a$,

$F$ – finite and nonempty set of rating function definitions for each product $p$,

$C$ – finite and nonempty set of products' orders.

**Decision variables:**

$x_s$ – finite set of customer products.

**Constraints:**

$s \in S$,

$x_s \subseteq P_s \subseteq P$,

$a \in A$.

**Functions:**

$\rho$ – rating function.

**Objective value:**

$$\min_{x_s} \rho(D_s, x_s, F, C) \quad \forall s \in S. \tag{1}$$

### 3.4. Optimization methods

Decision problem described in the previous section can be solved using:

- optimization techniques,
- simulation techniques or
- statistical analysis and data mining techniques.

Optimization and simulation methods give very good results but are very slow and resource consuming. Checking all combinations of products for dozen million of users would require as much resources of rating infrastructure as telecommunication operator possess multiplied by number of possible product combinations. Simulation is impossible in practice because of huge maintenance costs. On the contrary, optimization techniques are usually faster but also are time and resource consuming. Furthermore, both of those methods require precise knowledge about rating functions $F$ defined for each product and cascade definitions $C$ to apply functions correctly. Often knowledge about those functions is distributed between systems and functions are represented in different ways dedicated for tool and specially formatted data. Costs of data collection and algorithm standardization are very large and in consequence increase maintenance costs of optimization and simulation models to unacceptable level.

Statistical analysis and data mining techniques are less accurate then methods described earlier. However, the precise knowledge about rating functions is not needed and can be practically applicable for huge amount of data. Instead of rating knowledge they use statistical information about cost of service for different users who have installed different products. It is assumed that most of people buy products in order to reduce cost of telephone usage. Only some of them do not have time or they do not want make analysis to find the best products. Nevertheless, people who behave similarly should have analogous sets of products. Thus, the idea is to find similar users and recommend them products which are used most frequently in their group.

We decided to use clustering method and statistical analysis to solve the decision problem. Usually, in model creation process some transformations are performed on input data [8]. We add customer preference identification step to improve analysis. In that additional step conjoint analysis for preference identification is used.

Summing up, there are three main tasks to recommend products:

– user needs identification by conjoint analysis,
– user clustering,
– statistical analysis.

# 4. Conjoint analysis for customer preference identification

Conjoint analysis process consists of [16]:

– selection of utility factors,
– conjoint measure definition,
– conjoint model definition,
– questionnaire preparation,
– questionnaire data acquisition,
– statistical analysis,
– data interpretation.

For utility factors we get some attributes from behavioral data. The questionnaire preparation step is not required because historical data is analyzed. Hence, the questionnaire data acquisition step changes to the behavioral data preparation one.

### *4.1. Selection of utility factors*

Attributes which differentiate the cost of services most were chosen as utility factors. Among them there are: service, location, network, and day types with categories presented in Table 1. Original call data records were transformed to determine chosen attributes. Next, data is aggregated and statistics of call frequencies for each aggregation were calculated.

Table 1
Utility factors

| Attribute | Levels |
|---|---|
| Service | Voice |
| | SMS |
| | MMS |
| | GPRS |
| Location | Home |
| | Roaming |
| Net | To on-net |
| | To off-net (mobile operators) |
| | To fixed (fixed operators) |
| | To international (international operators) |
| Day type | Working days |
| | Weekend or holiday |

### *4.2. Conjoint measure definition*

The dependency between utility factors is defined by the conjoint measure. It consists of intercept coefficient $\mu$ and part-worth utilities associated with attributes $A$. If some attributes are correlated then the interaction between those attributes are added to the conjoint measure. Interactions between pairs are usually enough but sometimes interactions of higher types, for example between three variables are used. An example of conjoint measure defined for three attributes is presented in Eq. (2):

$$\begin{aligned} y \;=\; & \mu+\alpha_{A_1}+\alpha_{A_2}+\alpha_{A_3} \\ & +\beta_{A_1A_2}+\beta_{A_1A_3}+\beta_{A_2A_3} \\ & +\gamma_{A_1A_2A_3}+\varepsilon\,. \end{aligned} \tag{2}$$

In that example part worth utilities are presented by $\alpha$ vectors of utilities for attribute values, $\beta$ vectors of utilities for all combinations of values associated with two attributes and $\gamma$ vector of utilities for combination of values taken from attribute $A_1$, $A_2$ and $A_3$. If all values of part-worth utilities are known then utility value for each call can be counted.

To make the results unique the equation must also fulfill conditions:

$$\sum_{v_a\in V_a}\alpha_{av_a}=0,\quad \forall a\in A\,, \tag{3}$$

$$\sum_{v_a\in V_a}\beta_{abv_av_b}=0,\quad \forall a\in A, \forall b\in A, a\neq b, \forall v_b\in V_b\,, \tag{4}$$

$$\sum_{v_b\in V_b}\beta_{abv_av_b}=0,\quad \forall a\in A, \forall b\in A, a\neq b, \forall v_a\in V_a\,. \tag{5}$$

A similar condition for $\gamma$ parameters has to be defined.

For presented telecommunication task we have compared two measures. One of them consisted of linear terms and correlation between all pairs of attributes. Another one was extended by interactions between three attributes. After the analysis, the second measure with factors presented in Table 2 has been chosen.

Table 2
Conjoint measure factors

| Attribute | Levels |
|---|---|
| Service | 4 |
| Location | 2 |
| Net | 4 |
| Day type | 2 |
| Service*location | 8 |
| Service*net | 16 |
| Service*day type | 8 |
| Location*net | 8 |
| Location*day type | 4 |
| Net*day type | 8 |
| Service*net*day type | 32 |
| Total | 96 |

Finally, conjoint measure presents Eq. (6):

$$\begin{aligned} y \;=\; & \mu \\ & + \alpha_{service} + \alpha_{location} + \alpha_{net} + \alpha_{day\,type} \\ & + \beta_{service*location} + \beta_{service*net} \\ & + \beta_{service*day\,type} + \beta_{location*net} \\ & + \beta_{location*day\,type} + \beta_{net*day\,type} \\ & + \gamma_{service*net*day\,type} \\ & + \varepsilon\,. \end{aligned} \tag{6}$$

### 4.3. Conjoint model definition

Conjoint model is a statistical model that represents dependencies between utility of a profile and its attributes and is defined by Eq. (7):

$$y = \alpha^T x + \varepsilon\,. \tag{7}$$

Now $\alpha$ coefficient represent utilities associated with all conjoint factors $\alpha$, $\beta$ and $\gamma$ defined earlier. Because all of attributes of conjoint measure are categorical, dummy variables $x$ created to represent no metric information. One attribute with $k$ levels was replaced by $k-1$ binary attributes.

After adding dummy variables regression techniques can be used for part worth utilities identification. Dependant variable $y$ in the regression model represents utility of a profile. In analyzed problem it was calculated as probability of making a call which means that it has binomial distribution. That problem cannot be solved simply by linear regression as regression techniques required normal distribution of dependant variable. However, binomial distribution can be simply transformed to the normal one by logit function. In consequence, general linear model (GLM) was defined as

$$\ln\left(\frac{\mathrm{y}}{1-\mathrm{y}}\right) = \alpha^T x + \varepsilon\,, \tag{8}$$

$$y = \frac{\mathrm{e}^{\alpha^T x + \varepsilon}}{1 - \mathrm{e}^{\alpha^T x + \varepsilon}}\,. \tag{9}$$

## 5. Analytical results

### 5.1. Conjoint analysis

To make analysis we generated artificial CDR for 1000 users. The data were transformed in statistical analysis software (SAS) to prepare full profile ranking lists. Using SAS procedure TRANSREG [12] conjoint model was fitted individually for each user. The attributes were automatically coded to binary variables by that procedure. As a result we get relative importance of the attributes for each user and the part worth utilities connected with attribute values. The relative importance of each attribute was calculated from the utilities of attributes as [16]

$$I_a = \frac{\max_{v_a}\{U_{av_a}\} - \min_{v_a}\{U_{av_a}\}}{\sum\limits_{a\in A}(\max_{v_a}\{U_{av_a}\} - \min_{v_a}\{U_{av_a}\})}\,, \tag{10}$$

where:

$U_{av_a}$ – part worth utility associated with $v$-value of $a$-attribute,

$v_a$ – value of attribute $a$.

Analytical results are presented for two models:

– logit II: GLM model with logit transformation on dependant variable, linear term and interactions between all attribute pairs;

– logit III: logit II + the interaction of three variables: service, net and day type.

Comparison of average relative importance of conjoint model attributes and standard deviation statistics for two models are presented in Table 3. The service*net*day type attribute is quite significant in the model and statistical tests confirm that all coefficients are significantly greater then zero. However, standard deviations have similar values to averages what means that user groups are not homogenous. People in population behave differently: use different services, prefer different nets and make calls in different days.

Statistics presented in Table 4 shows that both logit II and logit III models are well filled to data. Average value of $R^2$ is 99% and standard deviation is very low. The worst

Table 3
Relative importance statistics in population

| Attribute | Logit II | | Logit III | |
|---|---|---|---|---|
| | avg | std | avg | std |
| Service | 21.0 | 15.2 | 20.1 | 14.9 |
| Location | 1.0 | 5.0 | 1.0 | 4.9 |
| Net | 22.8 | 14.4 | 22.1 | 14.2 |
| Day type | 13.9 | 10.5 | 13.0 | 10.5 |
| Service*location | 0.9 | 4.8 | 0.9 | 4.6 |
| Service*net | 18.8 | 15.9 | 17.4 | 15.5 |
| Service*day type | 8.5 | 8.2 | 5.2 | 7.8 |
| Location*net | 0.5 | 3.2 | 0.5 | 3.1 |
| Location*day type | 0.4 | 2.9 | 0.5 | 2.8 |
| Net*day type | 12.3 | 10.2 | 10.3 | 10.5 |
| Service*net*day type | . | . | 9.2 | 10.4 |

Table 4
ANOVA table

| Model | Logit II | Logit III |
|---|---|---|
| min $R^2$ | 0.47 | 0.64 |
| max $R^2$ | 1.00 | 1.00 |
| avg $R^2$ | 0.99 | 0.99 |
| std $R^2$ | 0.02 | 0.01 |
| avg $adj-R^2$ | 0.89 | 0.81 |
| std $adj-R^2$ | 0.21 | 0.30 |
| avg $p$-value | 0.17 | 0.22 |
| std $p$-value | 0.15 | 0.18 |

logit II model explains 47% of dependency in data and the worst logit III explains 67% of dependency in data. For further analysis logit III model has been chosen.

### *5.2. Customer clustering and product recommendations*

Analytical results show that all users do not create homogenous group and recommendations of products cannot be made, yet. To find users with similar preference structure we have used results of conjoint analysis. Preference structure is defined by part worth utilities which have been calculated for each user individually using conjoint analysis methods. Now those coefficients can be used to make users clustering.

There are two types of clustering: hierarchical clustering and partition clustering. Hierarchical clustering proceeds successively by either merging smaller clusters into larger ones, or by splitting larger clusters. Partition clustering, on the other hand, attempts to directly decompose the data set into a set of disjoint clusters. For huge amount of data hierarchical clustering is not practically applicable, thus we used partition clustering implemented in SAS as a FASTCLUS procedure. In partition clustering number of clusters has to be given as an input to the procedure. There are different strategies to choose value which gives homogenous groups. As clustering methods are not under consideration of this work, 5 clusters were chosen to show the methodology.

Table 5
Average relative importance of attributes in segments [%] (logit III)

| Attribute/segment | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Service | 19.4 | 13.9 | 30.4 | 26.4 | 15.8 |
| Location | 0.5 | 1.6 | 0.6 | 10.1 | 0.7 |
| Net | 20.9 | 13.1 | 23.7 | 18.1 | 21.8 |
| Day type | 9.7 | 3.1 | 10.1 | 5.6 | 14.6 |
| Service*location | 0.4 | 0.8 | 0.8 | 1.0 | 0.9 |
| Service*net | 32.1 | 8.5 | 14.2 | 5.8 | 18.9 |
| Service*day type | 3.7 | 6.1 | 5.6 | 5.0 | 5.2 |
| Location*net | 0.3 | 1.1 | 0.3 | 1.4 | 0.5 |
| Location*day type | 0.2 | 1.2 | 0.3 | 1.5 | 0.5 |
| Net*day type | 7.0 | 18.6 | 7.0 | 17.1 | 11.3 |
| Service*net*day type | 6.2 | 32.0 | 7.1 | 8.1 | 10.0 |

The results on average importance are presented in Table 5 and standard deviation statistics are illustrated in Table 6. The results show that users from those 5 segments behave differently. In the first segment service*net factor is mostly important (32%) while in the second segment service and net are correlated with day type and that coefficient is the most significant (32%). In other groups correlations of service and day type are much lower.

Table 6
Standard deviation of relative importance of attributes in segments [%] (logit III)

| Attribute/segment | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Service | 11.7 | 8.4 | 11.7 | 13.1 | 14.1 |
| Location | 3.2 | 5.1 | 3.3 | 14.1 | 4.1 |
| Net | 9.4 | 10.0 | 10.8 | 13.3 | 15.4 |
| Day type | 5.3 | 5.5 | 6.1 | 6.9 | 11.7 |
| Service*location | 2.9 | 3.6 | 4.2 | 4.4 | 4.8 |
| Service*net | 10.8 | 9.9 | 11.2 | 9.6 | 16.6 |
| Service*day type | 5.6 | 9.6 | 6.8 | 7.8 | 8.2 |
| Location*net | 2.2 | 4.3 | 2.3 | 5.2 | 3.3 |
| Location*day type | 1.7 | 3.9 | 2.0 | 5.1 | 3.0 |
| Net*day type | 6.7 | 10.5 | 6.8 | 11.0 | 11.3 |
| Service*net*day type | 6.0 | 12.6 | 7.4 | 10.3 | 11.2 |

Standard deviations of relative importance are lower than in the whole population but are still comparable with average values of importance and further clustering should be done to divide presented groups into subgroups. The process should be repeated iteratively while users within groups have different preference structures. After getting homogenous groups, information about products can be added to each user and statistics can be made in those groups to find most frequently used services. Those services should be recommended to outliers who had bought different services then those which are most frequently used.

## 6. Conclusions and future research

Motivation and the use of conjoint analysis in telecommunication field were presented in this paper. The decision problem of finding optimal set of products for customers was defined and possible attitudes to solving the problem were compared. Conjoint analysis methodology and connections with ANOVA as well as regression techniques were presented. At the end, an example of preference identification process was introduced. Although, results from the example have shown that defined model explains dependency in data and in consequence customers' preference structures are accurate, further experiments on real data should be made. Also, additional information about users should be added including information about their declared preferences. Declared preferences might be quite interesting as with comparison to real ones they can indicate optimal actions which would allow increasing customers' satisfaction [3] and their loyalty at the same time.

## References

[1] P. Aggarwal and R. Vaidyanathan, „Eliciting online customers' preferences: conjoint vs. self-explicated attribute-level measurements", *J. Market. Manage.*, vol. 19, pp. 157–177, 2003.

[2] J. Bissett, F. Falschini, Y. Jansen, R. Monti, and V. Massow, „Sparking connections: best practice in customer relationships and retail marketing", 2000, http://www.bcg.com

[3] P. J. Danaher, „Using conjoint analysis to determine the relative importance of service attributes measured in customer satisfaction surveys", *J. Retail.*, vol. 73, no. 2, pp. 235–260, 1997.

[4] W. S. DeSarbo *et al.*, „Representing heterogeneity in consumer response models", *Market. Lett.*, vol. 8, no. 3, pp. 335–348, 1997.

[5] C. Douglas and P. E. Green, „Psychometric methods in marketing research: part I, conjoint analysis", *J. Market. Res.*, vol. 32, no. 4, pp. 385–391, 1995.

[6] C. Douglas and P. E. Green, „Psychometric methods in marketing research: part II, multidimensional scaling", *J. Market. Res.*, vol. 34, no. 2, pp. 193–204, 1997.

[7] T. Evgeniou, C. Boussios, and G. Zacharia, „Generalized robust conjoint estimation", *Market. Sci.*, vol. 24, pp. 415–429, 2005.

[8] J. Granat, „Data mining and complex telecommunications problems modeling", *J. Telecommun. Inform. Technol.*, vol. 3, pp. 115–120, 2003.

[9] P. E. Green, S. M. Goldberg, and M. Montemayor, „A hybrid utility estimation model for conjoint analysis", *J. Market.*, vol. 45, no. 1, pp. 33–41, 1981.

[10] P. E. Green and A. M. Krieger, „Individualized hybrid models for conjoint analysis", *Manage. Sci.*, vol. 42, no. 6, pp. 850–868, 1996.

[11] P. E. Green, A. M. Krieger, and Y. Wind, „Thirty years of conjoint analysis: reflections and prospects", *Interfaces*, vol. 31, no. 3, part. 2, pp. 56–73, 2001.

[12] W. F. Kuhfeld, „Conjoint analysis", 2007, http://support.sas.com/techsup/technote/ts722h.pdf

[13] R. Johnson, http://www.sawtoothsoftware.com/education.shtml

[14] V. Srinivasan, „A conjunctive-compensatory approach to the self explication of multiattributed preferences", *Decis. Sci.*, vol. 19, no. 2, pp. 295–305, 1988.

[15] O. Toubia, J. R. Hauser, and D. I. Simester, „Polyhedral methods for adaptive choice-based conjoint analysis", *J. Market. Res.*, vol. 16, pp. 116–131, 2004.

[16] M. Walesiak and A. Bak, *Conjoint analysis w badaniach marketingowych*. Wrocław: WAE, 2000 (in Polish.

**Piotr Rzepakowski** received the M.Sc. degree in computer science from the Warsaw University of Technology, Poland, in 2003. Currently he is a Ph.D. candidate in computer science at the Warsaw University of Technology (Institute of Control and Computation Engineering). He is employed by National Institute of Telecommunications in Warsaw. Has taken part in projects related to data warehousing and analysis for a telecommunication operator. His research focuses on modeling, decision support, data mining, and customer preferences identification issues.

e-mail: Piotr.Rzepakowski@elka.pw.edu.pl
Institute of Control and Computation Engineering
Warsaw University of Technology
Nowowiejska st 15/19
00-665 Warsaw, Poland

e-mail: P.Rzepakowski@itl.waw.pl
National Institute of Telecommunications
Szachowa st 1
04-894 Warsaw, Poland