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Fuzzy multi-objective modeling of effectiveness and user experience in online advertising

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ABSTRACT

The focus placed on maximizing user engagement in online advertising negatively affects the user experience because of advertising clutter and increasing intrusiveness. An intelligent decision support system providing balance between user experience and profits from online advertising based on the fuzzy multi-objective optimization model is presented in this paper. The generalized mathematical model uses uncertain parameters for content descriptors that are difficult to be precisely defined and measured, such as the level of intrusiveness and the change in performance over time. The search for final decision solutions and the verification of the proposed model are based on experimental results from both perceptual studies, which are evaluating visibility and intrusiveness of marketing content as well as online campaigns providing interaction data for estimation of effectiveness. Surprisingly, the online response to the most noticeable advertisements with highly perceived visibility and intrusiveness was relatively low. During the field study performed in order to compute the model parameters, the best results were achieved for advertising content with moderate visual influence on web users. Simulations with the proposed model revealed that a growing level of persuasion can increase results only to a certain extent. Above a saturation point, a strategy based on extensive visual effects, such as high-frequency flashing, resulted in a very high increase of intrusiveness and a slightly better performance in terms of acquired interactions. Proposed balanced content design with the use of intelligent decision support system creates directions towards sustainable advertising and a friendlier online environment.

1. Introduction

The evolution of electronic media and the increasing role of online advertising within marketing strategies has created space for both researchers and practitioners to explore new areas. Attempts are frequently made to design online media and interactive content to achieve better results with the use of persuasion, colors, animations and call-to-action messages (Yun & Kim, 2005). Other areas include: the identification of the factors affecting effectiveness for specific sectors (Tsai, Chou, & Leu, 2011) or with more general applications (Robinson, Wysocka, & Hand, 2007), the real-time optimization of keyword selection (Cookhwan, Sungsik, Kwiseok, & Ch, 2012), and the use of methods based on multivariate testing or stochastic models (Chakrabarti, Agarwal, & Josifovski, 2008). While these methods are used in the operational environment, solutions which are implemented at tactical level require other approaches in terms of media planning. In this field, optimization methods are used for better advertisement allocation, and several solutions and models related to linear optimizations (Langheinrich, Nakamura, Abe, Kamba, & Koseki, 1999) are available, as well as their extensions (Chickering & Heckerman, 2000) towards recent models trying to deal with a multi-objective approach (Du & Xu, 2012). While earlier solutions focused mainly on increasing outcomes, the growing share of advertising content within websites is resulting in negative side effects. As a result, users perceive advertising clutter with a high share of advertising space being spread among editorial content (Ha & McCann, 2008). A drop in user experience

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is observed when more and more intrusive advertising techniques are used to attract user attention (Brajnik & Gabrielli, 2010; Zha & Wu, 2014). Earlier research in this field was mainly focused on the effect of intrusiveness on brand awareness and memory (Chatterjee, 2008). Dedicated measures were introduced to evaluate the level of intrusiveness based on scales defined by Li et al. (Li, Edwards, & Joo-Huyn, 2002) and later used in various areas (McCoy, Everard, Polak, & Galletta, 2007; Zha & Wu, 2014).

While most of the earlier methods focused on measuring intrusiveness or improving the performance of online marketing, the research presented in this paper proposes a multi-objective approach to media planning based on trade-off solutions while taking into account criteria related to user experience, web portal profits and results for advertisers. The study integrates results from perceptual and field experiments followed by simulations which use the proposed model based on fuzzy parameters. These parameters represent the uncertain characteristics related to the online environment and intrusiveness of the advertising content. The model includes effectiveness factors based on two elements: firstly, on direct responses in the form of those registered by advertising server interactions (e.g. clicks), and secondly, on the costs for advertisers related to the revenue of the web operator.

This study has yielded findings that have an impact on online system design, as well as managerial insights into interactive campaign planning. The conclusions are as follows:

- The highest number of interactions were acquired for content with the relatively low perceived intrusiveness detected in the perceptual study;
- Highly intrusive advertisements with vivid effects and a large flashing area attracted attention, but the number of acquired interactions was smaller than in the case of less intrusive content;
- Simulations showed that an increased level of persuasion can improve results to some extent only, which was made obvious by the relatively low online results for highly visible advertisements;
- The visibility of online advertisements increases results, but above certain saturation points, increases in the effect are very low and are noted by a high growth of intrusiveness;
- Different relationships between outcomes and the level of persuasion were observed for each campaign, but a saturation point denoted by a high immediate growth of intrusiveness was characteristic for all cases;
- For all campaigns, the substantial growth of intrusiveness resulted in only slightly better performance in terms of acquired interactions.

The proposed model makes it possible to search for a final decision during the interactive process. The model includes a representation of the global goals of the web portal owner and local objectives for specific advertisers with their own preferences. Results from the study are presented in seven sections. The structure of this paper is as follows: Section 2 presents the literature review related to online media optimization and planning, Section 3 includes the problem statement and the conceptual framework, Section 4 explains the optimization model with fuzzy parameters and the algorithm used to get solutions are presented, Section 5 presents the experimental results from the field experiment, and Sections 6 and 7 include the discussion and the conclusion, respectively.

2. Literature review

The increasing importance of interactive technologies in marketing has been observed recently, and new disciplines like marketing engineering, computational advertising or computational social science are gaining more and more attention from both practitioners and scientists. New forms of communication create areas in these fields with several directions, such as the design of advertising content, usage of persuasion and call to action messages, and testing different layouts or changing the structure of advertisements using data about consumer behavior (Urban, Liberali, MacDonald, Bordley, & Hauser, 2013; Zorn, Olaru, Veheim, Zhao, & Murphy, 2012). Other areas deal with real time campaign optimization and searching for the best methods for resource exploitation with the use of stochastic models (Chakrabarti, Kumar, Radlinski, & Upfal, 2008), adaptive personalization (Kazienko & Adamski, 2007), or context based ad selection (Teng-Kai & Chia-Hui, 2011). Looking at the problem of online campaign planning from another perspective, the managing of multiple resources with the use of operational research typically occurs at the strategic level.

Interactive media has created the ability to measure different effects and use them in the decision-making process. The new metrics are used in this field for media planning (Novak & Hoffman, 1996; Pavlou & Stewart, 2000) with quantitative approaches (Cookhwan, Kwiseok, & Ch, 2011; Hoffman & Novak, 2000). Planning methods are developed with the new specifics of online media; however, conventional media planning is also applicable (Cannon, 2001). The foundation for performing marketing actions is the planning and scheduling campaigns at different locations with the use of different creations. This can be based on the applications of the Rositer–Percy grid to online advertising and analysis based on the planned behaviors and site pre-visit intentions (Wu, 2007). Various scheduling and execution plans are implemented within advertising servers to select specific content as an answer to a request coming from a web browser (Amiri & Menon, 2003). One of the first applications of optimization models in this field is based on the analysis of keywords entered by the user to the search engine, which allows for optimization of the ad delivery process (Langheinrich et al., 1999). The task was formulated as a linear programming problem and the restrictions include impressions in a given period, which was related to the number of ads shown on behalf of each advertiser. An extension of the above concept is based on the research of Chickering and Heckerman, which shows the solution for a uniform distribution of emissions as a result of a two-stage optimization (Chickering & Heckerman, 2000) which identifies the likelihood of diversion from the issue of advertising in the analysis of data obtained from the operating environment.

The optimal emission plan allows calibrating the ad server in such a way to obtain the maximum number of interactions in a given period of time. Chickering stresses that the main drawback of this solution is the sensitivity of the results to small changes in the estimated probability. Another extension was proposed by Tomlin with the goal to avoid exposition to a narrow target group with the usage of statistically derived entropy maximization (Tomlin, 2000). The results showed that a nonlinear approach can be used as a component of other models for advertising inventory management. Decomposition of the problem and separation of the advertising impressions was made possible by adding a quadratic punishing which enabled better advertising efficacy (Jie & Ding-Wei, 2004). The model proposed in (Langheinrich et al., 1999) was extended towards the estimation of click-through rates and computing the probabilities of impressions based on the trade-off between exploration and exploitation (Nakamura & Abe, 2005). The presented approach introduced solutions for multiple banner impressions and advertising inventory management. Other approaches are based on the operational level and work through tracking user sessions and maximization of clicks probability (Gupta, Khurana, Lee, & Nawathe, 2011). The solution is based on Bayesian models and generates a ranking of advertisements with assigned probabilities. It is targeted to system operations in real time with connections to online advertising servers. In other solutions, the selection of the advertising content is based on the user profiles collected during the website browsing process (Giuffrida, Reforgiato, Tribulato, & Zarba, 2011). Another area is related to adjusting the pricing strategies for online advertising using the most popular CPM (cost per mile) and CPC (cost per click) models. A multi-objective model was proposed with the main goal of constructing pricing strategies and maximizing the revenue of the web portal, as well as minimizing the cost for the advertiser (Du & Xu, 2012).

Review of literatures shows that earlier approaches in the field of online campaign optimization are related to the maximization of profits and results to advertisers. However from the other point of view in the typical web design process the user experience should be taken into account in order to achieve better functionality and enable the creation of solutions addressed to the need of web users (Zha & Wu, 2014). This approach can be conflicting with financial priorities of portal owners' with a high focus on profits.

The questions arise to the level which it is worth, so as to increase the intrusiveness of marketing components to attract user attention and to keep profits at the acceptable level without invading user experience. Earlier research in this field was addressed to several aspects related to the intrusiveness of online content. Intrusiveness in the relation to online advertisements is defined as "a perception or psychological consequence that occurs when an audience's cognitive processes are interrupted" (Li et al., 2002). Ha and Litman defined intrusiveness as "[…] the degree to which advertisements in a media vehicle interrupt the flow of an editorial unit." (Ha & Litman, 1997). Li et al., 2002 introduced an approach based on the seven points scale defining content as distracting, disturbing, forced, interfering, intrusive, invasive and obtrusive with seven levels from "strongly agree" to "strongly disagree". Scale reduced from initial eleven items is based on psychological mechanisms and was later used for different experiments by other authors (McCoy et al., 2007). Excessive usage of video, audio and animations within online content causes overload problem of commercial content and is leading to side effects affecting negatively user experience (Rosenkrans, 2009).

The field experiments based on the analysis of interruptions of cognitive processes as effects of advertising activity based on pop-up advertisements were performed (Moe, 2006). Timing of popup-messages with on across-page delay and within-page delay and their effect on click-through rate and site exit behaviors were analyzed. In other research, emphasis was placed on the conflict within companies operating web portals where advertising content is a source of income but intensive exploitation of advertising space leads users to abandon a website (Goldstein, McAfee, & Suri, 2013). Earlier studies reported several usability problems related to online advertising with misleading information and difficult to find options to remove advertising content (Gibbs, 2008). Our earlier research focused on recommending interfaces with limited negative influence on web users (Jankowski, 2013) and balance between visual and verbal communication within web systems (Jankowski, Wątrobski & Ziemba, 2015).

As a result of excessive exploitation of online resources the growing problem for many companies is content avoidance especially when high intensity of influence on web users is used. In the situation when the most of web portals are trying to attract attention of web users with commercial content, online users are overloaded by the marketing content and only part of it attracts attention because of the limited ability to process information (Lang, 2000). Experienced web users are focused on completing tasks and are searching for information while they ignore irrelevant content (Chatterjee, 2008). Effects during web based tasks related to the unintentional content avoidance were identified as banner blindness by Benway (Benway & Lane, 1998) and extended by other researchers (Burke, Hornof, Nilsen, & Gorman, 2005). Apart from cognitive avoidance and banner blindness the physical avoidance of marketing content takes place. Applications are used for blocking advertising content and even all objects of specific types from the websites (Krammer, 2008). With the growing popularity of applications of this type physical delivery of content to users can be problematic.

While earlier research related to the optimization and planning of online advertising campaigns focused mainly on the effectiveness of advertising content, the research in this paper shows an integrated approach with main goal to support decisions based on multi criteria evaluation from the perspective of web users and the performance of commercial content. The conceptual framework is presented in the next stage followed by the results from experiments based on searching for a trade-off between content intrusiveness and user experience with the use of multi-objective methods. In proposed approach data from perceptual experiments is integrated with the online measurement and then global and local objectives are used to evaluate the results from different perspectives. The model presented in this paper makes it possible to define the aspiration levels and obtain solutions based on expectations of parties related to the online advertising processes.

3. Problem description and conceptual framework

Advertising activity in the interactive environments such as the Internet is based on dedicated control systems which allow the selection of advertising units by different criteria, as well as the measurement of results. Ad request parameters are generated during page views dynamically with the use of dedicated scripts responsible for displaying advertisements located within a website's code. After the comparison with the emission plans, which are designated as being the main factors determining advertising activity, the selection of advertising content is performed. Most of the available systems and optimization models are focused on the increasing of number of interactions within the website and are targeted to automated advertisement selection to maximize number of clicks or other response i.e. (Bertsimas & Mersereau, 2007; Chakrabarti,Agarwal, et al., 2008; Li et al., 2010). Even though maximizing profits with intrusive forms of advertising can increase outcome in the short term it may lead a decline in the audience and negative effects on brands (Goldstein et al., 2013). The solution presented in Fig. 1 assumes the integration of decision support system with an advertising server and the use of three information sources gathered from: perceptual experiments, online experiments and the preferences of decision makers. Perceptual experiment delivers information related to perceived intrusiveness, the manner in which the advertising content is affecting the user experience. Content evaluation is possible in terms of negative influence on web users, i.e. web usability. During an online experiment, the data related to the interactions, overall performance and user behavior is collected. Uncertainty of data is taken into account including changes of performance and portal audiences. Preferences gathered from decision makers like portal owner and advertisers are used in the fuzzy multi-objective system. The output from the system delivers various trade-off solutions that minimize negative impact on web users and maximize performance.

The detailed structure of the system and the integration with the real environment is presented in Fig. 2. Main components of this structure include emission system ES, monitoring subsystem responsible for gathering and processing data MS, database DB with historical data stored and decision support system DSS used for supporting planning activity. Following the exposition of the ad unit, upon receipt of the message by the recipient, the system can measure interaction with the advertising message expected by the advertiser. Collected data on the occurring interaction after receiv-

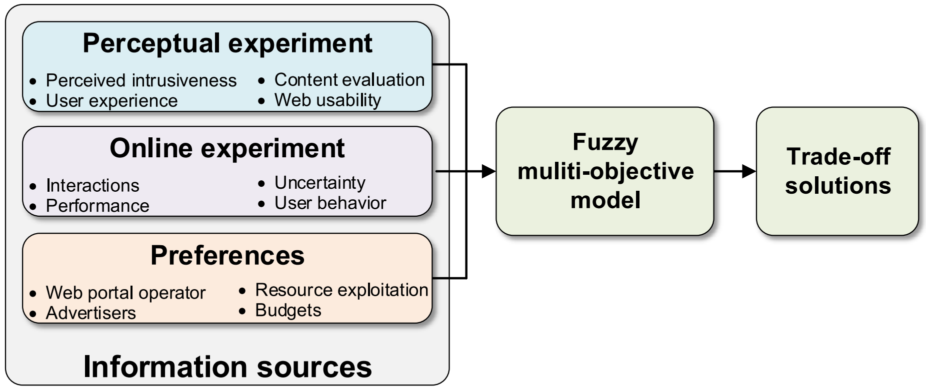

Fig. 1. Trade-off solutions achieved by means of fuzzy multi-objective modeling that aggregates three data sources.

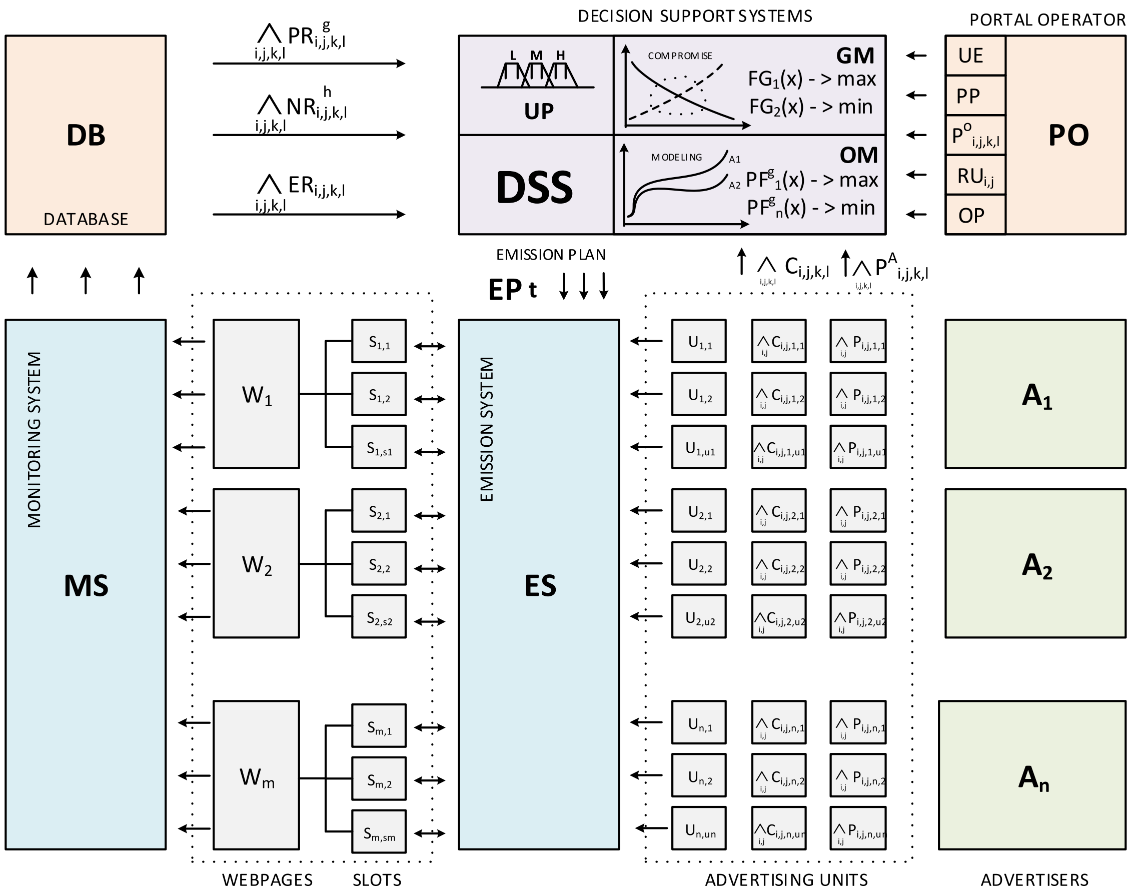

Fig. 2. Control in an interactive advertising emission system.

ing the message is used in the decision processes and to some extent may be a measure of efficiency.

Within a typical portal a set of m web pages $W=\{W_1,W_2,\ldots,W_m\}$ can be distinguished and a set of slots $S_i=\{S_{i,1},S_{i,2}\ldots,S_{i,si}\}$ assigned for each web page W_i ($i=1,\ldots,m$) and they are dedicated to displaying marketing content (s_i represents the number of slots located within page W_i). Advertising activities are conducted on behalf of n advertisers A_j where $j=1,\ldots,n$ from the set $A=\{A_1,\ldots,A_n\}$. For each advertiser $A_k\in A$ is given a set of ad units $U_k=\{U_{k,1},\ldots,U_{k,uk}\}$ where u_k represents the number of units delivered by an advertiser k for the usage within the portal. Advertising units can be based on different designs and formats which influence web users and various techniques used to attract attention. For each advertiser k and each ad unit $U_{k,l}$ where $l=1,\ldots,u_k$ are assigned emission costs $C_{i,j,k,l}$ thus defining costs of emission of one thousand ad units with the cost per mille model (CPM) of ad unit l delivered by advertiser k to be served within slot j on the webpage i. Cost is negotiated with a portal operator and is dependent on several factors related to used ad formats, levels of intrusiveness of marketing content and amounts spent on advertising campaign. The highest rates are usually connected to the growing intrusiveness affecting web user experience. Ad units are available for the emission system ES which is responding to requests from slots located within the website, which are sent by dedicated front-end scripts and are handled by a server side application. The selection of advertising content is performed according to the emission plan for the period t denoted as EP^t which specifies the preferred number of individual ad units issued for each advertiser in a given period of time t and consists of subplans $EP^t{}_k$ for each advertiser k where ($k=1\ldots,n$) in a set $EP^t=\{EP^t{}_1,\ldots,EP^t{}_n\}$. Within the plan of emission for each advertiser, the number of emissions is defined for each ad unit delivered by advertiser represented by $x^t_{i,j,k,l}$ which denotes the number of emissions planned for the period of time *t* within the webpage *i* and slot *j* of ad unit *l* on behalf of advertiser *k*.

The process on the strategic level is managed by a web portal operator (PO) who is controlling the process and takes part in parametrization of the system with the usage of decision support system DSS. Activity at the operational level is performed automatically within the emission system (ES). Delivered by PO parameters for the period of time *t* are used within the decision support system (DSS) and are related to keeping positive user experience within webpages (UE), portal profits (PP) with the assumption that increased profits may be occupied by dropping user experience, preferences $P^o_{i,j,k,l}$ representing the preferred number of impressions of ad unit *l* delivered by an advertiser *k*, within slot *j* on a web page *i*, the resources usage $RU_{i,j}$ related to available emission resources within slot *j* located within page *i*. A portal operator can use other preferences OP for system parametrization based i.e. on external surveys, analytics or evaluation of advertising content and its effect on the web users.

Apart from the input from the portal operator DSS system uses the input from advertisers in a form of cost preferences for ad units $C_{i,j,k,l}$ and emission preferences $P^A_{i,j,k,l}$ defined by advertiser *k* for ad unit *l* and emission within slot *j* on the page *i*. DSS uses input from the monitoring system MS and delivered information is related to the available emission resources $ER_{i,j}$ for website *i* and slot *j* based on the measurement of web traffic within a portal and of the audience within each subsite. The measurement system delivers an overall evaluation from the perspective of earlier effects in a form of interactions represented by a positive response denoted as $PR^g_{i,j,k,l}$ for advertiser *k*, ad unit *l*, showed within slot *j* at webpage *i* and can be measured using $g = 1,\ldots,m_p$ performance measures related to a number of interactions, conversions and other positive responses. The negative response $NR^h_{i,j,k,l}$ is related to the level of intrusiveness, negative feedback from users and possible negative influence on web users is used as well. It can be measured by $h = 1,\ldots,m_i$ intrusiveness measures using techniques based on server side measurement or user centric experiments. Because of volatile environment and condition changes related to audience, effectiveness system takes into account uncertain nature of delivered data and uncertain parameters are handled by uncertain data processing module UP.

The portal operator has an ability of planning the general strategy related to the user experience and portal profits using the global model GM for searching for the compromise between intrusiveness of advertising content and profits. Minimizing the negative impact on a web user takes place with the $FG_1(x)$ function and in case of maximizing profits the global evaluation function $FG_2(x)$ is proposed. As an extension can be used the operational model OM with the detailed criterions related to performance factors maximized for each advertiser *k* represented by functions $PF^g_k(x)$ for each $g = 1,\ldots, m_p$ performance measures. The final plan of emission is based on the mapping of preferences of the portal owner and advertisers into decision variable $x_{i,j,k,l}$ defining the number of emissions for each webpage *i* and slot *j* and advertiser *k* with an ad unit *l*. The search for compromise is based on the web portal operator preferences represented in balanced approach with the main goal being to deliver acceptable results in terms of portal profits PP, deliver positive response $PR^g_{i,j,k,l}$ to advertisers with minimal negative influence on web audience represented by negative response $NR^h_{i,j,k,l}$. Results from a generated plan of emission for period *t* are represented by EP_t and are used within the advertising server with the selection function SF(t) which maps the request parameters RQ_t on the selected ad unit for the emission to the specific user. The number of emitted advertisements depends on the available emission resources $ER_{i,j}$ for each slot *j* and webpage *i* and is dependent on the audience present within the portal.

4. Fuzzy multi-objective optimization model

While earlier research was mainly focused on maximization of the number of interactions and resources usage, taking into an account negative feedback and the level of intrusiveness of used content enables the implementation of solutions for compromise, without invading user experience within the portal. For the representation of data related to the levels of negative response and intrusiveness system inputs are based on the fuzzy representation. Uncertainty also arises from changing effectiveness and varying emission resources. The deterministic estimation of parameters for decision models would be less adequate because of uncertain character of used data. For emission optimization and searching for a compromise plan the multi-objective mathematical model with fuzzy parameters is proposed. There is an unknown value of emission plan $x_{i,j,k,l}$ for each *i, j, k, l* which defines the number of ad units *l* to be served within web page *i* and slot *j* served on behalf of *k*.

4.1. Assumptions for uncertain parameters and constrains

Depending on the relevance of the choice of the advertising unit and the adaptation to the current needs of the target customer will be achieved (or not) certain effects in the period *t*. Positive results and the negative influence determined for each advertiser *k* is measured and stored for usage in the next stages of the advertising campaigns. High volatility of the environment and changes of effectiveness or emission resources over time turns the adoption of deterministic nature of measurement parameters into a simplification. Available resources for the next period *t+1* are based on the average values and deterministic parameters representing i.e. page views and unique visitors and usually they do not use characteristics of a changing environment. In order to reflect the uncertain nature of the measurement data, the usage of fuzzy approach introduced by L.A. Zadeh is proposed; this is based on determining the membership functions of belonging to a set (Zadeh, 1965). For example using this approach in relation to the emission resources for the next time period t+1 can be estimated that "about" *n* advertising units may be emitted, which is a more accurate statement than the precise one, which stipulates that *n* units will be emitted. Fuzzy representations of input data can be used as parameters for decision support models during media planning for emission resources $ER_{i,j}$, positive response $PR^g_{i,j,k,l}$ as well as the negative response $NR^h_{i,j,k,l}$. The level of intrusiveness or positive response can be defined as fuzzy numbers with linguistic representations like a Low, Medium or High. In some cases, i.e. pulsing emissions, a fuzzy campaign budget B^t_k can be allocated and that representation makes such parameters more reliable than crisp values. Consideration of these factors requires a combination of different preferences and organization of model in such a way that is taking into account both environmental variability and specifics of the problem, as is shown in the next section.

4.2. Multi-objective model targeted to strategic planning

With the usage of the global decision support model GM, the portal operator has an ability to find decision solutions and parameters for planning based on two main goals. The first goal is to minimize negative influence on web users with $FG_1{}^t$ (x) to keep usability and user experience at high levels, while taking into account the level of intrusiveness assigned to interactive content. The second goal is to maximize profits and this is represented by a global function $FG_2{}^t$ (x) with the use of parameters related to the prices of emission of advertisements within the portal. Function $FG^t{}_1(x)$ is based on measures of intrusiveness represented by a negative response $NR^h_{i,j,k,l}$ of type *h* after an evaluation of ad unit *l* delivered by advertiser k and performed in connection with slot j within webpage i and is represented as follows:

$$FG_1^t(x) = \sum_{i=1}^{m}\sum_{j=1}^{s_m}\sum_{k=1}^{n}\sum_{l=1}^{u_n}\left(NR^1_{i,j,k,l} * x^t_{i,j,k,l} + NR^2_{i,j,k,l} * x^t_{i,j,k,l} + \ldots + NR^{mi}_{i,j,k,l} * x^t_{i,j,k,l}\right) \quad (1)$$

where:

$NR^h_{i,j,k,l}$ - the measure of negative response related to advertising unit l delivered by advertiser k served within webpage i and slot j represented by the measure of intrusiveness h,

$x^t_{i,j,k,l}$ - the number of ad units with the design variant l delivered by advertiser k to be used within the portal within the slot j at the page i in the period t.

The second goal related to profits of web portal operator is based on the prices $C_{i,j,k,l}$ assigned to emission within webpage i and slot j for ad unit l delivered by an advertiser k. It is dependent on the size, type and intrusiveness of advertising content and the location within the portal where it will be displayed. The function FG_2^t (x) is represented as follows:

$$FG_2^t(x) = \sum_{i=1}^{m}\sum_{j=1}^{s_m}\sum_{k=1}^{n}\left(C_{i,j,k,1} * x^t_{i,j,k,1} + C_{i,j,k,2} * x_{i,j,k,2} + \ldots + C^t_{i,j,k,u_n} * x_{i,j,k,u_n}\right) \quad (2)$$

where:

$C_{i,\,j,\,k,\,l}$ - the price of emission of an ad unit with the variant l on behalf of advertiser k within slot j located on the web page i,

$x^t_{i,j,k,l}$ - the number of ad units with the variant l delivered by advertiser k to be served in the period t within the webpage i and slot j in the period t.

The maximization of function (2) increases the overall financial performance of emission from the perspective of the web portal's and is dependent on prices of advertisements emission. While the costs of emission of intrusive advertisements are usually higher profits grow together with the growing intrusiveness of advertising content. From the perspective of the web portal owner, the maximization of function FG $^t{}_2$(x) can lead to short term profits increase because of higher rates for intrusive advertising content; however in the long run it can lead to audience loss because of dropping user experience. For better planning effects for individual advertisers additional sub criteria can be added and oriented on maximizing the number of interactions and positive response on behalf of each advertiser. In this process response factors $RF^g{}_{i,j,k,l}$ are used and they are computed with the use of positive response data $PR^g{}_{i,j,k,l}$ for measured interactions of type g divided by the number of impressions or other interactions. Depending on the type of measured interactions they can represent click-through ratios, conversion ratios or other typical performance metrics used in online advertising. Following this notion used for generalization purposes and maximizing the individual performance function (3) increases the number of interactions expressed by $RF^g{}_{i,j,k,l}$ factor for each type of interaction:

$$\bigwedge_k \bigwedge_g PF\,{}^g_k(x) = \sum_{i=1}^{m}\sum_{j=1}^{s_m}\left(RF^g_{i,j,k,1} * x\,{}^t_{i,j,k,1} + RF^g_{i,j,k,2} * x\,{}^t_{i,j,k,2} + \ldots + RF^g_{i,j,k,u_k} * x\,{}^t_{i,j,k,u_k}\right) \quad (3)$$

$RF^g_{i,j,k,l}$ - the response factor based on measures of expected by advertiser k response type g is registered by a measurement system within website i and slot j for ad unit l.

The model can take into an account the sub criteria for different types of interactions and conversions measured for advertiser, the choice of which depends on the purpose of advertising. Apart from the goal functions the main constraints of this model are defined and related to the resource limitations based on audience represented by an emission resources $ER^t{}_{i,j}$ estimated for period of time t for each slot j within a website i and are represented as follows:

$$\bigwedge_t \bigwedge_j \left(ER^t_{i,j} - \sum_{k=1}^{m}\sum_{l=1}^{u_m} x^t_{i,j,k,l}\right) \geq 0 \quad (4)$$

where:

$ER^t_{i,j}$ - the emission resources within slot j on page i is represented by number of requests of advertising units.

Next constraints are based on the available budget $B^t{}_k$ assigned to an advertiser k for the period of time t. It can be dependent on earlier budget allocation and is based on values assigned for the next period. Realization of the budget is based on the available resources and the ability to deliver to the advertiser specific number of impressions which is dependent on the audience changing over time and preferences of other advertisers:

$$\bigwedge_k \left(B\,{}^t_k - \sum_{i=1}^{m}\sum_{j=1}^{s_m}\sum_{l=1}^{u_n}\left(C_{i,j,k,l} * x\,{}^t_{i,j,k,l}\right)\right) \geq 0 \quad (5)$$

where:

$B\,{}^t_k$ - the representation of a budget for advertiser k assigned for the period of time t.

Representation of the budget parameter can be based on fuzzy values due to the possibility of the occurrence of deviations of the plan under varying conditions. They may arise for example because of varying the intensity of action in accordance with the pulse strategy. For more detailed parametrization of the system portal operator can deliver detailed preferences to emission specific advertising content on selected slots or webpages represented by $P^O{}_{i,j,k,l}$. Portal operator is aggregating preferences from all advertisers and includes own priorities. Set of preferences is defined as follows:

$$\bigwedge_{i,j,k,l} \left(P\,{}^O_{i,j,k,l} - x\,{}^t_{i,j,k,l}\right) \geq 0 \quad (6)$$

where:

$P\,{}^O_{i,j,k,l}$ - defined by portal operator the preferred number of impressions ad units l of advertiser k within the slot j located on the web page i.

Preferences are also delivered by advertisers, and they are used by portal operator in decision processes. Preferences are related to number of emissions for each ad unit within slots located on the web pages and are declared as follows:

$$\bigwedge_{i,j,k,l} \left(P\,{}^A_{i,j,k,l} - x\,{}^t_{i,j,k,l}\right) \geq 0 \quad (7)$$

where:

$P\,{}^A_{i,j,k,l}$ - the representation of the preferred by an advertisers number of impressions ad units l of advertiser k within the slot j located on the web page i.

An advertiser can disable impressions of specific ad units on selected slots and this is treated as a hard constrain. If an advertiser includes the preferred number of emissions, the final representation of the plan is dependent on the portal operator who is aggregating preferences from other advertisers. Final results may be based on costs, other conditions and contracts. While searching for compromise solutions, the portal operator uses his own attitude towards user experience within a portal UE, preferences for increasing portal profits PP, preferences for resource usages RU and vector of other preferences OP.

4.4. Algorithm for model solving

For the presented optimization task, the selection of the appropriate method is required for searching for decision solution with the use of fuzzy coefficients and restrictions in the model. When selecting the method of solving the model the need to adjust the levels of representation of the constraints' satisfaction should be taken into account. Assumptions for fuzzy modeling decisions are defined by Bellman and Zadeh (Bellman & Zadeh, 1970) and they have been used as the base of fuzzy multi-objective linear programming (Dubois & Prade, 1980) and in later studies (Sakawa, 1993; Zimmermann, 1991). These methods have been developed in the direction of the fuzzy coefficients of tasks, as well as the decision variables (Buckley & Feuring, 2000). The use of alternative methods of optimization involve genetic algorithms (Sakawa & Kato, 2009). In the article, the proposed solutions are based on the conversion of fuzzy model to the linear models. Occurrence of fuzzy coefficients in the model causes a number of problems related to computing the creation of membership function and the model soft restrictions. In order to solve the problem the method proposed in (Banaś, 2004) was used, which is an adaptation of the method STEM for solving fuzzy multi-objective optimization problems (Benayoun, de Montgolfier, Tergny, & Taritchev, 1971). The zero iteration follows the initialization of fuzzy coefficients and to determine the initial values for the four parametric degrees meeting the restrictions $\tilde{a}_i(x) \le \tilde{b}_i\ (\tau_i, w(\tau_i), \omega_i, w(\omega_i))^{(j)} = (1, 1, 0, 0)$ i $\in \{1,\ldots,m_F\}$}, where m_F - the number of fuzzy constraints. The use of parametric degrees to meet the restrictions is an approach based on the principle of expansion (Zadeh, 1965), which assumes the form of inequalities comparing the position of the left arm of fuzzy number defined in a trapezoidal form. In the next step, the designation of the two-parameter function of degrees to compromise takes place with the number of fuzzy objective functions. The next step is based on assigning limits of fuzzy aspiration levels for the functions with at least one fuzzy factor or deterministic levels of aspirations. Then an iterative procedure follows the introduced by the decision maker changes to the initial values parameter representing significance of constraints, degrees of compromise objective function, levels of aspiration. A deterministic task is based on the adopted coefficients and thus a multi-objective linear programming is generated:

$$\max \left\{ \left[(c_1^T x)^s{}_{(\alpha_1,\beta_1)^{(j)}} \ldots (c_q^T x)^s{}_{(\alpha_q,\beta_q)^{(j)}} \right]^T : x \in X^{(j)}_{(\tilde{\tau};\tilde{\omega})} \right\} \tag{8}$$

Functions $(c_k^T x)^s{}_{(\alpha_1,\beta_1)^{(j)}}$ for $k \in \{1, \ldots, q\}$ and $x \in X$ are determined according to the formula:

$$(c_k^T x)^s{}_{(\alpha_1,\beta_1)^{(j)}} = \begin{cases} c_k^L(x) - \chi_k^L(x)(1-\alpha_k^s) & \text{for } \alpha_k^s \in <0,1), s = L, \beta_k = 1 \\ c_k^R(x) - \chi_k^R(x)(1-\alpha_k^s) & \text{for } \alpha_k^s \in <0,1), s = R, \beta_k = 1 \\ c_k^L(x) + \left(c_k^R(x) - c_k^L(x)\right)\beta_k & \text{for } \alpha^s = 1, \beta_k < 0,1) \end{cases} \tag{9}$$

In order to solve the task usage of the procedure STEM is implemented (Benayoun et al., 1971). In the first step, the set of solutions is determined so as to optimize each function $f_i(x)$. In the next step is created a payoff matrix, and for each function $f_i(x)$ is determined nadir for k ∈ {1,..., q} which is the latest element of the *kth* column. To verify the proper solution a testing procedure is used in order to verify proper solution. As a result the decision maker receives $\bar{x}^{(l)}$ solutions and efficient graphical representation of membership functions of fuzzy numbers occurring in the inequalities $\tilde{a}_i(\bar{x}^{(l)}) \le \tilde{b}_i$ i ∈ {1,...,m} i $\tilde{c}_k(\bar{x}^{(l)}) \ge \tilde{d}_k$ k ∈ {1,..., q} and a four degrees of fulfillment of inequality. The procedure stops when the $\bar{x}^{(l)}$ solution provides a satisfactory level of achievement and the transition to the next stage is performed. When the solution $\bar{x}^{(l)}$ is not satisfactory but there is a satisfactory level of performance of fuzzy restrictions, the algorithm returns to the previous step. Based on the graphical representation of inequality $\tilde{c}_k(\bar{x}^{(l)}) \ge \tilde{d}_k$ k ∈ {1,...,q}, the position vector of $f(\bar{x}^{(l)})$ with respect to the objectives of the ideal y^M solution exchange rates and the decision maker selects the criteria k′, which may degrade and determines the maximum acceptable loss $\Delta_{y'k}$. On this basis in the iteration $1+1$ $X^{(l+1)}$, a collection is formed by connecting a set of constraints. When no satisfactory solution is obtained, the algorithm returns to the initial step and the new weighting factors are used.

5. Perceptual experiment and online field experiment

The model verification was conducted using the data from experimental advertising campaigns performed in the real environment based on the advertising content from five categories of products and services including fitness club, travel agency, social networking platform, portal with online games and virtual world. Data collected during experimental campaigns in periods t-3, t-2, t-1 was used for generating decision solution for planning advertising activity in the period *t* with included ability to minimize the negative influence on users and achieving assigned profits. Empirical research was conducted in three stages. The first stage includes the design of variants of advertising objects with different levels of intrusiveness based on attention catching techniques like flashing, vividness, animations with different sizes and styles. In the second stage perceptual experiment was performed using pair-wise testing of intrusiveness with main goal to assign intrusiveness level to each advertising unit. In the third stage online testing campaign was conducted based on five different products and services. Collected data from each experiment was used to compute fuzzy parameters for models. Finally comparison of results from both online and perceptual experiment was presented.

5.1. Advertising content design

The proposed approach is based on using components of a web interface, such as headers and advertisements in the form of objects decomposed into elements that provide the ability to create a specific influence on a target user. The purpose of many online systems is to get some kind of interaction that can be defined through various ways depending on the scope of the task and the business model. The main goal is to influence users to perform the desired actions. For each advertising object, the set of available elements $E = \{E_1, E_2, \ldots, E_n\}$ with the design options determined by $E_i = \{e_{i,1}, e_{i,2}, \ldots, e_{i,cnt(i)}\}$ is defined, where *cnt(i)* describes the number of possible design variants for the *ith* element. For each component $e_{i,j}$ the level of persuasion $p_{i,j}$ determines the strength of influence on a user. Objects created in that way can be used to test the system and the characteristics of the components used in both perceptual and online experiment. The purpose of the object generation is to choose elements from the given collection in accordance with the provided selection function. Based on the structure of the objects and sets, units with different characteristics are generated automatically and users' responses are gathered in the perceptual

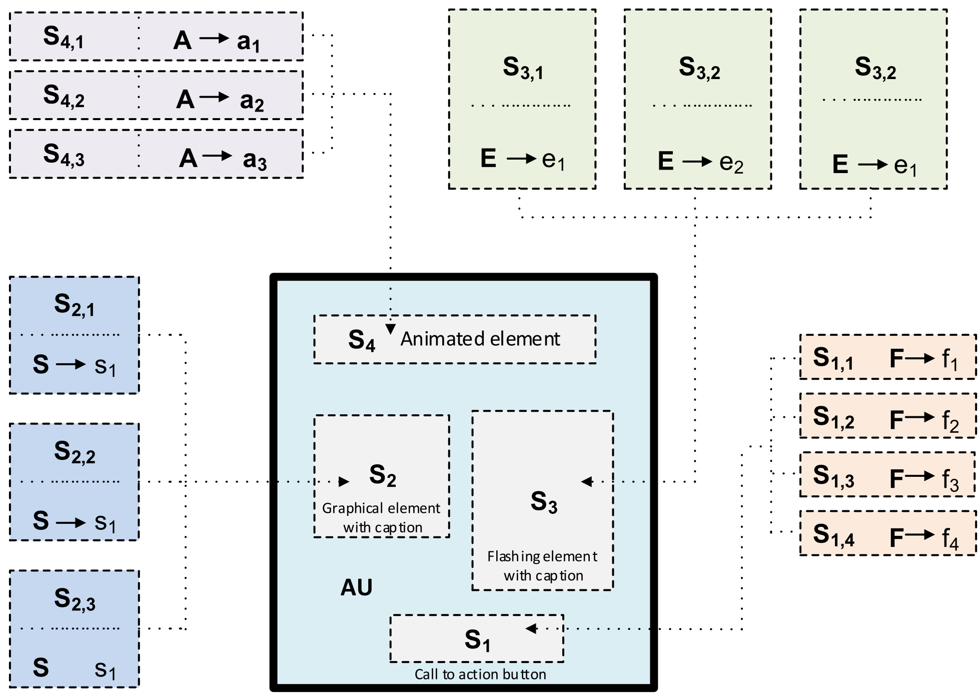

Fig. 3. The example structure of an experimental advertising unit.

experiment. In order to verify the presented solution, the experimental interactive object was built with mechanisms of variant selection that were integrated with a real system. Within this object the components were defined with different levels of influence on the user. The designed experimental interactive objects were in the form of an online advertisement, with the *call to action* messages integrated. The main goal was identified as redirecting the audience to the target website after clicking. These objects are composed of four sections: S_1, S_2, S_3 and S_4 illustrated in Fig. 3.

In section S_1 the influence element is in the form of a *call to action* button used with four flashing frequencies (F), from silent non-flashing mode through 50 ms and 25 ms towards high frequency flashing with vividness effect. In section S_2 active graphical elements were located with variants related to the size of the flashing area (S), from 10% through 20% and up to 40%. Section S_3 represents a set of graphical elements (E) with options to use flashing effects from the level one to the level three. Element S_4 was responsible for animations (A) with three conditions: disabled, horizontal or vertical. As a result experimental space consist from 10 advertising units $AU_1,...,AU_{10}$ for each of five campaigns.

5.2. Perceptual experiment - user experience analysis

During the perceptual experiment the interactive components were assessed through the Internet by inexperienced observers who were confirmed to have normal or corrected-to-normal vision. The age of the users varied between 20 and 68. Fourteen observers completed a pair-wise comparison experiment, the main task of which was to read text and select which of a given pair of advertisements influenced the performed task more negatively and distracted attention. For additional reliability all observers repeated the experiment three times so 42 repetitions were collected. In order to reduce the learning effect no repetitions took place on the same day. According to (Mantiuk, Tomaszewska, & Mantiuk, 2012), collecting 30–60 repetitions per condition is a sufficient sample size. Since the experiments were run through the Internet, the conditions were not stabilized, however that a proper design advertisement should influence similar impacts for observers despite the display conditions. Advertisements were shown on a 50 percent grey background, and the same background was used for the intervals between displayed pairs of images. The observers were free to adjust the viewing distance of their screen to their own preference. In the real-world applications, images are seen from varying distances on screens of different resolutions, so quality experiments are rarely performed in controlled conditions where viewing distance is restricted by a chin-rest and the display angular resolution (in pixels per degree) is kept constant. Because of this, the data gathered in the sample is more representative of real-world conditions because of variability due to uncontrolled viewing conditions included in the measurements. Observers were asked to read written instructions before each experiment. Following the ITU-R500 recommendation (ITU-R.REC.BT.500, 2002), the experiment started with a training session in which observers could familiarize themselves with the task and the interface. The training session included five trials with the advertisements from the original data set, which were selected to span a wide range of intrusive elements. To ensure that observers fully understood the experiment, three random trials were shown at the beginning of the main session without recording the results. The advertisements were displayed in the random order and with a different randomization for each session. Two consecutive trials showing the same test advertisement were avoided, wherever possible, and to prevent fatigue no session was longer than 30 min. Once we collected experimental data our goal was to find a scalar measure for each test advertisement that rates intrusiveness on a continuous interval scale. Results from perceptual experiment showed differences among subjects when intrusiveness of presented content was evaluated.

For the modeling purpose, the selection of the shape of the membership's function was important. For computational efficiency and easier data acquisition, the most frequently used representation of fuzzy numbers includes trapezoidal, triangular, L-R trapezoidal and L-R triangular representation (Chen & Hwang 1992, Klir & Yuan 1995). Trapezoidal approximation is a reasonable compromise between two opposite tendencies: to lose too much information and to introduce a form of approximation which is too

Table 1
Number of ad impressions for each campaign.

C	P_1	P_2	P_3	SD	L	A	B	C	R
C_1	44,235	113,980	30,449	44,780,66	30,449	46,669	62,888	88,434	113,980
C_2	60,671	104,876	59,206	25,955,02	59,206	67,062	74,918	89,897	104,876
C_3	76,998	89,555	16,408	39,113,74	16,408	38,698	60,987	75,271	89,555
C_4	130,751	172,559	29,028	73,820,31	29,028	69,904	110,779	141,669	172,559
C_5	64,097	182,975	18,407	84,953,11	18,407	53,450	88,493	135,734	182,975
Total	376,752	663,945	153,498	255,890,05	153,498	275,782	398,065	531,005	663,945

sophisticated (Brândaş, 2011). Core of trapezoidal function makes possible same evaluation of values from given range, what is closer to real behaviors and the evaluation of campaign efficiency. As a result for model parametrization, trapezoidal fuzzy representation was used. For each advertising unit in each campaign feedback from subjects allowed to build fuzzy representation for perceptual response using minimal values for left side L, maximal values for right side R, point B representing average value, point A = (B−L)/2 and point C = (R−B)/2.

Within each campaign the highest average negative perceptual response was observed for unit 6 with 40% flashing area and is highlighted in the table. Standard deviation for each campaign was identified at maximal and minimal level. For each campaign the lowest standard deviation was observed for the first ad unit without flashing effects or animations values (0.016, 0.0322, 0.0478, 0.0157, 0.0161) for campaigns (C_1,C_2,C_3,C_4,C_5) where obtained accordingly. Within campaign C_1 highest SD with value 0.2418 was obtained for $AU_{1,4}$ and same was observed within C_2 with maximal value for $AU_{2,4} = 0.2852$. For campaign C_3 highest for $AU_{3,10} = 0.2512$ while for campaign C_4 highest value 0,2643 was observed for $AU_{4,9}$. Within campaign C_5 highest SD was obtained for $AU_{5,4}$ with value 0.2491. Fuzzy parameters related to the perceptual response as a measure of intrusiveness where used within decision support models and make possible to represent uncertainty when the content is evaluated by different web users. Proposed fuzzy representation makes possible taking into an account uncertain values ability to use different evaluations of the level of intrusiveness of used advertising content.

5.3. Online field experiment – real user interaction

Based on the prepared content the field experiment was conducted in time three periods P_1, P_2, P_3 respectively t−3, t−2, t−1. For each period and advertisement, data related to the number of ad impressions and click through ratio based on the number of clicks was collected. In the Table 1 the number of impressions for each campaign C_i based on the available audience is showed. Results showed different number of total impressions for each period with the highest total value for P_2 equal to 663945 and minimal value obtained for P_3 equal to 153498. The number of impressions is affecting possible results and high variability is showing difficulties with the usage of deterministic parameters for the model.

In case of results obtained from testing periods fuzzy representation of emission resources is proposed as model parameters. Using the method proposed in (Piegat, 2010) fuzzy parameters were calculated from obtained dataset for each campaign with an assumption that the number of expositions can be a target for each advertiser and identified as a total portal resources in a form of a global emission resources constrain. Table 1 shows fuzzy coefficients L, A, B, C, R for trapezoidal membership functions based on earlier results. Example fuzzy representations for resources assigned for campaigns C_1 - C_5 are showed in Figs. 4–8. while Fig. 9. illustrates total fuzzy emission resources available for all campaigns.

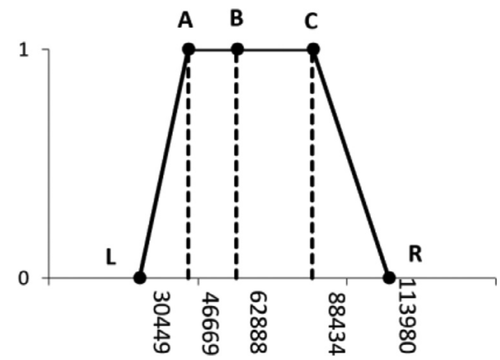

Fig. 4. Fuzzy emission resources allocated for campaign C_1.

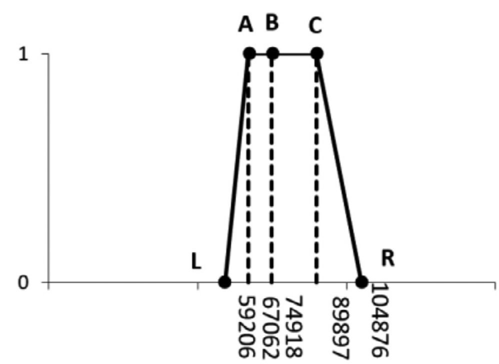

Fig. 5. Fuzzy emission resources allocated for campaign C_2.

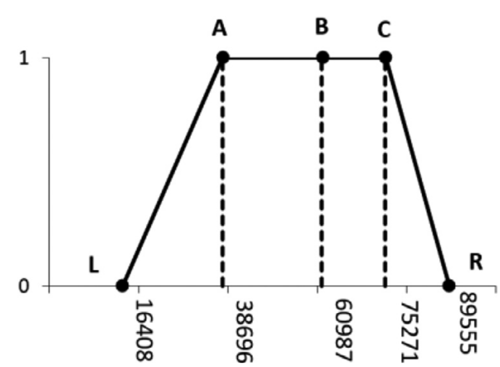

Fig. 6. Fuzzy emission resources allocated for campaign C_3.

The online experiment delivered data related to the number of registered interactions in a form of clicks. Using this data the click-through ratio which represents the number of clicks in the relation to the number of impressions was computed for each ad unit AU within each campaign for each period. Parameters of model were computed with the use of the number of clicks and computed click-through ratio (CTR) as a number of clicks divided by a number of impressions. Changes of response within analyzed periods were observed and can be a result of different timing, changes of

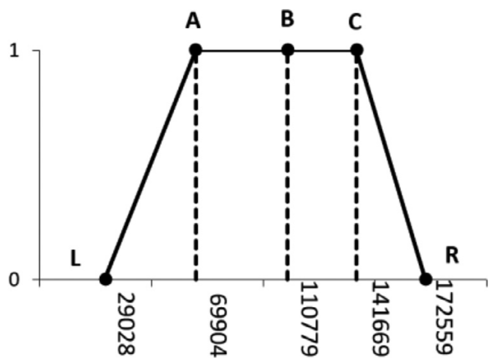

Fig. 7. Fuzzy emission resources allocated for campaign C_4.

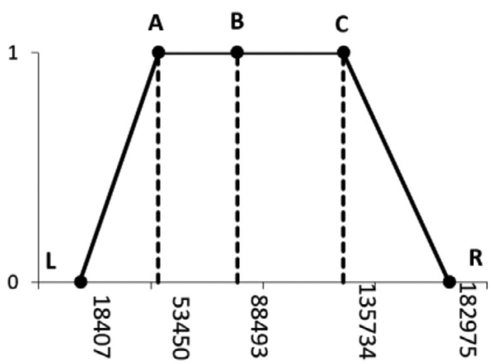

Fig. 8. Fuzzy emission resources allocated for campaign C_5.

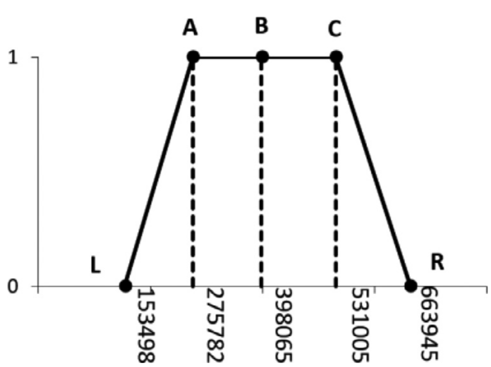

Fig. 9. Total fuzzy emission resources ER.

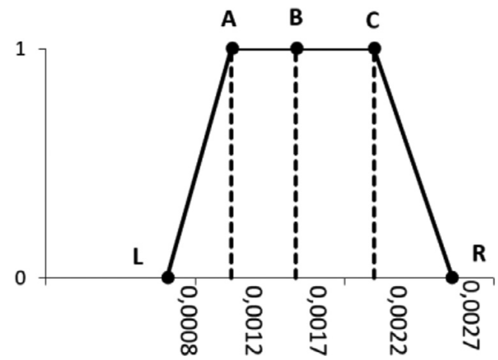

Fig. 10. Fuzzy CTR factor for ad unit $AU_{1,1}$.

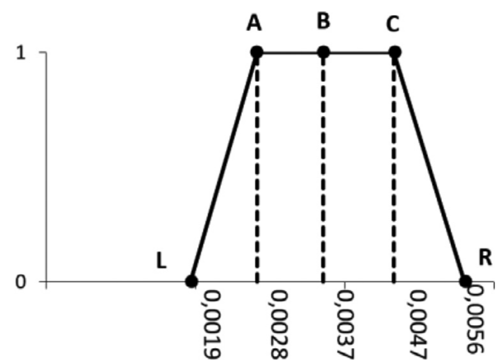

Fig. 11. Fuzzy CTR factor for ad unit $AU_{1,3}$.

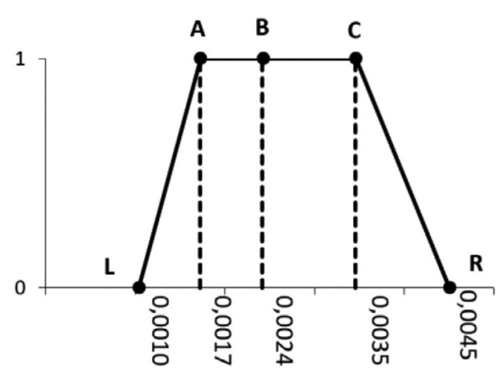

Fig. 12. Total fuzzy CTR factor all campaigns.

interest in advertised product, different audiences or banner blindness phenomenon (Burke et al., 2005).

An average CTR for all campaigns in the period P_1 was observed at the level 0.17% while in period P_2 it dropped to 0.12%. In the period P_3 an increase was observed to the level of 0.44% what was 266.53% increase when compared to the period P_1 and 373.86% increase when compare do the period P_2. Fuzzy coefficients where computed for each unit representing changes of response. Figs. 10 and 11 show graphical representation of the fuzzy numbers containing the values of direct responses for ad unit with lowest CTR observed ($AU_{1,1}$) within campaign C_1 and for the highest CTR ($AU_{1,3}$) within the same campaign. The total fuzzy CTR parameter registered for all campaigns is showed in Fig. 12.

Fuzzy representation of response parameters makes more realistic estimates for future planning and changes of environment can be taken into an account. Within the planning process the pessimistic, neutral and optimistic values can be used to obtain alternative solutions closer to reality than deterministic inputs based on average ranges from longer period. Other used parameters are related to advertising budgets and costs of emissions with detailed allocation and visual representation of fuzzy parameters.

Total costs were based on aggregated number of impressions of each advertisement with assigned costs per thousand impressions dependent on the intrusiveness of advertisement. Results showed differences between each period and uncertainty when planning possible budget usage for the next period. The complete summarized budget from campaigns represented profits of online publisher from selling the advertising space within the portal and is varying from minimal value 216.18 achieved in the period P3 up to the highest value 942.40 from the period P2. With the use of values from three experimental periods coefficients for fuzzy budget with trapezoidal representations were computed based on L, A, B, C and R values.

The used fuzzy representation makes possible to plan campaign using pessimistic, neutral or positive approach assuming future values more close to left, central or right range from the fuzzy representation respectively. For example for campaign C_1 pessimistic approach assumes used budget smaller than 66.70. Highest probability assigned to the range 66.70–128.10 can be treated as a neutral, optimistic for usage higher than 128.10 till not realistic 165.65.

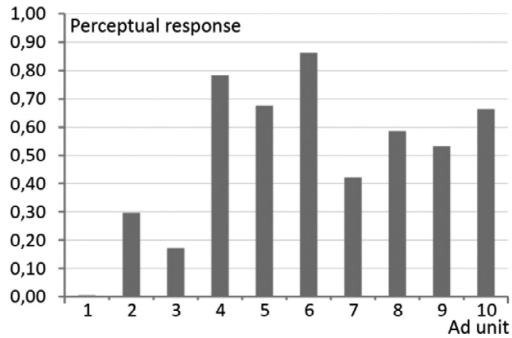

Fig. 13. Average perceptual response for all campaigns.

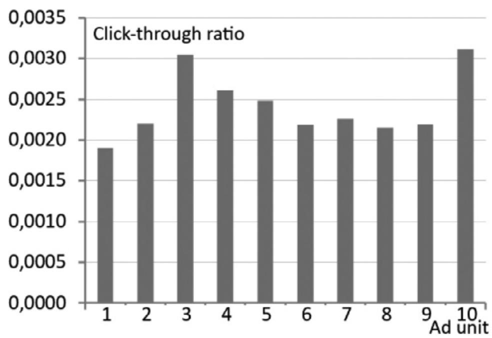

Fig. 14. Average online response for all campaigns.

5.4. Comparison of results from perceptual and online studies

In this stage of analysis the standardized results from the perceptual experiment were compared with the activity of online users in a form of registered interactions and these are shown in Fig. 13. Y axis represents the level of persuasion detected in perceptual experiment aggregated for different types of advertisements. Results showed that lowest negative impact was registered for AU_1 with static image used and it was unit with the lowest possible negative influence. Highest value 0.85 was obtained for AU_6 with 40% of flashing space and close to 0.90 for AU_6 with used vividness effect and high frequency flashing. Aggregated data from all periods of online experiments are showed in Fig. 14. The highest number of interactions measured CTR was obtained for AU_{10} with vertical animation and AU_3 with 50 ms flashing effect.

Ad units with the highest negative perceptual response and intrusive attention attracting elements did not get the highest number of clicks. Intrusive element AU_6 got CTR at the level of 0.0022 what was 32% lower result than for unit with highest CTR. The intrusive element AU_4 got CTR at the level of 0.0026 which was 19% lower result than results for unit with highest CTR. Even though AU_4 received relatively high response online and third position in the ranking, it was occupied by high negative perceptual response. A comparison of the results from both experiments shows that increased intensity of intrusiveness resulted in a highly negative impact on the participants of the perceptual experiment, but the high intensity was not justified by a higher response online. Animations resulted in a higher response and the intrusiveness was observed to be at the moderate level. Results showed that those multidimensional increase of influence level caused by implementation of intrusive elements in the message do not necessarily result in a better results. Using the presented methods would give the basis for specifying the scope of effects and persuasion levels where there is no significant improvement of conversion coefficients but there is a negative influence on the user.

6. Trade-off between user experience and effectiveness - fuzzy multi-objective modeling

In the next step data acquired during experimental research was used as parameters for fuzzy linear model validation with the different scenarios for general resources usage strategy and simulation. The main goal was to generate emission plan using different target values for interactions, outcome and negative effects. The other goal of the modeling process was to observe how changes of model parameters, aspirations level for goal functions were affecting plans and possible outcomes for both website operator and advertisers. Model validation was performed in two stages of simulations. In the first stage analysis was using two global criterions based on minimizing level of persuasion and maximizing the outcome from selling advertising space within the website was conducted. In the second stage detailed criteria functions for all advertisers were taken into an account to maximize the number of interactions and minimize negative impact for each advertiser while using maximization of total portal operator outcome.

6.1. Results from global modeling with two criteria

The main goal of applications of the proposed model is to plan future advertising actions within portal using feedback from earlier periods of campaigns and connecting them with the perceptual data to adjust negative impact on web users. In this stage research has been conducted for global optimization goals. The optimization process starts with processing fuzzy technical and economical parameters representing the direct effects indicators, perceptual response, emission resources and budgets. Research was done for global goal functions $FG^t{}_1(x)$ and $FG^t{}_2(x)$ for minimizing negative effect on web users and maximizing outcome of website operator from selling advertising space respectively. The main goal of modeling was searching for compromise solutions and emission plan with limited negative impact on users while outcome levels are acceptable for website operator. The process was performed using 53 steps and decision solutions were generated during simulations. In each step different aspiration functions were defined for outcome represented by $FG^t{}_2(x)$ and resulted different response from model and value of negative response represented by $FG^t{}_1(x)$. Results for both functions are shown and compared in Fig. 15 with Y axis representing the normalized measure of outcome and intrusiveness while X axis is representing the step of simulation. The dotted line illustrates the negative response and dashed line is showing web portal outcome.

From step from 1 to 27 it was observed that the growth of obtained values for criterion $FG^t{}_2(x)$ representing outcome and persuasion at very low levels. In the steps 27 - 32 $FG^t{}_2(x)$ stabilizes at the range of 0.6 and it is accompanied by slight growth of negative influence on users. From the step 33 till 49, the growth of outcome is smaller than the growth of persuasion. In this period the outcome grows from 0.62 till 0.87 while persuasion grows more than ten times from 0.05 till 0.6. Highest dynamics for growth of persuasion is observed from period 48 till 50 when value of 0.93 is achieved while outcome grows in smaller range and 12% only from 0.85 till 0.95. Solutions starting from 33 till 49 deliver higher outcome to 0.85 but are occupied by higher growth of persuasion. Results showed that possible solution in the steps 28 - 33 with very low persuasion and outcome in the range of 0.6. If this level of outcome is not acceptable, another option is selecting solution from range 45–49 where outcome is close to 0.8 and persuasion is at the 40% of maximal value. For each step of simulation was obtained emission plan as a decision solution showing how many ads from each campaign should be displayed to web users. Results showed that with using global criterions not all advertisements are used, what is shown in Figs. 16–20 where Y axis represents the

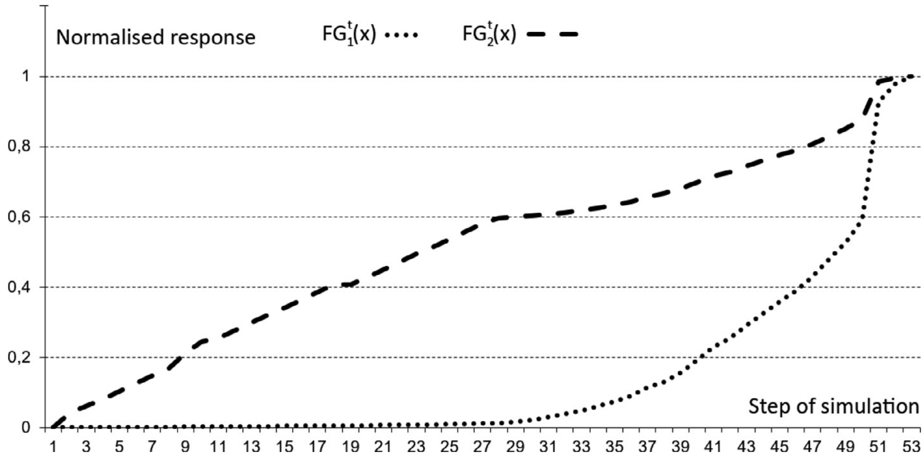

Fig. 15. Normalized results for global criterions $FG^t{}_1(x)$ and $FG^t{}_2(x)$.

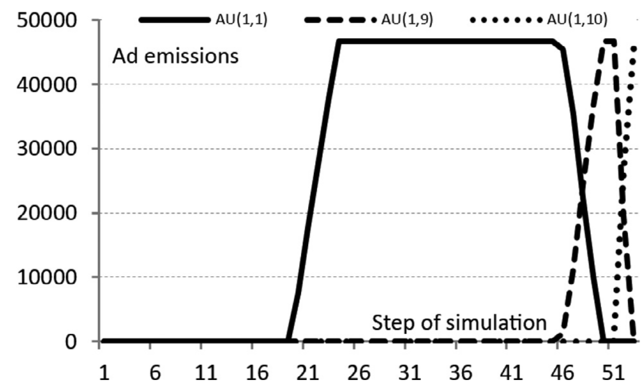

Fig. 16. Exposition plans for campaign C_1.

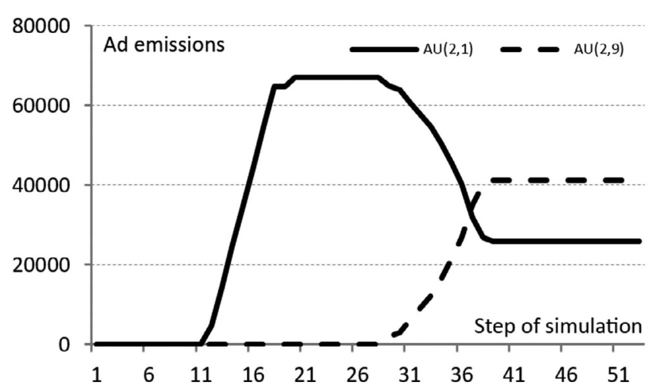

Fig. 17. Exposition plans for campaign C_2.

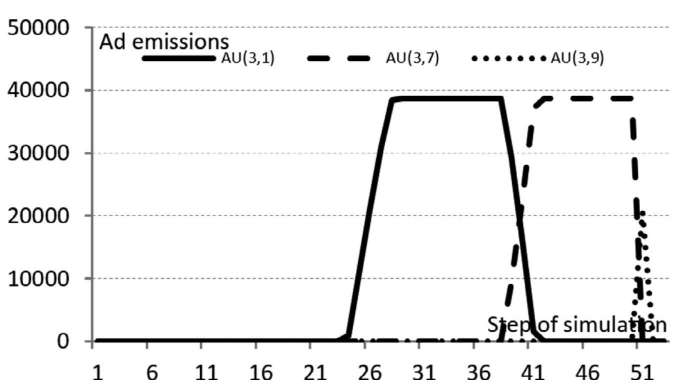

Fig. 18. Exposition plans for campaign C_3.

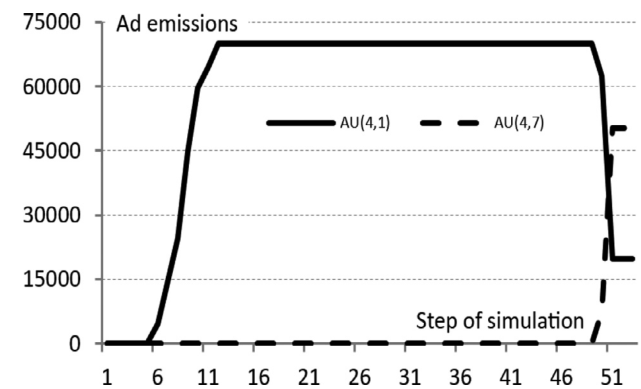

Fig. 19. Exposition plans for campaign C_4.

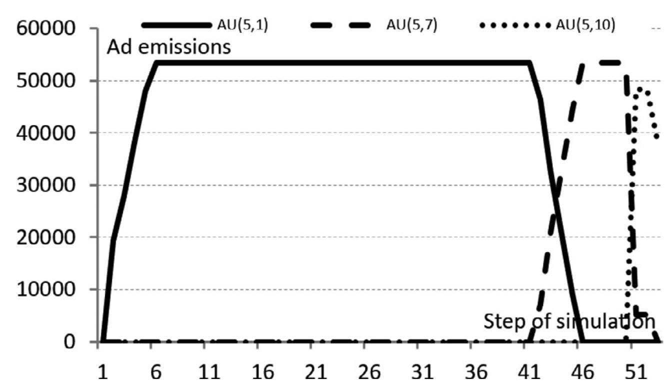

Fig. 20. Exposition plans for campaign C_5.

number of impression and the X axis is showing the step of simulation. Advertisements where switched On and Off depending on associated outcome and persuasion. Results showed that the model is working correctly and together with the growth of outcome it was observed the need for higher usage of advertisements with higher persuasion and higher costs of exposition within portal. In Fig. 21 is showed total number of expositions of all used ad units in each stage of simulation.

For campaign C_1 the advertisement $AU_{1,1}$ with the lowest intrusiveness and small emission costs was planned and the emission started at stage 20. It was among decision solutions with high intensity with planned 50,000 expositions till step 46 then it was accompanied with $AU_{1,9}$ with higher intrusiveness and then it was used till step 50 after $AU_{1,1}$ was stopped completely. From step 51

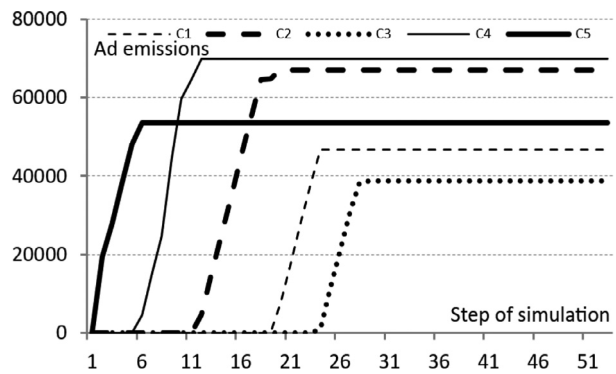

Fig. 21. Total expositions for campaigns C_1-C_5.

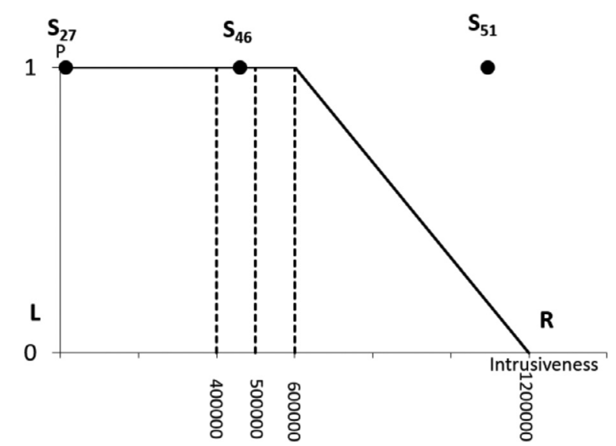

Fig. 22. Fuzzy aspiration level for function $FG^t{}_1(x)$ at stages S_{27}, S_{46} and S_{51}.

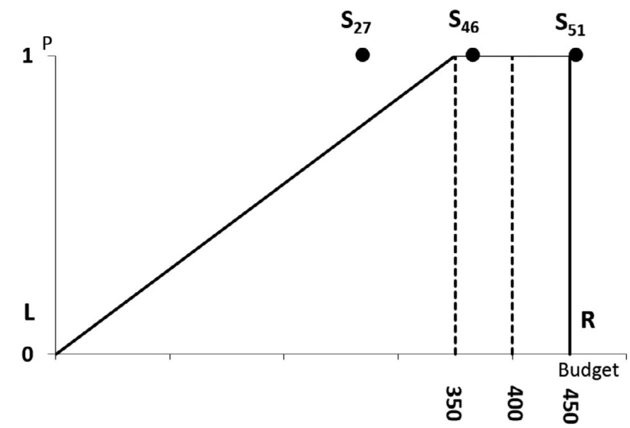

Fig. 23. Fuzzy aspiration level for function $FG^t{}_2(x)$ at stages S_{27}, S_{46} and S_{51}.

usage of highly intrusive $AU_{1,10}$ started and it replaced $AU_{1,9}$ completely at the end. Results for campaign C_2 showed that ad unit $AU_{2,1}$ was used from the step 12 with maximal usage 68,000 impressions till the end of modeling but at the stage 32 advertising unit $AU_{2,9}$ was turned on and was used with higher intensity from the step 38. The emission plan for campaign C_3 assumes usage of ad unit $AU_{3,1}$ with 39,000 impressions from the period 24 till 41 and usage of $AU_{3,7}$ from stage 38 till 50 followed by $AU_{3,9}$ in the last two stages. The emission plan for campaign C_4 is mainly based on $AU_{4,1}$ from the stage 6 and $AU_{4,7}$ started at the end. Campaign C_5 is the only one campaign with expositions of ad unit $AU_{5,1}$ planned for first simulation steps with accompanying $AU_{5,7}$ from the simulation stage 41 followed by $AU_{5,10}$ at the end of the process. Results showed that compromise from steps 27–32 used advertisements from all campaigns and then all budgets where used. This solution is acceptable not only because of acceptable outcome and relatively small negative feedback but the usage of advertising units takes place for all advertisers as well. During the modeling process aspiration functions where defined and fulfillment for constraints was monitored. Assigned aspiration levels for criterions $FG^t{}_1(x)$ and $FG^t{}_2(x)$ with results obtained in stages S_{27}, S_{46} and S_{51} of probability P of achieving assumed level of intrusiveness and budget usage are showed in Figs. 22 and 23.

Evaluation of results is based on the relation of achieved values to the shape of aspiration function and different values of the aspiration levels are observed. A kernel of fuzzy number has the highest preference to be reached, while left and right regions have smaller preferences. For fuzzy aspiration for $FG^t{}_1(x)$ the highest preference was assigned to the persuasion from zero till 600 K units. Representation is subjective, and based on the maximal possible persuasion on the users at the level 1200 K when most intrusive ads are used. Solution S_{27} with obtained value $FG^t{}_1(x) = 13{,}495.61$ delivers very low persuasion but it is associated with low outcome represented by value of $FG^t{}_2(x) = 268.03$ showed in Fig. 23 localized as a solution with low acceptance. Solution obtained in the stage S_{46} is affecting user experience at moderate level with $FG^t{}_1 = 459269.24$ while $FG^t{}_2$ is observed at accepted level 365.02 and following web operator's preferences with probability equal to 1. Solution obtained in S_{51} delivers high outcome at the level of 455.48 and it is covering preferences, but the high value is occupied by high intrusiveness with S_{51} close to maximal values and way above accepted levels. The analysis of aspiration functions confirms selection of solutions from the stage S_{46} as a plan for the next period of analyzed campaign. At the final decision stage of the process, the management responsible for planning marketing activities can take into account obtained results from different perspectives. Knowledge about uncertain conditions and balance between outcome and level of persuasion affecting user experience can be used. The global model enables the observation of budgets allocated for campaigns and makes possible planning the usage of resources and budgets allocation.

6.2. Results from modeling with sub-criteria

In the next stage, an operational model was validated with the main goal being to evaluate decision solutions in relation to single campaigns from the perspective of individual results in a form of interactions and negative influence on target users. The proposed model, apart from individual results and sub criteria for ach campaign, enables the evaluation of results in terms of costs to advertisers and outcome of portal's operator from campaigns. Results for campaigns C_1–C_5 are showed in Figs. 24–28. Searching for decision solutions was performed in 40 steps using different settings for aspiration functions. Results showed different relations between persuasion and the number of achieved interactions for each campaign. For example in Fig. 24 costs of this campaign grow within steps 1–15 and stabilizes at level 0.63 with slight increase with the decision solutions between step 15 and 31 while number of interactions is growing with higher dynamics than costs for advertiser. Persuasion is growing slowly till step 33 and then dynamics grows and solutions become more persuasive, but it is associated with the growth of the number of interactions. In the final stages 37–40 persuasion grows quickly from 0.4 till 1 and it is accompanied with the growth of costs from 0.72 till 1.0 but interactions in this steps are growing only from 0.9 till 1.0. Different specifics is observed for campaign C_2 where growth of costs is observed in all steps apart from 1–9 and 33–40. It shows that each increase of number of interactions is occupied but higher growth of costs than for campaign C_1 and distance between interactions and

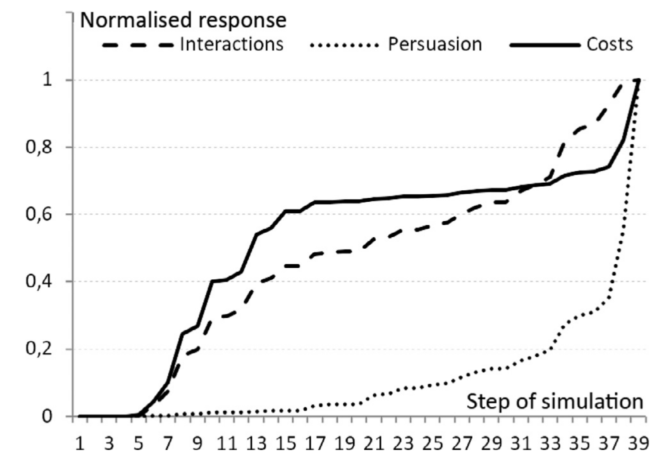

Fig. 24. Modeling the number of interactions and persuasion together with costs for campaign C_1.

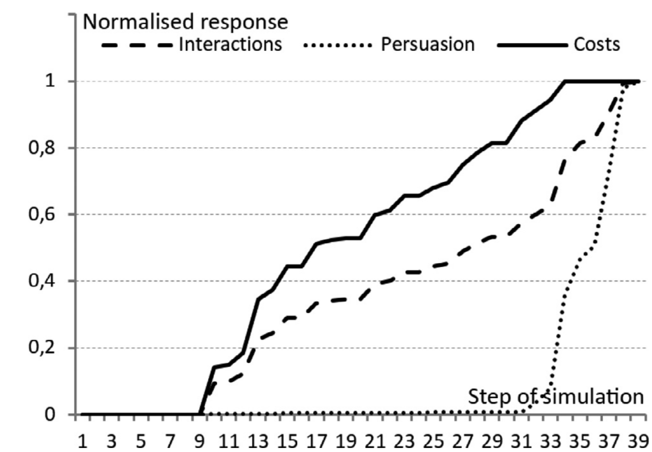

Fig. 25. Modeling the number of interactions and persuasion together with costs for campaign C_2.

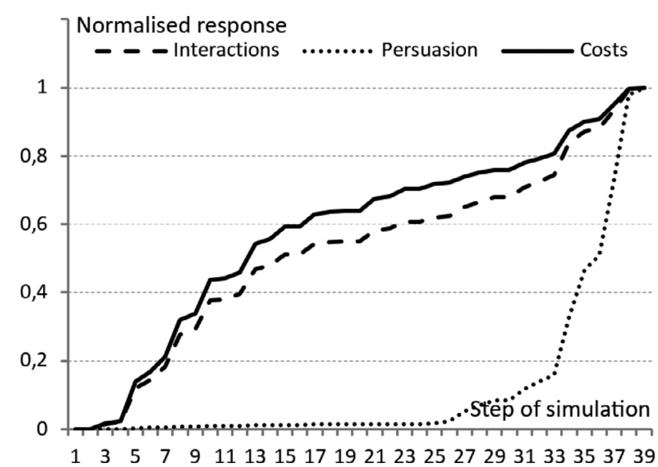

Fig. 26. Modeling the number of interactions and persuasion together with costs for campaign C3.

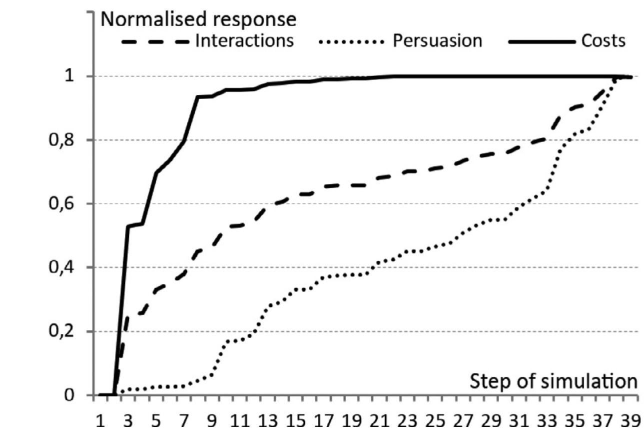

Fig. 27. Modeling the number of interactions and persuasion together with costs for campaign C4.

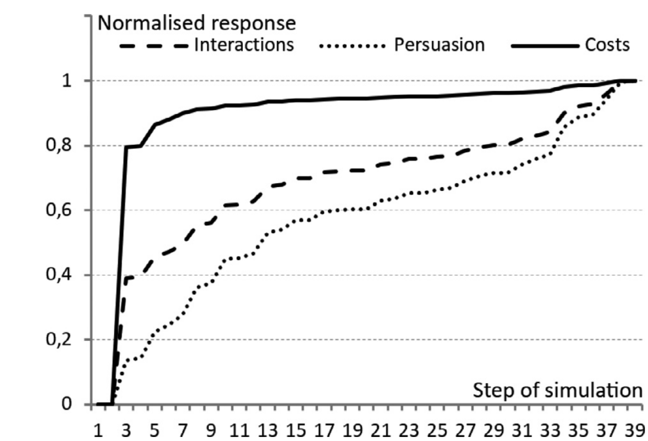

Fig. 28. Modeling the number of interactions and persuasion together with costs for campaign C5.

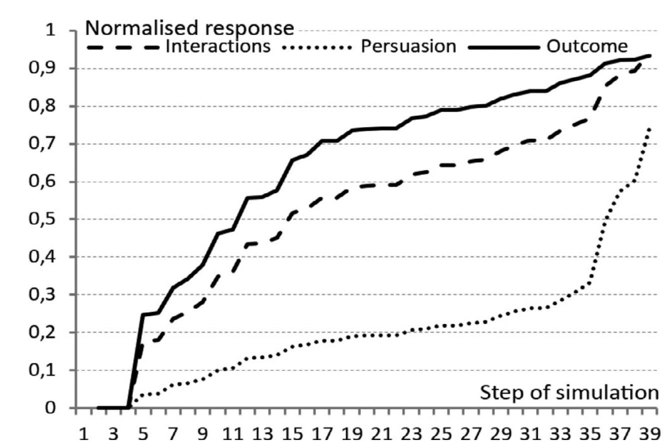

Fig. 29. Aggregated number of interactions and persuasion together with outcome for web portal owner.

outcome grows. Persuasion is observed at the very low level close to zero till period 32, then it starts growing with high dynamics till 1.0 in 40th step. Similar relations are showed for campaigns C_3–C_5 and the different relations are visible. Campaign C_3 is characterized by similar growth of costs and interactions while in campaigns C_4 and C_5 costs are growing very fast while dynamics in achieving interactions is smaller. In both cases growth of persuasion is observed since the beginning and it is higher for early steps than for campaigns C_1–C_3.

In Fig. 29 presented is the aggregated data from all campaigns in 40 steps of simulation. It shows the total number of interactions delivered to the advertisers and negative influence on web users within a portal. Total costs of advertisers are summarized in a form of outcome to web portal. It shows that highest growth of income was observed for obtained decision solutions in steps 4–18 and then it is still growing with smaller dynamics. From the beginning the number of interactions is growing more slowly than outcome and distance between both values grows till the periods 21–23. Then the distance was reduced and the higher dynamics for interactions than outcome is observed. Persuasion on the web users grows in steps 1–19 till low level 0.2 and then slowly grows till 0.3 obtained in the step 34. After that, it is growing fast till 0.8 and this growth is resulting higher number of interactions, however the outcome is growing slowly. Step 34 can be treated as a compromise solution where persuasion is only at 30% of maximal value and number of interactions delivered to the advertiser is at the level 0.75 and 0.88 of outcome. If a web portal owner would like to keep persuasion smaller at the level off 0.20 like it was obtained in the step 23 it would be resulting smaller number of interactions at the level 0.60 and outcome 0.75. This solution may deliver profit smaller than maximal by 25% but the potential of campaign is used only with 60%.

Simulation research based on global criteria revealed the relationship between the intrusiveness of used content and portal outcomes. These criteria enable the discovery of precise solutions that ensure the achievement of specific objectives in terms of user experience and typical measures related to the efficiency of online advertising. These solutions can lead to the elimination of ad expositions with low efficiency or high intrusiveness and to focusing on advertising content that receives a high number of user interactions with a relatively low level of intrusiveness. The solution may be found not only in the context of global objectives but also with respect to local criteria, for example individual preferences for advertisements related to intrusiveness and expected effects of the emission system. Opposite to other solutions, the proposed fuzzy model includes parameters related to the levels of intrusiveness, and it allows the solutions to be adjusted for a given implementation at a certain confidence level. It facilitates adaptation in a changing environment and can be used in strategic planning while searching for the rational use of available resources.

The process of searching for the solutions acceptable from different perspectives takes into account the goals of the advertisers and portal managers to reach the highest user responsiveness and the certainty of their execution. It gives the opportunity to evaluate many potential approaches with respect to different preferences of the decision makers. The model provides an answer to the question of how to obtain a compromise between the user experience that is affected negatively by the intrusiveness and the efficiency of advertising represented by a user's willingness to interact. It is achieved mainly by simulations that evaluate how changes in resources may affect the results, and to what extent it makes sense to increase the advertising budget or how to increase the income without invading user experience.

7. Conclusions

Expert and intelligent systems deliver support using available quantitative data and measurable characteristics for various areas related to web platforms, including web usage and content mining (Arbelaitz et al., 2013), recommendations (He, Parra, & Verbert, 2016), personalization (Hawalah & Fasli, 2015). However, the web designers have to face with dilemmas how to address the hardly measurable expectations of web users and marketers. Visual layer of web systems, web usability, user experience, persuasion or influence on web users require rather qualitative analysis. They usually rely on intuition or earlier experience with very limited support from intelligent systems. The paper contributes to interdisciplinary field combining expert and intelligent systems together with human-computer interaction and online marketing.

There are three main theoretical contributions of the paper. First, our approach integrates heterogeneous knowledge from sources such as quantitative data from online experiments with qualitative representation of subjective perceived intrusiveness as well as with business requirements. The other solutions related to online marketing concentrate on knowledge acquisition in supporting digital marketing strategy formulation from the marketers point of view (Li, Li, He, Ward, & Davies, 2011). We, however, integrate perceptual response and aspects related to user experience within the intelligent fuzzy multi-objective system in the online environment. By connecting commercial aspects and user experience towards compromise solutions, the presented work extends earlier attempts to build infrastructure for supporting usability design patterns (Henninger & Ashokkumar, 2005), knowledge representation (Sheriyev & Atymtayeva, 2015) and intelligent systems for design of human-computer interaction (Sheriyev, Atymtayeva, Beissembetov, & Kenzhaliyev, 2016). The previous work was mainly targeted to functional components of interfaces not taking into account marketing goals and their potential negative impact on web users. Second, the presented study provides a theoretical contribution and addresses research challenges related to engineering aspects of online marketing. It meets the identified need for solutions with better support for stakeholders involved in the creation, placement, evaluation, and publication of ecologically sustainable online advertising (Brajnik & Gabrielli, 2010). While earlier research was fragmented and based on surveys, our model makes possible to conduct large scale simulations and to generate decision variants for "WHAT-IF" scenarios. It also solves the problem with opposite preferences of marketers and content providers (Zhang, 2006) by finding a compromise between their conflicting goals. Third, paper shows alternative approach to measuring the level of content intrusiveness without the use of more subjective surveys and questionnaires like it was suggested earlier (Li et al., 2002). Presented approach is based on perceptual experiments with assigned relation to real online response. Results showed discrepancy between conscious actions within perceptual experiment and interactions from real online systems backed by unconscious data processing and spontaneous interactions. It opens the area for further research to explain factors affecting online response.

The new approach can be used by web designers for the automation of HCI engineering processes, in order to evaluate the impact of used marketing components on user experience. Overall, apart from above conceptual contributions four practical implications may be identified. First, we presented a conceptual framework for decomposition of interactive components, which in turn, enable to generate de-sign variants in real time. It can be used for experimental content creation for dynamic adjustment to the changes of environment. Second, our results prove the ability to find good trade-off solutions and to detect of saturation points within simulation environment after acquiring initial data samples from a real campaign. Third, online experiments revealed that willingness to interact with online interactive component is more related to content itself rather than to additional special effects and content visibility. This phenomenon is in contrast to earlier stages of Internet and the role of animations and active elements within marketing content considerably evolved. The evolution of web user behavior is especially visible if compared to earlier studies emphasizing the role of animations and visual effects at attention catching (Yun & Kim, 2005). Our study clearly showed that the content with high visibility not necessarily motivates to interactions. Fourth, the structure of proposed model can be directly used by practitioners to evaluate data from real campaigns. The proposed model has a generalization property; it can be used to evaluate a single campaign or even to create a reference database for marketing agencies. Using the reference database, the marketing content and its potential performance or influence on web users can be efficiently evaluated.

The perceptual, controlled online experiments and simulations led us to the following general conclusions:

- Perceived visibility and intensity of advertising content detected in the controlled perceptual experiment did not result in a higher number of acquired interactions;
- Based on the perceptual experiments, the most visible and potentially most effective elements are those with a high vividness effect and a 40% flashing area; however, the best results from the online experiment were achieved using much less invasive animated elements and slow frequency flashing. In other words, the most visible content does not motivate the user to intensively interact;
- The high intrusiveness of advertisements did not have an impact on better results, but it negatively affected the user experience;
- The introduced optimization model facilitates searching for a trade-off solution within the online resource exploitation process, taking into account opposite factors related to both profits and user experience;
- A saturation point can be detected where the increase of intrusiveness results only in very slow growth of user attention and only a small increase in the advertisers' and portal's profits;
- The usage of fuzzy model parameters allowed more natural representation of data related to the intrusiveness with imprecise and subjective evaluations.

Presented research is up to date with future directions of online marketing. While more than 144 million users are blocking marketing content with dedicated software (Krammer, 2008; Post & Sekharan, 2015), radical changes in marketing strategies are required and new strategies toward building more friendly environment should be explored.

Future research will focus on integrating the model with the operating environment, as well as its extension towards building a reference knowledge base with real advertising content from different sectors. A larger amount of real advertisements can be utilized to extraction of features affecting the perceived intrusiveness. While recent research was mainly focused on full screen browsers, the mobile technologies and other forms of intrusiveness for ads displayed within mobile applications can be explored. From the methodological perspective, verification of the model with different representations of fuzzy parameters can be studied and compared with current results. Yet another extension can include user behavior analysis using eye tracking and detection of factors negatively affecting the cognitive processes during editorial content absorption.

Acknowledgments

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