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SIMULATION OF COMPETITIVE MARKET SITUATIONS USING INTELLIGENT AGENTS[1]

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Abstract

The following paper describes a way for using Artificial Intelligence controlled simulation methodology in the simulation of various marketing problems. The paper first explores the potential challenges in the construction of market models, describes a guideline for the solution, and points out aspects where the Artificial Intelligence controlled simulation methodology can be applied. Special focus will be dedicated to the intelligent demon controlled simulation, especially the CASSANDRA system.

Keywords: simulation, market simulation, intelligent agents, demon, consumer decision.

1. Introduction

A primary goal of marketing science is to describe, model and predict the behavior of consumers and their attitudes towards the products of the market. The environment where marketing science 'operates' is rather complex and sophisticated, containing many factors, which are extremely difficult to describe and analyze.

On the other hand, simulation allows estimation of otherwise intractable models. Some form of simulation can provide estimation on the behavior of practically any models. The researcher is therefore freed from previous constraints on model specification – constraints that reflected mathematical convenience rather than the economic reality of the situation.

These two small pieces of thoughts clearly highlight the possibility of convergence between marketing and simulation. But even though marketing simulation is not a trivial nor an obvious success story. In order to operate, simulation requires a computationally interpretable representation of the real world system, the model. But in case of marketing simulation the real world system to be modelled is more than complex. It contains several (especially human) factors that are nearly impossible to interpret with analytical tools.

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In marketing research simulation models have a several-decades-old tradition. From a contemporary perspective the early attempts to mimic market phenomena by computer simulation were bound to fail [1]. The 'all-encompassing' simulation models were overambitious in terms of defining a reasonably sized and manageable sector of market reality. As a consequence simulation model builders were forced to introduce many ad hoc parameters with deliberate value settings to capture some faint cause–effect relationships they deemed important. In the end model builders were unable to unambiguously trace back the model output and the attempts failed because of the inverse relationship between model complexity and interpretability of the results. To override this problem the number of free parameters should be kept on a level as low as possible. The safest way to avoid over-parameterization is to assure modularity, to start with a system of a very modest size, and gradually to add complexity once the cause–effect relationships in the previous step have been properly understood. In this case it must be carefully kept in mind, that too much abstraction and simplification might threaten the homomorphism between market reality and the scope of the simulation model. Even the initial versions of the simulation environment have to respect a number of requirements, which – if they were abandoned – would render the simulation output meaningless.

While this train of thoughts is obviously proper, it must be emphasized that a general simulation has managed to produce new, innovative techniques in the recent years. For example, intelligent demons are able to control dynamic simulation runs in order to determine optimal solutions for various sophisticated problems. Using intelligent demon controlled simulation methodology, model builders are enabled to attack more complex segments. So thus applying the intelligent demon principle in market simulation can open up the scope of modelling and makes simulation a more reliable tool for the real world marketing researchers.

In order to achieve this goal an initial hypothesis about the market environment should be pinned down right at the start. With keeping all the pieces of advice above in mind, the base of the artificial market model will be a relatively simple structure:

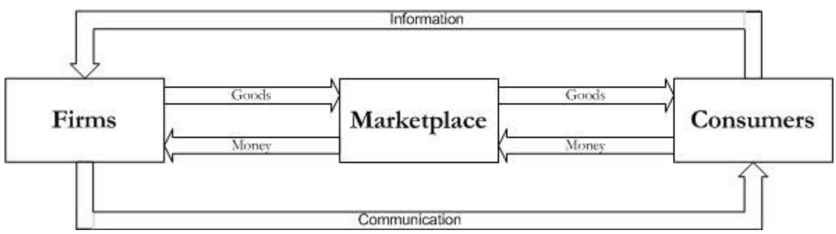

Fig. 1. Structure of the artificial market

The artificial market model consists of firms releasing goods to the marketplace and consumers that select the consumables from this marketplace. The marketplace in this case is degraded to be a 'meeting point', an intermediate storage place, where goods emitted from the firms are permanently stored, until consumers select and purchase them. Another significant abstraction in the concept is the fact that this artificial market is treated as a closed system and does not rely on external effects. Taking this into account all the interactions are marked in the figure.

After accepting the hypotheses above the intelligent agent controlled market simulation can be initiated after having a relevant model representation of Consumers and Firms.

2. Modelling Consumer

The challenge in market simulation model construction lies in the fact, that one of the actors in the real-world system is the most uninterpretable creature, the human being. The definition and the economic analysis of Consumer Theory are not in the scope of this paper. Only those aspects will be examined that are relevant for model construction.

In the simulation model the consumer has the following role:

- Selects and purchases goods from the marketplace,
- Transfers payment for the goods,
- Enables the firms to monitor its attributes,
- Perceives communication initiated by the firms.

From a modelling point of view, the most important process is the selection and purchase of goods, as it represents the individual decision and behavior of the consumer. A broad variety of efforts and theories that attempt to describe the factors, influencing the consumers in their purchasing decisions along with models which attempt to provide an estimate of the product's purchasing probabilities, has been developed. To have a representative model, the environmental behavior should be formalized and somehow described as a process.

In determining the driving factors that affect human behavior, it is practical to distinguish between macro-level factors that are roughly equal for all persons, and micro-level factors that often differ between persons [2]. The macro-level driving factors refer to the natural and human environment a person lives in, and they largely determine the behavioral options he or she has. The macro-level and micro-level of behavior determinants are interdependent. The main macro-level driving factors have got cultural, demographical, technological, economical and environmental roots.

At the micro level, the basic driving forces of behavior refer to human needs and values, behavioral opportunities, consumer abilities and consumer uncertainty. Combining needs with opportunity consumption results in a level of need satisfaction, which determines their motivation to consume certain opportunities and to elaborate on opportunities.

Various interest parties, e.g., firms, governments or consumer organizations use various strategies to influence people's behavior. These interest parties can operate on micro- or macro-level as well, according to their needs.

The resultant behavior is a cyclical process, in which the micro-level behavior of many individuals and the macro-level outcomes mutually affect each other.

This description of consumer behavior has been kept on as low complexity level as possible but it is still hardly interpretable for a simulation model builder. Formal consumer models suggested a high level of abstraction mainly due to the limited computational and modelling possibilities of simulation systems.

By utilizing the modelling capabilities of the CASSANDRA system [3] it became possible to produce a sophisticated consumer model, in which the consumer behavior has been mapped to the following process [4]:

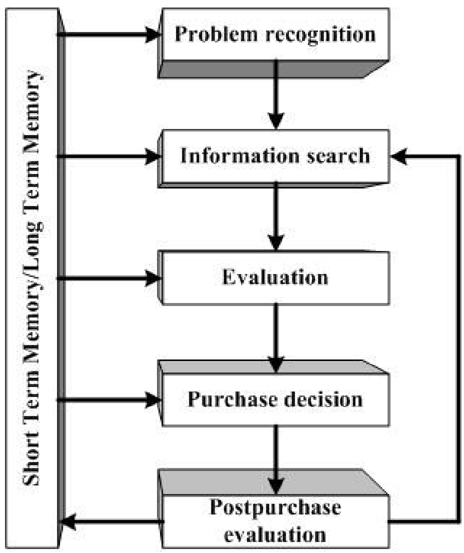

Fig. 2. Consumer behavior process

The model describes the consumer behavior as a five-step process:

2.1. *Problem Recognition*

The consumer process starts with the arousal of the need for consumption. From the simulation model's point of view, this step has got small relevance, so it has been kept on as low complexity level as possible, with only a few free parameters. Therefore, in the simulation the consumption time can be deterministic (with fixed interarrival times) or stochastic (with interarrival times calculated from predefined distributions).

2.2. Information Search

After the recognition of the needs, the consumer gathers information about the consumables that can cover the need. As a consequence of the artificial market's simple structure, the simulation model assumes a very simple procedure in this step. All information about every firm's product is equally available for the consumer. All existing products enter the evaluation steps with equal weights.

2.3. Evaluation

When the consumer has collected all the information from the marketplace, an evaluation procedure takes place. The evaluation is the first step of the consumer's decision-making process, which is very commonly approached by utility theory models [5, 6].

In these models consumers' preferences and their final choice result from the products' comparison according to a set of criteria. This implies that a utility function may be used to model the preferences and the final choice of consumers. According to the utility theory a product **B** will be preferred to a product **A** if the expected utility of **B** is greater than the expected utility of **A**, i.e., $\mathbf{A} \prec \mathbf{B} \Leftrightarrow \mathbf{U}(\mathbf{A}) < \mathbf{U}(\mathbf{B})$, where $\prec$ denotes the preference relationship.

The purpose of the evaluation process is to calculate the expected utility of the products present on the marketplace. As a first step the consumer collects the relevant attributes of the products:

$$\underline{g} = [g_1, g_2, \ldots, g_n]^T ,$$

which is the vector of criteria used by the consumer in the evaluation. To make the artificial market simpler, it is assumed, that there are only heterogeneous products on the marketplace, all featuring the same attribute space. After getting the attribute values the consumer applies the utility function

$$U(\underline{g}) = w_1 u_1(g_1) + w_2 u_2(g_2) + \ldots + w_n u_n(g_n),$$
$$\sum_{i=1}^{n} w_i = 1,$$

where $u_i(g_i)$ is the elemental utility function for attribute g_i, normalized between 0 and 1, and w_i is a positive number indicating the weight of the attribute. After calculating the expected utility of all the products, the consumer is ready to proceed for the purchase decision.

The $u_i(g_i)$ elemental utility function shapes and the weighting factors are tunable parameters of the simulation model.

2.4. *Purchase Decision*

When the consumer makes the purchase decision, he or she explicitly selects one of the products (brands) for consumption. The base of the decision of the i^{th} consumer is a probability vector

$$[P_i(a_1), P_i(a_2), \ldots, P_i(a_m)]^T ,$$

where

$$C = \{a_1, a_2, \ldots, a_m\}$$

is the set of the products available on the marketplace. From the expected utility vectors the consumer can create a purchase probability for each product and makes the decision according to these probabilities.

The purchase decision process of a consumer starts with the derivation of the probabilities, using the following methodology:

Let $\delta(0 \leq \delta \leq 1)$ be a parameter that represents the difference between the maximum and minimum values of the expected utility values, assigned implicitly by a consumer to the examined set of products. So, δ defines the range of assigned utilities:

$$\delta = U_{\max} - U_{\min}.$$

Depending on the δ range of utilities four distinct cases of consumer behavior can be defined [6]:

Table 1. Demon controlled simulation architecture

Value of δ	Decision making pattern
$0 \leq \delta \leq 0.1$	No segregation capability/random choice
$0.1 \leq \delta \leq 0.3$	Average segregation capability/reluctance
$0.3 \leq \delta \leq 0.6$	Efficient segregation capability/relative reluctance
$0.6 \leq \delta \leq 1$	Strong segregation capability/brand loyalty

Beside the range parameter, the skewness and kurtosis coefficients α_3 and α_4 of the expected utility value range should be calculated. A detailed discussion of the algorithm for this calculation can be found in [6].

The investigation on the distribution of expected utility values defines different types of consumer behavior. Based on the behavior pattern, different calculation methods exist to derive the probability values from the expected utility values. In the simulation model these should be taken into account. The rules could be easily adopted in a knowledge base to form an additional tool for the best representation of the consumer decision. The knowledge attributed Petri-net modelling approach [7] of the CASSANDRA system enables the direct usage of this knowledge base in simulation. The applied knowledge base dictates the selection of the calculation method according to the δ, α_3 and α_4 values in the following structure [6]:

Table 2. Consumer decision knowledge base

Value range of δ	Value range of α_3	Value range of α_4	Method
$0 \leq \delta \leq 0.1$			Equal probabilities
$0.1 \leq \delta \leq 0.3$	$\alpha_3 \leq -0.25$	$\alpha_4 \leq -0.5$	Width of utilities-1
		$-0.5 \leq \alpha_4 \leq 0.5$	Width of utilities-2
		$\alpha_4 \geq 0.5$	Luce
	$-0.25 \leq \alpha_3 \leq 0.25$	$\alpha_4 \leq -0.5$	McFadden-1
		$-0.5 \leq \alpha_4 \leq 0.5$	McFadden-2
		$\alpha_4 \geq 0.5$	Width of utilities-1
	$\alpha_3 \geq 0.25$	$\alpha_4 \leq -0.5$	McFadden-2
		$-0.5 \leq \alpha_4 \leq 0.5$	Width of utilities-1
		$\alpha_4 \geq 0.5$	Width of utilities-2
$0.3 \leq \delta \leq 0.6$	$\alpha_3 \leq -0.25$	$\alpha_4 \leq -0.5$	Width of utilities-2
		$-0.5 \leq \alpha_4 \leq 0.5$	Luce
		$\alpha_4 \geq 0.5$	Lesourne
	$-0.25 \leq \alpha_3 \leq 0.25$	$\alpha_4 \leq -0.5$	Width of utilities-1
		$-0.5 \leq \alpha_4 \leq 0.5$	Width of utilities-2
		$\alpha_4 \geq 0.5$	Luce
	$\alpha_3 \geq 0.25$	$\alpha_4 \leq -0.5$	McFadden-2
		$-0.5 \leq \alpha_4 \leq 0.5$	Width of utilities-1
		$\alpha_4 \geq 0.5$	Width of utilities-2
$0.6 \leq \delta \leq 1$	$\alpha_3 \leq -0.25$	$\alpha_4 \leq -0.5$	Lesourne
		$-0.5 \leq \alpha_4 \leq 0.5$	Maximum of utilities
		$\alpha_4 \geq 0.5$	Maximum of utilities
	$-0.25 \leq \alpha_3 \leq 0.25$	$\alpha_4 \leq -0.5$	Width of utilities-1
		$-0.5 \leq \alpha_4 \leq 0.5$	Luce
		$\alpha_4 \geq 0.5$	Width of utilities-2
	$\alpha_3 \geq 0.25$	$\alpha_4 \leq -0.5$	Luce
		$-0.5 \leq \alpha_4 \leq 0.5$	Lesourne
		$\alpha_4 \geq 0.5$	Maximum of utilities

The applied calculation models derive the purchase probability from the expected utility values with the following relationships:

$$\text{McFadden-1:} \quad P_{ij}(C) = \frac{e^{U_{ij}}}{\sum_{k \in C} e^{U_{ik}}},$$

$$\text{McFadden-2:} \quad P_{ij}(C) = \frac{e^{2U_{ij}}}{\sum_{k \in C} e^{2U_{ik}}},$$

$$\text{Width of utilities-1:} \quad P_{ij}(C) = \frac{U_{ij}^{U_{\max}-U_{\min}}}{\sum_{k\in C} U_{ik}^{U_{\max}-U_{\min}}},$$

$$\text{Width of utilities-1:} \quad P_{ij}(C) = \frac{e^{(U_{\max}-U_{\min})U_{ij}}}{\sum_{k\in C} e^{(U_{\max}-U_{\min})U_{ik}}},$$

$$\text{Luce:} \quad P_{ij}(C) = \frac{U_{ij}}{\sum_{k\in C} U_{ik}},$$

$$\text{Lesourne:} \quad P_{ij}(C) = \frac{U_{ij}^2}{\sum_{k\in C} U_{ik}^2},$$

$$\text{Maximum of utilities:} \quad P_{ij}(C) = 1, \text{ if } U_{ij} = \max(U), \text{ else } 0,$$

$$\text{Equal probabilities:} \quad P_{ij}(C) = \frac{1}{m}, \text{ where } C \text{ has } m \text{ elements}.$$

$P_{ij}(C)$ is the probability for consumer i to choose product j between a set of product C. U_{ij} is the utility that consumer i assigns to product j.

As soon as the adequate probability values are present, the consumer comes to a decision and consumes the selected product from the marketplace.

2.5. Post-Purchase Evaluation

The consumer behavioral model does not end with consumption. After completing the purchase, the consumer processes his or her observations and experiences with the product and the level of satisfaction. These conclusions cyclically influence the further behavior of the consumer. This experimental learning affects the consumers' Short Term Memory/Long Term Memory thus indirectly affecting the later decision making process. For example, it can cause changes in the $u_i(g_i)$ elemental utility function and in the w_i attribute weight parameter of the individual consumers.

Besides the indirect, learning mechanism-based effects, post-purchase evaluation can act directly as well, especially in the brand perception. For example, the consumer decides to ignore a specific product due to bad experiences.

In the constructed simulation model, the post-purchase evaluation has been retrenched, in order to avoid over-parameterization. Instead, the $u_i(g_i)$ and w_i consumer attributes are treated unchangeable for the consumer itself. And as the brand perception mechanism is simplistic, the result of the post-purchase has nothing to do with it.

3. Modelling Firms

All the efforts invested into the consumer behavior modelling were done in order to establish the base of the organizational behavior modelling of the firms.

In the assumed artificial market environment the firms' operation has been limited to the following roles:

- Emit products to the marketplace with attached attribute values,
- Receive payment for the goods,
- Monitor the attributes of consumers,
- Initiate communication towards consumers.

This compromise had to be made in order to avoid an overambitious simulation model definition and the introduction of many *ad hoc* parameters.

With the given abstraction, the primary role of the firms is the emission of products to the marketplace. In this fairly simple procedure the firm places a new product into the marketplace with setting

$$\underline{g} = [g_1, g_2, \ldots, g_n]^T$$

attribute values of the product. With this movement the firm completely releases the product and loses all relationship with it, only the appropriate payment arrives back when a consumer purchases the product.

The firm has also got the possibility to monitor the attributes of the consumers by collecting information about the individual consumers' $u_i(g_i)$ elementary utility functions, w_i weighting factors and the need arousal interarrival time distributions. This is the analogous activity to the real world a market survey in order to record the preferences of the consumers towards the products' specific features. The aggregated measure of the consumer preferences will be an input for the firm's decision-making process about the tuning of the $\underline{g}$ attribute values of the products.

Besides monitoring, the firm has also got the possibility to influence the consumer behavior by changing the values and characteristics of the individual consumer's $u_i(g_i)$ elementary utility functions, w_i weighting factors and the need arousal interarrival time distributions. This is the analogous process of the real world classical marketing activity.

In the implemented initial simulation model the firms are only able to act on the $\underline{g}$ attribute values of products. Neither consumer monitoring, nor consumer influencing have been implemented, since these are not necessary to have the first operating model. This trade-off gives a reasonably sized and manageable set of problems, which is enough for the initial simulation measurements, but it is a good platform for further developments.

As a result, firms can only alter their product attributes and have only an indirect feedback (incoming payments) about their performance on the market. The individual firms compete with each other through setting the attribute values of their products. As consumers are static conditions for the firms, their primary target is to find the optimal solution of the attribute vector for the given consumer population.

4. Application Possibilities of Intelligent Demons in the Artificial Market

The chapters above have described the initial model of an artificial market, which is the base for the deployment of intelligent demons.

The demons had been introduced [8] as an intelligent simulation entity possessing knowledge bases, inference engines, able to continuously monitor the trajectory of the simulation experiments and modify the model structure. With the usage of demons, the simulation control obtains feedback:

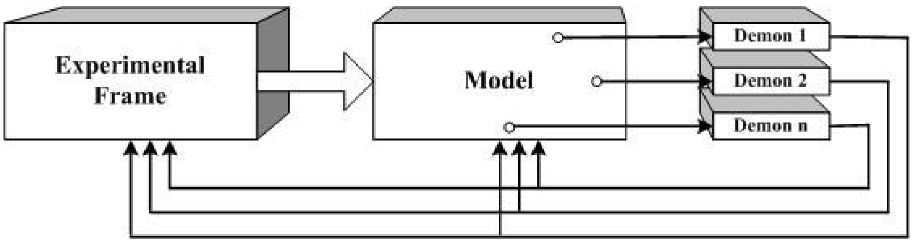

Fig. 3. Demon controlled simulation architecture

In the artificial market simulation demons can take two important roles.

The demon is a perfect tool for finding the optimal attribute vector value mix for the firms. The demons implemented in the CASSANDRA system featuring several search procedures and strategies, which give a powerful tool for dealing with complex problems. In the case of the described simulation model, the attribute vector value decision-making process is implemented by a demon, which takes the firm's income as an input and acts on the attribute vector of the firm's product.

By approaching the market simulation problem from another aspect, the demon concept can receive a more important role. There are significant, structured databases of historical data about almost every measurable real world market parameter. A huge number of researchers and institutions has done huge amounts of directed and specialized measurements on markets. A real world survey data of a simple, well-described market segment must be selected, which reflects for example the market performance after a product attribute/price change. The scenario must be inserted into the simulation models described above, and in the artificial market the same product attribute/price change must be completed. In this case the simulation's open parameters are the consumers' $u_i(g_i)$ and w_i parameters. During the simulation run the demons can be used to tune in the consumer parameters in order to have a matching simulation result to the real world measurements. *Ad hoc* consumer parameters can be determined with this algorithm, resulting a representative simulation model for the segment.

5. Conclusion

The purpose of the construction of the simulation model was to provide an initial application environment for the intelligent demons in market simulations. The model used significant simplifications at several places. The implementation of this model is already in progress using the CASSANDRA system. As the level of simplification can be decreased in the forthcoming development, the territory of the intelligent demons will become larger.

There are interesting possibilities in the behavioral modelling of firms, as it can be formalized easier than the decision of individuals. This is going to open up nice perspectives for the intelligent demons in the market simulation.

References

[1] BAIER, T. – MAZANEC, J. A., *The SIMSEG Project: A Simulation Environment for Market Segmentation and Positioning Strategies*, Working Paper Series, Vienna University of Economics and Management Science, 1999.
[2] JAGER, W., *Modelling Consumer Behavior*, Veenendaal, Universal Press, 2000.
[3] SZŰCS, G., User's Manual of the CASSANDRA System.
[4] ARNOULD, E. et al, *Consumers*, McGraw-Hill, 2001 May.
[5] LILIEN, G. L. – KOTLER, P. – MOORTHY, K. S., *Marketing Models*, Englewood Cliffs, NJ: Prentice-Hall 1992.
[6] MATSATSINIS, N. F. – SAMARAS, A. P., Brand Choice Model Selection Based on Consumers' Multicriteria Preferences and Experts' Knowledge.
[7] JÁVOR, A., Knowledge Attributed Petri Nets, *SAMS*, **13** (1993), pp. 5–12.
[8] JÁVOR, A. – BENKŐ, M. – LEITEREG, A. – MORÉ, G., AI Controlled Simulation of Complex Systems, *Computing & Control Engineering Journal*, **5** No. 2.