International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:5, No:12, 2011

Computational Modeling in Strategic Marketing

Petr Černohorský, Jan Voráček

Abstract—Well-developed strategic marketing planning is the essential prerequisite for establishment of the right and unique competitive advantage. Typical market, however, is a heterogeneous and decentralized structure with natural involvement of individual or group subjectivity and irrationality. These features cannot be fully expressed with one-shot rigorous formal models based on, e.g. mathematics, statistics or empirical formulas. We present an innovative solution, extending the domain of agent based computational economics towards the concept of hybrid modeling in service provider and consumer market such as telecommunications. The behavior of the market is described by two classes of agents - consumer and service provider agents - whose internal dynamics are fundamentally different. Customers are rather free multi-state structures, adjusting behavior and preferences quickly in accordance with time and changing environment. Producers, on the contrary, are traditionally structured companies with comparable internal processes and specific managerial policies. Their business momentum is higher and immediate reaction possibilities limited. This limitation underlines importance of proper strategic planning as the main process advising managers in time whether to continue with more or less the same business or whether to consider the need for future structural changes that would ensure retention of existing customers or acquisition of new ones.

Keywords—Agent-based computational economics, hybrid modeling, strategic marketing, system dynamics.

I. Introduction

BUSINESS environment today is becoming ever more competitive and ever more complex making it even harder for businesses to stay ahead of their competition. New methods and tools are being searched for to help businesses take better strategic decisions in order to maintain their competitive advantage and acquire higher share of their market. In majority of cases such critical business decisions can only be made as one-time decisions with no chance to step back later to change and pursue alternative path. Therefore, the key stakeholders require solid analysis or evidence to base their decisions on. In the past markets would have been analyzed by various mathematical, analytical and statistical tools that would typically apply to a specific sub-segment of the studied market or specific limited time period only. Is there however a tooling available to analyze the entire complex environment and predict its behavior at different phases in time? The system modeling addressing these exact requirements has been gaining traction since the second half of the 20th century. The modeling and subsequent simulation provides for a risk-free evaluation of alternatives (what-if analysis), predicts the future evolution of the modeled system and facilitates communication and common understanding between the key decision makers.

The initial research on system modeling and simulation goes back to J. W. Forrester [1], who has introduced the system dynamics, a system science methodology first studied within supply chain management, later finding wealth of applications in economics and also in management. System dynamics works with stocks and flows of model variables capturing the overall cumulative behavior of the studied system. This is suitable framework for cases where aggregate statistics exist and where the system is centralized and well structured. System dynamics is often referred to as top-down modeling approach working with overall cumulative behavior of the entire system.

In contrary to that systems science and fields of artificial intelligence have given rise to agent based modeling methodology, a bottom-up modeling technique focusing on the micro behavior and construction of the overall aggregate system behavior through interaction of agents as atomic parts of the studied environment. Specifically, agent based models have been used extending the traditional field of computational economics [2], [3] by generative and evolutionary approach to the study of economic systems and markets. In that case we talk about agent based computational economics (ACE) as introduced by Tesfatsion [4].

While both system dynamics and agent based modeling have received enormous attention each on its own, so far only limited attention has been paid to combined heterogeneous models blending the centralized top-down modeling approach of system dynamics with decentralized constructive bottom-up approach to modeling via agents. For early discussions on hybrid modeling, refer to for instance Akkermans [5]. Recent discussions on hybrid modeling and its applicability can be found in Lättilä et al [6]. The past limited attention to hybrid modeling may partly be also due to immaturity of the computational tools, which is however about to change with modeling toolboxes such as AnyLogic [7].

After introducing the need for modeling and simulation as a viable management decision support tool and after discussing the hybrid modeling methodology, let us focus specifically on the application of simulation in management strategy. It is noted by e.g. Kortelainen and Lättilä [8] and expressed as a fundamentally different approach to analytical methods from the past, highlighting the hybrid modeling as a better fit to the rapidly changing business environment and means to implementing the required strategic agility (Doz and Kosonen [9]). Agent based modeling is finding its way to practical business strategy already as summarized by Bonabeau [10] - different companies have favored agent based modeling and simulation to understand consumer behavior in retail shops

P. Černohorský is with the Department of Informatics, Faculty of Management, University of Economics in Prague, Czech Republic (e-mail: petr@cernohorsky.cz)
J. Voráček is with the Department of Informatics, Faculty of Management, University of Economics in Prague, Czech Republic (e-mail: voracekj@fm.vse.cz)

(Procter and Gamble or Unilever), or to define its human resources development strategy to build and maintain upper level of knowledge within the company (Hewlett-Packard).

This article deals with some rapidly developing markets, such as the telecommunications or generally service provider markets that are typically characterized by high volatility, unpredictability, overall non-linear trends and discontinuous changes in different dimensions, as noted for instance by Twomney and Cadman [11] and their example of explosive strictly non-linear uptake of mobile pre-paid services and fixed rate internet access. Due to all that it is no longer possible to capture the complexity through a single analytical or statistical model. Therefore a hybrid modeling approach is proposed and experimentally verified and framework modeling architecture is being defined for future extension into a tool to analyze the complex strategic marketing options and market phenomena - price setting, market differentiation, entry to saturated market, customer churn, new product introduction and market disruptive forces.

The need for modeling and simulation in future strategy setting and decision support systems is also being recognized by Gartner [12] in their search for top 10 strategic technologies in 2011. Gartner sees next generation analytics leveraging from the increased computational capabilities and improved connectivity of business systems to enable a shift in the way that businesses derive their operational and strategic decisions. Gartner research talks about simulations of business models predicting future outcomes rather than analysis of pure backward looking data. This will of course require extension to the existing business intelligence systems, but will potentially unlock significant improvements to actual business results.

II. Related Work

The proposed modeling and simulation framework builds on the foundation of systems science and complex systems theory - starting from the system dynamics introduced originally by J. W. Forrester [1] in 1960s and extended later by J. D. Sterman [13]. This article sees systems dynamics as very applicable for centralized well structured and process driven components of the studied environment - particularly the service provider firms (e.g. telecommunication operators).

Moreover, hybrid modeling is being considered and experimentally verified. The hybrid approach has originally been introduced in supply chain management problems by Akkermans [5] and is today further studied by Borshchev, Karpov, and Kharitonov [7] or Borshchev and Filippov [14] all of XJ Technologies Company in relation to their advanced hybrid modeling software tool AnyLogic. While [14] compares between system dynamics and agent based modeling - showing how same problem, for instance market diffusion, can be modeled by either approach; Rahmandad [15] deals with comparison of discrete event vs. agent based modeling, concluding correctly the fit for agent based approach to problems characterized by heterogeneity across individuals and networking relationships between actors within the environment. Lättilä and Hilletofth [6] also propose hybrid modeling consisting of system dynamics and agents. Specifically, Kortelainen and Lättilä[8] propose hybrid modeling to analyze business strategy options in rapidly developing markets.

There have been multiple attempts to model even entire industries, for example electricity - Mazhari et al. [16], Koritarov et al. [17], Conzelmann et al. [18] - where the last example focuses on the role of regulators and market rules. Works attempting to simulate entire markets build on the foundation laid down by computational economics - Amman, Kendrick and Rust [2]) - and its extension agent-based computational economics - Tesfatsion and Judd [3], Tesfatsion [19], [4], and Epstein [20].

Vast amount of research today is dedicated to pure agent based modeling, very often focused on heterogeneous consumer markets. North et al. [21] dealing with multi-agent modeling of consumer, retailer and manufacturer agents with research successfully applied to Procter and Gamble saving considerable amounts in costs. Said et al. [22] focus on consumer behavior to simulate effect of different marketing strategies. Siebers et al. deal with customer experience and retail market, and Schwaiger et al. [23] propose innovative approach to modeling consumer behavior and knowledge by means of behavior networks (Bayesian nets) and verify its application to category management. Finally, there are also attempts to employ only agent models to capture dynamics of entire industries, such as Twomey and Cadman [11] for telecommunications and Nikolic et al. [24] for metals production and consumption market.

To conclude with, most research is being carried out in the area of modeling and simulation, but there are only few studies conducted on the simulation optimization - some early examples can be found in April et al. [25]. The topic of model optimization is certailny going to receive more and more traction in the near future.

III. Baseline Model Scope

The real life management challenges are full of examples from complex environments in which there are parts (subsystems) of the problem (system) that behave as independent units with distributed decision behavior and actions that add up into the cumulative behavior of the sub-system, and other parts of the problem that behave in a centralized fashion where the cumulative behavior of the sub-system is rather straight-forward to observe and describe. The earlier subsystems would be typically modeled using a bottom-up approach and often represented with the agent based modeling approach, while the latter would typically be modeled in a top-down fashion and often implemented by means of the system dynamics modeling paradigm. A classical example of such environment would be a market for selling and buying of services or goods, which is typically represented by three key actors 1) the producers or service providers on one hand, 2) customers or consumers on the other hand and finally 3) environment policies or market regulation characterizing the constraints and overall conditions imposed by the environment. The current investigated model focuses on the case of service provider and the consumer market, with a specific example of mobile telecommunications operators in mind. However, where possible, the model tries to abstract to basic principles of any service provider market so to be applicable to also other oligopoly type of service provider markets. As stated earlier, the model consists of two stakeholder groups: service providers and consumers.

A. Service Providers

There are three service providers modeled in the market representing a typical oligopoly market with very high barriers to entry, thus a very low probability of new entrants. Of course for the future the model may be enriched with the possibility to add new entrants. This would actually represent one of the possibly interesting experiments showing what would be an entry strategy for new service provider entering into an established and saturated market. Nevertheless, for the initial model, this feature is not being considered. Further on, the market is simplified in such a way that it models only a single identical service (product) that is being offered by all of the service providers at the same time.

The service providers have key performance indicators (KPIs) that they need to optimize when they execute their business strategy:

- Maximize market share,
- Maximize revenue,
- Minimize costs.

Also, through the implementation of their internal process structure, each of the service providers will exhibit its behavior to the outside world through a vector of parameters (service provider parameters). These parameters are observable by all the consumers and also other service providers and can therefore be perceived as a basic characteristic of each service provider at any given time:

- *Price*: unit price for the service (price per unit of usage),
- *QoS*: quality of service, and
- *Brand*: perception of the brand.

It is important to distinguish that all of these parameters are driven by objective internal parameters and processes of the service providers, but from the outside environment they can not be measured exactly. They can only be perceived. Given the high-level KPIs and these generic parameters, each service provider will have the following strategic choices to make throughout the course of execution of the experiment:

- *Price*: set its new service price (will apply instantly for all new and ongoing contracts),
- *Hiring Rate*: increase or decrease the hiring rate for its service staff, and
- *Marketing Budget*: allocate budget to invest in its marketing campaign.

B. Consumers

For the sake of simplicity, only consumer market is considered in the initial version of the model. Enterprise, wholesale and other forms of business to business market schemes are not included. One of the reasons being that those markets would likely not behave as fully distributed and homogeneous, therefore the consumers would require to be represented by more agents of different types. Thus, for the initial model, only a single customer type is being considered consumer with fully distributed behavior populating its market environment typically in large numbers (thousands, or even millions of agents). The consumer population is considered a homogeneous mass represented by agents of a single class differentiated only by agent parameters.

Consumers are distributed in three example segments that are effectively represented by clusters of agents in their parameter space. The segmentation of the market is based on the utility weights vector that each consumer assigns to the service provider parameters when calculating its utility function (Equation 5). The following consumer weights are being defined:

- *Weight Price*,
- *Weight QoS*,
- *Weight Brand*.

Each consumer optimizes its KPI, i.e. maximizes its utility function, when choosing for consuming services from any specific service provider. The detailed design of the internal architecture and behavior of the service providers and consumers is detailed further in the following sections.

Of course, in the future, more granular segmentation of the consumers is to be introduced. There shall be a mapping of the utility function to the different internal and external characteristics of each consumer segment - for example age, marital status, education, health, wealth, gender would all have effects on respective agent's utility. Heuristics shall be captured in the consumer agent's behavior ideally backed up by actual real market statistics - showing for example the ability to switch between service providers more frequently for youngsters in contrary to elderly, or the effects of education and health on the preference of luxury brand and other behavioral patterns like this.

IV. Model Design

The model has been described in AnyLogic 6.6.0 [7]. The AnyLogic project consists of the following components:

- *Main / Environment*,
- *Person*,
- *Simulation*.

A. Main / Environment

The Main class of the model represents the execution logic of the model and also the views that are used to visualize the running simulation experiment. The diagram depicted in Figure 5 shows the main simulation view and a view summarizing the simulation statistics. The model is characterized by a set of parameters, variables, their mutual relation and the additional model code. The parameters and function used within the main class of the model are listed in Table I and Table II.

Besides ordinary variables, the Main class contains also two other special variables Persons and Environment. The first one denoting the collection of agents in the simulation and the second representing the environment in which the Person

Parameter	Description
Unit Salary	Salary paid to each service employee
Unit Marketing Cost	Costs for unit of marketing campaign
Market Share Trend Length	Number of simulation steps for which a trend of market share growth or decline is being measured
Initial Population Size	Amount of consumers (agents) at the beginning of the simulation
Birth Rate	Rate at which new agents are introduced into the simulation

TABLE I
MAIN CLASS PARAMETERS

Function	Description
Set Initial Sliders	Sets initial values of control parameters (Price, QoS, Brand) for each service provider
Create New Person	Adds new person agent into the simulation
Create Initial Population	Creates initial population of agents at the beginning of the simulation
Execute Strategy	Function executed at every simulation step that realizes the strategy followed by each of the service providers

TABLE II
MAIN CLASS FUNCTIONS

agents exist and interact. In AnyLogic terms the Person is a class of type Agent and the Environment is a Continuous 2D space providing a visual living space for the agents. Visual presentation of both the Persons collection and the Environment is depicted in Figure 1. As stated in the previous Section, the purpose of the model is to demonstrate a baseline heterogeneous model mixing agent based approach together with system dynamics. Next sections describe both parts into more detail.

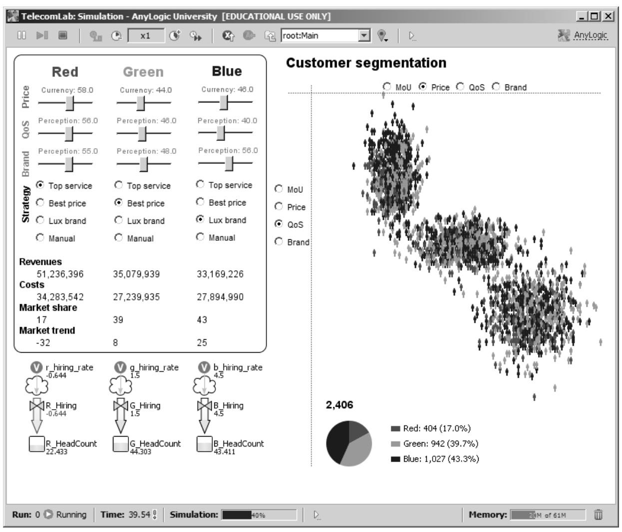

Fig. 1. Vsualisation of the simulation environment

B. Service Provider Model (System Dynamics)

The service provider model for each of the service providers (Red, Green, Blue) is characterized by a set of initial parameters (Table III) and a set of run-time variables (Table IV).The service provider model is centralized around a concept of Balanced Score Card (BSC) [26], which characterizes and measures the state of an enterprise from four key perspectives (see Figure 2):

- *Financial*,
- *Customer*,
- *Internal Business Processes*,
- *Learning and Growth*.

Fig. 2. Balanced Score Card

BSC has been selected as a viable abstraction of the complexity of an enterprise that has the power to capture its key complexities and dynamics. The current implementation works with a very simplistic implementation of BSC. Although originally the model has been designed with a mobile telecommunications market for consumers in mind, it has finally evolved into a generic service provider market. Still, when considering internal processes of service provider enterprises, a telecommunications market reference could be used as in that specific industry there already exist standard process models used across the industry, which with some effort, could be generalized to any other service provider market. The process model considered as a benchmark for further evolution of the framework is the Enhanced Telecommunications Operations Map (eTOM) [27] model and process library, see Figure 3 for its high-level representation. The currently implemented model does not however have the ambition of implementing the full scope of eTOM, this standard process model is considered as a reference for future work.

Before a more thorough process model is implemented the simplified BSC framework is being used. BSC financials are being tracked in terms of costs and revenues that derive from the labor and marketing costs and revenues deriving from the service providers market price and the amount of subscribers at each given billing period (e.g. each month one simulation step) during the simulation. Below formulas denote the total cost and revenue for each service provider Red / Green / Blue:

$$Cost = HeadCount*UnitSalary+Brand*UnitMktngCost \tag{1}$$

$$Revenue = Price * NumCustomers \tag{2}$$

Customers are being tracked as the amount of customers having a contract with one of the service providers Red, Green, or Blue - and these statistics are being updated during each simulation step as part of the Environment class. BSC

International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:5, No:12, 2011

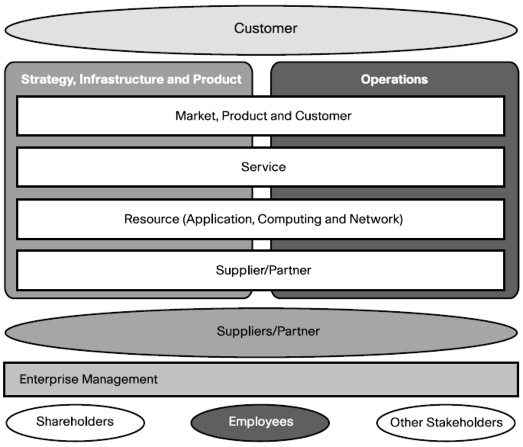

Fig. 3. Enhanced Telecommunications Operations Map (eTOM)

Parameter	Description
Initial Strategy	Initial strategy of a service provider
Initial Price	Initial price of a service provider
Initial QoS	Initial QoS of a service provider

TABLE III
SERVICE PROVIDERS, MAIN CLASS PARAMETERS

internal business processes & BSC learning and growth are consolidated in a joint representation by a system dynamics model of hiring service personnel. The rate at which employees are being hired or laid off is defined though a single variable per service provider called Hiring Rate.

$$MarketTrend = \sum_{1}^{N} \Delta_{MktShare} \tag{3}$$

The behavior of each service provider is guided by its strategy and history (there is an aspect of learning involved in the model). The strategy of a service provider is assigned during startup according to the values of the initial parameters (Table III), but can be adjusted also during run-time, through the control radio buttons in the strategy section in Figure 4. The possible service provider Strategies are:

1) *Top service*,
2) *Best price*,
3) *Luxurious brand*,
4) *Manual*.

Service provider running the Top service strategy will attempt to maximize its QoS statistics. The QoS statistics for each service provider are calculated as a proportion of service employees to the amount of customers of that service provider. The QoS is linearly proportional and equal to NumCustomers over HeadCount until it reaches the value of 100, which is its maximum.

$$QoS = \frac{NumCustomers}{HeadCount} \tag{4}$$

Service provider running the Best price strategy will attempt to always keep the lowest price in the market. Service provider running the Luxurious brand strategy will try to keep its brand

Variable	Description
Strategy	Current strategy that is being executed by the service provider (top service, best price, luxurious brand, manual)
Revenue / Cost	Total revenues and costs to date
Price / QoS / Brand	Current Price, QoS and Brand perception values
Market Share	Current percent market share
Market Trend	Sum of changes in percent market share over fixed amount of past simulation steps (Figure 3)
Hiring Rate	Rate at which new service staff is being hired (laid off if negative value)
Head Count	Actual amount of service staff

TABLE IV
SERVICE PROVIDERS, MAIN CLASS VARIABLES

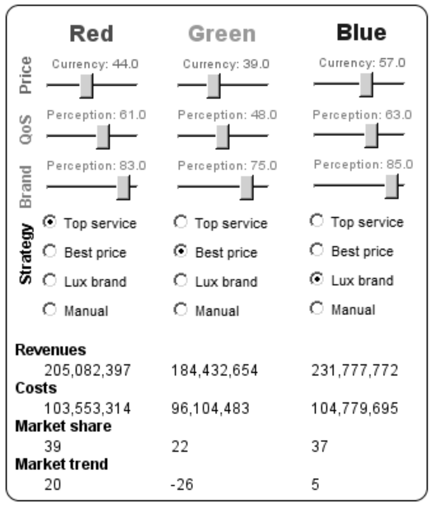

Fig. 4. Service Providers, Control Panel

perception value highest in the market, which on the other hand results in its highest marketing spending among the service providers. The last Manual strategy option allows for human control and manual specification of the service provider model control values Price, Brand, and Hiring Rate. Figure 5 shows example simulation experiments with each service provider running their unique market strategy. In the customer segmentation graph it can be observed that throughout a longer period of simulation customers are being distributed among the service providers where there is an alignment between the customer preferences (its utility) and the strategy of the particular service provider. There is a clear (almost linear) split into customer segments who are in preference of service provider with Top service (Red), Best price (Green) and Luxurious brand (Blue). When service providers execute their strategy, they will adhere to the following rules:

- *Market Share above competition & Market Share Trend positive ⇒ increase price by 1.*
- *Market Share under competition & Market Share Trend negative ⇒ decrease price by 1.*
- *Market Share below 50% or below competition & Costs don't exceed 80% of Revenues & Market Trend negative ⇒ increase Brand marketing by 1.*
- *Market Share above 50% and above competition & Costs*

Fig. 5. Example Experiment, QoS vs. Brand view

Parameter	Description
Utility MoU	target utility value seeked by the consumer in
Utility Price	-
Utility QoS	-
Utility Brand	-

TABLE V
PERSON AGENT, PARAMETERS

exceed 80% of Revenues & Market Trend positive ⇒ decrease Brand marketing by 1.
- *Set Hiring Rate to 50 - QoS / 2.*

If the service provider executes Top service strategy, it will increase its Hiring Rate by 50% each time it lags behind competition in QoS. If the service provider executes Best price strategy, it will set its price below all other competitors. If the service provider executes Luxurious brand strategy, it will set its Brand spending above all other competitors.

C. Consumer Model (Agent-based)

Each single customer in the model is represented by a separate instance of Person Agent class that represents the behavior of a consumer in a typical service market. Initial parameters and variables of each agent are listed in Table V and Table VI. Each agent is born with random values of the Utility MoU, Utility Price, Utility QoS, and Utility Brand parameters. The values of those parameters reflect the segmentation of the entire population of the Person Agents (more detailed description of the segmentation follows in further below).

Each Person Agent behaves as a finite state machine. The full definition of its states and transitions is provided in the Person Agents State Chart (Figure 6). When born, Person Agent starts in state NotCustomer and moves directly into state Prospect. When in state Prospect, it will calculate its Utility Function (Formula 5) for each of the service providers and will chose the one, to buy services from, that maximizes the utility function (Formula 6).

The market is characterized by 10% churn of customers for all the service providers. This is denoted by the reverse transition from each service provider back to the Prospect state. The Utility per service provider is calculated according to the following formula:

Variable	Description
Age	actual age of the agent
Utility	latest calculated utility for the agent

TABLE VI
PERSON AGENT, VARIABLES

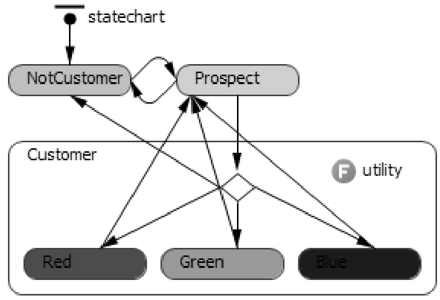

Fig. 6. Person Agent, state chart definition

$$U_{SP} = U^2_{Price} * (100 - Price) + U^2_{QoS} * QoS + U^2_{Brand} * Brand \quad (5)$$

When the Person Agent decides on which service provider it shall engage with, it will maximize the Utility in Formula (5) across the set of all the service providers:

$$SP = ArgMax_{i=\{R,G,B\}} U_i \quad (6)$$

The Person Agents do not yet implement any inter-agent behavior, however this is being considered as a natural extension to the model. For example the agents could maintain a small-world type of connections to other agents (representing e.g. close family, friends or co-workers) with whom they would like to share the same Service Provider to obtain group loyalty benefits and price discounts. Other common extension would be a word-of-mouth marketing implemented between clients, where the perception of a service provider brand by any individual Person Agent can be influenced by references from other random or friendly agents in the environment.

V. EXPERIMENTS

Equipped with the model described before, this section is going to elaborate on the detailed simulation and experiment scenarios. The default experiments that have been defined within the model will be described. The initial conditions of the default experiments will be presented and the section will finally conclude with evaluation of the actual executed experiments and a suggestion for future experiments and follow-up research.

A. Model Execution

The model is designed in such a way that all the Environment and Agent Person initial parameters, i.e. the initial conditions of the computational experiment, can be tuned before the actual execution of the model. That way the environment allows for calibration of the model to real world situation,

International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:5, No:12, 2011

Revenues			
	51,236,396	35,079,939	33,169,226
Costs			
	34,283,542	27,239,935	27,894,990
Market share			
	17	39	43
Market trend			
	-32	8	25

Fig. 7. Simulation, experiment statistics

Customer Segment	**Description**
Quality concerned	Group of consumers
whose priority is the QoS;	
	they are generated with the following random parameters: $MoU \sim \mathcal{N}(50, \sqrt{10})$ $Price \sim \mathcal{N}(50, \sqrt{10})$ $QoS \sim \mathcal{N}(50, \sqrt{5})$ $Brand \sim \mathcal{N}(50, \sqrt{10})$
Price sensitive customers	Customers who are looking for best price: in the market $MoU \sim \mathcal{N}(50, \sqrt{10})$ $Price \sim \mathcal{N}(20, \sqrt{5})$ $QoS \sim \mathcal{N}(20, \sqrt{10})$ $Brand \sim \mathcal{N}(20, \sqrt{10})$
Brand image seekers	Customers seking luxurous brand: $MoU \sim \mathcal{N}(50, \sqrt{10})$ $Price \sim \mathcal{N}(80, \sqrt{10})$ $QoS \sim \mathcal{N}(80, \sqrt{10})$ $Brand \sim \mathcal{N}(80, \sqrt{5})$

TABLE VII
MODEL EXECUTION, INITIAL CUSTOMER SEGMENTATION

or an execution of a multitude of different experiments with varying initial conditions in order to stress-test the model and explore its stability. Further sections describe the default input parameters used in the experiments and evaluate the obtained results.

During the execution statistics of costs, revenue, market share and market trend are being collected for each service provider (Figure 7). Next to that a total number of customers in the simulation and a market share of each of the service providers are also reported. The market trend is calculated as a cumulative sum of delta changes in market share during the past given number of simulation steps (Formula 3). Figure 5 depicts the typical visualization of a model simulation experiment.

1) Input Parameters: By default, when the model executes, three example customer segments are created each populated with an initial pre-defined number of agents. The three segments represent groups of consumers who are in preference of best market price, top quality service or luxurious service provider brand. The detailed characteristics of the segments are shown in Table VII.

B. Simulation Experiments

1) Default Strategy Game: By default, the simulation experiment is executed as a strategy game that is dynamically

#	**S**trategy	**R**evenue	**C**ost	**S**hare	**P**rofit
1.	S-P-B	293, 202, $\boxed{307}$	109, $\boxed{92}$, 111	21%, $\boxed{42\%}$, 35%	$\boxed{184}$, 110, 106
2.	S-P-P	$\boxed{227}$, 65, 84	109, $\boxed{77}$, 97	$\boxed{55\%}$, 7%, 36%	$\boxed{118}$, -12, -13
3.	S-B-B	107, $\boxed{444}$, 431	$\boxed{61}$, 147, 145	32%, 31%, $\boxed{35\%}$	46, $\boxed{297}$, 286
4.	P-S-S	240, $\boxed{291}$, 303	$\boxed{96}$, 106, 109	17%, 29%, $\boxed{53\%}$	144, 185, $\boxed{194}$
5.	P-B-B	81, 478, $\boxed{494}$	$\boxed{45}$, 151, 154	19%, $\boxed{45\%}$, 34%	36, 327, $\boxed{340}$
6.	B-S-S	287, 245, $\boxed{300}$	107, $\boxed{104}$, 111	19%, $\boxed{52\%}$, 27%	180, 141, $\boxed{189}$
7.	B-P-P	$\boxed{189}$, 52, 134	99, $\boxed{61}$, 123	$\boxed{46\%}$, 7%, $\boxed{46\%}$	$\boxed{90}$, -9, 11
8.	S-S-S	253, 267, $\boxed{293}$	$\boxed{98}$, 100, 102	$\boxed{61\%}$, 22%, 15%	155, 167, $\boxed{191}$
9.	P-P-P	$\boxed{130}$, 52, 73	108, $\boxed{61}$, 72	$\boxed{82\%}$, 8%, 9%	$\boxed{22}$, -9, 1
10.	B-B-B	290, 286, $\boxed{298}$	143, $\boxed{142}$, 144	34%, $\boxed{40\%}$, 24%	147, 144, $\boxed{154}$

TABLE VIII
MODEL EXECUTION, COMPARISON OF STRATEGY EXPERIMENTS (FINANCIALS IN MEUR)

complete [4] - the modeled system evolves independently over time solely on the basis of mutual agent-based and system dynamics model interactions. No interactions are required from the human modeler, the service providers all proceed with their operational decisions based on of the three predefined strategies. As an alternative, it is possible to interrupt the simulation experiment at any time and switch any given service provider to the manual mode in which it is possible for a human operator to impress outside strategy onto the selected service provider - the human operator is then able to choose the new price parameter, the new hiring rate, and also marketing expenses. In that way different strategic choices are being modeled and observed.

2) Evaluation: A number of experiments have been executed and evaluated, all with the default segmentation of customers and identical initial parameters. Table VIII shows the overall results. The different input strategies for each operator are denoted (S = top service, P = best price, B = lux brand) and the resulting performance for each operator in the simulated market environment is listed - total revenue, total cost, last market share, and total profit. The best result is always framed - top revenue, lowest cost, highest market share and best profit. Each simulation takes 100 simulation steps (each step being one billing period, i.e. one calendar month) and the total figures denote millions of EUR.

In 100% of cases, it can be observed that the lowest price strategy also brings the lowest total costs. However, it happens very rarely that the lowest price strategy would also bring the highest revenues - the oposite is usually the case. On the other hand, in all experiments except for #3, it is the top service strategy that brings the highest total profit. Possible interpretation of this result is that the lowest price or luxurious brand strategies bring considerable burdens to the total profits - the low price strategy bringing in lower levels of revenues and the luxurious brand strategy requiring over average costs to cover for the necessary marketing expenses.

Another conclusion that can be drawn is that not necessarily the highest market share would result in highest profits. The highest profits always tie closely to the prices of the respective operators. This set of initial experiments shows the relative robustness of the defined model with respect to long lasting strategies and their relation to behavior that would also be expected in real world. The model can already show the results of more operators running according to more or less the same

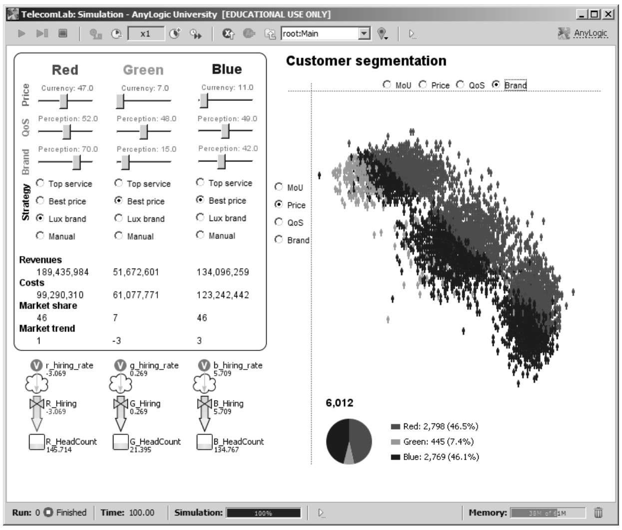

Fig. 8. Example Experiment #7 B-P-P, Price vs. Brand view

strategies. For example, all the experiments showing more than one service provider focusing on lowest price (experiments #2, #7, and #9) demonstrate the price war that is unleashed in the market resulting in some of the lowest profits for more or less all the companies in the market. It can also be observed that in majority of cases the luxurious brand strategy results in some of the highest profits. However, at the same time this strategy tends to generate also over average costs and rather lower share in the market. Therefore, not always this would be the final most profitable strategy.

Particularly interesting experiment is to have each service provider run their unique strategy - this is experiment #1 (S = top service, P = best price, B = luxurious brand). The outcome of this experiment is that despite the fact that the top service strategy brings the lowest market share, it generates the highest profits. Also, when executing the three unique strategies simultaneously it can be easily observed how the customers separate themselves (almost linearly) according to their preference / represented by their utility for QoS, price or brand. The linear separation is even clearer in the case of experiment #7 as depicted in Figure 8, the price optimizing agents tend to become customers of Green and Blue and those seeking luxurious brand tend to become customers with Red service provider.

3) Future Work: The presented model and experiments outline the way to study complex business reality, in which it is often beneficial to model different parts of the environment by alternative methods using either the agent technology or system dynamics in one combined model. An approach to modeling centralized and process based elements of the complex system through system dynamics is being suggested, while agent-based approach is being applied to distributed parts of the complex environment. Dynamically complete simulation environment is defined and few example experiments presented. The author believes that further study of the subject is going to bring additional benefits to business practice - outlining concrete methodology to use in business problem formulation, heterogeneous modeling and simulation and a final application of the simulation results in direct business decision processes. The studied examples have shown application of stable long term strategy, however, in the future the experiments shall be extended also to adaptive or agile strategy that is being outlined by Doz [9] and suggested as a viable way to react to rapid market changes that are becoming more and more common in fast developing service industries such as telecommunications. In line with this theory, the model shall allow for the service providers to switch between a set of strategies dynamically, not becoming stiff in the long run. The future intension is to extend the model into a practical business tool on one hand and a better theoretical model of the studied reality on the other hand. Future ideas for extending the framework are listed below:

- Add andor remove Service Providers during run-time (to explore strategic options of market entry).
- Add new consumer segments.
- Tune consumer segments according to state of the art research in customer segmentation - early adopters, followers, young professionals, stability seekers, etc.
- Extend the service product portfolio - System Dynamics of product development, marketing and support are particularly important to model.
- Calibrate model to real market environment, ideally engaging with a selected market research agency and applying the framework to a specific market study.
- Study of ideal calibration of the market model.
- Introduce Person Agent interaction - word-of-mouth marketing, small world environment (family circle or circle of close friends).
- Introduce loyalty programs.
- Study of market disruption scenarios (market exit, maket entry for Service Providers) andor disruption of the telecommunications market by over-the-top players.
- Comparison of pure Agent-based model vs. System Dynamics model.

VI. Conclusion

The presented article outlines an application of heterogeneous modeling methodology to real-life business problems. An example model is being discussed and a hypothesis is being outlined claiming that hybrid agent-based and system dynamics models tend to me much more effective and accurate compared to single paradigm models when it comes to typical business problem complexity. The final application field of the outlined research is thought to be primarily business strategy formulation and also real-time business decision support. Besides accurate business modeling, the future research shall also deal with integration of real-time business operational data, in order to achieve the latter goal of accurate and timely business support tool.

References

[1] J. W. Forrester, *Industrial Dynamics*. Productivity Press, 1961.
[2] H. M. Amman, D. A. Kendrick, and J. Rust, eds., *Handbook of Computational Economics*. North Holland, 1st ed., June 1996.

[3] L. Tesfatsion and K. L. Judd, eds., *Handbook of Computational Economics, Volume 2: Agent-Based Computational Economics*. North Holland, 1 ed., July 2006.
[4] L. Tesfatsion, "Chapter 16 Agent-Based Computational Economics: A Constructive Approach to Economic Theory," *Handbook of Computational Economics*, vol. 2, pp. 831–880, 2006.
[5] H. Akkermans, "Emergent supply networks: System dynamics simulation of adaptive supply agents," p. 63, 2001. cited By (since 1996) 8.
[6] L. Lättilä, P. Hilletofth, and B. Lin, "Hybrid simulation models - when, why, how?," *Expert Systems with Applications*, vol. 37, no. 12, pp. 7969–7975, 2010. cited By (since 1996) 1.
[7] A. Borshchev, Y. Karpov, and V. Kharitonov, "Distributed simulation of hybrid systems with AnyLogic and HLA," *Future Generation Computer Systems*, vol. 18, pp. 829–839, May 2002.
[8] S. Kortelainen and L. Lättilä, "Modeling strategic technology management with a hybrid model," in *Proceedings of the 27th International Conference of the System Dynamics Society*, (New Mexico, USA), 2009.
[9] Y. L. Doz and M. Kosonen, "Embedding strategic agility: A leadership agenda for accelerating business model renewal," *Long Range Planning*, vol. 43, no. 2-3, pp. 370–382, 2010. cited By (since 1996) 6.
[10] E. Bonabeau, "Predicting the unpredictable," *Harvard Business Review*, vol. 80, no. 3, p. 109, 2002. cited By (since 1996) 26.
[11] P. Twomey and R. Cadman, "Agent-based modelling of customer behaviour in the telecoms and media markets," *Info*, vol. 4, no. 1, pp. 56–63, 2002. cited By (since 1996) 7.
[12] C. Pettey *et al.*, "Gartner Identifies the Top 10 Strategic Technologies for 2011, Next Generation Analytics," in *Gartner Symposium / ITxpo*, (Orlando), Gartner, Inc., October 17-21 2010. http://www.gartner.com/it/page.jsp?id=1454221.
[13] J. D. Sterman, *Business Dynamics. Systems Thinking and Modeling for a Complex World.* McGraw-Hill Higher, 2000.
[14] A. Borshchev and A. Filippov, "From System Dynamics and Discrete Event to Practical Agent Based Modeling: Reasons, Techniques, Tools - Multimethod Simulation Software Tool AnyLogic," in *The 22nd International Conference of the System Dynamics Society*, (Oxford, England), July 25 - 29 2004.
[15] H. Rahmandad and J. Sterman, "Heterogeneity and Network Structure in the Dynamics of Diffusion: Comparing Agent-Based and Differential Equation Models," *MANAGEMENT SCIENCE*, vol. 54, pp. 998–1014, May 2008.
[16] E. Mazhari, J. Zhao, N. Celik, S. Lee, Y.-J. Son, and L. Head, "Hybrid simulation and optimization-based design and operation of integrated photovoltaic generation, storage units, and grid," *Simulation Modelling Practice and Theory*, vol. 19, no. 1, pp. 463–481, 2011.
[17] V. S. Koritarov, "Real-world market representation with agents," *IEEE Power and Energy Magazine*, vol. 2, no. 4, pp. 39–46, 2004. cited By (since 1996) 30.
[18] G. Conzelmann, G. Boyd, V. Koritarov, and T. Veselka, "Multi-agent power market simulation using emcas," vol. 3, pp. 2829–2834, 2005. cited By (since 1996) 7.
[19] L. Tesfatsion, "Agent-based computational economics: Growing economies from the bottom up," 2011. http://www.econ.iastate.edu/tesfatsi/ace.htm.
[20] J. M. Epstein, *Generative Social Science: Studies in Agent-Based Computational Modeling*. Princeton Studies in Complexity, Princeton University Press, Jan. 2007.
[21] M. J. North, C. M. Macal, J. S. Aubin, P. Thimmapuram, M. Bragen, J. Hahn, J. Karr, N. Brigham, M. E. Lacy, and D. Hampton, "Multiscale agent-based consumer market modeling," *Complexity*, vol. 15, no. 5, pp. 37–47, 2010.
[22] L. B. Said, T. Bouron, and A. Drogoul, "Agent-based interaction analysis of consumer behavior," in *AAMAS '02: Proceedings of the first international joint conference on Autonomous agents and multiagent systems*, (New York, NY, USA), pp. 184–190, ACM Press, 2002.
[23] S. B. Schwaiger, A., "Simmarket: Multiagent-based customer simulation and decision support for category management," vol. 2831, pp. 74–84, 2003. cited By (since 1996) 4.
[24] I. Nikolic, L. A. Bollinger, and C. B. Davis, "Agent based modeling of large-scale socio-technical metal networks," pp. 779–788, 2010. cited By (since 1996) 0.
[25] J. April, F. Glover, J. P. Kelly, and M. Laguna, "Simulation-based optimization: practical introduction to simulation optimization," in *WSC '03: Proceedings of the 35th conference on Winter simulation*, pp. 71–78, Winter Simulation Conference, 2003.
[26] R. S. Kaplan and D. P. Norton, *The Balanced Scorecard: Translating Strategy into Action*. Harvard Business Press, 1 ed., Sept. 1996.
[27] M. Calisti and D. Greenwood, "Goal-Oriented Autonomic Process Modeling and Execution for Next Generation Networks," in *Modelling Autonomic Communications Environments* (S. van der Meer, M. Burgess, and S. Denazis, eds.), vol. 5276 of *Lecture Notes in Computer Science*, ch. 4, pp. 38–49, Berlin, Heidelberg: Springer Berlin / Heidelberg, 2008.

Petr Černohorský received B.Sc. in software engineering and economics and M.Sc. in software engineering from Czech Technical University in Prague, Czech Republic, in 2001 and 2005, respectively. Later in 2008 he has acquired MBA from the University of Northern Virginia in Prague, Czech Republic. He is currently running for his Ph.D. degree in management and economics from the University of Economics, Prague, Czech Republic. He was Software Engineer and Manager with LogicaCMG from 2005 to 2007. Ever since late 2007, he has been with Ericsson as Solution Architect and in various other Solution, Project and Team Managerial roles. His professional and research interests include complex systems, social sciences, economics, business management and strategy.

Jan Voráček received both his M.Sc. and Ph.D. degrees from the Brno Technical University, Czech Republic in 1985 and 1992, all in Technical Cybernetics. Currently he is an Associate Professor in the Faculty of Management, University of Economics Prague, Czech. His special fields of interest include computer simulation of complex socio-technical systems and knowledge management.