Estimating e-Commerce Revenues by Web-based Simulation and System Dynamics Approach

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Abstract – The Internet has profoundly changed the nature of doing businesses worldwide. Since e-Commerce paradigm has radically prevailed in everyday shopping activities, calculating online revenue estimates has already become one of the most common questions regarding e-Commerce projects, especially the ones on the loom. Taking into account specific classes of e-Customers, the workload characterization of a given e-Commerce website, as well as the principles of the system thinking approach, the paper aims at describing the development of a Web-based simulation model, suitable for estimating the e-Commerce revenue across multiple operation profiles, i.e. working scenarios. The result of this research was the creation of a complete simulation model available online, which reflects the system dynamics logic, rather than the logic of conventional discrete-event simulation (DES) approach. Encompassing multiple adjustable input parameters, the model can be successfully utilized in making 'what-if'-like insights into plethora of business-oriented performance metrics for a given e-Commerce website. The project is also a great example of the power delivered by InsightMaker®, a free and Web-based tool, suitable for online development of any model following the systems thinking paradigm.

I. INTRODUCTION

Since e-Commerce paradigm has radically prevailed in everyday shopping activities, e-Commerce companies started out their everlasting longing for attracting more e-Customers and for increasing their vital performance metrics, in order to generate more revenues. In business, revenue typically refers to the total amount of money received by the company for goods sold or services provided during a certain time. Among all other business-oriented metrics (e.g. Revenue per Visit, Revenue per Visitor, Conversion Rate, Average Order Value, Buy-to-Visit Ratio etc.), revenue is the ultimate one that reflects the wealth and current positioning of e-Commerce companies on the global market. Apart from selling goods or services, many online companies generate revenues from multiple, yet different income streams, such as advertising, subscription, transaction fees, or affiliate marketing, altogether known as 'revenue models'. However, the sales revenue remains the keystone of doing business online.

Realizing the gravity of estimating e-Commerce sales revenue, authors suggest a standardized way for its calculation. They suggest, with negligible differences, that Revenue [$] can be assessed by using few business-oriented metrics, including the number of Visitors (daily, monthly …), the Conversion Rate [%], being a ratio between the number of Buyers and Visitors, and Average Order Value [$/order], as in (1) [1] [2] [3]. The product of AOV and CR is also known as Revenue per Visitor [$/visitor].

$$R\,[\$] = AOV\,[\$/\text{order}] \times CR\,[\%] \times V \qquad (1)$$

Estimating e-Commerce sales revenues according to (1) is quite straightforward, though somewhat disputable, since it approximates roughly the input variables, which yields a significant estimation error. Furthermore, (1) is purely deterministic by its nature, i.e. it does not include any stochastic parameters. Finally, (1) does not include any behavioral components specific to various e-Customers' classes, nor does it takes into account the workload characterization.

Having minded previously elaborated shortcomings of the standardized way, in this paper we propose a significantly different approach to estimating e-Commerce sales revenues, based on Web-based simulation, and using system dynamics logic. In particular, our aim is to develop a framework, i.e. a simulation model based on the workload characterization of a hypothetic e-Commerce website that will take into account not only various e-Customer classes, but also various operating profiles, i.e. working scenarios.

II. WEB-BASED SIMULATION

Until recently, technology stood on the way of achieving high levels of flexibility and business performance. Thanks to the emergence of the Web 2.0 paradigm and open standards, technology now gives an opportunity to all companies, including those that deal with e-Commerce, to become more innovative and to gain substantial competitive advantage. More and more, the Web is being considered an online environment suitable for providing both modeling and simulation tasks. The emerging new innovative and alternative approach to computer simulation, which strives to become *de facto* an adequate replacement of the traditional workstation-based computer simulation, has been named as a 'Web-based simulation' (WBS). Simply, WBS is an integration of the Web with the field of simulation. It assumes an invocation of computer simulation services over the World Wide Web, specifically through a user's Web browser [4] [5] [6] [7]. WBS is currently becoming a quickly evolving area in computer science, which is of significant interest for both simulation researchers and simulation practitioners. Such great interest is a direct consequence of the successfulness of the Web 2.0 paradigm, and its associated technologies, e.g. HTML, HTTP, CGI, etc., as well as the great popularity of, and reliance upon, computer simulation, as being a problem-solving and decision-support system (DSS) approach. Therefore, WBS, as being an emerging area of exploration and application within the simulation community, has already been considered a state-of-the-art discipline, which is expected to proliferate and even prevail in the forthcoming years [6] [8] [9].

III. THE SYSTEM DYNAMICS APPROACH AND INSIGHT MAKER®

System Dynamics (SD) modeling is a powerful method for exploring systems on an aggregate level. By 'aggregate', it is meant that SD models look at collections of objects, not the objects themselves. For instance, a SD model of e-Customers population would look at the population as a whole, not at the individual e-Customers. If compared to Discrete-Event Simulation (DES), System Dynamics uses a quite different approach. Contrary to DES, SD is essentially deterministic by nature. It models a system as a series of stocks and flows, whilst state changes are continuous, resembling a motion of a fluid, flowing through a system of 'reservoirs' or 'tanks', connected by 'pipes'.

SD models are visually constructed from a set of basic building blocks also known as 'primitives'. However, behind the scene, these primitives are 'converted' into differential equations that describe the modeled system mathematically. Since only the dynamics of extremely small and/or well-known systems could possibly be solved analytically, the dynamics of large and/or ill-known systems requires numerical simulation [10].

The key SD primitives are Stocks, Flows, Variables and Links.

- Stocks are graphically presented by rectangles; they store some kind of 'material', e.g. a population of e-Customers.
- Flows, graphically depicted by bolded solid lines with arrows, move the 'material' between stocks; they can be either inflows (inputs into stocks), or outflows (outputs from stocks), e.g. a flow of e-Customers' arrival in the online store.
- Variables are graphically portrayed by ovals; they can be dynamically calculated values that change over time (governed by an equation) or they can be constants (fixed values), e.g. e-Customer arrival rate.
- Links, graphically shown by dashed lines with arrows, show the transfer of information between the different primitives in the model. If two primitives are linked, they are related in some way. Links are generally used in conjunction with variables to build mathematical expressions.

Because of its great flexibility, its ability to combine both qualitative and quantitative aspects of the modeled system, and its tendency to model and simulate the dynamics of a system at a higher, strategic level, SD has been applied in many fields. The aim is to gain a holistic insight into the dynamic behavior and interrelations among different parts of the complex system under study.

To demonstrate the usefulness of Web-based simulations being applied in estimating e-Commerce sales revenues, we revert to Stock-and-Flow simulations, which are constituent part of the SD paradigm: a methodology, as well as a mathematical modeling and simulation technique, suitable for framing, understanding, and discussing complex issues and problems.

Insight Maker® is an innovative, free-of-charge, Web 2.0-based, multi-user, general-purpose, online modeling and simulation environment, completely implemented in JavaScript, which promotes online sharing and collaborative working. It integrates three general modeling approaches, including: (1) system dynamics, (2) agent-based modeling, and (3) imperative programming in a unified modeling framework. The environment provides a GUI aimed at model construction, offering advanced features, such as model scripting and an optimization tool. Insight Maker® has been developed for several years, and has gained significant adoption. Currently it has almost 26,000 registered users [11].

To the best of our knowledge, it is the first, yet the one and only free-of-charge Web 2.0-based Internet service that can deliver a plethora of advanced features to its online users, including Causal Loop Diagrams, Rich Pictures Diagrams, Dialogue Mapping, Mind Mapping, as well as Stock & Flow simulation. All these can offer thorough insights into various aspects of a system's dynamics. By supporting agent-based scenarios, storytelling and sensitivity analysis, Insight Maker® exhibits a wide gamut of features that not only rival, but also, in many cases, outperform the traditional, commercially available simulation software packages.

IV. WORKLOAD CHARACTERIZATION

The workload of a system can be defined as "the set of all inputs that the system receives from its environment during any given period of time", whilst workload characterization is "the process of precisely describing, in a qualitative and quantitative manner, the global workload of an e-business site" [12]. Since it is difficult to handle real workloads due to the large number of constituting elements, it is more practical to reduce and summarize the information needed to describe the workload. However, the choice of characteristics and parameters that will describe the workload depends solely on the purpose of the study, having minded the fact that the model needs to capture the most relevant characteristics of the real workload. This way, in order to reflect changes in the system and/or in the actual workload, it is possible to gain various insights into the system's behavior simply by changing its model parameters.

We have based the workload characterization of a hypothetic e-Commerce website on two fundamental premises: (1) e-Customers' online shopping behaviors mutually differ; (2) e-Customers access the e-Commerce website and invoke the specific e-Commerce functions in a rather unpredictable and stochastic manner [13].

The first premise reflects the qualitative aspects of workload characterization. Many studies have pointed out the fact that it is possible to distinguish among different classes of e-Customers, regarding their specific online shopping behaviors [14] [15]. Recently, the fields of behavioral economics, buyer psychology and neuroeconomics have been put in focus due to their great contribution in understanding why and how e-Customers make purchases, which are a proven route to successful marketing, as well as to producing conversions and revenues. By combining research methods from neuroscience, experimental and behavioral economics, psychiatry, statistics, as well as cognitive and social psychology, neuroeconomics is defined as "an interdisciplinary field that seeks to explain human decision making, the ability to process multiple alternatives and to follow a course of action" [16]. Previous research endeavors in this field reported the existence of three main/universal types of e-Customers, regardless of the type of industry, including (1) 'Tightwads', (2) 'Average Spenders', and (3) 'Spendthrifts' [17]. Moreover, the latest research findings claim that in any population of e-Customers, 'Tightwads' comprise 24%, 'Average Spenders' cover 61% and 'Spendthrifts' involve 15% [18] [19]. Based on these three classes of e-Customers, a discrete random variable that resembles the operating profile, along with its probability mass function (pmf), can be defined. The operating profile defines the mix constituted by various e-Customer classes: if k classes of e-Customers have been identified, (t_1, t_2, t_3, …, t_k), then each class can be associated a corresponding probability, drawn from the probability mass function vector (p_1, p_2, p_3, …, p_k), such that $\sum_{i=1}^{k} p_i = 1$. These probabilities are, in fact, a measure of the participation of each e-Customer class within the workload mix.

The second premise is related to the quantitative aspects of the workload characterization. The arrivals of e-Customers in an e-Commerce website can be mathematically described by a Poisson process, defined by the number of arrivals per unit time, i.e. the arrival rate λ [e-Customers/s]. The times elapsing between each consecutive arrival comprise an i.i.d. (independent and identically distributed) random variable, exponentially distributed. Since the Markov property of the exponential distribution holds for each particular moment, the expected (mean) time to the next arrival is a constant, given by $1/\lambda$. Moreover, let λ be the total arrival intensity of e-Customers belonging to different classes (t_1, t_2, t_3 …, t_k), which comprise the workload mix. If the probability of classes' presence in the workload mix is represented by the probability vector (p_1, p_2, p_3, …, p_k), where $\sum_{i=1}^{k} p_i = 1$, then the arrival intensity of e-Customers, belonging to each particular class t_i (i = 1, 2, 3, …, k), is given by the product $\lambda \times p_i$ (i = 1, 2, 3, …, k) [20].

V. THE WEB-BASED SIMULATION MODEL

The Web-based simulation model is completely done using Insight Maker®, and it is freely available for use at https://insightmaker.com/insight/34138/e-Commerce-Revenue-Estimator. It entirely incorporates the system dynamics approach. Due to its robustness, it can be logically divided into three parts (*A*, *B*, and *C*).

A. e-Customer classes and the operating profile

The first part of the simulation model is depicted on Fig. 1.

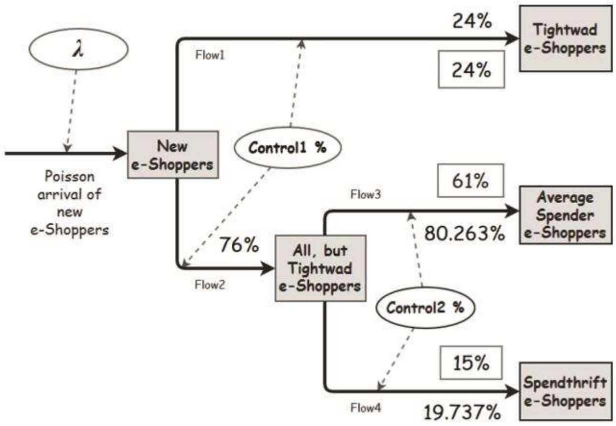

Figure 1. The first part of the Insight Maker® simulation model

On Fig. 1, the flow entering the container 'New e-Shoppers' denotes the arrival of new e-Customers into the online shop, which is a Poisson process with intensity λ [e-Customers/s], described by the expression =RandPoisson([λ]). The intensity λ is an adjustable variable, linked to the input flow. At time t = 0, the container labeled 'New e-Shoppers' contains 0 (zero) e-Customers, although its initial quantity may be set to any positive integer. As simulation time elapses, the inflow causes filling the container 'New e-Shoppers' with intensity λ. The adjustable variable 'Control1 %', being initially set to 24 [%], defines the portion of the total number of e-Customers that belong to the 'Tightwad' class. These e-Customers, through the flow labeled 'Flow1', pour into the container named 'Tightwad e-Shoppers', in accordance with the following equation: =[New e-Shoppers]*[Control1 %]/100. The rest of e-Customers (i.e. 76%) through the flow 'Flow2' go into the container named 'All, but Tightwad e-Shoppers', according to the following equation: [New e-Shoppers]*(100–[Control1 %])/100. Now, identically, the adjustable variable 'Control2 %' separates the number of e-Customers that belong to the two other classes, by initially setting the flow of 'Average Spender' e-Customers to 80.263 [%] (out of 76%), which yields exactly 61%. The rest of e-Customers (19.737 [%] out of 76%, which yields exactly 15%) flow into the container labeled 'Spendthrift e-Shoppers'.

In this manner, the first part of the simulation model introduces the three e-Customer classes as discussed in the previous section, i.e. t_1 = 'Tightwad', t_2 = 'Average Spender', and t_3 = 'Spendthrift' e-Customers. The vector of corresponding initial probabilities (p_1 = 0.24, p_2 = 0.61,

p_3 = 0.15) defines the operating profile, i.e. the level of participation of each particular e-Customer class into the workload mix.

B. *Logic and dynamics of online shopping sessions*

Fig. 2 shows the second part of the simulation model: both the logic and the dynamics of 'Tightwad' e-Customers initiating online session, which is identical by its structure for the other two types of e-Customers.

The flow labeled 'Start Session - Tightwad', which is an output from the container labeled 'Tightwad e-Shoppers', represents the Poisson arrival of 'Tightwad' e-Customers into the online shop, controlled by the adjustable variable 'λ1'. This flow is an input to the container labeled 'Browse-Search 1', which contains the e-Customers who are currently browsing or searching for items. This container has three outflows, including 'Flow5' (those who have put something into their shopping carts), 'Flow6' (those who have terminated the session without putting anything in their shopping carts), and 'Flow7' (those who have continued to browse/search for items). 'Flow5' goes into the container labeled 'Put items in cart 1', 'Flow6' is directed towards container labeled 'Tightwad e-Shoppers', and 'Flow7' pours back into the same container from where it came out, represented by its 'ghost' primitive. Each of these outflows is controlled by a corresponding variable. The value of one of them ('Add to cart rate T %') is adjustable, the other one ('Terminate session rate T-1 %') is drawn from the Normal distribution $N(\mu, \sigma)$ with fixed values for its parameters that correspond to each particular type of e-Customer, and the third one ('Continue session rate T-1 %') complements the sum of previous ones to 100.

The similar logic has been applied with the container labeled 'Put items in cart 1'. There are three flows going out from this container, including 'Flow8' (those who have paid for the items already put in the shopping cart), 'Flow9' (those who have terminated their online session leaving the non-empty shopping cart unpaid), and 'Flow10' (those who have continued browsing or searching for other items). 'Flow8' goes into the container labeled 'Pay items in cart 1', 'Flow9' is directed towards container labeled 'Tightwad e-Shoppers', and 'Flow10' pours back into the container labeled 'Browse-Search 1'. Each of these outflows is controlled by a corresponding variable. The value of one of them ('Buy rate T %') is adjustable, the other one ('Terminate session rate T-2 %') is drawn from the Normal distribution $N(\mu, \sigma)$ with fixed values for its parameters that correspond to each particular type of e-Customer, and the third one ('Continue session rate T-2 %') complements the sum of previous ones to 100.

The container labeled 'Pay items in cart 1' has two outflows: one ('Flow11') is going back towards the container labeled 'Browse-Search 1', and the other one ('Flow12') is pouring back into the container labeled 'Tightwad e-Shoppers'. Both of them are controlled by two distinct variables. The value of the first of them ('Terminate session rate T-3 %') is drawn from the Normal distribution $N(\mu, \sigma)$ with fixed values for its parameters that correspond to each particular type of e-Customer, whilst the second one ('Continue session rate T-3 %') complements the first one to 100.

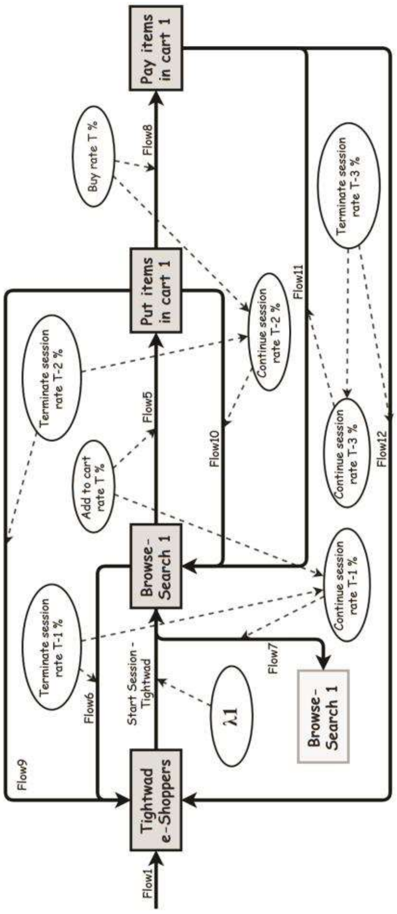

Figure 2. The second part of the Insight Maker® simulation model (a fragment that corresponds to 'Tightwad' e-Customers)

Table 1 contains the equations, as well as range values associated to the variables and flows presented in Fig. 2.

C. *Estimating sales revenues for each e-Customer class and the total sales revenue*

The third part of the simulation model, which corresponds solely to the class of 'Tightwad' e-Customers, is presented on Fig. 3. In each particular time instance t, the container labeled 'Pay items in cart 1' contains the fraction of those e-Customers who have paid for the items put in the shopping cart. Knowing this number (C_t), and assuming that there are M items in total available for selling, whose buying probabilities (i.e. relative buying frequencies) are b_i (i = 1, 2, …, M) at selling prices pr_i (i = 1, 2, …, M), the revenue R_t, gained at time instance t, can be estimated by (2).

Based on (2), which is used for calculating the value of the output variable 'Revenue - Tightwad', one can estimate the cumulative revenue (CR_T), up to the time T, according to (3). Just for testing purposes, our simulation model includes only three items, whose buying probabilities and selling prices are shown in Table 2.

On Fig. 3, the output variable 'Cumulative revenue - Tightwad' uses the following expression to estimate this value: =Sum(pastValues([Revenue - Tightwad])). For the other two classes of e-Customers, cumulative revenues are estimated in an identical manner.

TABLE I. FLOWS AND VARIABLE SETTINGS ('TIGHTWAD')

SD Primitive	Equation/Value associated
'Tightwad' e-Customers	
Variable: λ1	adjustable; Values: 0 ≤ λ1 ≤ 50, step 0.1
Variable: Add to cart rate T %	adjustable; Values: 0% - 10%, step 0.1
Variable: Buy rate T %	adjustable: Values: 0.00% - 0.50%
Variable: Continue Variable: session rate T-1 %	=100–([Terminate session rate T-1 %]+[Add to cart rate T %])
Variable: Continue session rate T-2 %	=100– ([Terminate session rate T-2 %]+[Buy rate T %])
Variable: Continue session rate T-3 %	=100– [Terminate session rate T-3 %]
Variable: Terminate session rate T-1 %	=Abs(RandNormal(75, 8.33333))
Variable: Terminate session rate T-2 %	=Abs(RandNormal(75, 8.33333))
Variable: Terminate session rate T-3 %	=Abs(RandNormal(75, 8.33333))
Flow: Start Session - Tightwad	=RandPoisson([λ1])
Flow: Flow5	=[Browse-Search 1]*[Add to cart rate T %]/100
Flow: Flow6	=[Browse-Search 1]*[Terminate session rate T-1 %]/100
Flow: Flow7	=[Browse-Search 1]*[Continue session rate T-1 %]/100
Flow: Flow8	=[Put items in cart 1]*[Buy rate T %]/100
Flow: Flow9	=[Put items in cart 1]*[Terminate session rate T-2 %]/100
Flow: Flow10	=[Put items in cart 1]*[Continue session rate T-2 %]/100
Flow: Flow11	=[Pay items in cart 1]*[Continue session rate T-3 %]/100
Flow: Flow12	=[Pay items in cart 1]*[Terminate session rate T-3 %]/100

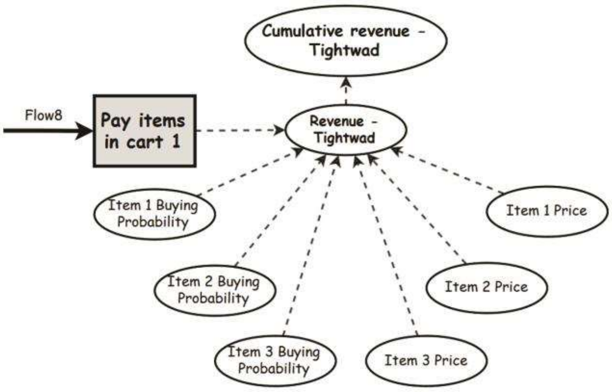

Figure 3. The third part of the Insight Maker® simulation model (a fragment that corresponds to 'Tightwad' e-Customers)

$$R_t = c_t \times \sum_{i=1}^{M} b_i \times pr_i \qquad (2)$$

$$CR_T = \sum_{t=1}^{T} R_t \qquad (3)$$

TABLE II. BUYING PROBABILITIES AND SELLING PRICES

Item #	Buying probability	Selling price
1	0.3	$6.00
2	0.1	$10.00
3	0.6	$2.00

Finally, Fig. 4 portrays the fragment of the simulation model, needed to estimate the total cumulative revenue, given the cumulative values that correspond to each particular e-Customer class.

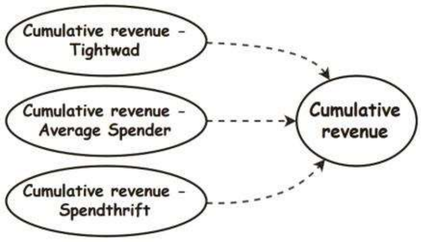

Figure 4. The final part of the Insight Maker® simulation model

The output variable 'Cumulative revenue' is calculated using the following expression: =[Cumulative revenue - Tightwad] + [Cumulative revenue - Average Spender] + [Cumulative revenue - Spendthrift].

VI. SIMULATION RESULTS

The simulation run took into account a time window of T = 60 [s]. It was accomplished according to the working parameters' values as shown in Table 3. Based on these settings, the estimated revenues for each particular e-Customer class are graphically shown on Fig. 5; the estimated cumulative revenues for each particular e-Customer class are graphically shown on Fig. 6, whilst the estimated total cumulative revenue is shown on Fig. 7.

TABLE III. WORKING PARAMETERS SETTING

Variable	Value
Control1 %	24.000
Control2 %	80.263
λ	1.1
λ1	5.5
λ2	3.5
λ3	1.5
Buy rate T %	0.25
Buy rate AS %	1.50
Buy rate S %	5.00
Add to cart rate T %	5
Add to cart rate AS %	20
Add to cart rate S %	50

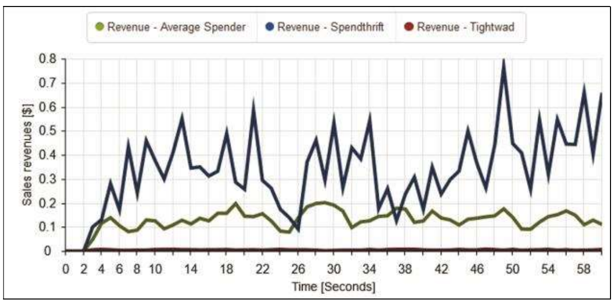

Figure 5. Estimated revenues for each particular e-Customer class

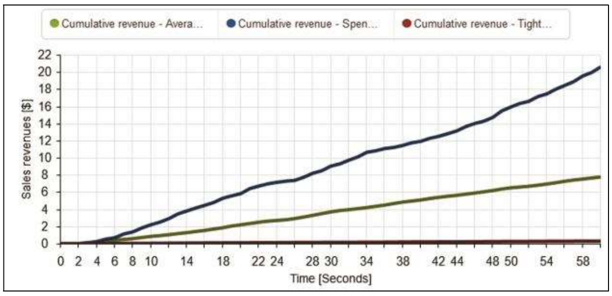

Figure 6. Estimated cumulative revenues for particular e-Customer classes ($T = 60$ [s])

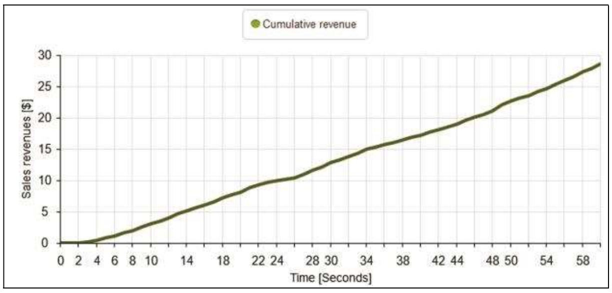

Figure 7. Estimated total cumulative sales revenue ($T = 60$ [s])

VII. Conclusion

In highly demanding online business environments, such as e-Commerce, estimating sales revenues is one of the crucial tasks that can be successfully accomplished using simulations. Web 2.0-based simulations, based on the system dynamics approach, can reveal new and significant insights into business processes, which will increase their effectiveness, performances and flexibility, thus creating an unprecedented competitive advantage for companies on a long term. In addition, Insight Maker® has proven to be a great innovative tool for mapping ideas by graphically visualizing them, and then, by converting maps into computational simulation models, to display specific behaviors and dynamics of the modeled system over time, as well as to carry out multiple scenario runs. However, the main drawback of the system dynamics approach vis-à-vis our resulting simulation model could possibly be the increased model complexity in the case if new e-Customer classes and/or new items are introduced.

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