Investigating The Adoption of Internet of Things Technology Using Agent-Based Simulation

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Abstract

Internet of Things (IoT) is a vision of integrated networks covering physical devices that can collect and exchange data. It enables unconnected applications and objects to become connected through communication technology such as radio frequency identification tags (RFID). This paper presents a conceptual study of a business model based on IoT technology using agent-based simulations (ABS) to determine IoT adoption and life cycle. Business model canvas is used to propose a predictive maintenance software business model; the physical objects of the system are integrated and connected to RFID tags and sensors to collect and exchange data stored in cloud-based system. Subsequently, this will improve predictive analytics and hence attain better decision making. The behavior of the customer market in the USA is simulated using ABS to examine the potential of a proposed business model.

Keyword
Agent-Based Simulation, Internet of Things, Predictive Maintenance Software

1 Introduction

Business analytics is considered one of the most important areas today as many companies use business analytics prior to making decisions in their processes and operations. Business analytics use mathematical models and optimization techniques in order to augment the use of scarce resources as well as promote waste reduction in a company (Khalili-Damghani, Sadi-Nezhad, Lotfi, & Tavana, 2013; Rabelo & Hughes, 2005). The aim of this paper is to propose a new business model based on Internet of Things (IoT) and predictive maintenance and to use simulation modeling to investigate the adoption of IoT technology. Agent-Based Simulation (ABS) model can be applied to capture and test the feasibility of such a business model as the proposed one. In addition, the flexibility and capability of the ABS models aid to capture system complexity and provide a meaningful result (Behdani, 2012; Demirel, 2006; Siebers, Macal, Garnett, Buxton, & Pidd, 2010). ABS modeling can be used in a wide range of fields, such as marketing, economics, and artificial intelligence; more recently, many conference proceedings and journal articles call for papers for ABS modeling, which shows the popularity and growth in this area (Macal & North, 2009). Well-known applications of ABS modeling applied in 1940's include the Epidemic model and Schelling segregation (Borshchev, 2013).

This paper is organized into five sections including the introduction. Section 2 provides a brief review of literature related to ABS. Section 3 discusses our proposed business model. Section 4 shows a case study to demonstrate the application of ABS to simulate customer behavior of the IoT market in the United States. Finally, Section 5 concludes this research work and describes the future work.

2 Related Work

In the 1990s, social scientists discovered the potential benefits of ABS modeling when they started to form research groups that investigated the use of ABS for modeling individuals' behaviors (Brailsford, 2014; Macal & North, 2009). Recently, ABS was applied in areas where human behavior is important due to its powerful capability of capturing human behavior in detail and imitating system interactions and dynamics (Brailsford, 2014). Agents can also be part

of hybrid systems, where several hierarchical layers of an organization are modeled with corresponding interactions (Rabelo, Eskandari, Shaalan, & Helal, 2007). These hybrid systems fuse different paradigms in simulation such as agents, system dynamics, and discrete-event simulation (Mykoniatis, 2015). In this paper, an *agent* is defined as one that uses a modified automaton in order to accommodate some level of behavior and decision making based on data collected from preliminary survey studies. Numerous agents give rise to an emergent behavior in order to observe and define technology life cycles (Meade & Rabelo, 2004). The technology life cycle guides the investment and the diffusion of the IoT technology with the corresponding operational strategies. The operational strategies will depend upon the acceptance level and the length of the life cycle.

3 Predictive Maintenance Software (PMS)

There is a need for cross-fertilization among today's businesses, smarter maintenance practices, and better corporate financial results will help companies manage expensive, efforts and maintain efficiently their facilities, processes, and machines (Manyika et al., 2015). This is where the proposed predictive maintenance software comes into play, as an Internet of Things-enabled analytics platform that can tie any organization's maintenance investment to its most important assets. By combining and/or integrating IoT with cognitive computation, PMS can provide companies with both information and statistical analysis in order to virtually test various aspects of their operations as well as to assist in creating efficient new business models.

3.1 PMS System Description

PMS based on IoT helps to continuously analyze real-time sensor data via machine monitoring to predict when maintenance requirements. The collected data can transit to business intelligence and analytics tools in order to help discover and resolve the system's performance. PMS provides customers with different services such as predicting and scheduling maintenance for their devices, accessing the maintenance manuals and some of the proposed solutions for particular cases, and enabling customers to compare the statistics of similar equipment that used by different clients. The main PMS services and benefits are described below.

- Predict which, when, and how likely a device will fail to perform under certain conditions.
- Identify primary variables through root and cause analysis, and help maintain device performance and quality.
- Reduce product quality and reliability issues to meet customer delivery times.
- Optimize inventory, reducing spare parts stocking.
- Reduce operation costs by enhancing planning operations and sales.
- Provide information to budget and planning teams prior to upcoming costly event failure occurrences.

Figure1 illustrates a high-level view of the proposed PMS architecture.

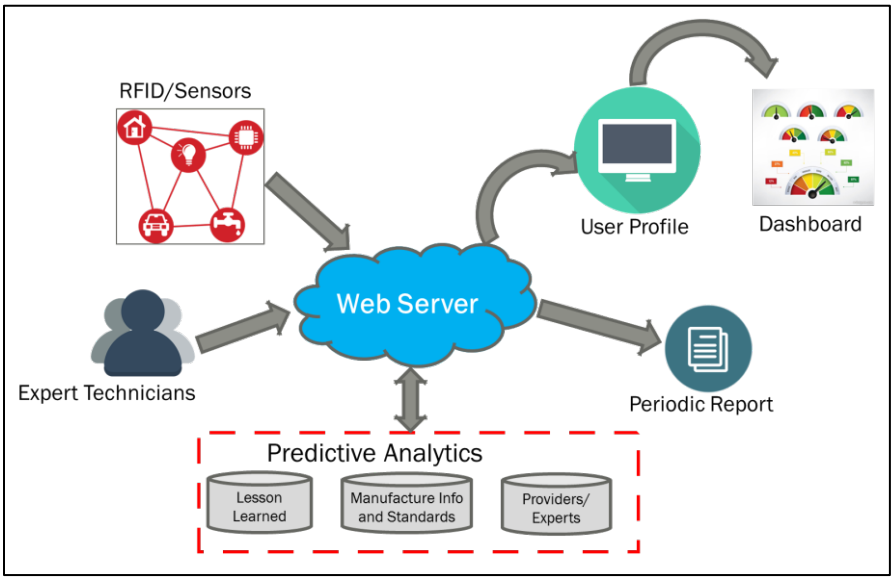

Figure 1. The architecture of PMS

Figure 2 describes suggested preliminary canvas business model based on Internet of Things for the proposed predictive maintenance software. This business model was created by following the methodology proposed by Osterwalder and Pigneur (2010). Currently, our platform and the assumptions are under investigation.

PMS Business Model

Team or Company Name: Predictive Maintenance Software

Date: 04/24/2017

[X] Primary Canvas
[ ] Alternative Canva

Key Partners

- Specialized software development teams across various sectors such as manufacturing, logistics, healthcare, transportation and entertainment industry.
- Suppliers are chips providers, API and gateway solutions that allow "devices/ things" connect, sense and communicate to machine generated data.
- Resources we acquire enable us to transform business embed IoT capabilities into existing solutions, improve operations and enhance customer engagement.
- Our partners add value to our PM software offering for asset & facilities management and continuous engineering.

Key Activities

- Enabling devices to connect to PMS using IoT.
- IoT application awareness and knowledge center.
- PMS service subscription

Key Resources

- Skilled development teams
- Events, webinar, demos & Advertising
- Subscription & Partnership

Value Proposition

- Asset management
- Work management
- Inventory management
- Health safety & environment
- Real time mobile solution
- Monitor for maintenance device health
- Predict asset failure
- Improve Quality
- Reduce warranty cost
- Customized tools based on initial feasibility study.
- Reduce maintenance cost up to half of what you are currently spending wasting resources

Customer Relationships

- Continuous Engineering Solutions that enables them detect failure early on and support.
- PMS provides data real time using root cause analysis, primary variables are known.
- Based on the size of the company a feasibility study determines the product need for each client

Channels

- Advertising, Direct Sale and Word of Mouth.
- Seminars and tech talks.
- Word of mouth is the best method to reach a customer as social engineering is a very powerful resource.

Customer Segments

- PMS can be customized for wide variety of customers who need to use smart devices for operations, clients not limited to:
  - Automotive
  - Buildings
  - Electronics
  - Manufacturing
  - Retail
  - Shipping
  - Logistics
  - Transportation
  - Medical & Healthcare
  - Information technology
  - Banking and Finance

Cost Structure

- Software Development cost as skilled resources is required, software licensing and customizing for implementation tailored to each client's unique need.
- PMS installation and training, and developing API's

Revenue Streams

- Reducing cost & improving quality ultimately makes a client more efficient, subscription to PMS gives them a competitive edge in the marketplace.
- Increase machines runtime and meet their customer expectation.
- Most companies have manual maintenance schedule, PMS will eliminate them completely, added security and assurance feature.
- PMS offers customized solutions across a common platform over IoT technology

Figure 2: Business model for PMS

4 Case Study: ABS Model for Predictive Maintenance Software Based On IOT Technology

An Agent-Based model was developed to simulate the behavior of the US market and its environment in order to test the acceptance and reliability of IoT predictive maintenance software (PMS) proposed in Section 3. In our case study, we focused on investigating the adoption rate of the PMS based on IoT for four types of potential customers/users (agents): Information Technology (IT) companies, manufacturers, banks, and service companies such as healthcare, education, transportation, hotels, and entertainment. These customer segments were chosen based on the geolocalization and accessibility of customers (Table 1). Moreover, we assumed that:

- There are no other competitors in the market providing PMS
- Customers of different segments behave the same way
- No demographic characteristics were taken into consideration
- Communication can be achieved among all the customers
- The adoption fraction and direct sales effect are 30% and 15% respectively
- Word of mouth and advertisement effectiveness are 18% and 17% respectively (according to McKinsey

Quarterly report issued in April 2010 (Bughin, Doogan, & Vetvik, 2010))

Table 1. Types of Agents

#	Types of Agents
Agent 1	Information Technology companies
Agent 2	Banks
Agent 3	Manufacturer
Agent 4	Services companies

Distinctive variables and parameters were used for each type of agent. Statecharts were structured as a clear and an intuitive way of representing agents' behavior. AnyLogic software was used as a simulation tool to build the ABS model. This software was selected because of its capability to provide a high degree of flexibility and its ability to capture system complexity.

4.1 Agent Statechart

Three Statecharts were used to simulate the purchasing behaviors for each customer and to capture the transition from one state to another. The statechart structure for each type of agent is illustrated in Figure 3. Purchasing behavior is defined by three different states: Interested state, PotentialUser state, and User state. PotentialUser state includes customers who are potentially interested in buying the software product but have not made the purchasing decision yet, while User state includes customers who have already purchased the product. Customers in the Interested state have decided to buy the product but have not purchased it yet.

The transition between states in Figure 3 is triggered by internal and external factors. In our ABS model, direct sales and advertisements are considered to be external parameters which affect customer behavior directly. We studied the effectiveness of three types of advertisements: online advertisements, broadcast advertisements, and print advertisements (e.g., newsletters, booklets, newspapers, magazines). Additionally, the communication between agents through word of mouth (WOM) is considered to be an internal factor that affects user decision indirectly. Different types of agents can also communicate with each other. There are two types of communications: internal communication (communication within the same agent) and external communication (communication between different types of agents). In our ABS model, an IT company (Agent 1) can contact another IT company. Also, an IT company can communicate a bank (Agent 2), a manufacturer (Agent 3), or a service company (Agent 4).

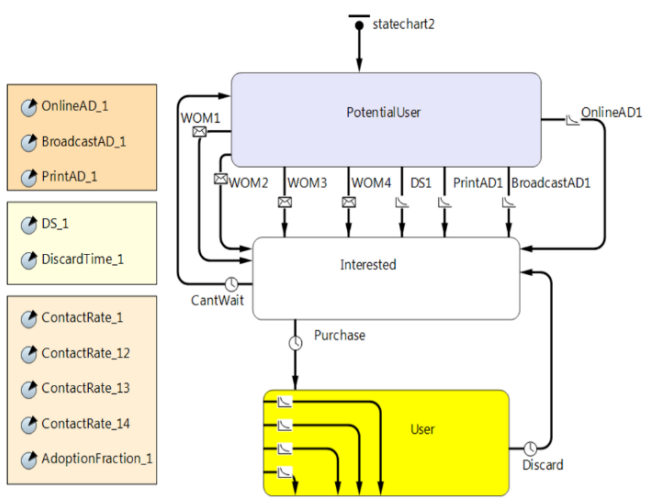

Figure 3. Structure of agent statechart

There are several different ways to model agent communication. In the ABS model, we used internal transition and message passing to simulate WOM. An agent is able to send messages to an individual agent or to a group of different agents. For example, the IT company (Agent 1) can send the message "Buy_1" to another IT company using the internal transition. Also, the IT company can send the message "Buy_1To2" to a bank (Agent 2), "Buy_1To3" to a manufacturer (Agent 3), or "Buy_1To4" to a service company (Agent4). In the internal transition, we defined the contact rate between agents. After sending the messages, the agent state is changed from PotentialUser to Interested state based on a specified rate (adoption rate).

Every transition in the statechart (Figure 3) was triggered by a specified rate. For example, the WOM effectiveness rate was 18% per year, based on the McKinsey Quarterly report issued in April 2010 (Bughin et al., 2010); on average, 18 percent of potential users will be influenced to buy the product in a given year through agent communications. Also, the McKinsey Quarterly report proposes that the advertisement effect rate is 17% per year, which means, on average, 17 percent of potential users will buy the hypothetical product in a given year.

4.2 Data Collection Method

Agent-based simulation modeling requires data that represent the dynamic environment of the real world. In this work, we investigate the adoption of Internet of Things as an emerging technology. More specifically, the majority of big data has just been collected in the past two years. Due to this reason, our collection method was limited to: 1) Searching in well-known industry reports generated by similar industries, and 2) approaching individuals working in businesses from various industries to determine their awareness of the Internet of Things and Big data analytics. We conducted a survey of various technology industry experts in technology which included the four agent types (i.e., information technology, manufacturing, banking, and the finance & service sector).

ABS model characterizes each agent under certain behavioral constraints and patterns. Based on 50 data points we collected, our survey results provided us with statistical results and probabilistic patterns on how these agents would receive information and how advertisements and direct sales would affect their decision. We also queried how potential customers/business would be likely to recommend a certain product to another business within the same domain or another area.

While designing the survey, we considered the following factors:

1) Agents: Agents are basically businesses or consumers that are more than likely to adopt IoT technology in their work now or in future spanned across the United States.
2) Properties: Each business/agent will need a list of properties that describe that agent. Each agent will have a probability of adopting due to mass media efforts, and a probability of adopting due to word-of-mouth effects. In the network design, each agent will also have three additional neighboring agents that they will interact with.

4.3 Preliminary Results

The developed ABS model was considered for a pilot testing to help us understand how a system reacts due to different inputs. It enabled us to realize the effect of specific parameters such as WOM, advertisement effect and adjust the firm's strategy accordingly. For example, Figure 4 illustrates how various sales channels, such as advertisements and direct sales, would improve the adoption process for each type of agent (we can change and play with the parameters values during the simulation run and observe how the adoption rate changes). Therefore, we focused on investing in the best sales channel for each agent type in order to enhance the firm's net profit. Table 2 & 3 represent the simulation input to our ABS model, gathered after the analysis of the survey results and well-known industry reports. Based on the McKinsey Quarterly report issued in April 2010 (Bughin et al., 2010), the advertisement influence effectiveness rate is considered to be 17% which we used as a benchmark to analyze our collected data in Table 2.

Table 2. External Parameters

	Parameter	Data	Type	Source
Agent 1	Online AD	0.15	Rate / Year	Data Analysis
	Broad Cast AD	0.043	Rate / Year	Data Analysis
	Print AD	0.074	Rate / Year	Data Analysis
	Direct Sale	0.15	Rate / Year	Assumption

Agent 2	Online AD	0.17	Rate / Year	Data Analysis
	Broad Cast AD	0.023	Rate / Year	Data Analysis
	Print AD	0.049	Rate / Year	Data Analysis
	Direct Sale	0.15	Rate / Year	Assumption
Agent 3	Online AD	0.11	Rate / Year	Data Analysis
	Broad Cast AD	0.07	Rate / Year	Data Analysis
	Print AD	0.11	Rate / Year	Data Analysis
	Direct Sale	0.15	Rate / Year	Assumption
Agent 4	Online AD	0.142	Rate / Year	Data Analysis
	Broad Cast AD	0.028	Rate / Year	Data Analysis
	Print AD	0.142	Rate / Year	Data Analysis
	Direct Sale	0.15	Rate / Year	Assumption

Also McKinsey Quarterly report (Bughin et al., 2010), states that the WOM influence effectiveness rate is considered to be 18% which we used as a benchmark to analyze our collected data in Table 3.

Table 3. Internal Parameter

	Parameter	**Data**	**Type**	**Source**
Agent 1 to 1	Interaction	0.16	Rate / Day	Data Analysis
Agent 1 to 2	Interaction	0.011	Rate / Day	Data Analysis
Agent 1 to 3	Interaction	0	Rate / Day	Data Analysis
Agent 1 to 4	Interaction	0	Rate / Day	Data Analysis
Agent 2 to 1	Interaction	0.02	Rate / Day	Data Analysis
Agent 2 to 2	Interaction	0.16	Rate / Day	Data Analysis
Agent 2 to 3	Interaction	0	Rate / Day	Data Analysis
Agent 2 to 4	Interaction	0	Rate / Day	Data Analysis
Agent 3 to 1	Interaction	0.08	Rate / Day	Data Analysis
Agent 3 to 2	Interaction	0	Rate / Day	Data Analysis
Agent 3 to 3	Interaction	0.103	Rate / Day	Data Analysis
Agent 3 to 4	Interaction	0.03	Rate / Day	Data Analysis
Agent 4 to 1	Interaction	0.03	Rate / Day	Data Analysis
Agent 4 to 2	Interaction	0	Rate / Day	Data Analysis
Agent 4 to 3	Interaction	0	Rate / Day	Data Analysis
Agent 4 to 4	Interaction	0.15	Rate / Day	Data Analysis
For All Agents	Adoption Fraction	0.3	Percentage	Assumption

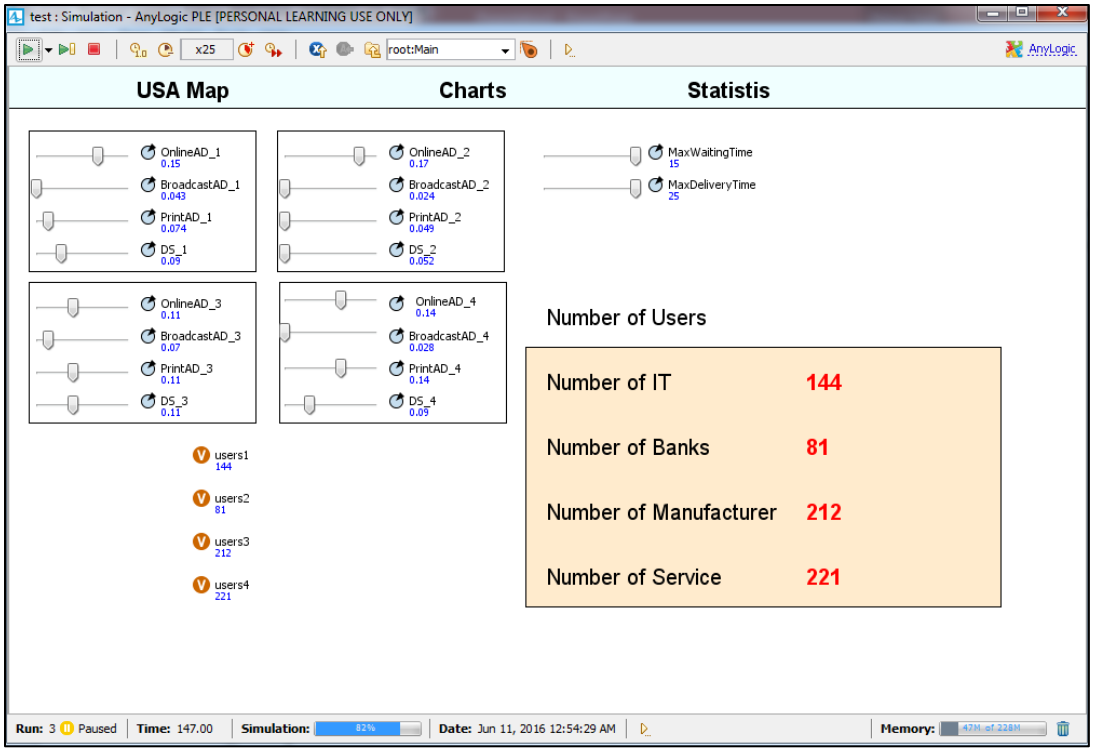

Figure 4. The effect of different sales channels on adoption rate during the simulation run

Table 4 shows the adoption rate of different customer segments after running the simulation for two years.

Table 4. The adoption process of each agent type

Day # 730	IT companies	Banks	Manufacturers	Services companies
# of Potential Users	120	88	155	60
# of Users	69	11	42	19
# of Interested	11	1	3	1

The time stack chart of Figure 5 illustrates the history of the data point contribution to the total amount of stacked areas during the newest time horizon. The data values are stacked repeatedly, one on top of the next, with the earliest added data point at the bottom.

Figure 6 shows the visualization of ABS animation for the four types of agents in the United States after running the simulation for two years. Each agent type has a different shape and state that is represented by different colors. The color changing in the animation during the simulation run represents the state transition of each agent (Table 5). For example, a color changes from lavender to yellow color indicates that IT company state is changed from potential user to user. This simulation output allows us to understand the market movement and customer behaviors more clearly.

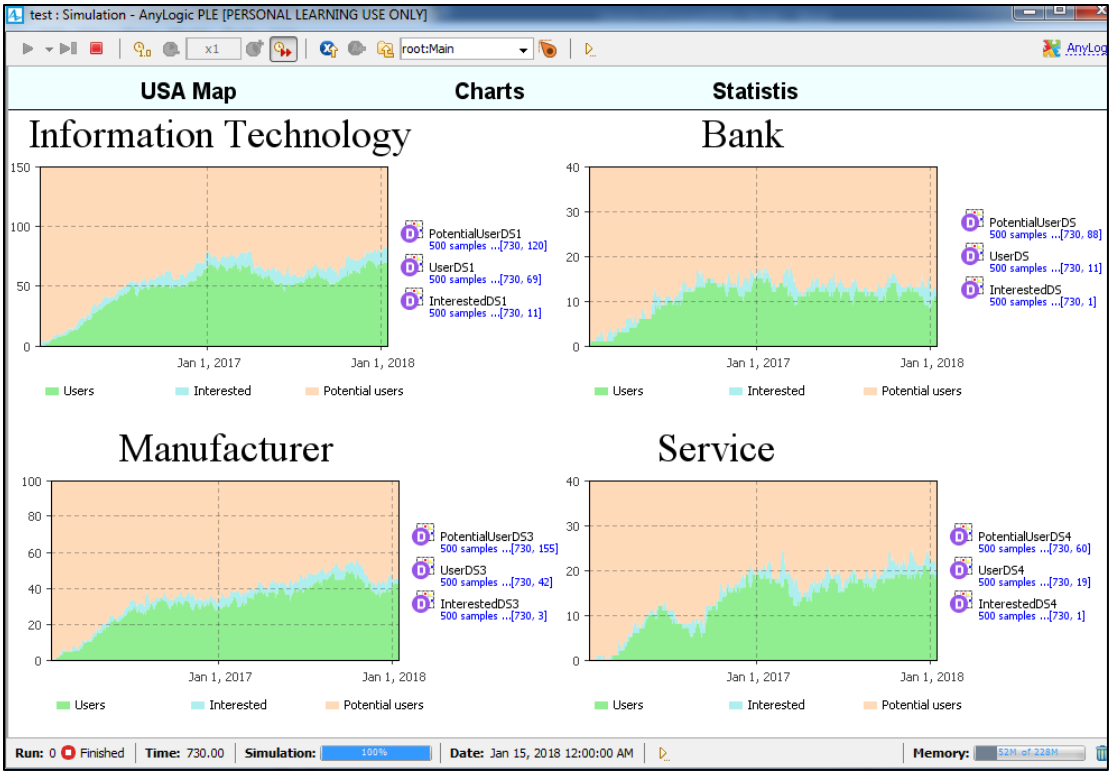

Figure 5. Time Stack Chart

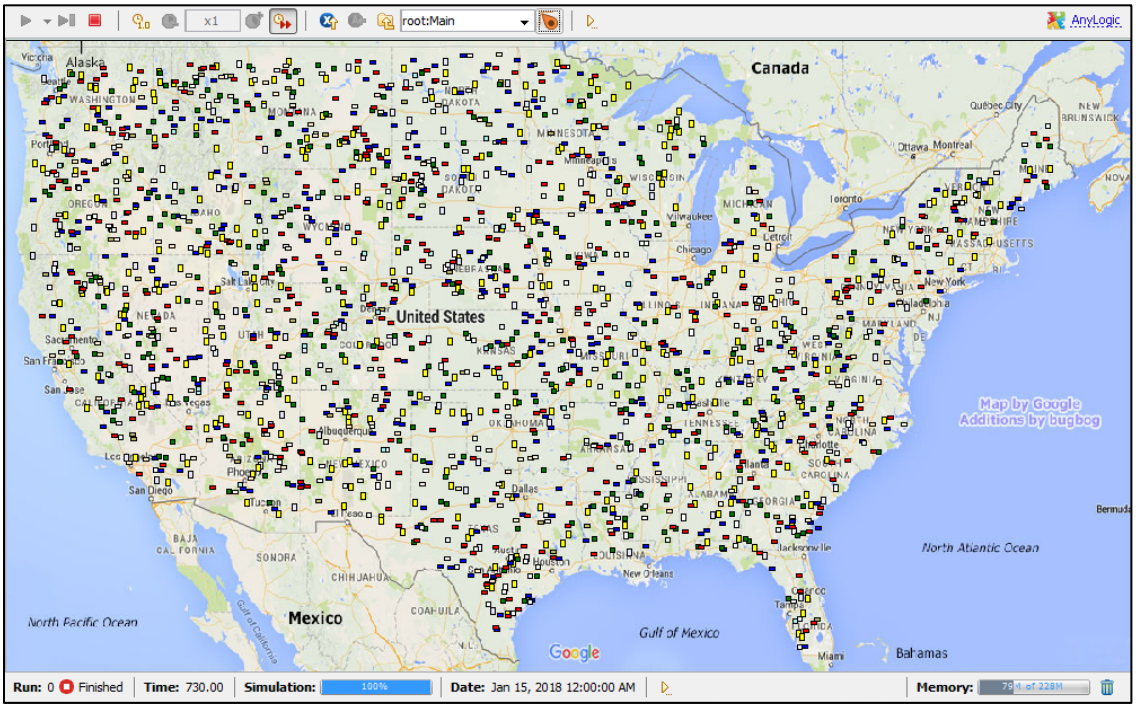

Figure 6. ABS animation of agents types in the USA

Table 5. Different color for each agent type in every state

Agent Type / State	IT company	Banks	Manufacturer	Services company
Potential User	Lavender	MintCream	Snow	Almond
Interested	white	Turquoise	Khaki	Beige
User	Yellow	Green	Blue	Red

4.4 Optimization

Simulation runs were observed under certain conditions, the purpose was to learn and improve system performance by making system parameter and/or structure decisions using optimization capabilities, such as the one provided by AnyLogic. We conducted an optimization experiment in order to find an optimal combination of parameters that result in the maximize the net profit. The optimization process consists of repetitive simulations of a single logic with different parameters.

In our ABS model, the purpose is to investigate the adoption of IoT by simulating marketing behavior for our Predictive Maintenance Software. We determine how to maximize the net profit by using the effectiveness of marketing strategies which included an advertisement (e.g., online, broadcast, and print media), word of mouth, and direct sales. After our initial run, we observed the net profit based on the effectiveness of the parameter obtained from our survey data, and simultaneously ran the optimization.

To understand the parameters in our case study, we need to understand the input and output. The inputs are the parameters defined by the survey result while the outputs display the maximum profit with the minimal cost associated with advertisement constraints. In this section, we provide a straightforward example of applying the optimization experiment for the developed ABS model. Based on the defined input parameters, we made some assumptions related to the advertisement cost and sales revenue to understand the optimization logic (Table 6). The observed results are displayed in Figure 7.

Table 6: Cost & Revenue assumptions

Parameter	Data	Type	Source
Revenue per User	120	$	Assumption
Cost of Online AD per user	5	$	Assumption
Cost of Broadcast AD per user	3	$	Assumption
Cost of Print AD per user	2	$	Assumption
Fixed Cost per user	100	$	Assumption

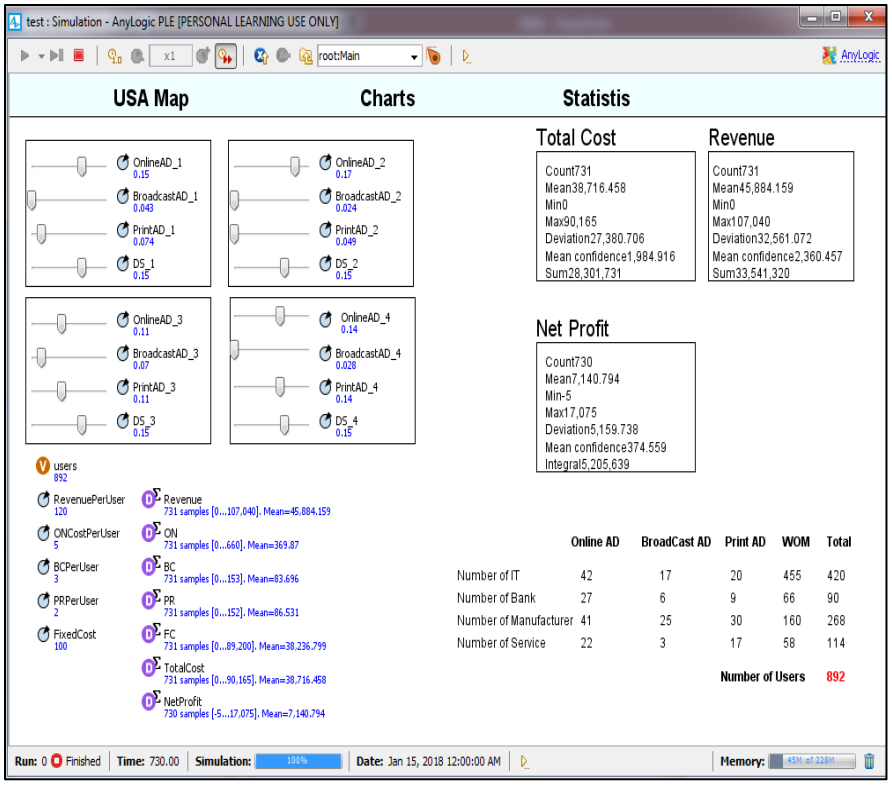

Figure 7. ABS observed results.

After observing the results from the above model, we run an optimization experiment based on the constraints defined on in Figure 8 (for 100 iterations /3 replications per iteration) to obtain the best case scenario for our model. Our goal is to find the maximum net profit under the two following constraints: 1- The net profit must be at least 20 % greater than total cost 2- The maximum number of customers is 950 users (Figure 9).

Parameters

Parameters:

Parameter	Type	Value	
		Min	Max
RevenuePerUser	fixed	120	
OnlineAD_1	continuous	.15	0.20
OnlineAD_2	continuous	.15	0.20
OnlineAD_3	continuous	.15	0.20
DS_1	continuous	0.2	0.4
DS_2	continuous	0.2	0.4
DS_3	continuous	0.2	0.4
OnlineAD_4	continuous	.15	0.20
DS_4	continuous	0.2	0.4
BroadcastAD_1	continuous	0.05	0.1
PrintAD_1	continuous	0.02	0.05
BroadcastAD_2	continuous	0.07	0.12
PrintAD_2	continuous	0.02	0.05
BroadcastAD_3	continuous	0.07	0.12
PrintAD_3	continuous	0.02	0.05
BroadcastAD_4	continuous	0.07	0.12
PrintAD_4	continuous	0.02	0.05

Figure 8. Model constraints

Requirements

Requirements (are tested after a simulation run to determine whether the solution is feasible):

Enabled	Expression	Type	Bound
☑	(root.NetProfit.max()/root.TotalCost.max())	>=	1.2
☑	root.users	<=	950.0

Figure 9. Model requirements

Figure 10 displays the maximum Net profit based on the given constrains. Optimization manipulates the parameters to its optimal capacity, using many permutation and combinations within its algorithm and presents the optimal or best case for maximizing Net Profit which in our case was increased by 1.6%.

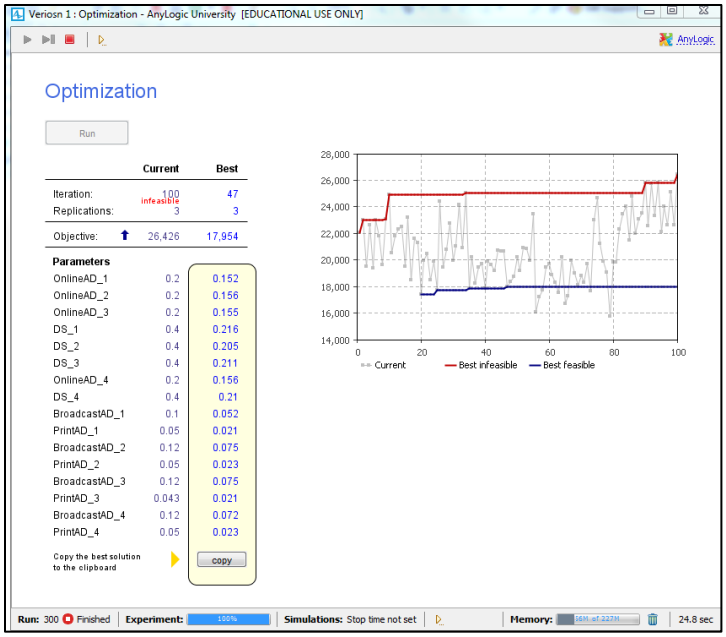

Figure 10. Optimization Results

Figure 11 & 12 shows the comparisons between the simulation results. (after and before the optimization)

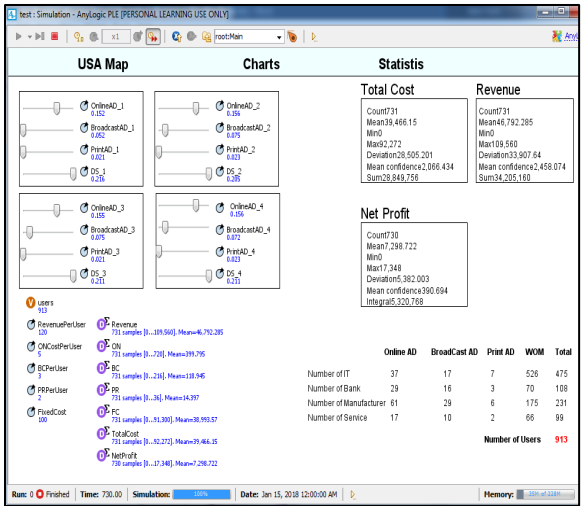

Figure 11. Simulation results after optimization

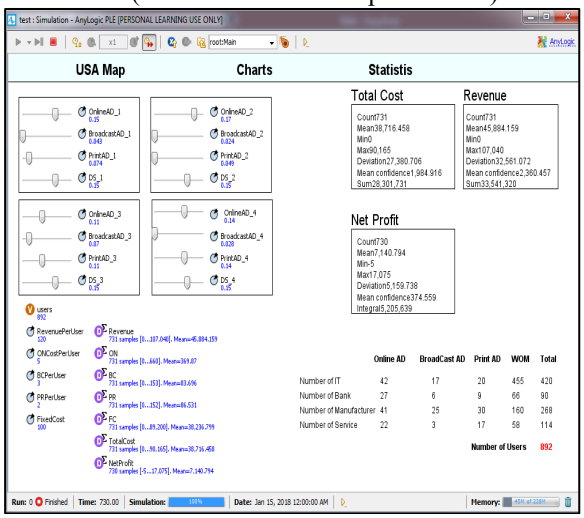

Figure 12. Current simulation results

5 Conclusion and Future Work

In this hypothetical market model, ABS allowed us to simulate potential user behaviors which may results in useful predictions. Since testing the business model effectiveness based on Internet of Things using ABS is at an early stage, we concentrate more to provide a conceptual approach in this study by proposing a preliminary design. The future work includes the validation of ABS and increase the data sample size. The assumptions we made related to advertisement effectiveness and word of mouth influence need further investigation in order to simulate agents'

behavior variances Also, system dynamics fragments can be included inside each agent of ABS to capture user's behavior continuous in time. Lastly, agent demographics can be included by considering the exact physical locations of each agent in the United States in order to simulate the differences in customer behavior according to agent's locations.

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Biography

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