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A Methodology for Internet of Things Business Modeling and Analysis using Agent-Based Simulation

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INTERNET OF THINGS BUSINESS MODELING AND ANALYSIS USING AGENT-BASED SIMULATION

by

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ABSTRACT

Internet of Things (IoT) is a new vision of an integrated network covering physical objects that are able to collect and exchange data. It enables previously unconnected devices and objects to become connected using equipping devices with communication technology such as sensors and radio frequency identification tags (RFID). As technology progresses towards new paradigm such as IoT, there is a need for an approach to identify the significance of these projects. Conventional simulation modeling and data analysis approaches are not able to capture the system complexity or suffer from a lack of data needed that can help to build a prediction. Agent-based Simulation (ABM) proposes an efficient simulation scheme to capture the structure of this dimension and offer a potential solution.

Two case studies were proposed in this research. The first one introduces a conceptual case study addressing the use of agent-based simulations to verify the effectiveness of the business model of IoT. The objective of the study is to assess the feasibility of such application, of the market in the city of Orlando (Florida, United States). The second case study seeks to use ABM to simulate the operational behavior of refrigeration units (7,420) in one of largest retail organizations in Saudi Arabia and assess the economic feasibility of IoT implementation by estimating the return on investment (ROI).

I dedicate this work to:

My great father, **Salem**, for his support

My beloved mother, **Aziza**, for her encouragement

My lovely wife, **Samar**, for all of her love and help

My little son, **Salem**, for the happiness that he brings to my life

My beautiful siblings, **Basmah**, **Fatemah**, and **Ahmad**, for their constant assistance

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CHAPTER 1: INTRODUCTION

1.1 Introduction to Business Model

The concept of business model has received a great attention especially from researchers in the fields of strategy and entrepreneurship (Zott, Amit, & Massa, 2010). It started to get more attention around 1990 with the improvement of internet technology. The number of research projects, popular books, academic papers, and pedagogical material describing the business model concept is the evidence of this interest (Brannon, 2011).

Zott et al. (2010) and George and Bock (2011) have provided a literature review of the business model. In the literature, numerous business model definitions have been suggested without one specific version (George & Bock, 2011). The complexity level within each definition differs depending upon the distinct research study and research intent. Amit and Zott (2001) argue that the construct of business model has the potential to bridge between strategy and entrepreneurship with the focus on value creation. They suggest that the business model captures several value creation sources and empirically clarifies value creation. According to Afuah (2004), the business model is a framework for illustrating how an organization operates. Brannon (2011), defines the business model as an explanation of the capabilities and routines design that allows a business to gain value for its customers.

Although an agreed framework is not existing, management researchers have started work on developing and elaborating this concept (Brannon, 2011). The research questions in the literature create and revitalize the business model for a new venture (Hamel, 2002). Brannon (2011), focuses on the innovative business models which help organizations to gain value in new and different approach. Several journal papers provide an indication of the continued research interest in the field of innovative business models (Amit & Zott, 2010; Gambardella & McGahan, 2010; Teece, 2010).

Designing effective business model requires sufficient data. The amount and variety of data collected automatically from various smart devices help to deal with problems and enable the improvement of embedded models and services. Fleisch (2010) and Deng, Han, and Varshney (2012) have recognized the significance of implementing business models based on the internet of things (IoT). Big data and internet of things (IoT) contribute to advance the business analytics. The definition of IoT is still in the improving process. According to S. Li, Xu, and Zhao (2015), IoT is a global network of physical objects that can communicate with each other. Presently, IoT applications started to gain a rapid attention from a variety of business industries and a wide range of customers (I. Lee & Lee, 2015; Whitmore, Agarwal, & Da Xu, 2015). Smart IoT objects nowadays facilitate novel applications and business models (Bohn, Coroamă, Langheinrich, Mattern, & Rohs, 2005).

1.2 Internet of Things (IoT)

The concept of the internet of things (IoT) was firstly proposed by Kevin Ashton in 1999. Ashton defined the IoT as identifiable connected devices with radio-frequency identification (RFID). However, until now the IoT does not have an exact description. The definition of IoT is still in the developing process (S. Li et al., 2015). According to Lee & Lee (2015), IoT is a global network of physical objects that can interact and communicate with each other. The internet of things, also known the internet of everything, is considered as one of the most significant future technologies. Therefore, IoT applications started to gain a rapid attention from a variety of industries and a wide range of customers (I. Lee & Lee, 2015).

1.3 Expected Utilization of IoT

The IoT defines the next generation of the Internet where the physical objects can be identified and accessed through the Internet (S. Li et al., 2015). The utilization of the IoT technology is expected to increase significantly in the upcoming years. People have become more interested in IoT technologies such as smart home, Google glasses, smart TV, etc. The smart home is considered as one of the outstanding IoT innovations for public users. Users can control home temperature, adjust lights, unlock doors, and manage the security system remotely. The devices and appliances in these smart homes are controlled through a tablet, computer, or smartphone using a wireless network technology (I. Lee & Lee, 2015).

The evolution of IoT can be demonstrated by several stages as shown in Figure 1-1. The IoT is started by the use of radio frequency identification (RFID) technology, which is widely used in pharmaceutical production, logistics, retail, and various industries. The developing of wireless sensory technologies has extended the devices sensory capabilities significantly. Therefore, the previous concept of IoT is extended to autonomous control and ambient intelligence. Barcodes, intelligent sensing, RFID, wireless sensor networks (WSNs), low energy wireless communications are some examples of the IoT technologies available nowadays (S. Li et al., 2015).

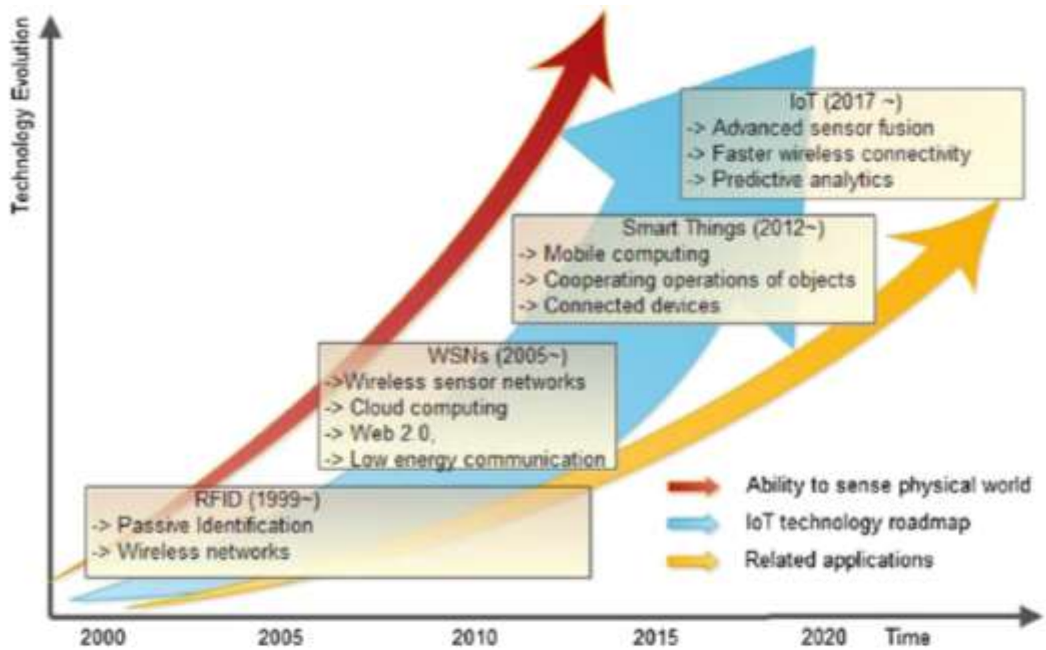


Figure 1-1: The evolution of IoT technology (S. Li et al., 2015)

Some of the research trends of IoT include combining social networking with IoT solutions, employing artificial intelligence to create smart objects and intelligent things, developing green IoT technologies, and integrating IoT and cloud computing (Xu, He, & Li, 2014).

The adoption of IoT is gaining attention rapidly as societal, technological, and competitive pressures motivate enterprises to invest and move forward. As IoT technologies develop and the number of the enterprises that adopt IoT increases, IoT revenue and cost analysis will become one of the major concerns for enterprises. Because of the uncertainty and the high costs of IoT investments, enterprises need to assess and analyze the IoT challenges opportunities very carefully (I. Lee & Lee, 2015).

1.4 The Expected Global Benefits of IoT

Many countries are interested in the development of internet of things standards since it can bring incredible economic benefits in the upcoming years. Currently, many organizations such as International Electro-Technical Commission, International Telecommunication, and American National Standards Institute are trying to develop numerous IoT standards. By forming accepted IoT standards, developers will be able to implement IoT services and applications that can be used on a wide range. Many countries started to invest in IoT enabling technologies after realizing its importance and potential benefits. For instance, the UK government invested a £5 million project on IoT innovation and technology. China is also taking the development of IoT very seriously and suggests to spend $800 million to improve IoT technology. Moreover, Japan launched i-Japan strategy in 2008 and u-Japan strategy in 2009 to develop IoT to support daily activities (Xu et al., 2014).

According to Gartner (2014), the IoT is expected to generate 26 billion units by 2020 (I. Lee & Lee, 2015). IoT evolution will affect the information and data available to the supply chain partners. Also, how the supply chain operates will be impacted significantly. The IoT will convert the business processes entirely by offering more precise and real-time analysis of the materials and products flow. Enterprises will invest in the IoT to reestablish organizations workflows, optimize the costs of distribution and improve materials tracking. For example, UPS already uses IoT-enabling technologies to reduce costs and improve its supply chain. In addition to the manufacturer's implementation of IoT, numerous service businesses and industries started to adopt the IoT technologies to increase income through improved services to the customers and become leaders in their domains (I. Lee & Lee, 2015).

According to Bradley, Handler, and Barbier (2013), the IoT will gain $14.4 trillion in value; combining the increased incomes and the reduced costs of companies adopting IoT from 2013 to 2022 (I. Lee & Lee, 2015). From an industry viewpoint, four industries generate more than the half of the $ 14.4 trillion in value. These four industries include manufacturing with 27%, retail trade with11%, finance, insurance with 9%, information services with 9% and other industries such as education, healthcare, wholesale with a range from 1% to 7% (I. Lee & Lee, 2015).

1.5 IoT Technologies

The Radio frequency identification (RFID) is the foundational technology for IoT. RFID is widely used in pharmaceutical production, logistics, retail, and various industries. Also, wireless sensor networks (WSNs) can be considered as another foundational technology for IoT. They are widely used in environmental monitoring, healthcare monitoring, industrial monitoring, traffic monitoring, etc. The development in RFID and WSN contribute significantly to the progress of IoT. Moreover, many other devices and technologies (Figure 1-2) such as barcodes, intelligent sensing, and smartphones, etc. are used to form a network to support IoT (Xu et al., 2014).

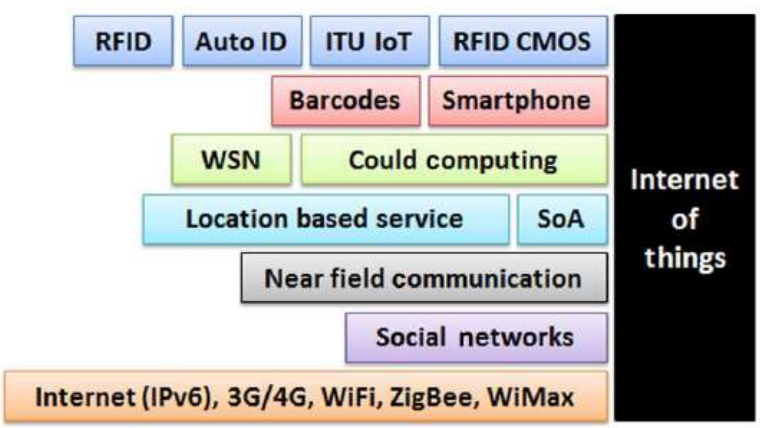


Figure 1-2: Technologies and devices associated with IoT (Xu et al., 2014)

According to Lee & Lee (2015), the IoT devices and technologies which are widely used for the deployment of IoT-based services and products are radio frequency identification (RFID), wireless sensor networks (WSN), middleware, cloud computing, and IoT application software.

Radio frequency identification allows automatic data capture and identification using radio waves, a reader, and a tag. The tag is similar to the traditional barcode however it can be used to store more information than a barcode. There are three types of tags: passive RFID, active RFID, and semi-passive RFID. Passive RFID does not use a battery, and it relies on radio frequency energy coming from the reader to power the tag. Applications of passive RFID can be found in passports, supply chains, electronic tolls, etc. Active RFID can initiate communication with the reader using its own battery. Applications of active RFID can be found in manufacturing and hospital laboratories. Semi-passive RFID uses its battery to power the chip while communicating by taking power from the reader (I. Lee & Lee, 2015).

Wireless sensor networks consist of distributed sensor-equipped devices to monitor environmental and physical conditions. WSNs can cooperate with RFID to provide better tracking of things such as temperature, location, and movements. WSNs have been used primarily in cold chain logistics. Also, WSNs can be used for tracking systems and maintenance. For example, General Electric (GE) installed a large number of sensors in its wind farms, turbines, and jet engines. After analyzing the collected data in real-time, GE was able to reduce preventive maintenance costs significantly (I. Lee & Lee, 2015).

Middleware is a software layer among the software applications that helps developers to perform communication. In the 1980s, middleware started to gain popularity due to its significant role in integration the old technologies with the new ones. It also simplified the enlargement of new technologies in the distributed computing setting. A complicated distributed infrastructure of IoT with a large number of devices requires facilitating the growth of new services and applications. Therefore, the use of middleware software has become a perfect fit with IoT technology development (I. Lee & Lee, 2015).

Cloud computing can be defined as an Internet-based computing that offers data and resource processing on demand which can be provisioned as Software as a Service (SaaS) or Infrastructure as a Service (IaaS). One of the most significant results of IoT is a large amount of data produced by IoT devices. Various IoT applications need huge data storage and massive processing speed to support real-time decision making. Cloud computing offers an ideal solution to handle the huge amount of data streams and processes them in real time (I. Lee & Lee, 2015).

While devices and networks offer the physical connectivity, IoT applications enable human-to-device and device-to-device interactions in a robust and reliable manner. It is significant for IoT applications to be constructed with intelligence so IoT devices can control the environment, interact with each other, identify system problems, and handle problems without people intervention (I. Lee & Lee, 2015).

1.6 The Connectivity between IoT and Big Data

Internet of things (IoT) includes a huge number of sensor nodes that can be installed on different machines and devices to accomplish a particular job. These sensors are deployed in various inaccessible, hostile and dynamic environments in order to gather a different type of information. The nodes are able to sense the environment to collect information such as geographical information, environment data, etc. In unlike paradigms, different kinds of data are collected (D, 2015). IoT and big data have some related features. According to HP report, the number of sensor nodes in 2030 will reach up to one trillion. With this huge number of sensors, it will be quite difficult to manage all these data created by IoT without big data analytics tools. Also, another report was published by Intel highlights the connectivity between big data IoT which are:

1- IoT generates a huge amount of data

2- IoT usually generates semi-structured and unstructured data

3- The data generated from IoT contain significant information and valuable insights (Fang et al., 2014).

1.7 Problem Definition

IoT brings uncountable benefits to the business. However, firms today face challenges while adapting IoT technology because of the variety of the connected objects in IoT, the absence of structure in the ecosystem regarding roles of the various participants, and the lack of a dominant design of an IoT setting.

While business model frameworks are well identified and established for a single company, most of these frameworks do not consider the interdependencies companies which are developing in the same direction and the opportunities they offer. As a result, a decent demonstrating of business models based on the internet of things (IoT) ecosystems is not well recognized yet.

1.8 Research Objectives

This objective of this research study is to develop a framework to propose an IoT business solution for a specific industry. In the era of information, organizations should be able to deal with big data issues, especially in this age where the information is increasing each minute due to the external and internal transactions and the interactions between human and business. The proposed framework also aims to introduce a study to test the acceptance of an IoT business solution using agent-based simulations in order to determine its adoption and life cycle. The paradigm of agent-based simulation is utilized to verify the effectiveness of the business model and simulate the behavior of agents. Many earlier studies proposed empirical testing for firm's business models. However, the examples are infrequent because of the limitations access to the company database.

1.9 Research Questions

This research covers the following questions:

1. What are the benefits and different factors to be considered when proposing a business solution based on IoT?
2. How to model the various communication between market resources to exchange and share data for a better decision making? And how to address the communication effect on the components of the system individually and holistically?
3. How to test the effectiveness of the proposed internet of things (IoT) business solution?

1.10 Contribution

This research contributes to the body of knowledge by proposing an integrated framework to resolve the problems associated with the adoption of IoT technology. This research also offers the following contributions to the simulation field and business industry:

1. The suitable recognition of the value of agent-based simulation will have a significant effect on the simulation and business industry.
2. The proposed framework will enable a comprehensive testing of IoT business solution using agent-based simulation which helps executives and managers to achieve better decisions and therefore benefits the performance and profitability of the firms.

1.11 Organization of the Document

This document is organized into six chapters including the Introduction. Chapter 2, reviews and explores the literature to recognize the efforts that have been made regarding the area of testing business models. This includes a summary of earlier studies, and some gaps are outlined in details. After summarizing the literature, a research methodology is explained in Chapter 3, and the framework of this research is introduced in Chapter 4. Then, Chapter 5 demonstrates two case studies to validate the framework. Finally, the work is concluded in Chapter 6 with a brief summary of the achievement and some directions for further researches.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter covers the past research efforts in the area of developing IoT business model and indicates some of the gaps that are still remaining for further research. Through these research gaps, this study justifies the improvement of the methodology for designing business model based on IoT. In order to build a solid base about the different aspects related to the research problem, this chapter starts with the background of business modeling. Then, it explores the existing business models that have been used in big data environment in order to recognize and understand the gap in the literature and then form a valid methodology that contributes in bridging that gap and solving the defined problem. In addition to that, this chapter explains how advanced analytics is used to discover hidden patterns and trends from the huge amount of data.

one of the tools used in this study to test the effectiveness of the proposed business model is an agent-based simulation (ABM). Therefore, there is a higher focus on the earlier studies that consider ABM and its applications. In addition to that, this chapter clarifies the advantages of using ABM versus the other types of simulations for decision making and business modeling. Moreover, it provides evidence from the literature that ABM yield better results than the other types of simulations such as discrete event simulation and system dynamics under certain scenarios.

2.2 Business Model Background

The significance of business models in scientific research is an area of focus getting more attention and greater scrutiny. Business models began to get more attention in 1990 especially with the improvement of internet technology. The impact of technology on the nature of and development of business has generated a new level of change in the industry. Therefore, organizations and leading companies realized the importance of developing the appropriate business models to capture the changing opportunities in a certain market constantly (Rhoads, 2013; Teece, 2010). Even though an agreed framework of business model is not existing, management researchers have started work on elaborating and developing and this concept. Table 2-1 shows some examples of the publications that use various business model frameworks.

Table 2-1: Publications of business model with different conceptualizations/ frameworks

Authors (year)	Outlet
(Timmers, 1998)	Electronic Markets
(Markides, 1999)	Book: All the right moves
(Hamel, 2000)	Book: Leading the revolution
(Amit & Zott, 2001)	Strategic Management Journal
(Chesbrough & Rosenbloom, 2002)	Industrial and Corporate Change
(Magretta, 2002)	Harvard Business Review
(Afuah, 2004)	Book: Business model generation
(Morris, Schindehutte, & Allen, 2005)	Journal of Business Research
(Christensen, Johnson, & Kagermann, 2008)	Harvard Business Review
(Osterwalder & Pigneur, 2010)	Book: Business models

The business model continued to develop beyond the Information Technology sector by exploring and examining the various nature of business models and providing different construct. Generally, a business model concept describes a strategy for engaging business activities

(Applegate, 2001; Weill & Vitale, 2013), a presentation of business (George & Bock, 2011; Osterwalder, 2004), or a framework of operating a business (Amit & Zott, 2001).

A more recent work was published in one of the best management journals combines most of the aspects of the earlier studies and depicts business models as the structure and governance of the business transactions (Amit & Zott, 2001; Zott & Amit, 2008). Teece (2010) refines both the domain and the nature of business models. He also portrays business models as the logic and the value structure of costs and revenues for the firm focusing on new business opportunities (Teece, 2010). Lastly, George & Bock (2011) define the business models as the configuration approach of organizational structure to generate value through entrepreneurial representation while the strategy is the dynamic procedure of processes to enable the organization to compete.

Even though business models have become more recognized as an essential aspect of the business, many significant challenges appear which generate barriers to have a complete understanding of the general nature of business models and how the business model has a significant effect on firms (Rhoads, 2013; Zott et al., 2010). One of the main challenges to understand a business model is that many researchers focus more on the established organizations. As an organization matures, some aspects such as business strategy and business model become more entangled and difficult to realize the business components (Yip, 2004).

Previously, most of the management researches focused on defining the business model properties. However, many current types of research have recognized the need to continue moving beyond the existing properties of business model to be able to understand the nature of the construct more clearly (Rhoads, 2013; Zott et al., 2010).

Nowadays, IoT enables sharing of devices and recourses in network nodes and integrates them which results in having unlimited ways to share and utilize data. Bucherer and Uckelmann (2011) highlight that the framework of IoT network enables incremental and radical business changes. However, they suggest that the full potential is not leveraged until now. Moreover, they stress that data exchange between IoT objects and the stakeholder's involvement in data exchange are the significant elements in designing the IoT business model.

2.3 Business Models Based on IoT

Smart IoT devices facilitate novel business models and applications (Bohn et al., 2005). However, designing effective business model needs sufficient data. The variety and the amount of data that collected automatically from IoT devices help to handle problems and enable the improvement of embedded services and models.

Fleisch (2010) and Deng et al. (2012) have identified the significance of implementing IoT business models. Even though many earlier studies illustrated the importance of IoT business models, the main focus of the majority of IoT researches is on the technology and various technology layers (Leminen, Westerlund, Rajahonka, & Siuruainen, 2012). According to Leminen et al. (2012), there are only sparse academic attempts to increase recognizing the evolving IoT business models with ecosystems by applying:

- Structural approaches: includes finding the value chain in ubiquitous computing environments (H. J. Lee & Leem, 2005), IOT value identification (Fleisch, 2010), the analysis of IOT value chain (Banniza et al., 2009), and discussion of digital business ecosystems (Nachira, Nicolai, Dini, Le Louarn, & Leon, 2007).
- Methodology approaches: includes improvement methodology of the business model in ubiquitous computing environments (Banniza et al., 2009) and multipath deployment adoption (Levä et al., 2010).
- Design approaches: includes a networked business model for emerging technology-based services (Ulkuniemi, Pekkarinen, Palo, & Tähtinen, 2011) and the framework of business model canvas based on IoT (Bucherer & Uckelmann, 2011).

IoT enables sharing of resources and devices in networks that have numerous nodes and it links between them which means there are unlimited ways to utilize and share information. Bucherer and Uckelmann (2011) highlight that the infrastructure of IoT network enables radical and incremental business changes. However, they believe that the full potential is not leveraged until now. Moreover, they stress that data exchange between IoT objects and the stakeholder's involvement in data exchange are the significant elements in designing the IoT business model.

Even though designing IoT business model needs sufficient data, there are absences of integration of data exchange (Fleisch, 2004). Kourouthanassis, Giaglis, and Karaiskos (2010) suggest that the types of required data are context-specific, and a supportive infrastructure to handle the complexity and difficulty between users and devices is needed. Platforms underlie the primary global businesses where data is constantly changed. In principle, there are two types of platforms: one-sided platforms & two-sided platforms, in which the competition is taking place (Leminen et al., 2012). The competition concentrates on how to charge parties in the various platforms sides (Eisenmann, Parker, & Van Alstyne, 2006; Rochet & Tirole, 2003). Modularity may support to win the competition since it could increase flexibility and decrease the complexity of a system (Baldwin & Clark, 2000; Schilling & Steensma, 2001).

Fleisch, Sarma, and Thiesse (2009) state that IoT combines systems and various technologies together by merging functionalities and technologies. A complex service or product from small subsystems can be designed and constructed independently. Additionally, there are two main paradigms in the business value of IoT: business process decomposition & real-world visibility (Haller, Karnouskos, & Schroth, 2008). Business process decomposition leads to a power shift towards the network edge. Also, IoT improves the modularization of a business process which enhances the performance and scalability of the system. Business process decomposition allows decision making in a decentralized fashion (Haller et al., 2008). Voss and Hsuan (2009) apply the principles of modularity in the service architecture since in the extreme scenario of IoT, all objects would offer functionality as a web service.

Mejtoft (2011) shows 3 layers of value creation in the Internet of Things: supporting, manufacturing, and value co-creation. The supporting layer generates value as the collected information can be utilized in various industries. The manufacturing layer means that retailers or manufacturers benefit from the possibility of tracking individual items. The third layer considers Internet of Things as a co-creative partner since the network of things is able to think for itself. Leminen et al. (2012) draws on these various views on IoT and use the design approach for business modeling in order to establish a useful framework for analyzing and identifying IoT business models.

2.4 The Existing Internet of Things Business Models

In order to develop a business solution for IoT application, we need first to know the existing IoT business model and the most business model components used in the literature. Osterwalder (2004) clarifies that customer relationships, value propositions, customer segments, cost structure channels, key resources, key partnerships, key activities, and revenue streams are the most components in the literature used to develop a business model. Dijkman, Sprenkels, Peeters, and Janssen (2015) used the keyword “Internet of Things” and “Business model” in Science Direct, Springer, the ACM Digital Library, IEEE Explore and Web of Science to find the existing IoT business model. Using these search terms, they found that there are 20 papers available. Only 5 out of these papers have an actual business model, and two of these papers used business model canvas to develop IoT business model. Table 2-2 shows the most business model components covered by these 5 models. As it is shown in the table, two models covered all the components by using business model canvas. Liu and Jia (2010) and Fan and Zhou (2011) cover some of these components. H. Li and Xu (2013) use various terminologies to present their business model and mainly focus on the various stakeholders in establishing an IoT platform and the actions that how stakeholders must perform.

Dijkman et al. (2015) review the five existing IoT business model and then they use the business model canvas to propose their business model for IoT. They empirically validate their business model since none of the previous IoT business models have been validated.

Table 2-2: Business model components covered in IoT (Dijkman et al., 2015)

	Sun, Yan, Lu, Bie, and Thomas (2012)	Bucherer and Uckelmann (2011)	Fan and Zhou (2011)	Liu and Jia (2010)	H. Li and Xu (2013)
Key partners	x	x	x	x	x
Key activities	x	x		x	x
Key resources	x	x			
Value propositions	x	x	x		
Customer relationships	x	x			x
Channels	x	x			
Customer segments	x	x	x	x	x
Cost structure	x	x			x
Revenue streams	x	x	x	x	x

2.5 Advanced Analytics

The great velocity of the current world requires sophisticated and accurate analytics to support decision making, better allocate of resources, and identify new opportunities. Advanced analytics is a general term that includes data mining, data analysis, and machine learning. Indeed, it is responsible for numerous advanced applications which we use frequently. For example, web analytics helps to allocate the resources better and balance the load of the web servers by tracking page views and user visits. Also, network intrusion detection systems (NIDS) can rapidly process and analyze network and server logs in order to identify undesirable visitors (Shkapsky, 2016).

The development of the advanced analytics is a repeated process requires involving a variety of systems and tools. These tools help in:

1- Joining, aggregating, and filtering several datasets

2- Designing and testing complicated learning model

3- Ensuring that the application can appropriately scale

Big data concept proposes that there is an opportunity of having great insights in every bite of data. The more data, the more unseen information can be exposed. The key benefit of analyzing and processing big data in various industries is the probability to find important information such as market trend, customer requirement, market growth, etc. (Marder, 2015). Nowadays, advanced analytics have been used widely for real-time investigation (D, 2015). Exploring the unseen information help firms not only in making appropriate decisions but it also helps in gaining a new source of revenue.

According to Shkapsky (2016), big data environment is a very suitable application area for advanced analytics due to the variety, availability, and the massive amount of data. Together, academia and industry have realized the importance of having powerful big data analytics tools. For example, Google, IBM, and many leading companies use big data analytics in order to store, process, and analyze the limitless amount of data. In addition to that, researchers have proposed many academic publications related to advanced analytics applications.

2.6 Simulation

Leading companies and big organizations have faced various challenges in analyzing and processing huge amounts of data. Manipulating a large quantity of data would provide organizations with valuable information and great insights (Ahmed & Robinson, 2014). Data variables can be displayed and managed using modeling and simulations methods. These methods allow data scientists to explore causality and predict the actual system outcomes via manipulating the inputs and changing the model parameters (Ahmed & Robinson, 2014; Plaza et al., 2011).

2.6.1 Simulation Definition

Simulation is the process of creating a model of a real system (GoldSim, 2015). According to Schiavenato (2009), simulation is the representation of the system characteristics and behavior. One of the main purposes of using simulation techniques is to predict the future characteristics and behaviors of a real system and determine the anticipated results of different model scenarios. Moreover, simulation can be used to identify any required and necessary changes in the model to imitate the real system correctly (GoldSim, 2015). Using simulation model that imitates the real system would help organizations significantly to:

- Understand the real system and its behavior
- Developing strategies for system operation
- Draw conclusions and obtain valuable information to improve the real system (Sokolowski & Banks, 2009)

Simulation is considered as a powerful tool that provides various model designs which can be examined and evaluated without disturbing the real system (Schiavenato, 2009) . Different scenarios can be applied in the simulation model to understand how the actual system would behave when changing the model parameters (GoldSim, 2015).

2.6.2 Types of Simulation Models

Sufficient details of the real system should be considered when creating a simulation model, in order to draw useful conclusions (Sokolowski & Banks, 2009). The types of simulation model can be described as follow:

- Static model vs. Dynamic model:

- ✓ Static models (also sometimes known as Monte Carlo) are representative of the system at a specific point in time
- ✓ Dynamic models are representative of the system changes over time

- Deterministic model vs. Stochastic model:
  - ✓ Deterministic models are simulation models with known inputs (no random variables) and predictable behaviors
  - ✓ Stochastic model are simulation models with random inputs variables and not entirely predictable behaviors
- Discrete model vs. Continuous model:
  - ✓ Discrete models are when the changes of state happen on countable points of time
  - ✓ Continuous models are when the changes of state happen continuously (Banks, Carson, & Nelson, 1996)

2.6.3 Types of Simulation Tools

Various simulation tools exist to simulate and imitate real system characteristics. These tools are specialized and designed to solve a specific type of problem (GoldSim, 2015). For example, the simulation tool which used to simulate a water movement is not applicable to simulate a call center or a shipping facility. According to GoldSim (2015), there are four types of simulation tools:

1. Discrete Event Simulators
2. Agent-Based Simulators
3. Continuous Simulators
4. Hybrid Simulators

➢ Discrete Event Simulation

Discrete event simulation is used to model a system with a flow approach which moves in discrete steps such as shipping facility or call center (GoldSim, 2015). It simulates a system with a sequence of events that occur at discrete time points (Zhang, 2012). The model consists of the entity, resources that serve the entity, and control elements that define the entity and resource states. In the discrete event simulation, the event is scheduled and performed according to a defined list. The strategies of discrete event simulation are:

- Activity-oriented simulation
- Event-oriented simulation
- Process-oriented simulation (Evon & Asim, 2010)

✓ *Activity-oriented simulation*

The activities will start in this type of simulation only when specific conditions are satisfied. In the activity-oriented simulation, there is usually a simulation clock that increases in a constant time. These activities are scanned during simulation, and the activity will start when it becomes eligible. Usually, physical devices are used in activity-oriented simulation (Evon & Asim, 2010).

✓ *Event-oriented simulation*

In the event-oriented simulation, the events will be defined then the event routine will be written. The event routine not only schedules new events but also it reschedules the existing events. Event-oriented simulation focuses more on sending and controlling events, and usually it uses a priority queue (Evon & Asim, 2010).

✓ *Process-oriented simulation*

In the process-oriented simulation, the process such as transactions will be defined. Also, the model and how the processes interact will be identified. The processes can be executed in parallel since they are independent. The processes in process-oriented simulation use resource-oriented and transaction-oriented as resources of the model (Evon & Asim, 2010).

➢ Agent-Based Simulation

The Agent-based simulation is considered as a special type of discrete event simulation (GoldSim, 2015). This type of simulation has become one of the most interesting research topics (Legéndi, Gulyás, & Mansury, 2013). Agent-based simulation can be applied in many fields such as marketing & economics (Bunn & Oliveira, 2003; Kiesling, Günther, Stummer, & Wakolbinger, 2012; Negahban & Yilmaz, 2014) and artificial intelligence (Zhang, 2012) because of its powerful capabilities to imitate the system interactions and dynamics (Wu, 2008; Zhang, 2012). The moveable entities in the agent-based simulation are known as agents (Zhang, 2012). The entity in the traditional discrete event simulation has only its attributes. However, the entity in agent-based simulation has both methods and attributes (GoldSim, 2015; Zhang, 2012). The entity's attributes are the properties which control the interaction between the entity and the other resources in the model while the entity's methods are the rules of interacting between the entity and the other agents. Agent-based simulation can be used not only to validate the effectiveness of business models (Tian, Zhou, Yao, Zhang, & Li, 2014), but also to optimize resources (Deckert & Klein, 2014). Simulating how the animals interact with each other is a good example of agent-based simulation (GoldSim, 2015).

➢ Continuous Simulation

The differential equations which describe the developments of a system can be solved by continuous simulation using continuous equations (GoldSim, 2015). The continuous simulation would be more applicable to use when the information or materials that need to be simulated are moving continuously while discrete event simulation would be more appropriate to use when the information or materials are moving in discrete packets. However, continuous simulation can be used to simulate information or materials that move in discrete steps only if the number of entities in the systems is very large because the entities can be considered as a flow in the large-scale system (GoldSim, 2015). System dynamics are powerful tools which can be used in continuous simulation effectively. Simulating a water movement through pipes is one of the good examples to describe continuous simulation (GoldSim, 2015).

➢ Hybrid Simulation

According to GoldSim (2015), a hybrid simulation is a combination of continuous simulation and discrete simulation. The tools in this type of simulation would be able to solve differential equations by overlying the discrete events on the continuous system (GoldSim, 2015; Wu, 2008). GoldSim is powerful simulation software which can be in a hybrid simulation.

2.6.4 Areas of Application

Simulation can be applied in many fields such as:

- Manufacturing Processes (Plaza et al., 2011)
- Chemical Industry (Ni, Rui, Wang, & Cheng, 2014)

- Education (Gates, Parr, & Hughen, 2012; Kumalasari, 2010; C. M. Macal & North, 2013; Schiavenato, 2009; Seybert & Barton, 2007)
- Traffic and Transportation & (Bowman, 2014)
- Business Processes (Ahmed & Robinson, 2014)
- Health Care (Barach, Satish, & Streufert, 2001)

2.7 Simulation in IoT environment

Many leading companies nowadays have realized the importance of having powerful big data analytics since IoT big data provides valuable insights after in-depth investigations. Also, manipulation of IoT data offers significant information. Simulation and modeling techniques have become among the powerful tools that used to analyze and process data generated from IoT devices. Simulation allows organizations to display and process various IoT data variables effectively. The methods used in modeling and simulation not only allow consultants and researchers to discover and explore causality but also they help data scientists to predict the actual system outcomes by manipulating the inputs and changing the model parameters (Ahmed & Robinson, 2014; Plaza et al., 2011).

Using simulation in IoT environments can be applied in many domains including traffic, weather, manufacturing, production, and urban populations (Wintersim.org, 2015). In complex systems, managers and executives may experience, on a regular basis, difficulties in making decisions. It has become impossible to make critical decisions based on manager’s intuition especially with the availability of large quantity of data. However, simulation can be used to develop and evaluate different scenarios to support the decisions making process (Wintersim.org, 2015). Also, Simulation methodology can be used effectively to overcome the IoT big data challenges because of its powerful ability to predict the future characteristics and behaviors of a real system and determine the anticipated results of different model scenarios.

IoT big data has brought many challenges to the simulation and modeling field (Staff, 2014). IoT big data makes the simulation and modeling more difficult since simulation has to deal with a large quantity of data. According to Staff (2014), the simulation researchers should take the following into considerations while developing simulation models to overcome the IoT big data challenges:

- Combine the researchers in the engineering field with the computer science field
- Establish simulation paradigm
- Realize the integration of the IoT huge amounts of data and the complex computing

However, IoT big data not only has brought challenges to the simulation and modeling field but also opportunities (Staff, 2014). Since the outputs analysis in the traditional simulation is usually simple and straightforward, IoT big data can offer more in-depth investigations. It also allows researchers not only to develop new methods but also to create new modeling types to solve large-scale data problems. IoT big data has encouraged simulation scientists and researchers to increase their effort in the modeling research (Staff, 2014). Developing a new way of simulating and modeling complex and complicated systems is one of the most interesting research topics (Staff, 2014). According to Staff (2014), IoT big data has brought the following opportunities for modeling and simulation field:

- IoT big data provides simulations and modeling field with remarkable opportunity to develop new modeling methodology
- IoT big data encourages simulation scientists to improve the existing simulation and modeling scientific thinking
- IoT big data opens new doors for scientific and modeling research such as intelligent simulation tools

Interacting with simulation model can help organizations to understand their IoT big data and therefore achieve better results by making the right decisions (Hogarth & Soyer, 2015). Even though statistical analyses and tools can help organizations to achieve better decisions, people sometimes make some decisions depending on their experience. Hogarth & Soyer (2015) realized the importance of developing simulated experience. Simulated experience is a method to gain experience about the possible results of different scenarios by interacting with a simulation model. This simulation model is capable of transferring the complex information into beneficial knowledge by letting people live the problems many times in the simulation model.

Hogarth & Soyer (2015) published numerous papers in the psychology field to determine whether the simulated experience is effective or not. In addition, many experiments have been done to find how managers and executives would make decisions with the availability of large quantities of data. For example, they asked 257 economics experts simple regression questions to identify whether using statistical tools would lead the experts to make the same decisions or not. Hogarth & Soyer (2015) found that the experts made different decisions and therefore they concluded that the obtained information from the statistical tools could be misleading. Moreover, they designed another type of experiments using simulation and modeling. They let managers and executives interact with the simulated system over and over again until they gain some experience. The following are some important findings:

- In a complex and large-scale system, people tend to rely more on their experiences rather than their analytical ability
- With huge amount of data, simulated experience would be a good approach to gain experience and therefore make right decisions
- There is a gap between what the analysts find and what the decisions makers, such as managers and executives, understand

2.8 Agent-Based Simulation (ABM)

The moveable entities in the agent-based simulation are known as agents (Borshchev & Filippov, 2004). ABM has gained more popularity recently, especially in areas where human behavior is important, because of its powerful capability of capturing human behavior in detail and imitating the system interactions and dynamics (Brailsford, 2014). The increasing numbers of conference proceedings and journal articles that call for agent-based models are evidence of ABM popularity and growth (C. Macal & North, 2009). The epidemic model and Schelling segregation model are good examples of agent-based simulations (Borshchev, 2013).

2.8.1 Background of ABM

The first appearance of agent-based simulation was in the 1940's when John von Neumann invented the idea of cellular automata and the results of well-known models such as Conway's Game of Life and Schelling Segregation Model (Brailsford, 2014). Primarily, computer scientists were more interested than others in ABM because of its powerful use for artificial intelligence. However, in the 1990's social scientists have realized the potential benefits of ABM. They started to form research groups to discover the use of ABM for modeling individuals' behaviors (Axtell, 2000; Brailsford, 2014; C. Macal & North, 2009).

2.8.2 ABM Applications

ABM can be applied in many fields such as marketing & economics and artificial intelligence. A sample of agent-based applications is shown in Table 2-3.

Table 2-3: A Sample of agent-based applications (C. Macal & North, 2009)

Application Area	Model Description
Air Traffic Control	Agent-based model of air traffic control to analyze control policies and performance of an air traffic management facility (Conway 2006)
Anthropology	Agent-based model of prehistoric settlement patterns and political consolidation in the Lake Titicaca basin of Peru and Bolivia (Griffin and Stanish 2007)
Biomedical Research	The Basic Immune Simulator, an agent-based model to study the interactions between innate and adaptive immunity (Folcik, An and Orosz 2007)
Chemistry	An agent-based approach to modeling molecular self-assembly (Troisi, Wong and Ratner 2005)
Crime Analysis	Agent-based model that uses a realistic virtual urban environment, populated with virtual burglar agents (Malleson 2009).
Ecology	Agent-based model of predator-prey relationships between transient killer whales and other marine mammals (Mock and Testa 2007).
Energy Analysis	Agent-based model for scenario development of offshore wind energy (Mast et al. 2007).
Epidemic Modeling	BioWar, a scalable citywide multi-agent model, that simulates individuals embedded in social, health, and professional networks and tracks the incidence of background and maliciously introduced diseases (Carley et al. 2006).
Market Analysis	Agent-based simulation that models the possibilities for a future market in sub-orbital space tour-ism (Charania et al. 2006).
Organizational Decision Making	Agent based modeling approach to allow negotiations in order to achieve a global objective, specifically for planning the location of intermodal freight hubs (van Dam et al. 2007).

2.8.3 Advantages of ABM

The need for agent-based simulation has increased lately for the following reasons:

- The key features of ABM which make it different from other types of simulations are the capability of ABM to capture emergence. Emergence is a system property which arises from the individual’s properties within the system, and it is not possessed by any of the system individuals. Traffic flow congestion is a good example of emergence. For instance, in a circular car track any variability in the car speed will result in building queues in an opposite direction of cars flow. This queue is an emergent property of the system, and it is not a characteristic of the individual car. This scenario can be captured and visualized by any ABM software. However, modeling and coding the car-race in DES is not possible (Brailsford, 2014)
- Agent-based simulation models are flexible, and it can be used to adopt new constraints. For example, we might not know the whole behavior of the system that we need to model. However, we have some ideas about how the objects of the systems behave individually. In such situation, ABM can be used to build the model from the bottom up and define these objects and their behaviors (Borshchev, 2013)
- Agent-based simulation models can be used when the systems have natural representations as being comprised of agents (C. Macal & North, 2009).For example, modeling shoppers’ movements in a supermarket can be modeled more naturally by ABM approach rather than using differential equations to describe the dynamics of the supermarket shoppers.

Since traditional modeling tools may not be able to capture system complexity nowadays, the agent-based simulation would provide better results under certain scenarios.

2.8.4 Why and When ABM

Macal & North (2009) discussed numerous reasons for using agent-based modeling as compared to traditional tools, such as discrete event and system dynamics, to model economic systems. They illustrated that agents would obtain better results under the following scenarios:

- When there are behaviors and decisions that can be defined well
- When it is significant that the agent has behavior reflects how other individuals behave
- When it is significant that the agent changes and adapts his behavior
- When it is significant that the agent engages and learns in dynamic interactions
- When it is important that the agent has dynamic relationships with other individuals, and agent relationships decay, adapt, and form
- When it is significant to model the organization's processes where agents learning and adaptation are significant at the organization level
- When it is significant that agent has spatial components to his interactions and behaviors.
- When the past cannot predict the future since the processes of the change are dynamic
- When growth to arbitrary levels is significant in terms of agent numbers, agent states, and agent communications
- When the structural change has to be to be an endogenous outcome of the model, instead of an input parameter to the model

2.8.5 ABM versus Other Types of Simulation

Axtell (2000) explained the potential benefits of using agent-based simulation versus other types of simulations. In this study, the advantages of using ABM are clarified. For example, writing numerous equations in some cases is not a handy activity when solving systematic problems. In such situations, using ABM could be the only way to discover processes systematically. Moreover, ABM can be advantageous when the mathematical model can be written but not solved entirely. In this case, agent-based simulation (ABM) can be used to obtain significant insight to a possible solution, explore the dynamical behaviors of the model, and help to test the dependence of outcomes on assumptions and parameters (Axtell, 2000).

Borshchev & Filippov (2004) compared the three main types of simulation modeling: agent-based simulation (ABM), discrete event (DES) and system dynamics (SD). In this study, detailed information on how ABM can be constructed from current discrete event simulation and system dynamics are illustrated. The main focus of this study is to build a model that can imitate complex system that contains large numbers of dynamic objects such as people, animals, cars, etc. (Borshchev & Filippov, 2004).

Demirel (2006) compared between SD and ABM by modeling supply chain processes containing retailers, manufacturers, and wholesalers. In this study, many issues such as the policy of ordering, active pricing, supplier's behavior and customer's loyalty are modeled and analyzed with both SD and ABM models. Demirel's results display the overall conclusions about the comparison between SD and ABM. The analysis of this study shows that some elements are challenging or impossible to be defined using SD models. For example, the interactions between the agents were not very clear by discrete factors. The SD model was not able to capture dynamic details, such as which supplier price to select, since there was no distinction between agents and entities in the model. Therefore, there could be important elements that affect the behavior of the supply chain significantly, but SD models cannot capture the dynamics formed by these elements (Demirel, 2006).

Macal & North (2009) prepared a tutorial to introduce agent-based simulation and illustrated the origins of ABM. Also in this paper, the needs of ABM and some of the ABM applications & software are described. The last part of this paper talks about why and when to use ABM. Actually, Macal & North (2009) agreed with Axtell (2000) that there are potential benefits of using agent-based simulation versus the other types of simulations such as DES under certain scenarios (C. Macal & North, 2009).

Siebers, Macal, Garnett, Buxton, & Pidd (2010) answered fundamental questions in a panel discussion about why ABM is not used as widely as DES in operation research and other disciplines such as economics, computer science, and social sciences. Also, opportunities regarding agent-based simulation were stated during this discussion. Macal, one of the panelists, listed a numerous number of reasons why ABM in some situations may be preferred to use over DES. For example, ABM is preferred when agents engage and learn in dynamic interactions.

Moreover, one of the panelists tried to use DES to model human behavior, but he did not succeed. However, he was successfully able to model human behavior using ABM, which means that ABM may obtain better results over DES in some situations. Siebers, one of the panelists, compared typical ABM with DES models and he summarized the significant attributes to distinguish between the two models in Table 2-4. Another panelist stated that ABM and SD might be applicable to solve similar kinds of problems. However, ABM would be easier to follow as the model complexity increases because of the lower level of abstraction in ABM (Siebers, Macal, Garnett, Buxton, & Pidd, 2010).

Behdani (2012) showed that selecting the appropriate simulation model is an important step in the development process. In this study, collections of simulation paradigms for supply chain modeling are clarified. The supply chain is illustrated by two system theories: socio-technical systems and complex adaptive systems. This study compares the three simulation models, ABM, DES, and SD based on categorized features for the complex supply chains. Moreover, Behdani (2012) agreed with Demirel (2006) that ABM could obtain better results than SD in some certain situations. Table 2-5 shows a summary of how different simulation models fit with different supply chain properties. As it is shown in Table 2-5, ABM is the only model that can capture the characteristics of complex supply chains (Behdani, 2012).

Table 2-4: Attributes that define the model type (Siebers et al., 2010)

DES models	*ABS models*
Process oriented (top-down modelling approach); focus is on modelling the system in detail, not the entities	Individual based (bottom-up modelling approach); focus is on modelling the entities and interactions between them
Top-down modelling approach	Bottom-up modelling approach
One thread of control (centralised)	Each agent has its own thread of control (decentralised)
Passive entities, that is something is done to the entities while they move trough the system; intelligence (eg. decision making) is modelled as part in the system	Active entities, that is the entities themselves can take on the initiative to do something; intelligence is represented within each individual entity
Queues are a key element	No concept of queues
Flow of entities through a system; macro behaviour is modelled	No concept of flows; macro behaviour is not modelled, it emerges from the micro decisions of the individual agents
Input distributions are often based on collect/measured (objective) data	Input distributions are often based on theories or subjective data

Brailsford (2014) showed that Hybrid models, where ABM and DES are combined, have gained more popularity recently especially in applications related to the service industry. However, in this study, Brailsford (2014) argued with Siebers et al. (2010) that many of the distinctions illustrated in the panel discussion in Simulation Workshop SW10, between the agents in ABM and the entities in DES are artificial. In Siebers et al. (2010), Macal listed a numerous number of reasons why ABM in some situations may be preferred to use over DES. Brailsford (2014) selected some of these reasons and responded. For example, one of the reasons that were mentioned by Macal in Siebers et al. (2010) is that: "ABM is preferred over DES when agents have dynamic relationships with other agents." Brailsford (2014) responded that HIV model which presented by Rauner et al. (2005) is a typical DES where the entities (baby and mother) are connected and liked. Also, the relationships between entities change over time as babies grow and lose their immunity. Keeping this dynamic connection between entities (baby and mother) was significant for model accuracy (Brailsford, 2014).

Table 2-5: Comparison of simulation models for supply chain modeling (Behdani, 2012)

		System Dynamics (SD)	Discrete-event Simulation (DES)	Agent-based Simulation
micro-level complexity	Numerousness and heterogeneity	No distinctive entities; working with average system observables (homogenous entities)	distinctive and heterogeneous entities in the technical level	distinctive and heterogeneous entities in both technical and social level
	Local Interactions	Average value for interactions	Interactions in technical level	Interactions in both social and technical level
	Nestedness	Hard to present	Not usually presented	Straightforward to present
	Adaptiveness	No adptiveness at individual level	No adptiveness at individual level	Adaptiveness as agent property
macro-level complexity	Emergence	Debatable because of lack of modeling more than one system level	Debatable because of pre-designed system properties	Capable to capture because of modeling system in two distinctive levels
	Self-organization	Hard to capture due to lack of modeling the individual decision making	Hard to capture due to lack of modeling the individual decision making	Capable to capture because of modeling autonomous agents
	Co-evolution	Hard to capture because system structure is fixed	Hard to capture because processes are fixed	Capable to capture because network structure is modified by agents interactions
	Path dependency	Debatable because of no explicit consideration of history to determine future state	Debatable because of no explicit consideration of history to determine future state	Capable to capture because current and future state can be explicitly defined based on system history

However, Brailsford (2014) agreed that DES and ABM are not the same things. He believes that there are some ABM models do not have any discrete event. In this study, he stated that the key features of ABM which make it different from DES are the capability of ABM to capture emergence. Emergence is a system property which arises from the individual's properties within the system, and it is not possessed by any of the system individuals. Traffic flow congestion is a good example of emergence. Let us assume that a car race moves around a circular track under one rule: each car will follow the car in front. Therefore, the system will be steady as long as the speed of the cars is constant. However, any variability in the car speed will result in building queues. Of course, the queues will build up in an opposite direction of cars flow. In this case, the queue is an emergent property of the system, and it is not an individual car characteristic. This scenario can be captured and visualized by any ABM software. However, modeling and coding the car-race in DES is not possible (Brailsford, 2014).

2.9 Research Gap Analysis

As specified earlier, there is lack of reliable methodology to validate IoT business solution. The need for innovative IoT business models that develop in various industries is crucial. There are several reasons cause plenty of research gaps associated with IoT business models. First, there is a small number of researchers related to IoT business models. Second, the existing literature defines business models within a single firm and not across the firm's networks. Lastly, there are virtually unlimited possibilities to connect things, consumers, and businesses together, which makes this almost impossible to create a particular business model. However, Industrial engineers play an important role in the development of IoT business solution and test its feasibility through simulation and optimization. One of the critical decisions that management must consider upon testing the feasibility of its IoT business model is the appropriate validation methodology. This includes understanding the market behaviors and customer needs.

Figure 2-1 summarizes the existing IoT business models and illustrates the research gaps in each business model to recognize the common gaps and develop a methodology to fill the identified gaps and benefit from these exiting business models.

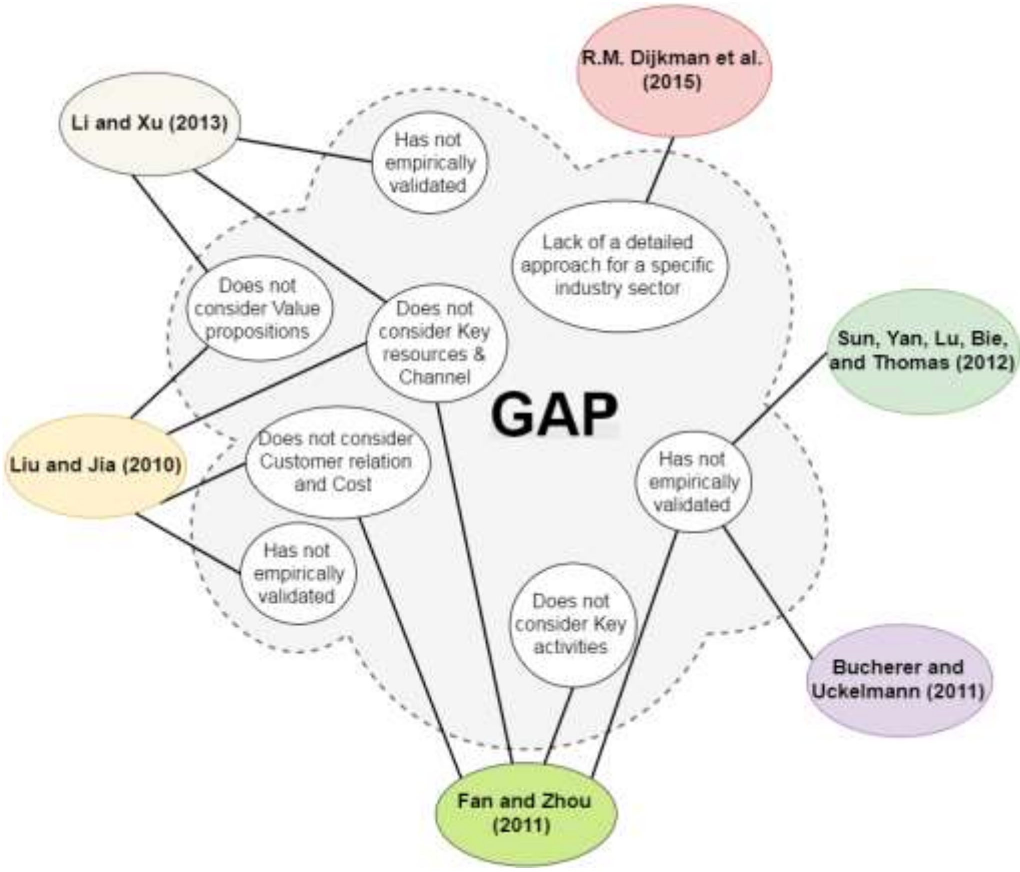


Figure 2-1: The existing IoT business models and the identified gaps in each model

CHAPTER 3: METHODOLOGY

3.1 Introduction

This chapter demonstrates the research methodology applied in this study. The methodology covers several stages that function together starting from identifying the problem to problem-solving. It is a systematic approach to satisfy the research question and bridge the defined research gap.

3.2 Research Methodology

The following diagram illustrates the research methodology followed in this study. It shows the progress of the research thoughts as we move forward in this dissertation. The remaining of this chapter gives an overview of each process and its techniques. The processes in the Figure 3-1 include the research idea, literature review, research gaps analysis, the proposed framework, validating the framework through case studies, framework analysis, and finally conclusion and future work.

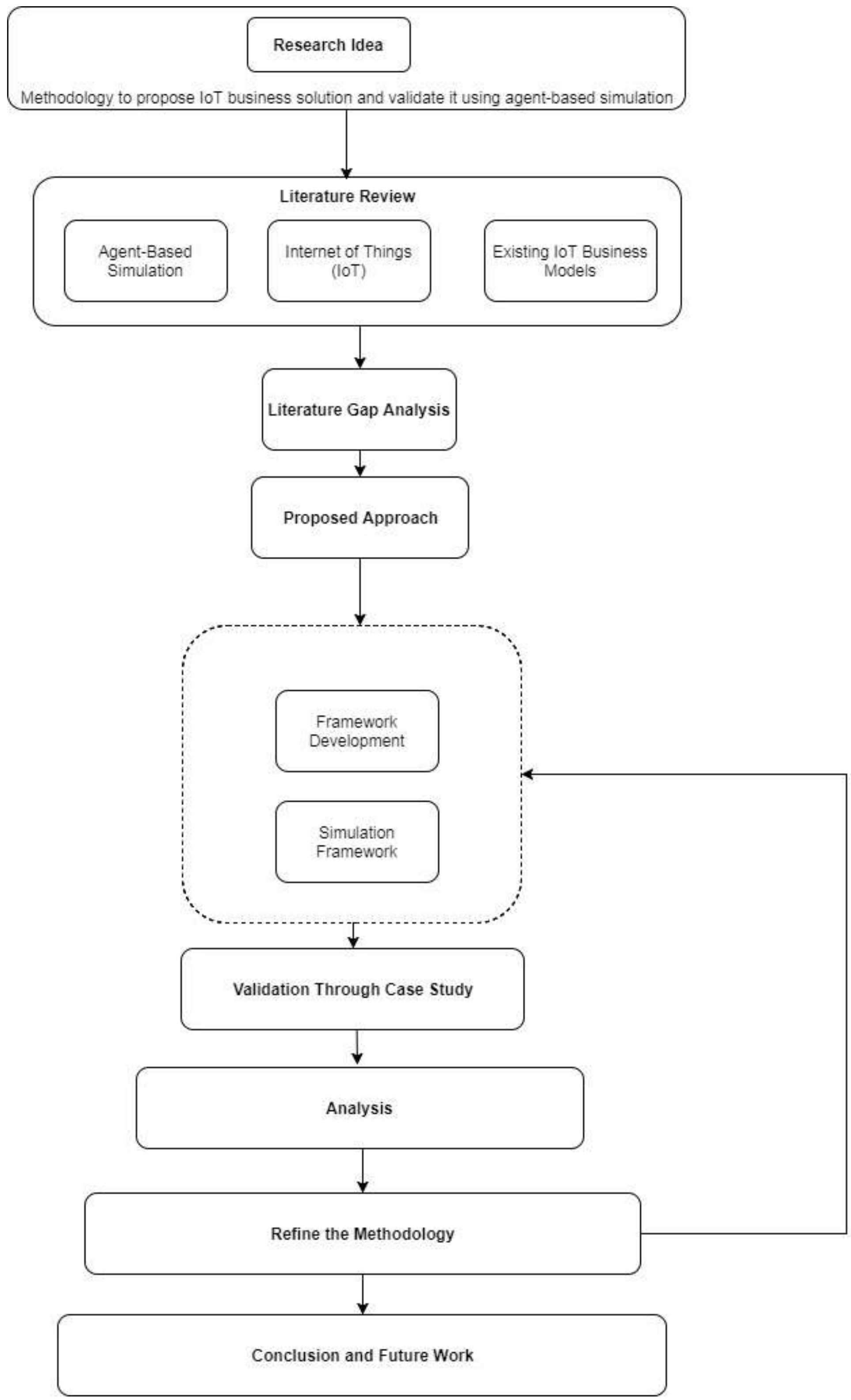


Figure 3-1: Research methodology diagram

3.3 Research Idea

The research idea was initiated after participation in I-Corps competition at University of Central Florida (UCF). Since I-Corps program in UCF help students to develop a deep understanding of various technologies and discover new market opportunities, a UCF research team contributed together to develop a predictive software which provides a maintenance service using Radio Frequency Identification (RFID). A business model canvas was developed as a lean startup outline to describe infrastructure, value proposition, finances, and customers. Testing the effectiveness and feasibility of a business model is essential for any firm to sustain its success. However, it was recognized that a few papers had been published in the literature related to developing a business model based on IoT and investigating the adoption of this technology using simulation modeling.

3.4 Literature Gap

After having a clear research idea, the next step was to go over the literature to have a deep understanding of the previous effort that has been made and then starts building on the existing knowledge. In order to establish a solid base in this area of research, the review began with exploring the development of a business model based on IoT. The different existing business models that have been used in big data environment in the literature were discovered. In addition to that, the review included understanding the adoption of IoT technology in business industry and analyzing it using ABM. Reviewing the literature in these areas is essential to help in solving the defined problems and bridging the research gap of this study.

3.5 Gap Analysis

It was very crucial to review the literature and discover the different existing IoT business in order to recognize and identify the research gap. This helps to form an integrated framework that contributes to solving the proposed research problem. Moreover, study the relationship between the existing business model and distinguish between them are important at this stage of research.

As indicated earlier, there is lack of a reliable framework to validate IoT business solution and the ways needed to create them in the big data environment. The necessity for innovative IoT business models that develop in various industries is crucial.

3.6 Framework Development

Firms aim to enlarge market shares, maximize net profits and minimize overall costs. However, one of the key obstacles that could prevent these firms to achieve their objectives is the effectiveness of their business models. Having a vital business model is crucial to describe customers segment, infrastructure, finances and value proposition.

Fulfilling the research gap with an integrated framework to optimally develop a feasible IoT business solution will support top managers in their decision-making process. Industrial engineers are encouraged and inspired with many operational tools and effective techniques that will advance the market economy and chase a better future. Combining software engineering with computer science will result in having a vital methodology to answer the research questions. The framework will function as a strategic direction to build an effective IoT business solution and analyze it using agent-based simulation.

Before developing the framework, some important considerations have to be taken into account. These considerations are highlighted below.

3.6.1 Ecosystem of IoT

Nowadays, IoT allows sharing of recourses and devices in network nodes and integrates them to have unlimited ways to utilize and share data. Many studies state that the IoT framework allows radical and incremental business changes. However, researchers propose that the complete potential is not leveraged till now. The exchange of data between IoT objects and the stakeholder's participation in data exchange are important elements to design valid IoT business solution.

Smart IoT objects assist novel business models and applications. However, establishing effective IoT business solution requires adequate data. The amount and variety of data collected automatically from IoT objects assist in handling business problems and enabling the improvement of embedded models and services. There are only several academic types of research attempt to increase the evolving of business models based on IoT with ecosystems by applying structural approaches, methodology approaches, and design approaches. In this research, the design approach is used to establish a business model canvas based on IoT.

3.6.2 Financial consideration

Firms always aim to increase market shares, minimize overall costs, and maximize net profits. Revenue and cost are the most important elements in determining business success. When a business has a high revenue, it will be going out of business if the cost is higher than the income. Managing revenues and costs to increase net profit is an important factor for any business.

3.7 Simulation Framework

Agent-based simulation (ABM) will be used to simulate agent's behaviors in this study because of its capability to capture system complexity and provide a high degree of flexibility. The first step to build ABM model is to identify the agents and their behaviors. Then, ABM can be built from the bottom up. Even though we might not understand how the whole system we want to imitate behaves, we should at least have some perceptions and insights on how each agent behaves individually.

Each agent in the model has its variables, parameters, and behaviors. Agent behaviors can be affected by internal and external factors. Internal factors are factors that directly affect agent behaviors such as agent communications while the external factors are factors that indirectly affect the behaviors such as environmental influence.

Based on specific factors that are identified earlier, the simulation model framework will help decision makers to test the feasibility of their IoT business solution. Consequently, the simulation model framework will highly consider the planning requirements and the characteristics of system component to improve the strategic planning of a firm based on the market requirements.

The simulation model is developed for various purposes such as understanding the real system and improving system design. The model users rely on the information obtained from the results of these model, especially in the decision-making process. However, the main concern is whether a simulation model and the obtained results are correct for its use or not. This concern is addressed in model verification and validation. The model verification and validation begins after finalizing the initial development of a model, and it is an iterative process throughout the model development.

Model verification can be defined as guaranteeing that the software program of the model and its implementations are correct while model validation can be defined as checking the accuracy of the representation of the real system. Since a model should be constructed for a certain objective, its validity can be determined with respect to that objective. There are numerous methodologies can be applied to validate a simulation model. One of widely used approach for model validation is testing the model assumptions by comparing the simulation model output with the corresponding output of the real system.

3.8 Validation Through Case Studies

The main objective of the case study is to validate the proposed framework. The case study results will help to test the hypothesis of this research and modify them when needed. Two case studies were proposed in this research. The first one introduces a conceptual study of business modeling of IoT using agent-based simulations in order to determine its adoption. ABM is utilized to verify the effectiveness of the business model and simulate the behavior of the market in Orlando city (Florida, United States). The second case study is addressed to evaluate the return on investment (ROI) of installing sensors to monitor the condition of refrigerators in one of the important organizations in the retail sector in Saudi Arabia. ABM is developed to simulate Panda's refrigerators behaviors and determine how returns can be achieved.

3.9 Analysis

The results of the case study will be analyzed for effectiveness and accuracy. Moreover, the proposed framework will be refined if necessary based on the obtained results from the case study.

3.10 Conclusion and Future Work

This section will include a summary of the results and findings. Also, recommendations and final conclusions about the proposed framework will be illustrated. Since constant improvement is required to expand the body of knowledge, future work and some opportunities for further research in the area will be demonstrated.

CHAPTER 4: THE FRAMEWORK

4.1 Introduction

This chapter proposes the heart of the study, "the framework". It contains structured conceptual layers. The elements of the framework are combinations from the fields of business and simulation engineering. Linking these elements to form an integrated framework is the contribution of this study. Based on the analysis of chapter two, there is a need for an integrated framework to help organizations in making decisions during the adoption of IoT technology. As described in the literature review, various approaches have been used to tackle this problem. To the best of the author's knowledge, an integrated framework that aids as a guidance to propose IoT solution and tests its feasibility using simulation does not exist.

The proposed framework assists as a strategic guidance to analyze IoT solutions and investigate its adoption and related challenges. Clarifying and identifying the tangible opportunity and its challenges is not easy. This is true for the internet of things (IoT) and many other strategic problems. Because of that, it would be beneficial to use a systematic approach to recognize strategic concerns and solve them holistically.

4.2 The Proposed Framework

This section explicates the proposed framework. This framework was adapted from a well-known creative problem-solving model called Isaksen and Treffinger model (Isaksen & Treffinger, 2004). There are three major steps in the framework (Figure 4-1). Each step is demonstrated in a separate section. The first step in section (4.2.1), produces a wide range of thoughts and potential solutions in IoT world. The second step in section (4.2.2) seeks to expose the IoT concerns, its challenges, and offer an overall perception including conflicting opinions and views. This step also determines the analytics platform which leads to value in IoT environment, the different IoT technology strategy considerations, and the various levels of the technology depth for the internet of things platforms. The third step in section (4.2.3) is the main focus of this study. This step not only assesses the IoT potential solutions produced but also analyzes a suggested solution to be implemented in the future using agent-based simulation (ABM). It is important to realize the risk and the impact of this step in order to develop a feasible business model. The output of this step is the recommended solution to be implemented supported by business, financial, and technical feasibility.

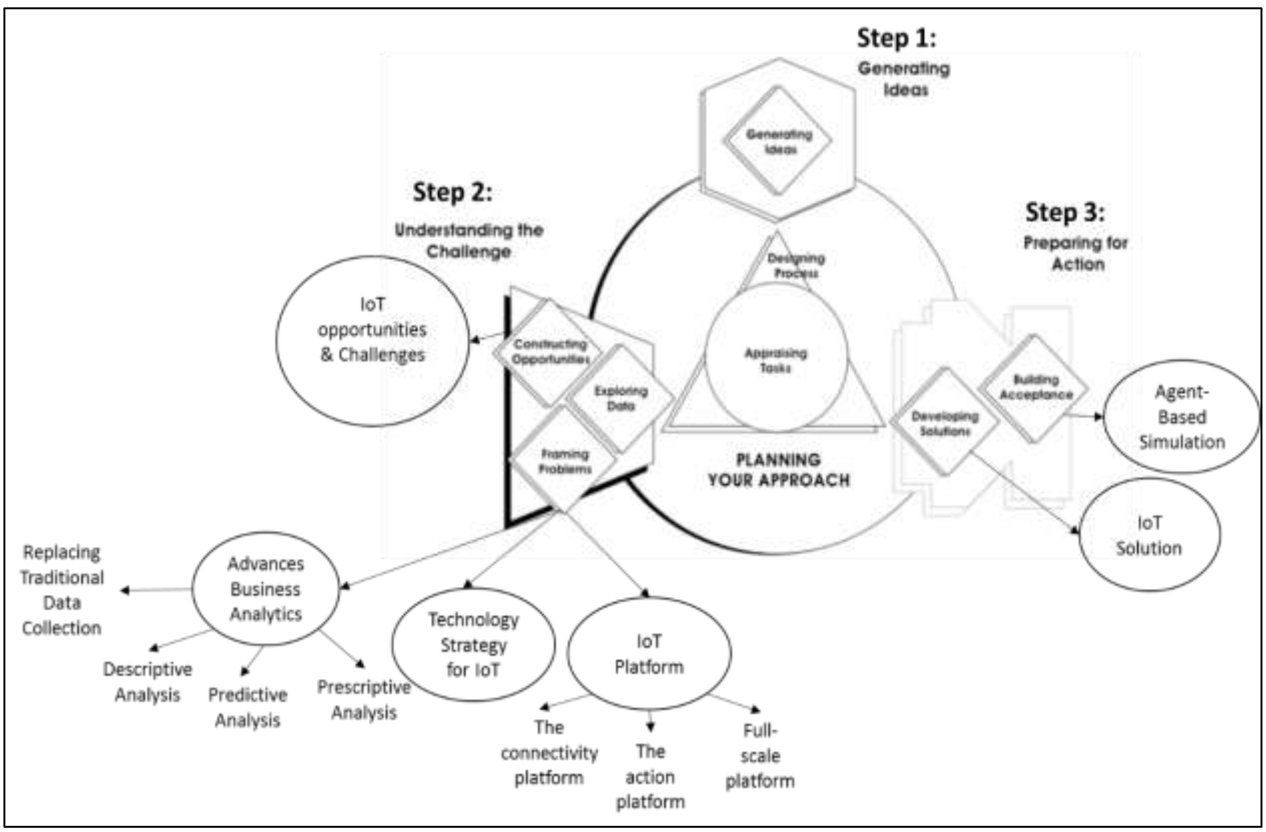


Figure 4-1: Proposed framework for IoT

The strength of the proposed framework for identifying technology strategy concerns is that it ensures that the IoT technology is driven by considering the customer and business perception of value from the start. Also, it ensures the correct stakeholders are considered and that all perspectives are identified. Below is an explanation of how this framework can be applied in IoT environment.

4.2.1 Generating Ideas

The objective of this step is to produce a wide range of potential solutions and thoughts to respond to the actual strategic concern. The primary principle of this step is to challenge assumptions, including all selections. It is not unusual for a solution that appears unfitting initially to be developed into very operative solution. For IoT world, this would include listing all the different selections in which security might be provided, all options for providing roaming, all possibilities of providing service ubiquity, etc.

4.2.2 Understanding the Challenges

This is an investigative step that pursues to uncover the problems and issues generally to provide an overall perception including conflicting opinions and views. The output of this step will be a generalized opinion of the situation listing possible problems and issues. For IoT environment, this contains detailing the various participants from different businesses and industries, the expected services to emerging, the expected connectivity environments, the different platforms among industries, etc.

4.2.2.1 Constructing Opportunities

As illustrated in chapter 1, IoT brings huge opportunities to businesses. Figure 4-2 summarizes some of the interesting IoT opportunities.

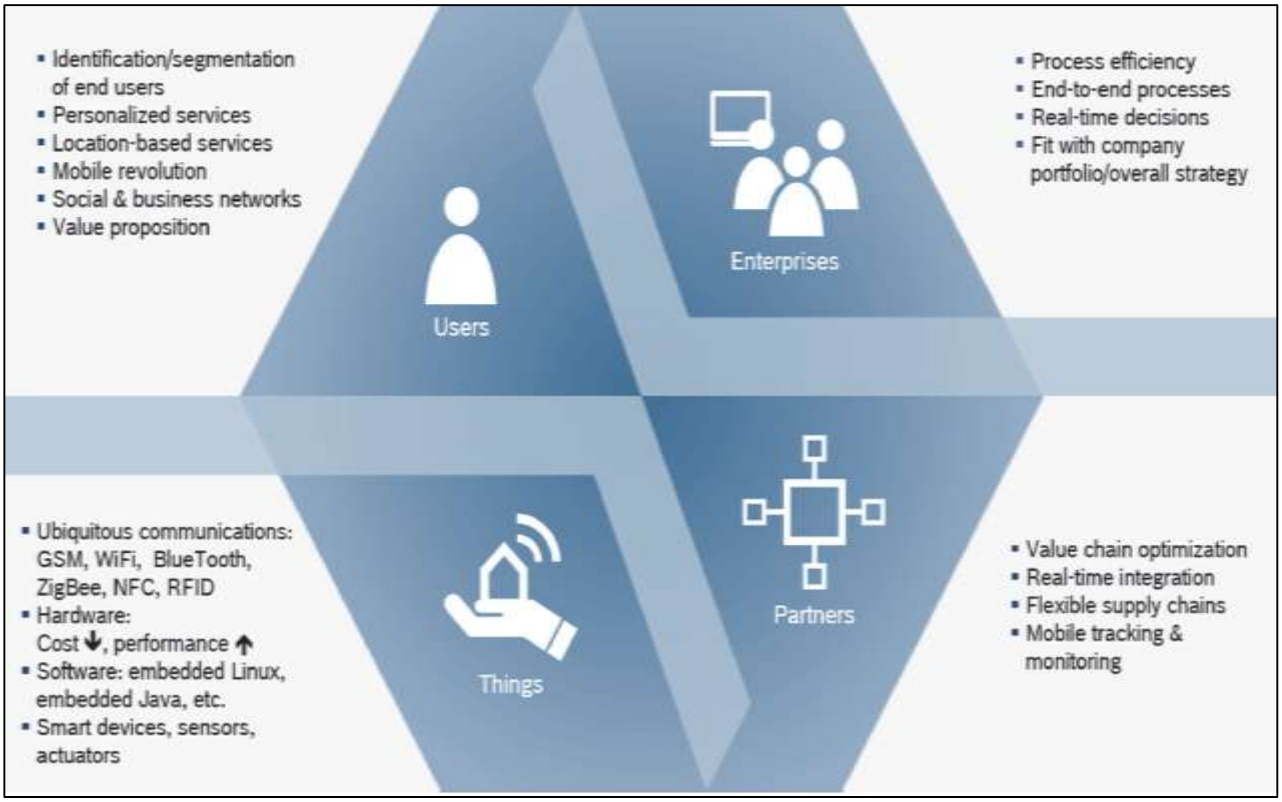


Figure 4-2: IoT opportunities (Bilgeri, Brandt, Lang, Tesch, & Weinberger, 2015)

4.2.2.2 Exploring Data

This step mainly examines stakeholders and their perspectives to make sure that all the dimensions of the problem are recognized. In this step, viewpoints of customers, actors, worldview, transformation processes, owner and environmental constraints are considered. The output of this step would be the various stakeholder standpoints, business activity models and the required systems, and business strategy consideration.

4.2.2.3 Framing Problems

This step tightens the problem by recognizing the specific needs that the technology strategy should respond to. It recognizes the customers in the selected space and pursues to understand what these customers observe as value and what their preferred outcomes are. The output of this step will be the specific elements that should be addressed to achieve the objective of the business and therefore to meet customer needs. For IoT world, the output of this step might include a need to make sure zero downtime, need for improve security, need to offer connectivity for remote objects as a differentiator, etc. This step will answer the following questions:

1- What are the different types of analytics platforms that lead to value in an IoT environment?

2- What are the IoT technology strategy considerations?

3- What are the various levels of the technological depth of the internet of things platforms?

➢ **Advanced Analytics**

The great velocity of data in the current world requires accurate and sophisticated analytics to support the decision-making process, allocating resources effectively, and identifying various opportunities. Advanced analytics is a general term that includes data analysis, data mining, and machine learning. Indeed, it is responsible for various advanced applications that used frequently. For example, web analytics supports to allocate resources better and balance the load of the web servers by tracking web page views and user visits. Also, network intrusion detection systems (NIDS) can quickly process and analyze network and server logs to recognize undesirable visitors (Shkapsky, 2016).

- ✓ *Architecting Analytics Deployment in IoT Environment*

Developing an analytics strategy is important to obtain a true business value for an organization that is trying to take advantage of IoT technology and the big data it is generating. (Chakraborty, Svilar, & Banerjee, 2016). The first step is to build a data supply chain to mobilize data for consumption appropriately. When establishing a data supply chain, companies must utilize a data service platform which makes all data easily accessible to those need it, while at the same time integrating all the data from multiple sources. By allowing data to flow quickly and easily through the entire firm, and ultimately throughout each company ecosystem of partners, firms are on their way to identifying the true value hidden in big data.

Next, to gain the full benefits of IoT, it is significant to build a robust analytical platform which brings together the capabilities of sensor-driven computing and intelligent devices applications. Numerous analytics tools can examine through and analyze data once they programmed with the parameters. Whatever the advanced tools used, the ideal purpose is to automate the analytics process of processing and analyzing raw data, which will then be utilized to offer business insight.

The final stage of analytics on the IoT data is “The Intelligent Enterprise”. This contains a journey from rule-based automation depends on the IoT data (where the automated actions are performed based on the data triggers of IoT such as turning a thermostat on in case the temperature is under 60 degrees), to machine learning on the IoT data to automatically produce rules for automation (where the thermostat knows when to turn the heating on depending on the preferences of a user), and lastly into the domain of cognitive computing, where the automated system starts behaving with nearly human intelligence to understand, sense and act.

When developing IoT platform, it is important to pay attention to trust issues and data privacy. Conventional security technique works in the operational technology (OT) domain and the information technology (IT) domain. However, the power IoT systems are the OT-IT convergence, and these systems usually require newer methods of security and data governance. A roadmap to develop an analytics platform which leads to value in IoT environment is illustrated below:

- The first layer of the analytics platform (Replacing Traditional Data Collection) applies the analytics directly to the raw data of IoT sensors. The layer substitutes old data and then collects, integrates, and filters data from wide spectrums of IoT devices and sensors. After this, it applies additional processing approaches, such as feature extraction and low-level analytics tools (e.g., using video analytics to get the location data of a moving device in a video stream, that would then be used to track that device).
- The second layer of the analytics (Descriptive analysis) generates valuable context and meaning for the user. It includes richer analytics, such as event classification, pattern recognition, behavior learning and anomaly detection, object tracking clustering, activity recognition, etc.
- The third layer of the analytics platform (Predictive analysis) contains complex operational capabilities that significantly generate more business value. It contains big data methodologies, advanced analytics, simulation and optimization techniques, and that can extract valuable data coming from IoT objects.

- The fourth layer of the analytics (Prescriptive Analysis) is when automated systems begin to perform almost similar to human intelligence to understand, sense and act.

Table 4-1: Architecting analytics deployment in IoT

Layer	Analytical Requirements
Replacing Traditional Data Collection	• Transform and integrate IoT data with existing data • Investment in Big Data storage environment is necessary given scale of data, even if data is filtered in-stream
Descriptive Analysis	• Analyze stored data at rest to provide overview of historical outcomes and performance • Analyze data in-stream to provide real-time understanding of current state operations
Predictive Analysis	• Use advanced analytics and machine learning algorithms to identify probabilities of potential outcomes and likely results of specific operations • Provide real-time predictive indicators and likely portfolio of outcomes
Prescriptive Analysis (Automation)	• Contextualize live stream events within current business requirements • Provide specific recommendations based on live streaming data to an employee or to • automatically initiate a process • Learn from past outcomes to optimize future recommendations

The technology architecture (summarized in Table 4-1) is not only applied for product operation and application development and but also to enable the analysis, processing, and sharing the huge quantities of data produced by IoT device. Establishing the technology stack for connected devices requires a new range of abilities such as systems engineering, software development, online security expertise, and data analytics.

- **IoT platform**

IoT application platform is the backbone of IoT system. It is centered on connectivity. All objects which are components of IoT and are connected to each other via the internet share a connection with IoT platform as it offers a common link between these objects and their data (Díaz, Martín, & Rubio, 2016).

Currently, many companies provide IoT platforms. All of these companies also offer some level of analytics tools, but they are completely offer different software applications. For somebody who is new in IoT field, it might not be easy to recognize that this term refers to a mature IoT cloud platform. Moreover, several software applications stretched to the point of being named IoT application platforms even when they just describe an element of an IoT platform or even something entirely different (Floarea & Sgârciu, 2016).

There are four key types of the internet of things (IoT) platforms:

- Connectivity / M2M platforms: these IoT platforms focus on the connected IoT objects via telecommunication networks. However, they do not provide to process data.

- IaaS (Infrastructure-as-a-service) backends: these platforms are more like a platform interface than a platform. They provide controls to organize the hosting space and processing power for various types of applications.
- Hardware-specific software platforms: these platforms are proprietary software applications which come with some objects.
- Consumer/Enterprise software extensions: these platforms are frequently firm's software program of packages that provide functionalities of an IoT applications platform. (Floarea & Sgârciu, 2016).

The main objective of an IoT application platform is facilitating object communication. Besides this key element, an IoT complete application platform might feature a lot of other significant functionalities which are meant to enhance either the capabilities of IoT system and its performance or the life quality of the platform client or consumer. A complete IoT application platform contains the following eight elements (Figure 4-3).

- Connectivity: unifies several data formats and protocols underneath a software interface guaranteeing accurate and continuous data communication with all objects.
- Device management: controls the connected objects and guarantees right connectivity between objects.
- Database: consists of the storage of object data, implementing data velocity, variety, volume, and veracity requirements.
- Processing & action management: involves rule-based triggers allowing execution of a particular action based on IoT sensor data.

- Analytics: produces reports based on data grouping extracting the insights out of the data-stream from IoT objects.
- Visualization: provides a clear graphical representation of trends and patterns through different types of charts.
- Additional tools: involves implementation tests, examples, and prototypes.
- External interfaces: provides methods to integrate with third-party systems thru application programming interfaces. It can also consist of software improvement kits to expand the implementation of IoT (Floarea & Sgârciu, 2016).

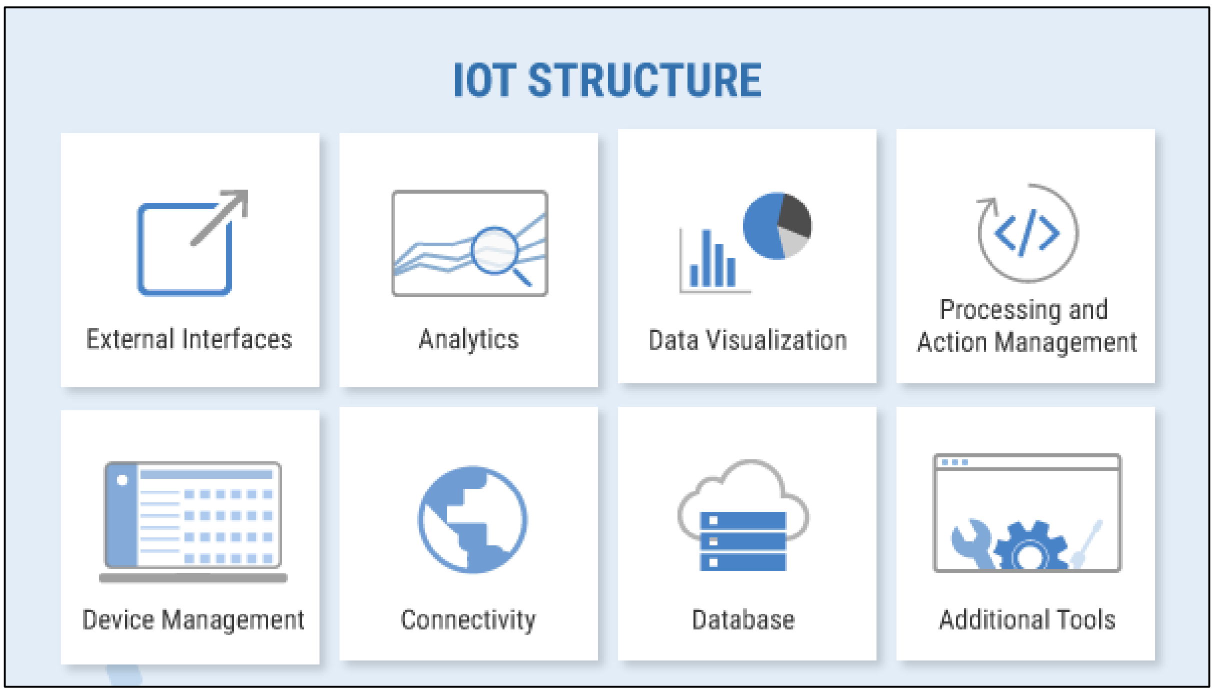


Figure 4-3: Complete features of IoT platform (Floarea & Sgârciu, 2016)

✓ *Technological depth*

Developing an integrated IoT application platform and integration into IoT standards needs numerous years of focused work and effort. Therefore, various levels of technological depth for IoT application platforms exist as shown in Figure 4-4 (IoT Analytics GmbH, 2015).

LEVEL 1: The connectivity IoT platform. The simplest platforms that behave as data collectors and offer a simple messaging bus.

LEVEL 2: The action IoT platform: these platforms not only control the connection but also help to trigger activities based on particular events. For example, these IoT platforms allow to turn on lights when the sensors indicate somebody is home.

LEVEL 3: Full-scale IoT platform: this is the most advanced IoT platforms. These platforms go further more than connectivity and action by splitting various platform modules, supporting a wide range of standards and protocols, and allowing outside interfaces seamlessly. Also, these IoT platforms always come with a highly advanced database that enables scalability to many objects and big data sets.

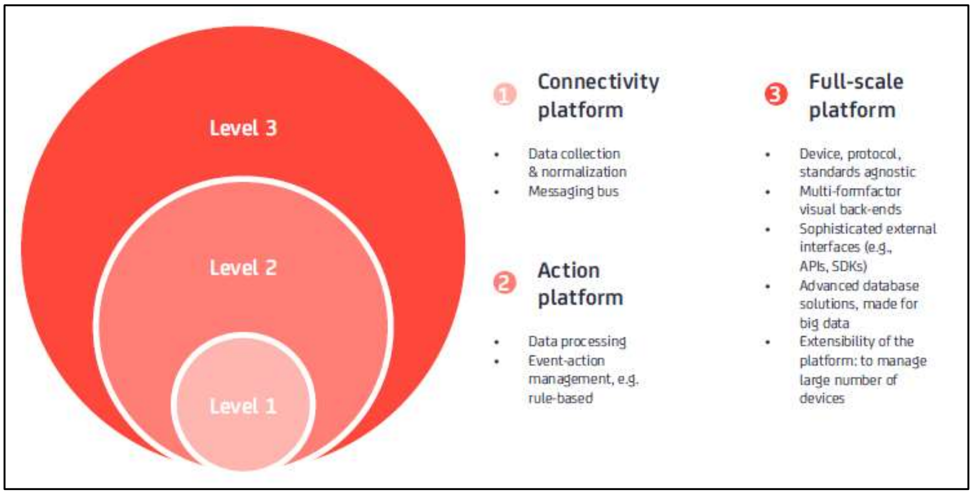


Figure 4-4: Technological depth of IoT

- **Technology Strategy**

In any IoT system, all of the things should be able to communicate in a common framework. When this framework is well defined, the true value of IoT is recognized. Unfortunately, numerous firms underestimate the complexity and difficulty of this framework. Usually, they do not take into consideration the need for advanced server technologies. Frequently development begins on its own and then it is distributed in the market which leads to a quick increase of users producing issues of scaling and performance.

To solve these issues of scaling and performance, IoT-operatives frequently favor the improvement of a central system concentrating on the objects themselves. However, this usually does not solve the mentioned problem. Occasionally developers start by creating a system from scratch, and they do not have adequate time and resources to apply the system technological core. An existing and tested IoT application platform will be a more useful option. The following is a list of some **technology strategy** considerations for IoT environment:

- Controlling communications between devices and servers in the event of untrusted operation through satellite links and wireless
- Unification of the data objects, regardless of object's physical location
- Storage of huge volume of collected historical data in databases of various kinds (relational, ring, NoSQL)
- Visual structure of complex and complicated chains of background processing and correlation of events
- The quick construction of the interface without programming

- The execution of integration scenario by using ready-made common connectors (SQL, HTTP, SNMP, SOAP, etc.)

✓ *Example of Technology Strategy for Cloudera*

Given the features of IoT data streams, well-known companies around the world are using Cloudera Enterprise based on Apache Hadoop as the data analytics and management platform for processing, managing and driving analytics of IoT data. With Cloudera Enterprise, companies are able to easily get information from several sources onto a unified platform at a significantly lower price per terabyte. This involves customer data, sensor data, transaction data, etc. Furthermore, because Hadoop is constructed on a highly flexible and scalable file system, any kind of data can be uploaded into Cloudera Enterprise without changing its format. Data that generated by sensors are collected in real time and analyzed directly in Cloudera Enterprise. Additionally, because Hadoop works on standard hardware, on the cloud or appliances, the rate per terabyte of storage and analyzing is, on average, ten times cheaper than a traditional data warehouse system (Figure 4-5).

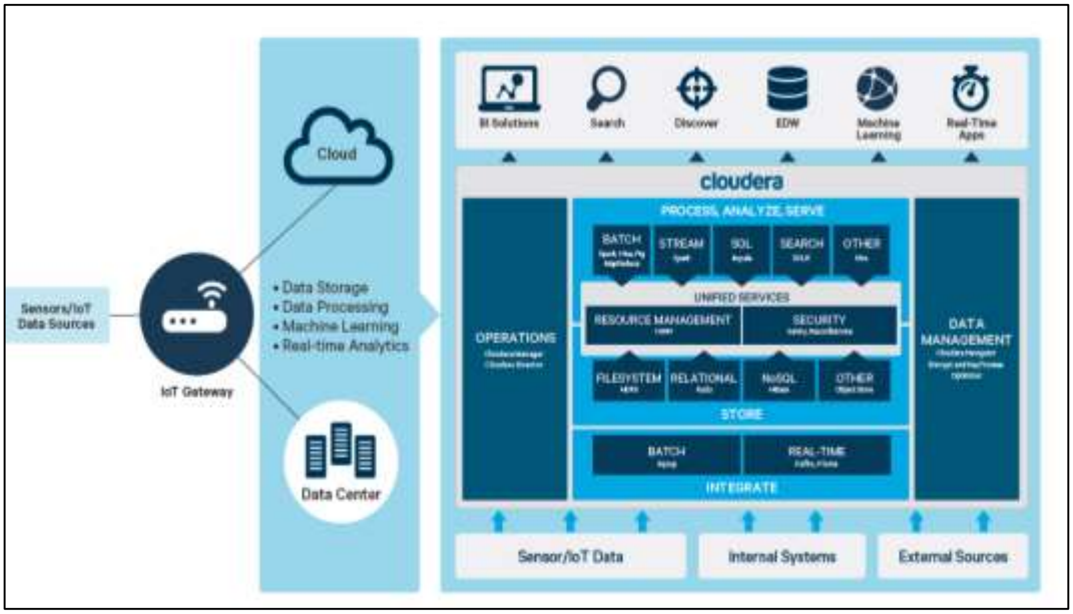


Figure 4-5: Example of technology strategy for Cloudera (Cloudera, 2017)

The main attributes of having a good technology strategy for IoT data management and analytics such as Cloudera Enterprise:

- Flexible Data Ingest: simply ingests data from several data sources, and supports batches as well as real-time data ingest from various sensors using tools such as Apache Flume and Apache Kafka and
- Scalable, Reliable, Always-on Data Ingest: supports constant streaming ingest, IoT data drift and IoT data pipeline visualization.
- Handles Data Variety: efficiently handles several IoT data-types and schemas, from sensor readings of pressure and temperature to real-time data or streaming video feeds
- Real-Time Insights: supports real-time analyzing on streaming data like spark streaming, with extra support from storage options such as Apache Kudu and Apache HBase

- Batch Processing: Apache Spark offers the standard for in-memory data analyzing a diversity of workloads involving analytics, advanced modeling, and batch processing. As an integrated platform of Cloudera, Spark profits from the simple administration (via Cloudera Manager), compliance-ready governance and security (via Cloudera Navigator and Apache Sentry), and unified resource management (via YARN) which are all important for running in production.
- Scalable IoT Platform: scales efficiently based on the data growth, enabling an enterprise to store limitless quantities of data. More significantly, the IoT platform enables to smoothly combine data from IoT sensor with other external and internal data sources to guarantee interoperability and have deeper business perceptions.
- Deployment Flexibility: deploys the IoT platform in the cloud or a hybrid setting based on the needs, while still profiting from the centralized management
- Fundamentally Secure: security is vital in IoT words. With Cloudera, firms can benefit from the Hadoop platform with several layers of security.
- Fast Analytics: opens the data to self-service analytics and business intelligence with tools such as machine learning libraries, Apache Impala, and integrations with BI partner tools.

Moreover, Cloudera works with Intel and its ecosystem of partners to provide clients with end-to-end IoT solutions. Many leading firms from various industries such as healthcare, automotive, insurance utilities, industrial automation, telecom, and technology, and manufacturing have adopted Cloudera Enterprise as their data analytics platform for IoT, processing millions of data/second to produce actionable business perceptions. From industrial IoT, smart cities connected vehicles and telematics, healthcare IoT, Cloudera is running some of the most persuasive IoT use cases in the industry nowadays (Cloudera, 2017).

4.2.3 Preparing for Action

“Preparing for action’ is the main focus of this research study. This step not only evaluates the IoT potential solutions generated but also analyzes a suggested solution to be implemented using ABM. It is important to realize the risk and the impact of this step to develop a feasible business model. The output of this step is the recommended solution to be implemented supported by business, financial, and technical feasibility.

4.2.3.1 Developing Solution

- **IoT Business Solution:**

In this step, a business model for IoT technology is proposed. Nowadays, smart IoT objects facilitate novel business models and applications (Bohn et al., 2005). However, designing an effective business model needs sufficient data. The data variety and volume collected automatically from IoT objects help to handle business problems and enable the development of the embedded services.

Fleisch (2010) and Deng et al. (2012) have recognized the significance of implementing IoT business models. Even though many earlier studies demonstrated the importance of IoT business models, the main focus of the majority of IoT researches is on the various technology layers (Leminen et al., 2012). According to Leminen et al. (2012), there are only sparse academic efforts recognize the evolving IoT business models with ecosystems by applying:

- Structural approaches: includes finding the value chain in ubiquitous computing environments (H. J. Lee & Leem, 2005), IoT value identification (Fleisch, 2010), the analysis of IoT value chain (Banniza et al., 2009), and discussion of digital business ecosystems (Nachira et al., 2007).
- Methodology approaches include improvement methodology of the business model in ubiquitous computing environments (Banniza et al., 2009) and multipath deployment adoption (Levä et al., 2010).
- Design approaches: includes a networked business model for emerging technology-based services (Ulkuniemi et al., 2011) and the framework of **business model canvas based** on IoT (Bucherer & Uckelmann, 2011).

- **Business Model Canvas:**

In this study, the design approach is used to propose business model canvas based on IoT. Business model canvas is a strategic management for establishing a new business model or documenting an existing one (Barquet, Cunha, Oliveira, & Rozenfeld, 2011). It is a visual diagram with essential elements describing an organizations infrastructure, value proposition, finances, and customers (Osterwalder & Pigneur, 2010). It helps organizations to align their activities by clarifying potential trade-offs. Initially, this model was suggested by Alexander Osterwalder based on his previous work on business model ontology (Osterwalder, 2004). After Osterwalder's publication in 2008, several canvases have appeared.

Formal explanations of the businesses become the building blocks for their activities. Many various businesses conceptualizations exist nowadays. However, Osterwalder's work proposes a distinct reference model based on the likenesses of a wide variety of business models conceptualizations. With his business model design template shown in Figure 4-6, any firm can easily describe its business model. Following is the description of each block in business model canvas proposed by Osterwalder.

❖ *Infrastructure*:

- Key Activities: The most significant activities in executing a firm's value proposition. For example, developing an effective supply chain to reduce costs would be one of the key activities for pen manufacturer.
- Partner Network: To reduce risks and optimize operations of a business model, the firm regularly develop supplier-buyer relationships, so they are able to concentrate on their core activity.
- Key Resources: The resources which are necessary to generate value for a customer. These resources such as human, physical and intellectual are considered an asset to a firm, which is required to support and sustain the business.

❖ *Offering:*

Value Propositions: The collection of services and products offered by a business to meet the needs and expectations of its customers. According to Osterwalder (2004), a firm's value proposition is what differentiates itself from competitors. The value proposition offers value through different factors such as performance, newness, design, customization, brand/status, price, accessibility, risk reduction, cost reduction, and convenience/usability. The value propositions may be:

- Qualitative – overall customer outcome and experience
- Quantitative – efficiency and price

❖ *Customers:*

- Customer Segments: To establish an operative business model, a firm must determine which customer it is going to serve. Different sets of customers could be segmented based on the various attributes to ensure proper implementation of a business strategy that meets the characteristics of the selected group of customers. The various types of customer segments contain:

✓ Mass Market: There is no exact segmentation for a firm that follows Mass Market elements as the company displays a wide range of potential customers such as Automotive industry.

✓ Niche Market: A customer segmentation generally is based on specialized characteristics and needs of its customers.

✓ Diversify: A business serves various customer segments with various characteristics and needs.

✓ Segmented: A firm applies additional segmentation inside existing client segment. In the segmented situation, a business might further differentiate its customers based on age, gender, and income.

- Channels: A firm can provide its value proposition to its selected customers through various channels. Channels will distribute a firm’s value proposition in ways which are efficient and cost-effective. A firm can reach its customers either via its own channels, partner channels, or a combination of both.

- Customer Relationships: To guarantee the survival and the success of the business, firms must determine the kind of the relationship they want to generate with their customer segments. Different forms of client relationships contain:

- ✓ Personal Assistance: Assistance in the form of customer-employee interaction. This type of assistance is implemented during and after sales.
- ✓ Dedicated Personal Assistance: The greatest intimate on personal assistance where the sales representatives are assigned to handle all the questions and needs of a special set of customers.
- ✓ Self Service: This type of relationship translates from the indirect interaction and communication between the firm and its clients. Here, a firm offers the tools required for the clients to serve themselves effectively and easily.
- ✓ Automated Services: This is similar to a self-service but more modified as it can determine individual clients and his preferences. A good example of Automated service would be when Amazon creates a book suggestion for a customer based on the characteristics of the prior book purchased.
- ✓ Communities: Creating a community enables for direct interaction and communication with various clients and the firm. The community platform generates a scenario where the knowledge is shared, and the problems are solved by various clients.
- ✓ Co-creation: An individual relationship is generated via the client's direct input in the outcome of the firm's services.

❖ *Finances:*

- Cost Structure: This defines the most significant consequences while functioning under various business models.

- ✓ Classes of the Business Structures:
- Cost-Driven: These business model focus on reducing all costs. Low-cost airlines would be a good example here.

- Value-Driven: Less focused on cost, these business models focus on making value for their services and products.
- ✓ Characteristics of the Cost Structures:
- Variable Costs: These costs differ based on the volume of production of goods and services.
- Fixed Costs: These costs are fixed across various applications such as salary and rent.
- Economies of Scale – These costs are reduced as the volume of good is produced or ordered.
- Economies of Scope – These costs are reduced due to joining other businesses that have direct relations to the original product.

- Revenue Streams: The way a firm gains income from its customer segment. Many ways to create a revenue stream:

- ✓ Usage Fee: Money created from the use of a specific service.
- ✓ Asset Sale: Selling ownership right to physical good.
- ✓ Subscription Fees: Revenue created by offering a continuous service.
- ✓ Lending/Leasing: Giving the right to an asset for a specific period.
- ✓ Licensing: Revenue created from the use of the protected intellectual property.
- ✓ Brokerage Fees: Revenue created from intermediate service between two parties.
- ✓ Advertising: Revenue created from product advertising.

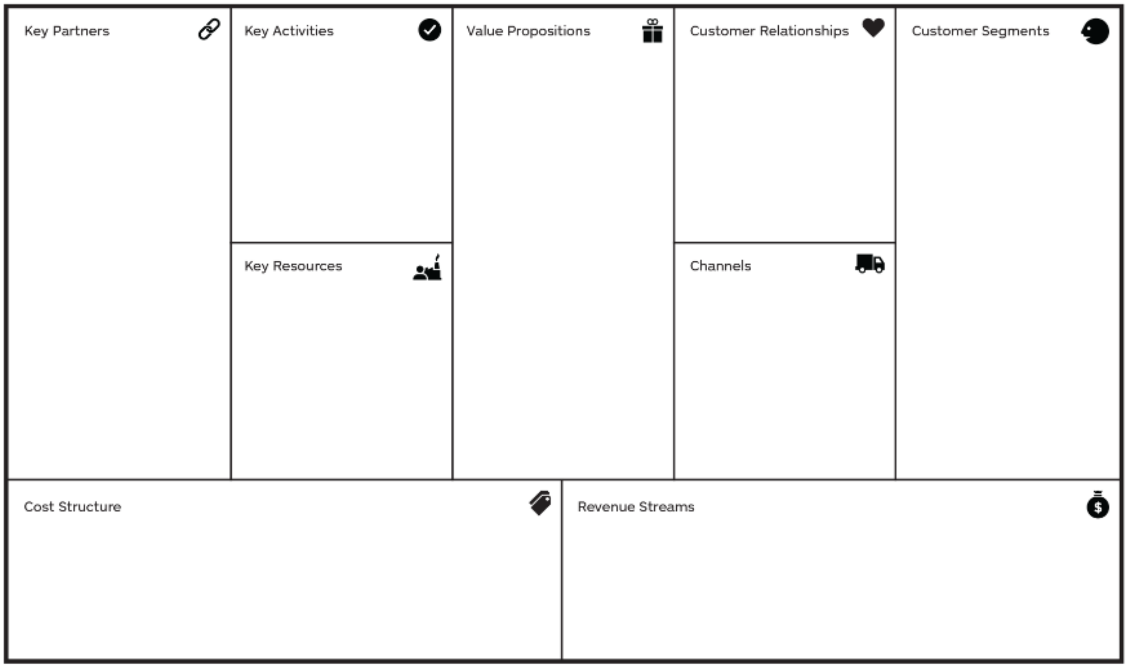


Figure 4-6: Business model canvas

- **Predictive Maintenance in IoT environment:**

In this study, the proposed business model canvas for IoT is applied to the predictive maintenance industry. Nowadays, IoT allowed predictive maintenance. IoT is basically converting the maintenance model from repair/replace to predict/prevent. By utilizing data streaming from devices and sensors, a business can gain visibility into the condition of its valuable assets and its particular components in real time. The significance of predictive maintenance is to control the condition of the assets in real-time and then intervene before the device fails (Figure 4-7). Utilizing IoT sensor data from devices, predictive maintenance allows firms to efficiently predict how and when an asset may fail by recognizing warning signals, detecting variances, and tracking any signs that might indicate a potential failure or breakdown. Currently, leading firms are using machine learning to perfectly predict the chances of a device being down containing how and when an asset will fail. This allows corrective measures to be introduced and planned most efficiently, thereby avoiding unexpected downtimes and costly resources (Cloudera, 2017).

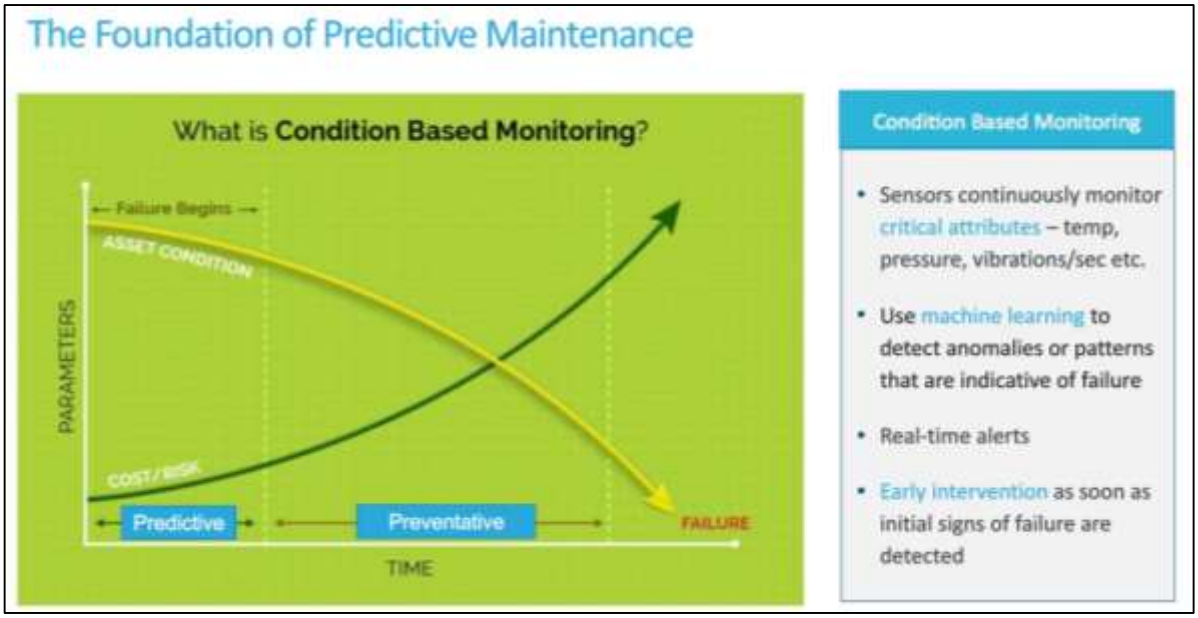


Figure 4-7: Foundation of predictive maintenance (Cloudera, 2017)

Predictive maintenance can have a deep impact, particularly on asset-heavy industry such as mining, energy, utilities, and manufacturing, automotive, etc., bringing lowered equipment stoppages, lowered the costs associated with the maintenance, and improved quality and productivity.

✓ *Key Data Management Challenges:*

Although there is an important value to be gained from continuous monitoring and observing of assets and having predictive maintenance, firms struggle to keep up with the variety, velocity, and volume of the IoT data coming from millions of devices and sensors in real time.

Some of the main challenges firms face regarding data management for predictive maintenance involve:

- Cost of the data management: Traditional data management tends to be notoriously costly, and are not perfect for processing and capturing the petabytes of data coming from connected devices. Firms need a data management platform which can easily store, process, manage all of these streaming at a lower price per terabyte.
- Ability to handle the variety and volume of IoT sensor data: To enable continuous monitoring and observing IoT, firms need a different type of data platform which can handle various data structures, including everything from alternating readings on pressure and temperature per second to handling entirely unstructured data (video, images, and text) or other different forms such as sound/noise from device.
- Handling the difficulty of real-time data: For continuous observing and predictive maintenance, firms need a platform which can store and analyze the data coming from devices in real time or near-real time to rapidly drive perceptions.
- Diverse Analytical Capabilities: Existing platforms provide limited capability to offer analytics and insights. To efficiently drive predictive maintenance, firms need a platform that can offer a wide range of analytical tools, including machine learning capabilities, SQL analytics, and integration with the business intelligence tools.
- Predictive Modeling Capabilities: Existing platforms offer limited modeling or machine learning abilities to predict or prevent problems before they affect the operations.

Thus, to efficiently drive observing and predictive maintenance, firms need an elastic, cost-effective, scalable data management platform which can handle the velocity, volume, and variety of data produced by IoT. Moreover, the platform must be able to deal with the difficulty of both data at rest and in motion, provide enterprise-grade management tool and security, and deliver a wide range of analytical tools including proven predictive modeling capabilities and machine learning.

✓ *Examples of how IoT predictive maintenance benefits firms:*

Table 4-2 shows a summary of a various set of use cases that illustrate how some clients are utilizing Cloudera and the power of Apache Hadoop to drive predictive maintenance (Cloudera, 2017).

Table 4-2: Example of usage of Cloudera predictive maintenance

Setting	Use Cases	Customer Case Study—Description
Automotive	Predictive Maintenance – Connected Vehicles	One of the leading auto manufacturers in North America is using Cloudera as the data management platform to monitor the health of 180,000+ trucks in real time in order to improve uptime and reduce fleet maintenance costs by 30 to 40 percent.
Manufacturing	Predictive Maintenance – Industrial IoT	A leading industrial automation company is utilizing Cloudera in an IoT setting to ingest, store, and analyze petabytes of sensor data from thousands of diverse manufacturing systems, in real time, in order to eliminate machine downtime.
Heavy Machinery	Predictive Maintenance – Heavy Machinery	One of the biggest heavy equipment fleet manufacturers in North America is using Cloudera to parse large-volume and high-velocity data from sensors to continuously monitor the performance of their fleet and to do predictive maintenance as well as advanced defect detection.
Buildings/ Airports	Predictive Maintenance – Smart Buildings	One of the busiest airports in Europe is running Cloudera on Azure to capture, secure, and correlate sensor data collected from equipment within the airport (e.g., escalators, elevators, and baggage carousels) to prevent breakdowns and improve airport efficiency and passenger safety.
Ports	Predictive Maintenance – Smart Ports	A leading provider of cargo-handling solutions is utilizing Cloudera to ingest and process IoT data that is streaming from sensors in port terminal machinery, including cranes and cargo-handling equipment, to improve operational efficiencies and increase uptime.

4.2.3.2 Building Acceptance

This step identifies how efficiently the selected solution meets both the customer and business needs using simulation. The output of this step is validated requirements and action plan. As technology progresses towards new paradigms such as IoT, there is a need for business executives and leaders for a reliable technique to identify the value of assisting these ventures. Traditional simulation and analysis techniques are not able to model the complex systems. However, agent-based simulation (ABM) presents an attractive simulation technique to capture these underlying difficulties and offer a solution.

- **Simulation Model**

The simulation model is used to test the acceptance of the IoT business model by simulating agent's behaviors. "AnyLogic" is the simulation software that is used in this research.

- **Agent-Based**

Agents can take any form of object including patients, machines, parts, patients, ideas, firms, etc. In the context of this research, customers (in case study 1) and refrigerators (in case study 2) are considered to be agents that have their own behaviors. These behaviors are the various states that agents can present. Agents can communicate with each other through messages. Also, they are able to communicate with non-agents such as a queue in a discrete event model.

✓ *Agent communication:*

One of the key concepts when modeling behaviors are the agents' communication. Nowadays, various technologies are used to exchange data and communicate such as wireless sensors network (WSN) and radio frequency identification (RFID). In IoT world, each object (thing) is connected to sensors (s) (Bi, Da Xu, & Wang, 2014). One of the key purposes of exploiting agent-based simulation is to model the communication between different agents.

✓ *Message Sequence Diagram*

Message sequence diagram is a graphical demonstration depicts the communication between different agents. Each agent is placed vertically while messaging and communication between agents are horizontal. Time begins from top to bottom. An internal event for an agent can be represented vertically within the agent line. When an agent sends a message, an event is taking place. Figure 4-8 illustrates the Message sequence diagram.

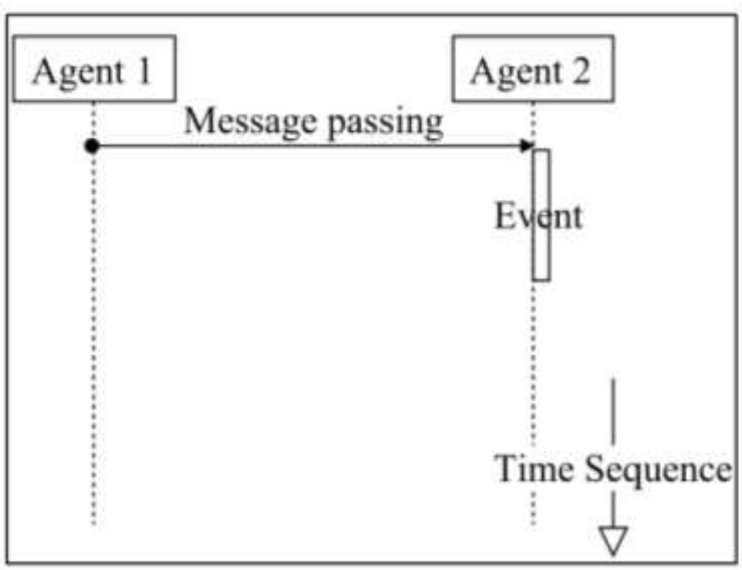


Figure 4-8: Message sequence diagram

✓ *Statecharts*

According to Borshchev (2013), a statechart is a graphical illustration that enables defining events and time-driven behaviors for various agents. Each statechart contains states and transitions. States are defined as the various situations an agent can present while transition enables agents to move from a state to another. Figure 4-9 shows a simple structure of statechart.

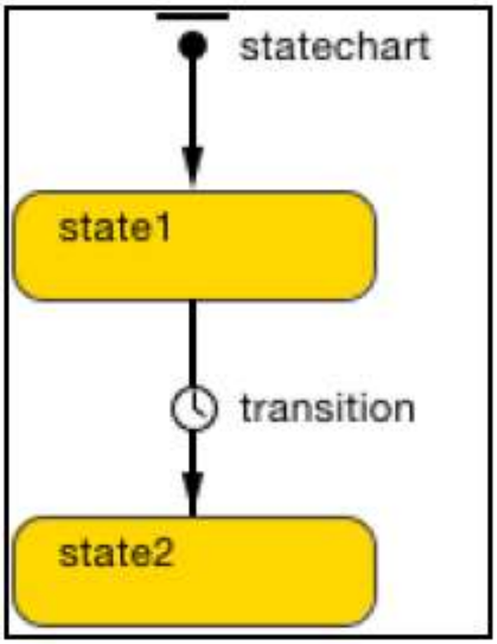


Figure 4-9: Statechart

In Figure 4-9, statechart is the entrance to the model. State one represents the initial state. The agents stay in this state until a certain trigger occurs. The agents are moved from state one to state two using transitions. These transitions are triggered by messages, rate, timeout, etc.

Figure 4-10 shows an example of the structure of statechart. Statechart is used to model customer behaviors and simulate the changing from one state to another. Customer behavior is defined by three states: PotentialUser state, WantsToBuy state, and User state. A customer in the

PotentialUser state is only who is potentially interested in purchasing the product while a customer in the User state has already purchased the product. WantsToBuy state includes a customer who has decided to buy the product but has not done so. The transition between states is triggered by external influence and internal influence. In this example, advertisements and direct sales are considered as external factors that affect agent behavior while Word of Mouth (WOM) is considered as an internal influence. Each transition is triggered by a specified rate.

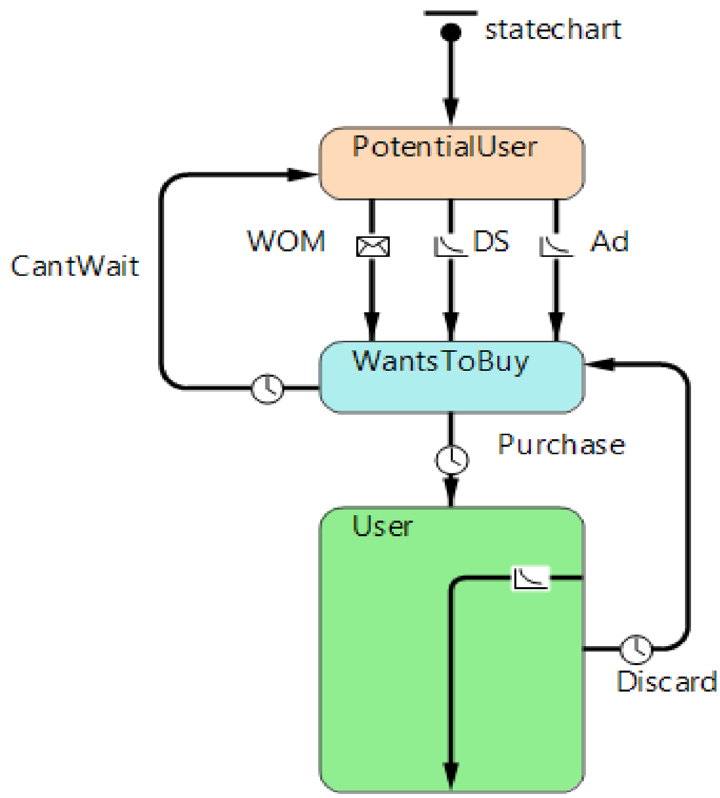


Figure 4-10: The structure of the statechart

Discrete Event-Simulation

The discrete event simulation is a sequence of a process performed by entities. Figure 4-11 illustrates a simple example of a discrete model that contains entry point, a queue that typically can handle a specific number of entities, and a delay where the entities are held for some time before they are released.

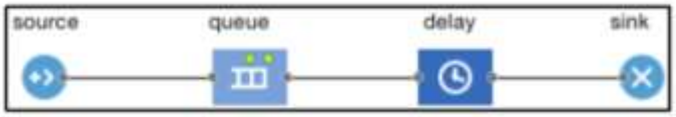


Figure 4-11: Simple discrete model

Figure 4-12 shows an example of a discrete model used in case study 2, where entities are considered to be trucks. The model consists of different elements such as trucks, packing and unpacking area, queue prior each store, etc.

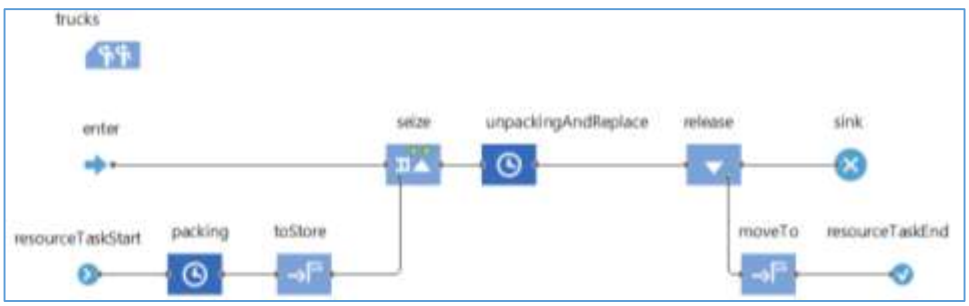


Figure 4-12: Example of discrete model

- **Hybrid Simulation:**

Figure 4-13 illustrates an interaction between discrete event model and agent model. For example, the discrete event model on the left-hand side deals with trucks movement. Trucks move from agent 1 (manufacturer) to agent 2 (store) based on a certain message (trigger) sent by agent 2 then trucks move back from agent 2 to agent 1 after a certain time (timeout). In this example, once the truck enters the (queue) module, it goes into a different simulation type (agent-based model). Depends on the design of the statechart of agents, trucks are moving.

AnyLogic software is based on Java. For agents' interactions with discrete models or other agents, java codes have to be inserted properly into the model.

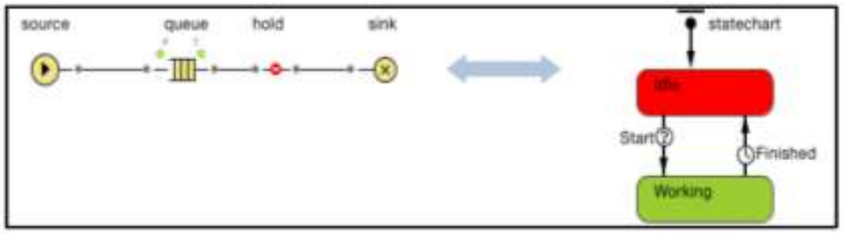


Figure 4-13: Simple hybrid simulation model

➢ **Verification and validation:**

According to Sargent (2013), verification is building the simulation model correctly in a right manner while validation is to ensure that the model represents the real system. This study is considering the following techniques for validation and verification (Figure 4-14):

- Animation**:** the graphical model demonstration during the simulation running time.
- Face validation: this involves the input of human with experience in the subject of the simulation model. The human experts evaluate the plausibility of the operation and output of the ABM.
- Sensitivity analysis: the step is to evaluate the effect of various combinations of the parameters on the overall behavior of the ABM and potentially identify redundant parameters.
- Calibration: the aim of the calibration is to set unknown parameters to reasonable values that will produce output approximating the real-life system. In many cases, this step may be combined with the sensitivity analysis step.

- Statistical validation: this step is to show that the simulation is valid by comparing the simulation outputs with the true value from the historical data. (Houston et al., 2017).

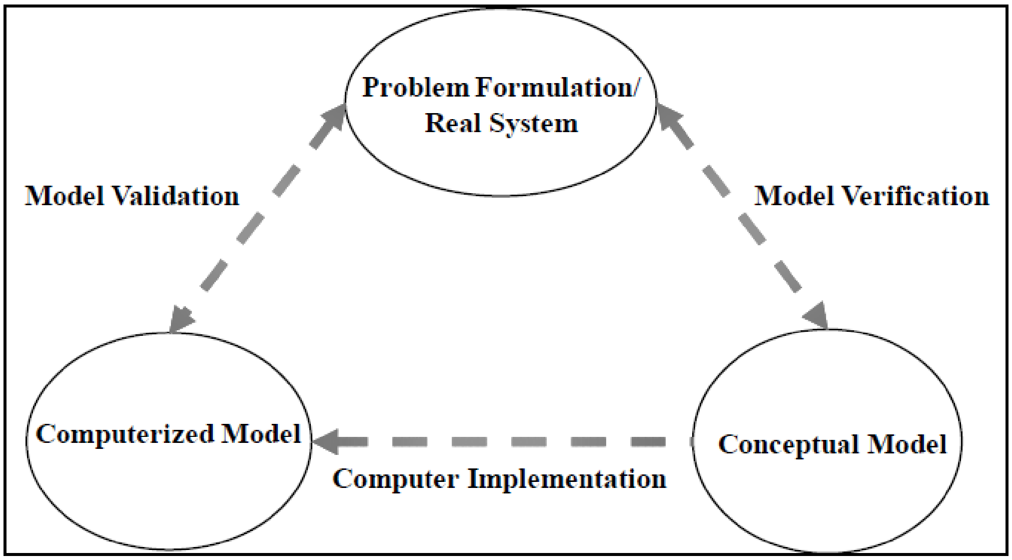


Figure 4-14: Verification and validation development

4.3 Conclusion

This chapter proposes the framework. The objective of the framework is to analyze IoT solution and investigate its adoption. There are three different phases. In the first phase, a wide range of thoughts and potential solutions in IoT world is generated. The second phase seeks to expose the IoT concerns, its challenges, and offer an overall perception including conflicting opinions and views. This phase also determines the analytics platform which leads to value in IoT environment, the different IoT technology strategy considerations, and the various levels of the technology depth for the internet of things platforms. The third phase is the substantial step of this framework. This step not only assesses the IoT potential solutions produced but also analyzes a suggested solution to be implemented using ABM. It is important to realize the risk and the impact of this step in order to develop a feasible business model. The output of this step is the recommended solution to be implemented supported by business, financial, and technical feasibility.

As technology progresses towards new paradigms such as IoT, there is a need for business executives and leaders for a reliable technique to identify the value of assisting these ventures. Traditional simulation and analysis techniques are not able to model the complex systems. However, ABM presents an attractive simulation technique to capture these underlying difficulties and offer a solution. Hybrid simulation (agent-based and discrete-event) is used to model the system. The system interaction and behavior are captured via message sequence diagram, a graphical demonstration to depicts the communication between different agents. Internal events for agents can be represented vertically within the agent line. Statecharts represent the different state an agent can present. The agent moves from a state to another via a transition. Each transition has a trigger that allows the agent to change its state.

Next chapter serves as a verification stage for this framework. Two case studies have been chosen to test the framework. ABM is developed to simulate market behaviors in the first case study and simulate operational behaviors of refrigerators at an existing manufacturing facility in the second case study.

CHAPTER 5: IMPLEMENTATION AND RESULTS

5.1 Introduction

This chapter focuses on implementing the proposed framework in chapter 4 (mainly step 3) to verify and evaluate its effectiveness. Also, it illustrates the application of the agent-based simulation (ABM) to simulate agent's behaviors. Different assumptions are taking into consideration while building the hybrid simulation model. Two case studies have been chosen to test the framework. The first one introduces a conceptual study of business modeling of IoT using agent-based simulations in order to determine its adoption and life cycle. The second case study is addressed to evaluate the return on investment (ROI) of installing sensors to monitor the condition of refrigerators units (around 7,420) in one of largest retail organizations in Saudi Arabia. These two case studies are discussed in section 5.2 and section 5.3.

5.2 Case Study # 1

5.2.1 Introduction

In the last three decades, it has been an increasing tendency for companies seeking to incorporate business analytics into their business model pursuing economic, environmental, social, and government benefits. The objective of these businesses analytics is to optimize the use of scarce resources and promote waste reduction using mathematical model and optimization techniques (Khalili-Damghani, Sadi-Nezhad, Lotfi, & Tavana, 2013; Rabelo & Hughes, 2005). In addition, business analytics can support decision making in particular when historical data is not available.

This case study proposes a conceptual study of IoT business modeling. It has two objectives: 1) propose a business model based on IoT, especially for predictive maintenance. 2) investigate the adoption of this technology using simulation modeling. The highlighted elements in the proposed framework (Figure 5-1) are considered in this case study.

After realizing the internet of things (IoT) challenges and opportunities described in chapter 2, now it is the time to develop an IoT solution and test its acceptance (step 3), which is the main focus of this study.

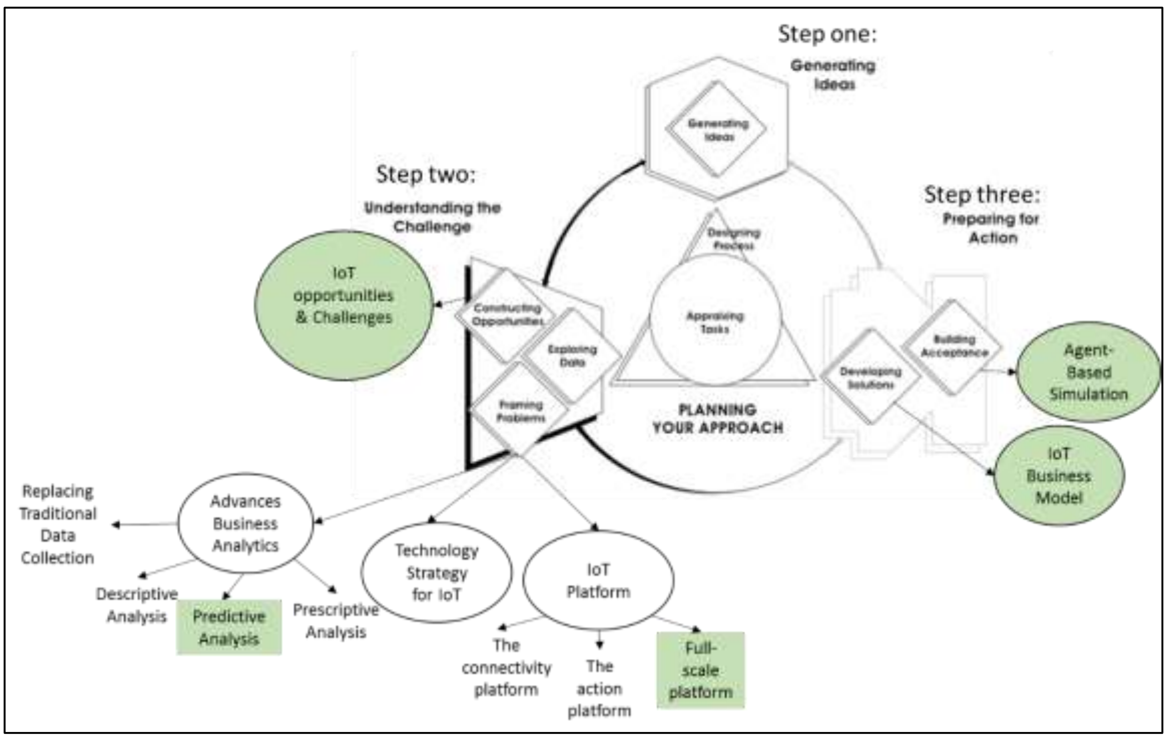


Figure 5-1: Proposed framework for case study # 1

One of the simulation methods proposed to be used in order to test the feasibility of the business model is an agent-based simulation (ABM). Since the traditional modeling tools may not be able to capture system details, the agent-based simulation has been applied widely nowadays because of its flexibility and capability to capture system complexity and therefore provide better results (Behdani, 2012; Demirel, 2006; Siebers et al., 2010). ABM can be applied effectively in many fields such as marketing & economics and artificial intelligence (C. Macal & North, 2009). For this case study, ABM is developed to simulate the behavior of the market in Orlando City (Florida, United States). The simulated time includes two years in order to see the potential of this business model and its feasibility.

5.2.2 Business Model Based on IoT

Under the IoT environment, data analytics faces big data issues, which refers to the methods and techniques to extract patterns and new information from structured, semi-structured, and unstructured data. The big data generated by the IoT is enormous regarding volume, variety, velocity and veracity (Tolk, 2015). The term volume refers to the size of data, which depends on the current technology (Jacobs, 2009). The variety refers to different characteristics of the format (excel, word, .jpg, etc.), velocity refers to the speed, which data is generated, and finally, the veracity refers to how reliable the date is depending on how the data was generated from different sources (Laney, 2001).

Most of the companies do not include business analytics through their missions and strategic plans. More specifically in firms where maintenance is a key task to be a successful business. In this era of information, enterprises institutions should handle big data issues, particularly for multinational institutions where the information is growing each minute due to internal and external transactions and human interaction with the business (Chen & Zhang, 2014).

In a survey of 560 enterprises (Chen & Zhang, 2014) shows how the use of big data analytics techniques represents advantages for the improvement in the business, above 50% agree that with these techniques they can reach enterprise optimization. These insights and protection allow us to achieve and manage four fundamental objectives for an organization: return on capital, growth, risk management, and innovation. As a consequence, this permits and maintain the long-term gratification of stakeholders when is related to maintenance issues.

The business model supported by the methodologies was proposed by (Hamel, 2002; Kaplan & Norton, 2001; Porter, 2008). Figure 5-2 shows the research process and how it proposes the hybrid use of quantitative and qualitative methodologies and tools to reach innovation through business model optimization. For this business model the four main areas are:

- **Customer interface:** fulfillment and support for users, information and insights from the predictive analytics perspective and relationships dynamics.
- **Core strategy:** predictive algorithms and agent-based simulation.
- **Value network:** software suppliers, possible partner, and coalitions with software and consultant companies.
- **Strategic resources:** competences in data mining and predictive analytics, infrastructure to support big data manipulation.

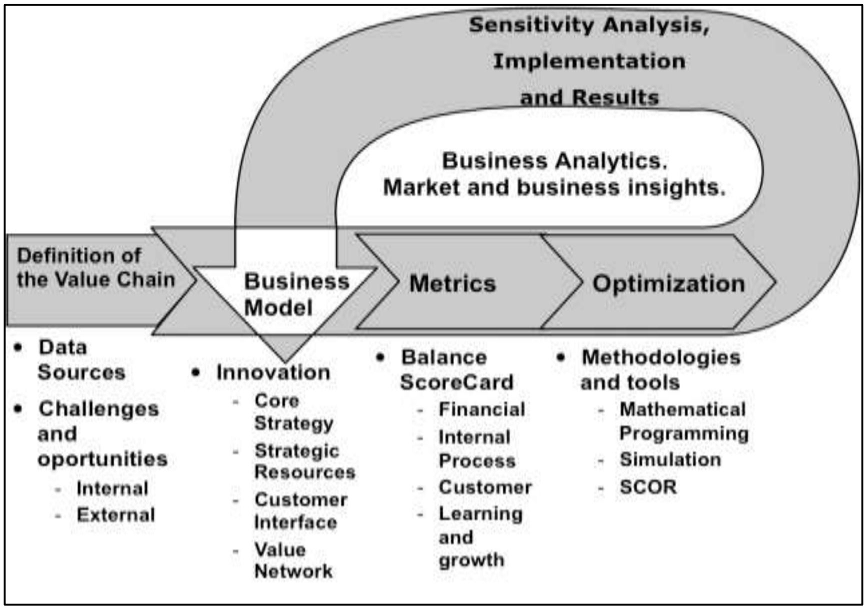


Figure 5-2: Business model concept

Being crowded by information related to the company will expect that most of the companies include business analytics in their missions and strategic plans, but this is not the case. Currently, there are very powerful and popular tools which facilitate the data acquisition of internal and external transactions, sensors, human interactions with the environment among others (Chen & Zhang, 2014).

Internet of Things (IoT) contributes to advance the business analytics. The definition of IoT is still in the developing process (S. Li et al., 2015). IoT is a global network of physical objects that can interact and communicate with each other. Currently, IoT applications started to gain a rapid attention from a variety of industries and a wide range of customers (I. Lee & Lee, 2015; Whitmore et al., 2015). For this research, a business model based on the IoT is applied to the predictive maintenance industry. Many companies in this industry, to maximize revenue, they battle to minimize their costs without affecting their daily operations. Figure 5-3 shows the integrated architecture of the business model and different IoT technologies. The proposed business model in this case study will help customers to handle big data challenges by providing a web-based platform which gives customers the ability to use collective community data and therefore estimates and schedule maintenance. Customer will be able to access maintenance manuals, some of the proposed solutions for particular cases, vendors' information. Also, customers can communicate with third proprietary software and compare the statistics of similar equipment used by different clients.

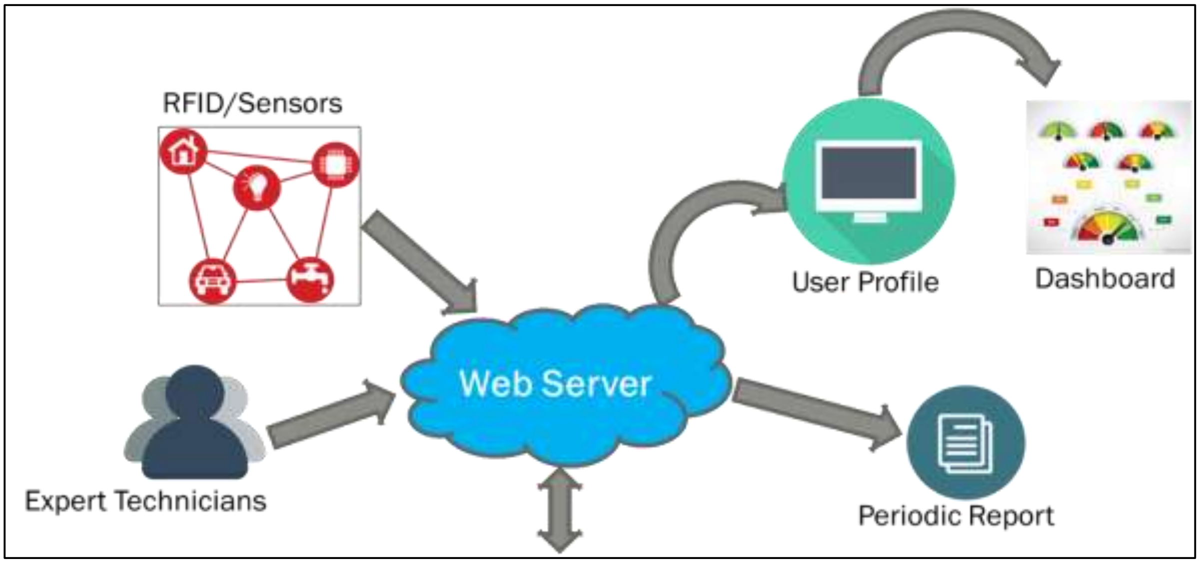


Figure 5-3: Integrated architecture of different technologies

The costs of the service are distributed among development, maintenance, monitoring and advertisement of the system. Existing market solutions do not provide all these capabilities as a holistic solution. Currently, this platform is under development, and the marketing strategy for reaching desired goals has been defined. Figure 5-4 shows the proposed business model based on IoT for predictive maintenance. This business model is based on the methodologies proposed by Osterwalder (2004).

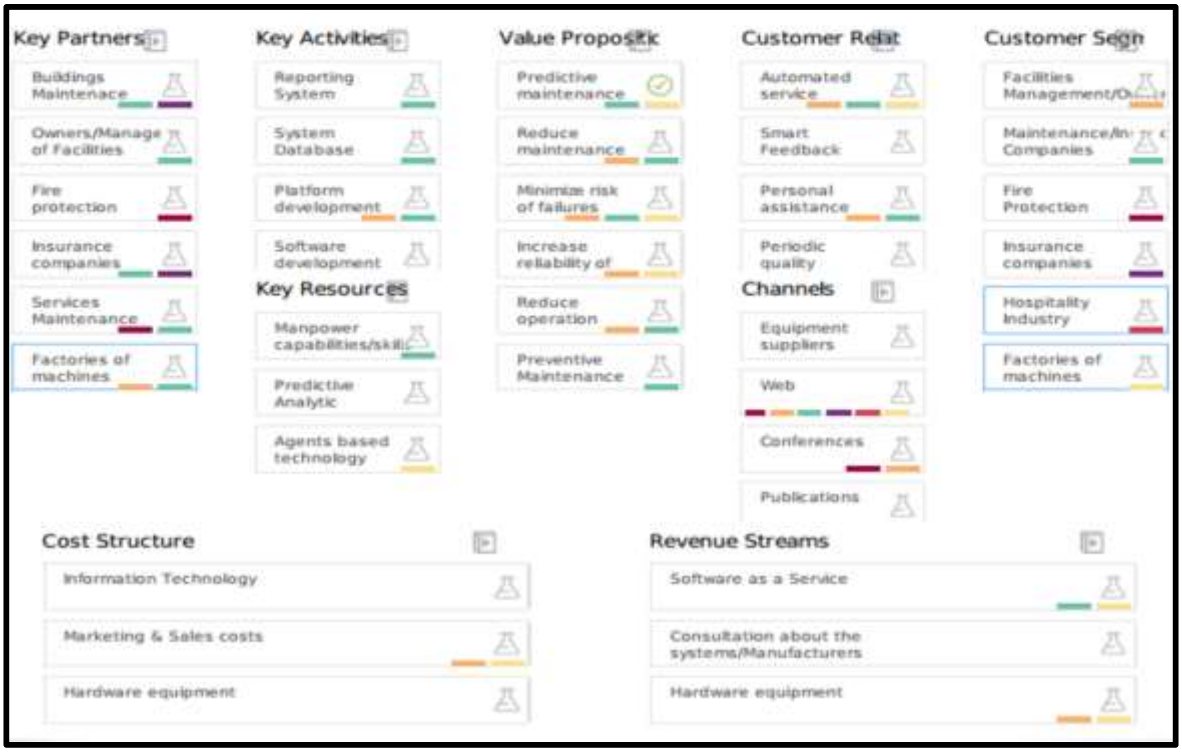


Figure 5-4: Launchpad Business Model Canvas

Figure 5-4 shows the assumptions that are currently in the process of validation and the relationships between the market segments. Furthermore, it shows the business model process and how it proposes the hybrid use of quantitative and qualitative methodologies, software as a service, and tools to reach innovation through business model optimization.

5.2.3 ABM Development

The first step to build the ABM model is to identify the agents and their behaviors. Then, ABM can be built from the bottom up. Even though we might not understand how the whole system we want to imitate behaves, we should at least have some perceptions and insights on how each agent behaves individually (Borshchev, 2013). According to (Borshchev & Filippov, 2004), Decentralization is essentially the key characteristic of ABM. In customer market models, agents typically represent enterprises, projects, people, branches, etc. Each agent in the model has its parameters, variables, and behaviors. There could be internal factors that affect agent behaviors directly such as a network of communications between agents which can be used to capture the exchange of information. Also, agent behaviors can be affected indirectly by external factors such as environmental influence as shown in Figure 5-5 (Borshchev & Filippov, 2004).

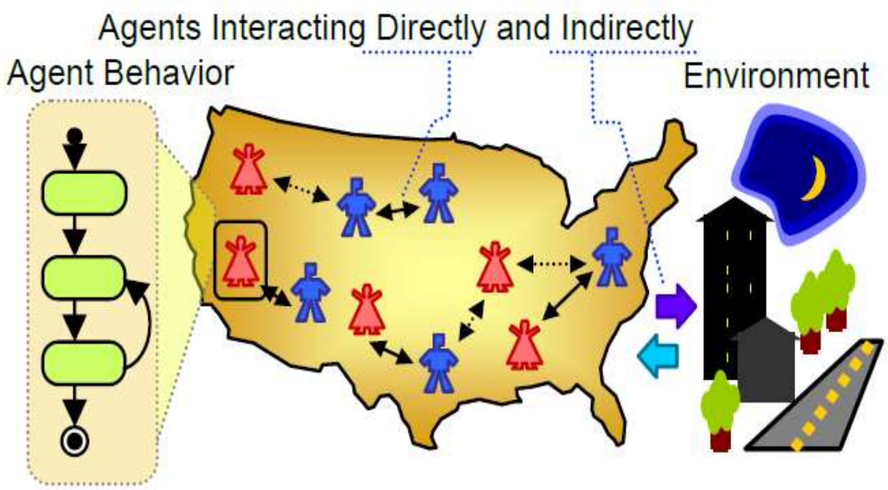


Figure 5-5: Agent-based model structure (Borshchev, 2013)

The behavior of the market and its environments are simulated using the ABM model, which is built in order to assess the reliability of the business model. In this section, the adoption rate of the maintenance software as a forecast tool is studied for customers, which are hotel owners, inspection companies, and office buildings in Orlando city (Florida, United States). The three types of the potential customers were chosen under approachability and geolocalization. Unique parameter and variable are used according to each type of customers. AnyLogic software is used to build the ABM model because the software is suitable for providing high flexibility for the combination of the three modeling techniques (agent-based, discrete event, and system dynamics). Figure 5-6 shows a Unified Modeling Language (UML) state diagram of the customer agent.

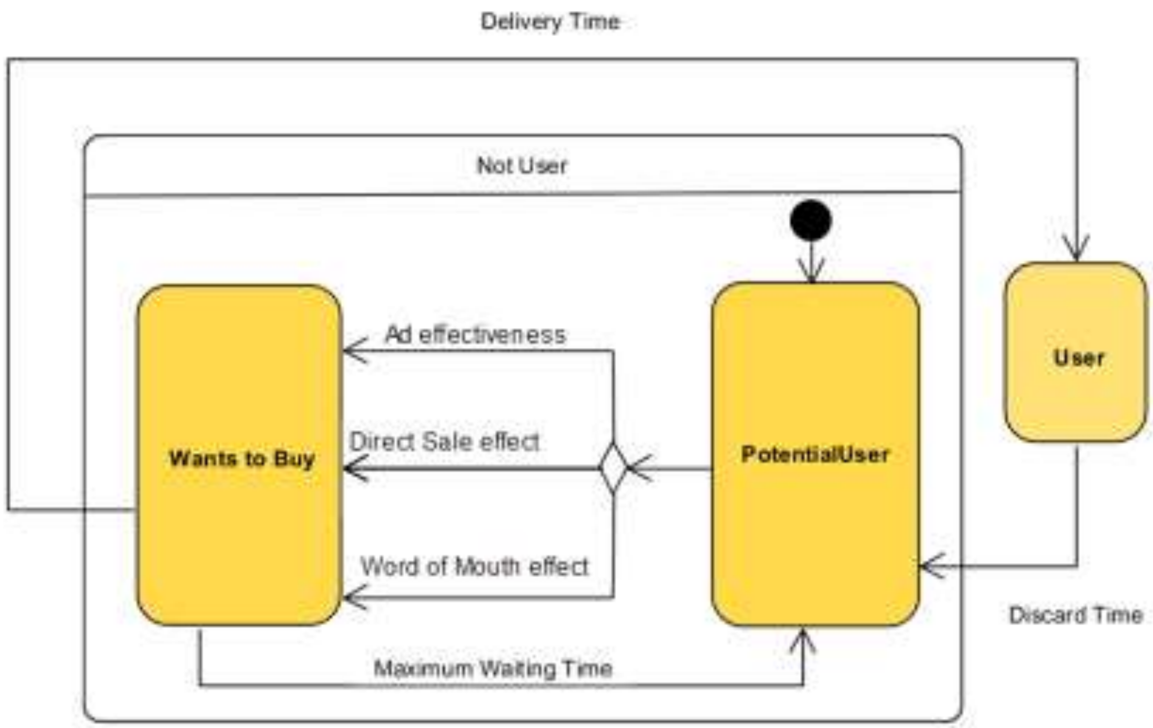


Figure 5-6: UML state diagram for the customer agent

In order to describe the structure of the system, a UML class diagram shown in Figure 5-7 was developed. This class diagram shows the system's classes, their attributes and the relationships between agents and objects.

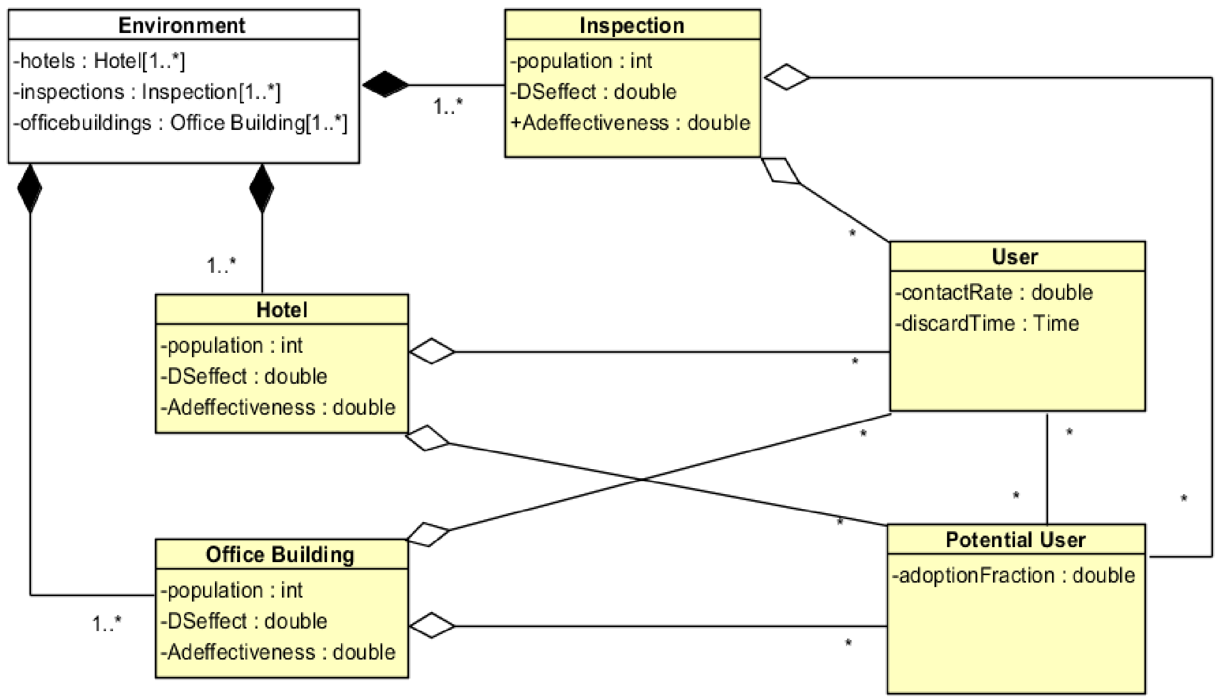


Figure 5-7: UML class diagram displays links between customer agent

A UML sequence diagram was also developed (Figure 5-8) to show agents communications arranged in time sequence. It shows the sequence of messages exchanged between the agents needed to perform the functionality of different scenarios. Table 5-1 summarizes all input parameter values used in the ABM.

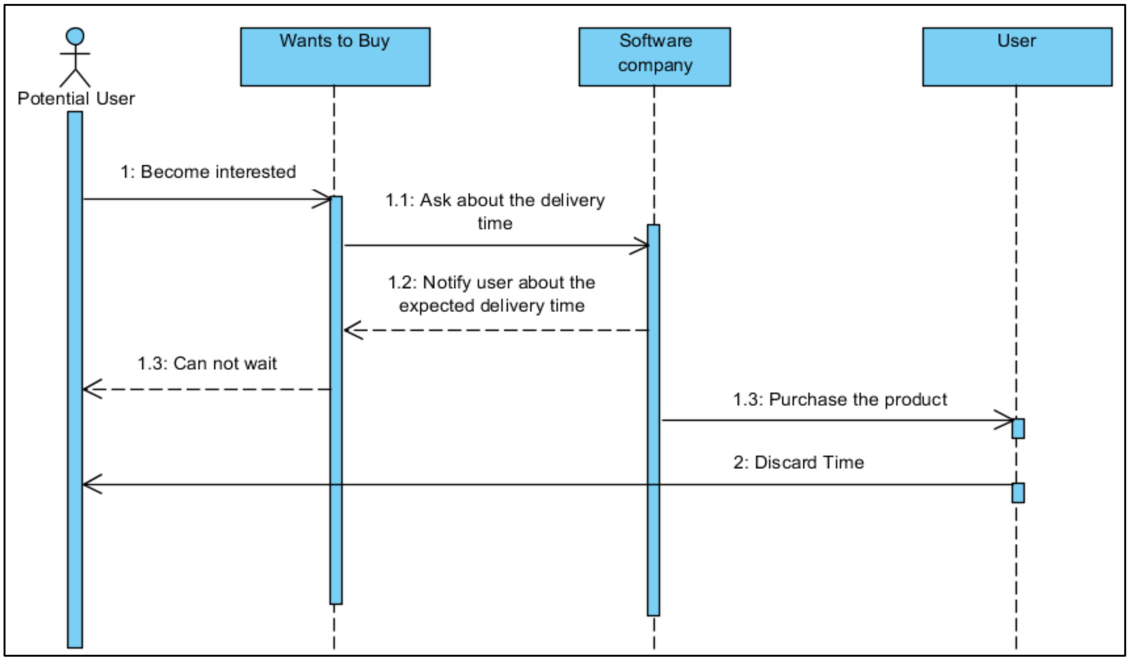


Figure 5-8: UML diagram shows the sequence of messages exchanged between customer agent

Table 5-1: Input parameter values for entities in the simulation

Parameter	Value	Source
Number of Hotel Owners	800	Online Search
Number of Inspection Companies	2500	Online Search
Number of Office Buildings	200	Online Search
Advertisement effectiveness	17%	McKinsey Report (2010)
The effect of Direct Sale	18%	McKinsey Report (2010)
The adoption fraction	10%	Assumption
Contact Rate	1 per day	Assumption
Discard Time	8.6 month	Assumption
Maximum Waiting Time	Triangular (2, 5, 7)	Assumption

- Agent Statechart:

Figure 5-9 shows the structure of statechart to model customer behaviors for each type and transition from i state to i+1 state. Three states, which are PotentialUser, WantsToBuy, and User, are defined to present customer behaviors. The PotentialUser shows a customer who is potentially interested in buying the software, whereas WantsToBuy represents a customer who has decided to purchase the software but has not purchased it yet. A user is a customer who has already bought the software. External and internal influences cause the transition from i state to i+1 state. In this case study, the external elements are considered as direct sales and advertisements, whereas the internal element is Word of Mouth (WOM) that triggers the state transition. A specified rate is applied for each transition. The parameter values for advertisement effectiveness rate and WOM effectiveness rate were applied in ABM model based on the McKinsey Quarterly published in April 2010 (Manyika et al., 2015). The advertisement effectiveness rate used is 17% per year, which means on average 17% of potential users will purchase the product in a given year. Also, McKinsey Quarterly (April 2010) suggests that WOM effect rate is 18% per year, which means on average 18% of potential users will be convinced to purchase the product in a given year through agent communications.

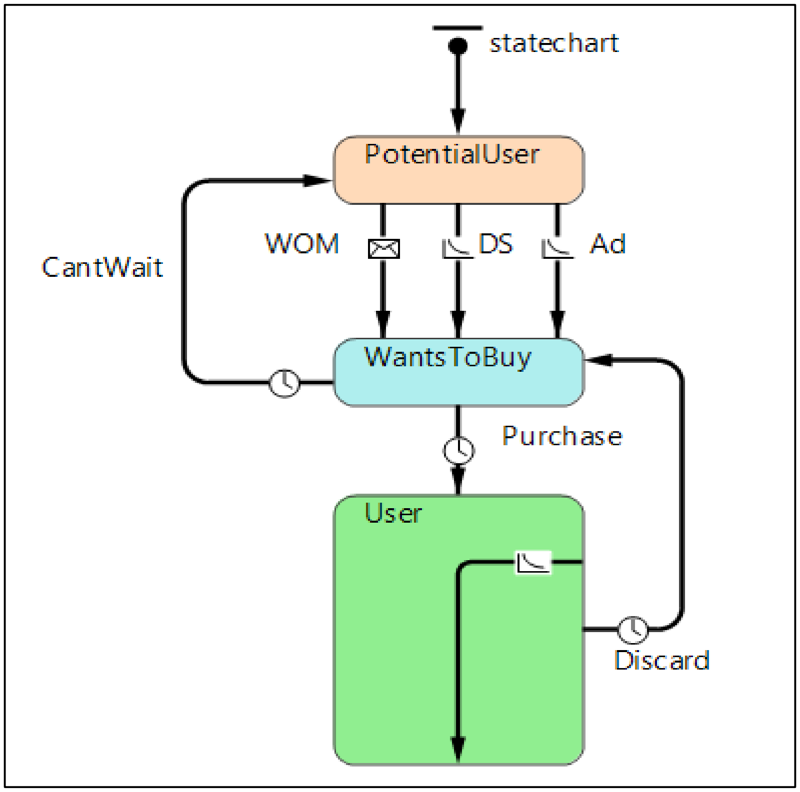


Figure 5-9: The structure of the statechart

5.2.4 Preliminary Results

ABM model can be considered as a test bench enabling to observe different results according to various inputs. It can help us to identify the essential factors of decisions and enhance the enterprise strategies. For example, how various sales channels such as advertisements, WOM, or direct sales could move up the adoption rate for each type of customers will be identified. Thus the enterprise could decide how to invest in the best sales channel for each type of customers to maximize the company net income. The main sources of data used to build model parameterization for each type of customers were publications and well-known reports issued by similar industries. Table 5-2 represents how different customer sectors adopt the predictive maintenance software based on the results of the simulation for two years.

Table 5-2: The adoption process for customers

Day # 730	Hotel Owners	Inspection Companies	Office Buildings
# of Potential Users	662	166	2030
# of Users	127	33	432
# of Want to Buy	11	1	38

The time stack chart in Figure 5-10 shows the history of the contribution of data items, as stacked areas, into a total during the newest time horizon. These data values are stacked continually one on top of the following with the earliest added data at the bottom. Figure 5-11 shows the model animation of agents in Orlando city after running the simulation for 2 years. Each type of agent is represented by different shape and color. Also, each type of agent state has different colors (Table 5-3). The simulation results enable us to understand the customer purchasing behaviors and the market movements more clearly.

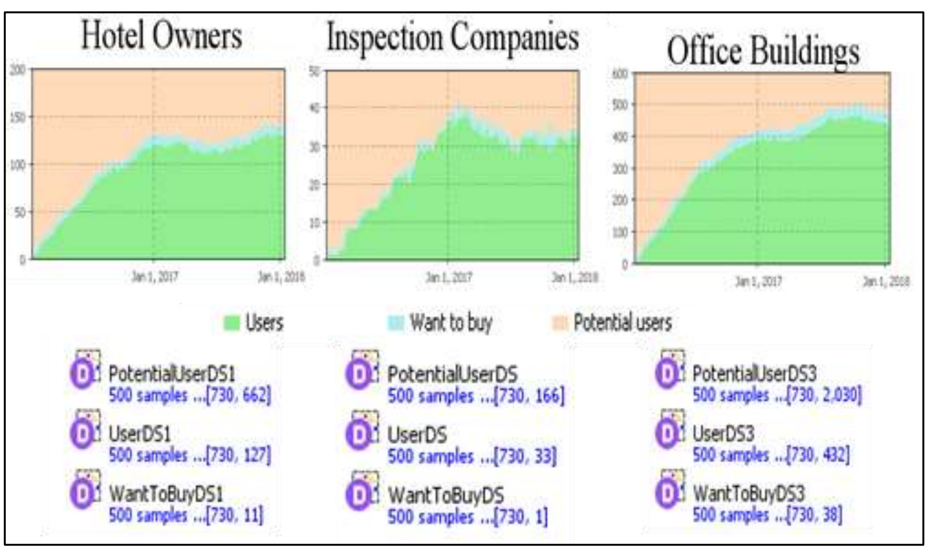


Figure 5-10: The time stack chart

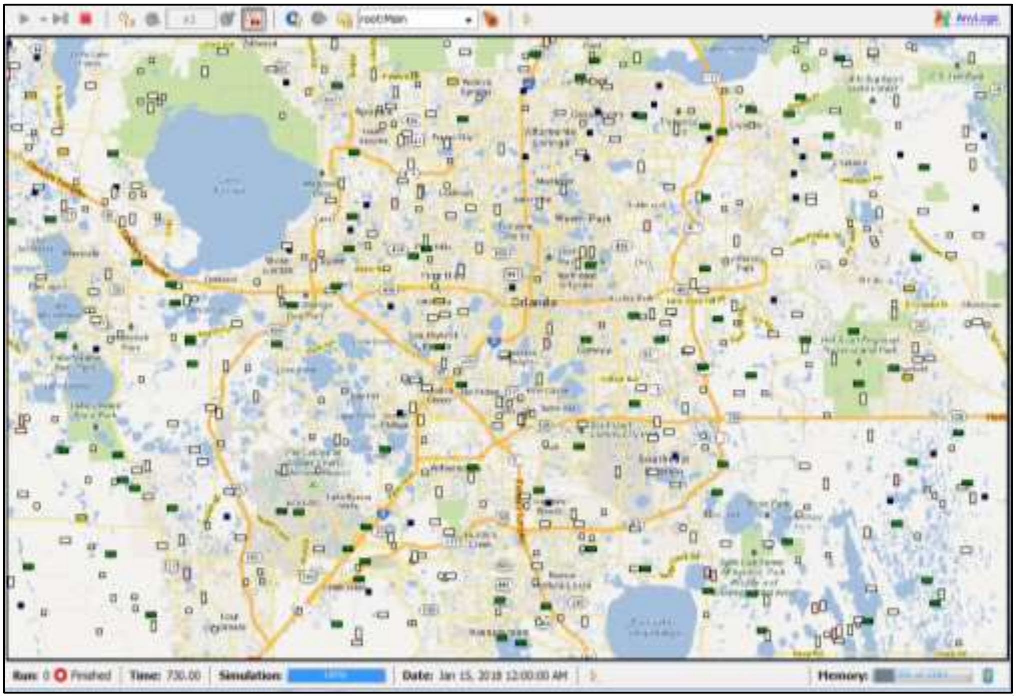


Figure 5-11: Model animation of agents in the city of Orlando (Florida, USA)

Table 5-3: Different colors for each type of agent in every state

Agent Type / **State**	**Hotel Owners**	**Inspection Companies**	**Office Buildings**
Potential User	Ivory	Light Yellow	Beige
Wants To Buy	Gold	Wheat	Azure
User	Green	Dark Blue	Pink

5.2.5 Conclusion and Future Work

The proposed framework of this study suggests using ABM as a tool to test the acceptance of an IoT business solution. This case study has validated step 3 of the framework which is the main focus of the research. This case study shows a positive outcome in this stage by investigating the potential of using ABM in IoT environment.

ABM applications have been increased lately. Many leading firms have realized the vitality of modeling their system using ABM. The capability of ABM to capture system complexity makes it distinctive from the other types of simulation such as system dynamics and discrete simulation. In customer market model, ABM enables the modeler to imitate detailed customer behaviors more than any static or equation-based models which allow higher quality predictions.

In this case study, the proposed analysis for a business model is a new concept that allows verifying the effectiveness of an IoT business model by considering the different required variables. Since testing the business model feasibility based on IoT using ABM simulation is at an early stage, the main focus of this case study was to introduce a conceptual approach by proposing a preliminary design. The future work includes the validation of ABM and increases the data sample size. The assumptions made related to advertisement effectiveness and WOM need further investigation in order to simulate agents' behavior variances Also, system dynamics fragments can be included in each agent of ABM to capture user's behavior continuous in time. Lastly, agent demographics can be included by considering the exact physical locations of each agent in Orlando city (Florida, United States) in order to simulate the differences in customer behavior according to agent's locations.

5.3 Case Study # 2

5.3.1 Introduction

Panda, one of the main organizations in the retail sector in Saudi Arabia, has an annual cost of 1.4 million dollars due to refrigerators failure and food waste. Panda suggests installation of condition monitoring sensors to its refrigerators could be one of the most logical solutions to have the greatest financial impact. The question that this case study aims to address is what are the benefits and ROI of installing remote condition monitoring sensors on Panda's refrigerators. The objective is to utilize agent-based model (ABM) in providing an answer to the problem. Installation these sensors would enable predictive maintenance capabilities through continuous remote condition monitoring. It would represent a significant step to realize the IoT.

Nowadays, there is interest in this type of solution within the industry (Houston et al., 2017). For example, many leading organizations are pursuing continuous condition monitoring in collaboration with big data analytics tools such as Microsoft Azure. However, a clear value of return on investment (ROI) does not exist for monitoring a refrigerator conditions and, as a result, few leading organizations are confident enough to invest in this technology (Houston et al., 2017). In this case study, the development of an agent-based model (ABM) makes it possible to potentially justify two types of IoT investments by investigating the what-if scenario where sensors are installed. ABM was initially built with limited details, and then it was further developed with sufficient level of details.

The highlighted elements in the proposed framework (Figure 5-12) are considered in this case study. As it is shown in the figure, the first two steps are generating ideas and understanding the IoT opportunities. After realizing the internet of things (IoT) challenges and opportunities described in chapter 2, now it is the time to develop an IoT solution and test its acceptance (step 3), which is the main focus of this study. The methodology followed for Panda's case study has some similarities to the one proposed by Houston et al. (2017).

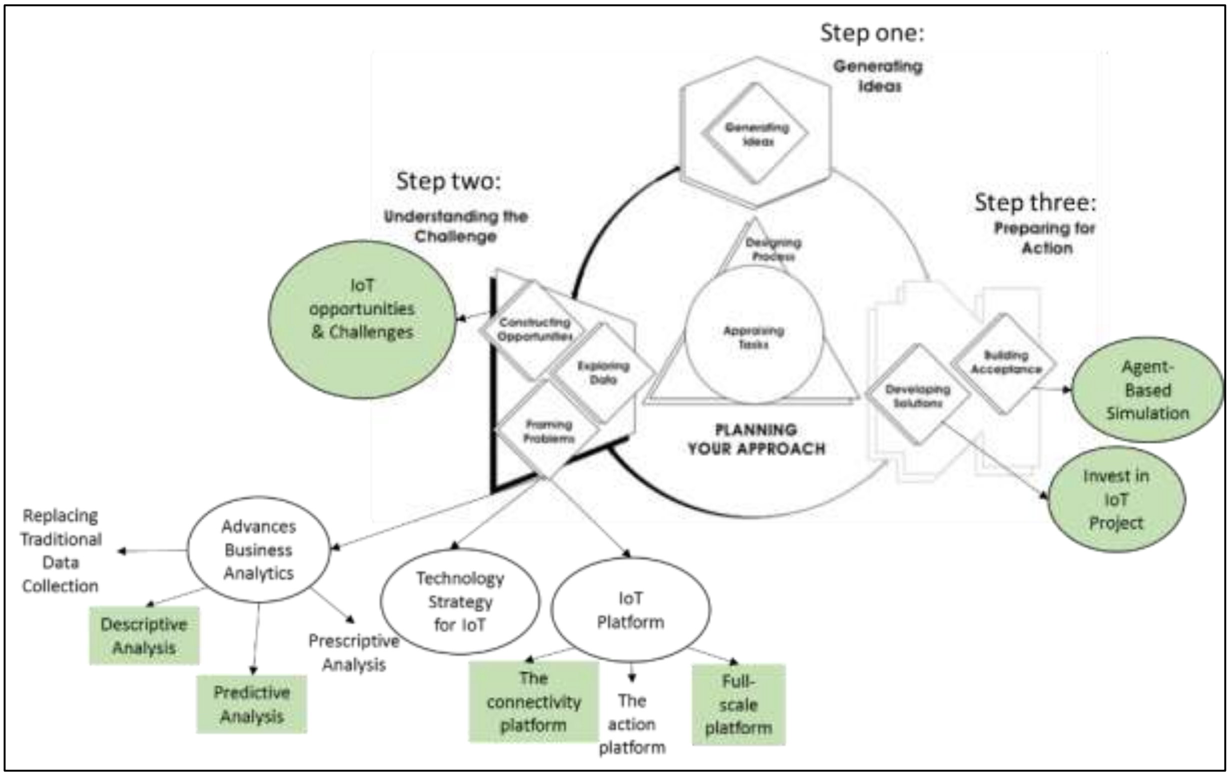


Figure 5-12: Proposed framework for case study # 2

5.3.2 Available Data

Panda has 7,420 refrigerators in 212 different stores in Saudi Arabia. There are three different types of refrigerators as shown in Figure 5-13. Failure data for each type was provided by Panda. Table 5-4 shows a sample of failure data (in days) of Panda's refrigerators.

Figure 5-13: Three different types of Panda's refrigerators

Table 5-4: Sample of failure data of Panda's refrigerators

	Time (Days)		
#	**Type A**	**Type B**	**Type C**
1	0.15	0.26	0.313
2	0.31	0.50	0.718
3	0.46	0.74	0.910
4	0.60	0.97	1.378
5	0.75	1.20	1.900
6	0.89	1.42	2.271
7	1.03	1.64	2.621
8	1.17	1.86	2.929
9	1.31	2.07	3.224
10	1.45	2.29	3.692
11	1.58	2.51	4.044
12	1.72	2.73	4.440
13	1.85	2.95	4.984
14	1.98	3.17	5.323
15	2.11	3.38	5.744
16	2.25	3.60	6.115
17	2.38	3.82	6.580
18	2.51	4.03	6.945
19	2.63	4.24	7.291
20	2.76	4.45	8.178

Since ABM model utilizes the integrated GIS functionality to locate Panda's stores in the model as well as automatically define the routes based on the roads from the GIS provider, coordinate data (longitude and latitude) for each Panda's store was necessary. Table 5-5 shows an example of coordinate data for 20 stores.

Table 5-5: Coordinate data for 20 Panda's stores

#	Store ID	Latitude	Longitude
1	70009	24.6939	46.6962
2	70007	24.6940	46.7270
3	70006	24.7199	46.6907
4	70005	24.6653	46.7110
5	70004	24.6500	46.7260
6	70002	24.6278	46.6817
7	70001	24.7419	46.8076
8	50004	24.6771	46.7439
9	50003	24.5986	46.6844
10	50002	24.6125	46.7271
11	50001	24.7607	46.6738
12	40021	24.1636	47.3328
13	40020	24.6384	46.6933
14	40016	26.3476	43.9771
15	40013	25.8677	43.4895
16	40012	26.3651	43.9353
17	40011	26.1567	43.6542
18	40009	26.4388	50.0714
19	40008	26.3047	50.1980
20	40006	27.1132	49.5371

5.3.2.1 Failure Probability

Insight into refrigerator's changing probability of failure over time is essential to reduce the risk of unnecessary time out of service. "In the field of reliability engineering, key concepts exist for evaluating the likelihood of asset failures" (Dhillon, 2002) and are summarized below.

"Firstly, if $t = 0$ be the time at which an asset is considered new, then random variable showing failure time $t = T$ could be described by a cumulative distribution function, $F(t)$. This gives the probability that an asset fails before or at time t. The probability density function, $f(t)$, characterizes the expected frequency of asset failures in the interval t to $t+dt$. In reliability engineering, it is typically common for these to be expressed in the form of a reliability function $R(t)$ which represents the probability of no failure occurring up to time t" (Houston et al., 2017). The failure data provided by Panda was analyzed. Each type of refrigerators has different failure data. $F(t)$, $R(t)$, $f(t)$, and $\lambda(t)$ were calculated using the equations shown in Figure 5-14.

i	Time (Days)	R(t)	F(t)	f(t)	h(t)
0	0.00	1	0	0.02146	0.02146
1	0.15	0.99668	0.00332	0.02168	0.02175
2	0.31	0.99336	0.00664	0.02256	0.02271
3	0.46	0.99003	0.00997	0.02253	0.02276
4	0.60	0.98671	0.01329	0.023	0.02331
5	0.75	0.98339	0.01661	0.02362	0.02402
6	0.89	0.98007	0.01993	0.02391	0.0244
7	1.03	0.97674	0.02326	0.02385	0.02442
8	1.17	0.97342	0.02658	0.0238	0.02445
9	1.31	0.9701	0.0299	0.02374	0.02447
10	1.45	0.96678	0.03322	0.02444	0.02528
11	1.58	0.96346	0.03654	0.02472	0.02565
12	1.72	0.96013	0.03987	0.02483	0.02586
13	1.85	0.95681	0.04319	0.02505	0.02618
14	1.98	0.95349	0.04651	0.02522	0.02645
15	2.11	0.95017	0.04983	0.02535	0.02667
16	2.25	0.94684	0.05316	0.02534	0.02677
17	2.38	0.94352	0.05648	0.02576	0.0273
18	2.51	0.9402	0.0598	0.02578	0.02742

$$\hat{R}(t_i) = \frac{n+1-i}{n+1}$$ Reliability

$$\hat{F}(t_i) = 1 - \hat{R}(t_i) = \frac{i}{n}$$ Cumulative distribution function

$$\hat{f}(t) = -\frac{\hat{R}(t_{i+1}) - \hat{R}(t_i)}{t_{i+1} - t_i}$$ Probability density function

$$\hat{\lambda}(t) = \frac{\hat{f}(t)}{\hat{R}(t)} = \frac{1}{(t_{i+1} - t_i)(n+1-i)} \quad \text{for } t_i < t < t_{i+1}$$ Failure Rate

Figure 5-14: F(t), R(t), f(t), and λ(t) for failure data

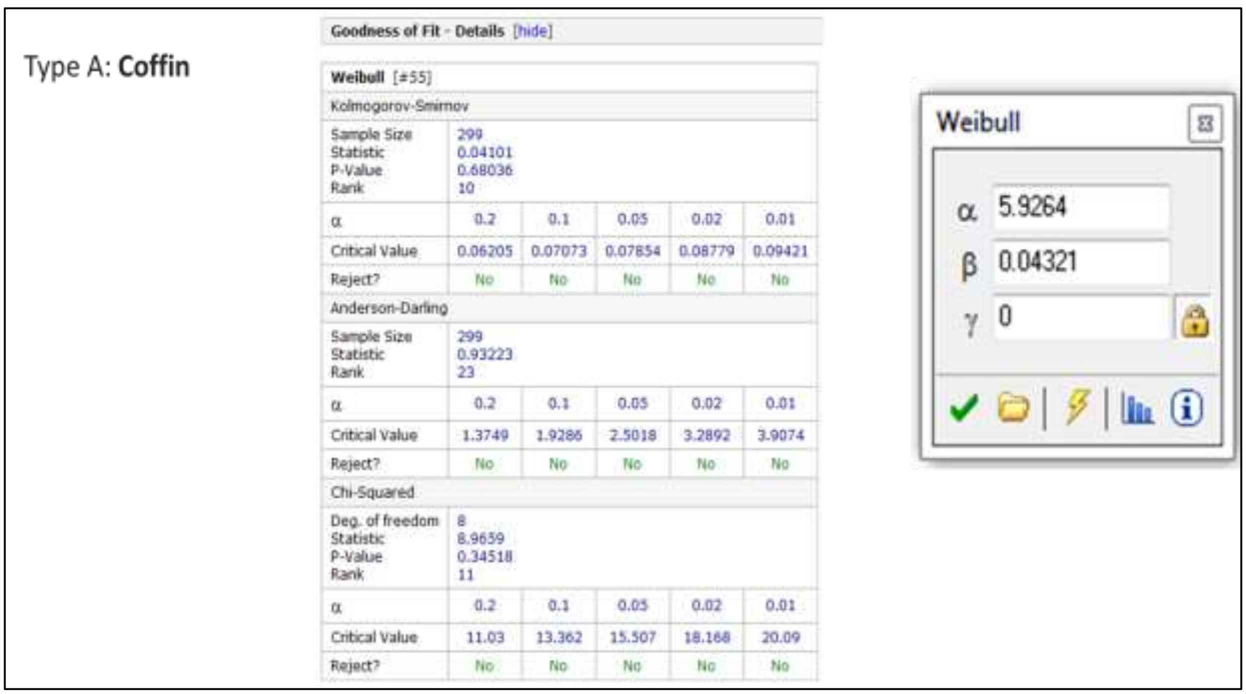
Reliability modeling based on lifetime distributions is perhaps one of the most commonly used reliability engineering techniques. This technique enables predicting the reliability of a component or the probability that a component will complete its required function during a certain period of time under stated conditions (Mathwave, 2004).

To develop a valid ABM model, an appropriate probability distribution should be selected and used for modeling survival data. Since survival times are non-negative by nature, it makes sense to use probability distributions having a non-negative range of definition. In reliability analysis, several probability distributions are commonly used. Among them are the Exponential, Weibull, and Lognormal distributions.

It is very significant to choose the best fitting survival distribution because the model it represents will be used to make key decisions. For example, Exponential distribution cannot be chosen just because it is the simplest one. The use of incorrect models can lead to serious problems such as damage to expensive equipment. The best way to prevent possible modeling errors, develop more valid models, and thus make better decisions, is to apply distribution fitting. This technique allows choosing the probability distribution that best describes the reliability of a component, based on available historical data. However, the use of the distribution fitting is attached to complex calculations that require special knowledge in the field of programming skills and statistics (Mathwave, 2004).

The concern of selecting the best fitting distribution can be easily solved by using the specialized distribution fitting software EasyFit (distribution fitting software). EasyFit software is designed to automate the whole distribution fitting process. It performs all required calculations.

All the failure rate data for the three types of Panda refrigerators (A, B, and C) was analyzed using EasyFit to select the best fitting distribution. The goodness of fit tests (Kolmogorov-Smirnov, Anderson-Darling, and Chi-squared) to compare the fitted distributions were applied. The selected probability distribution and the goodness of fit tests result from EasyFit for refrigerators A, B, and C are shown in Figure 5-15, Figure 5-16, and Figure 5-17 respectively.



Type A: **Coffin**

Goodness of Fit - Details [hide]

Weibull [#55]					
Kolmogorov-Smirnov					
Sample Size Statistic P-Value Rank	299 0.04101 0.68036 10				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.06205	0.07073	0.07854	0.08779	0.09421
Reject?	No	No	No	No	No
Anderson-Darling					
Sample Size Statistic Rank	299 0.93223 23				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	1.3749	1.9286	2.5018	3.2892	3.9074
Reject?	No	No	No	No	No
Chi-Squared					
Deg. of freedom Statistic P-Value Rank	8 8.9659 0.34518 11				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	11.03	13.362	15.507	18.168	20.09
Reject?	No	No	No	No	No

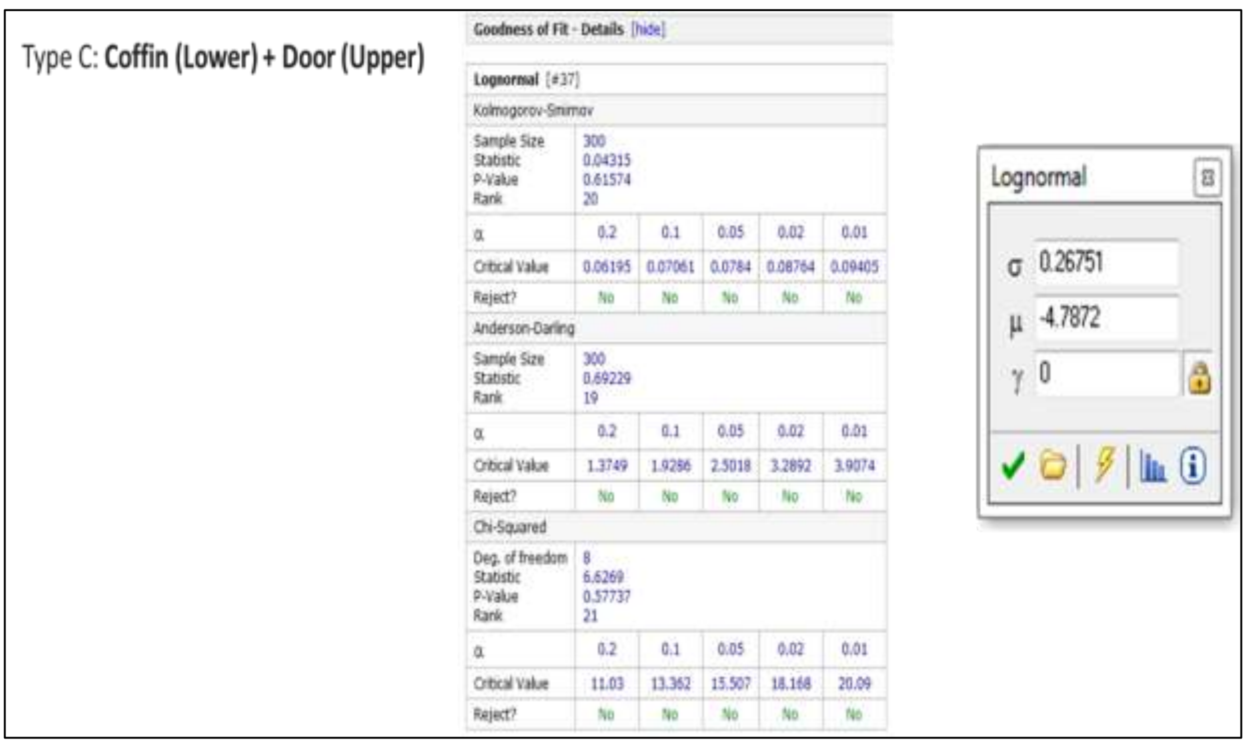
Figure 5-15: Probability destitution for refrigerator Type A

Kolmogorov-Smirnov					
Sample Size	299				
Statistic	0.03595				
P-Value	0.82076				
Rank	2				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.06205	0.07073	0.07854	0.08779	0.09421
Reject?	No	No	No	No	No

Anderson-Darling					
Sample Size	299				
Statistic	0.69838				
Rank	17				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	1.3749	1.9286	2.5018	3.2892	3.9074
Reject?	No	No	No	No	No

Chi-Squared					
Deg. of freedom	8				
Statistic	5.6281				
P-Value	0.68881				
Rank	2				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	11.03	13.362	15.507	18.168	20.09
Reject?	No	No	No	No	No

Figure 5-16: Probability destitution for refrigerator Type B



Kolmogorov-Smirnov					
Sample Size	300				
Statistic	0.04315				
P-Value	0.61574				
Rank	20				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	0.06195	0.07061	0.0784	0.08764	0.09405
Reject?	No	No	No	No	No

Anderson-Darling					
Sample Size	300				
Statistic	0.69229				
Rank	19				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	1.3749	1.9286	2.5018	3.2892	3.9074
Reject?	No	No	No	No	No

Chi-Squared					
Deg. of freedom	8				
Statistic	6.6269				
P-Value	0.57737				
Rank	21				
α	0.2	0.1	0.05	0.02	0.01
Critical Value	11.03	13.362	15.507	18.168	20.09
Reject?	No	No	No	No	No

Figure 5-17: Probability destitution for refrigerator Type C

For refrigerator type A, the following reliability function graph (Figure 5-18) help to visually compare the fitted Weibull distribution with the empirical reliability function.

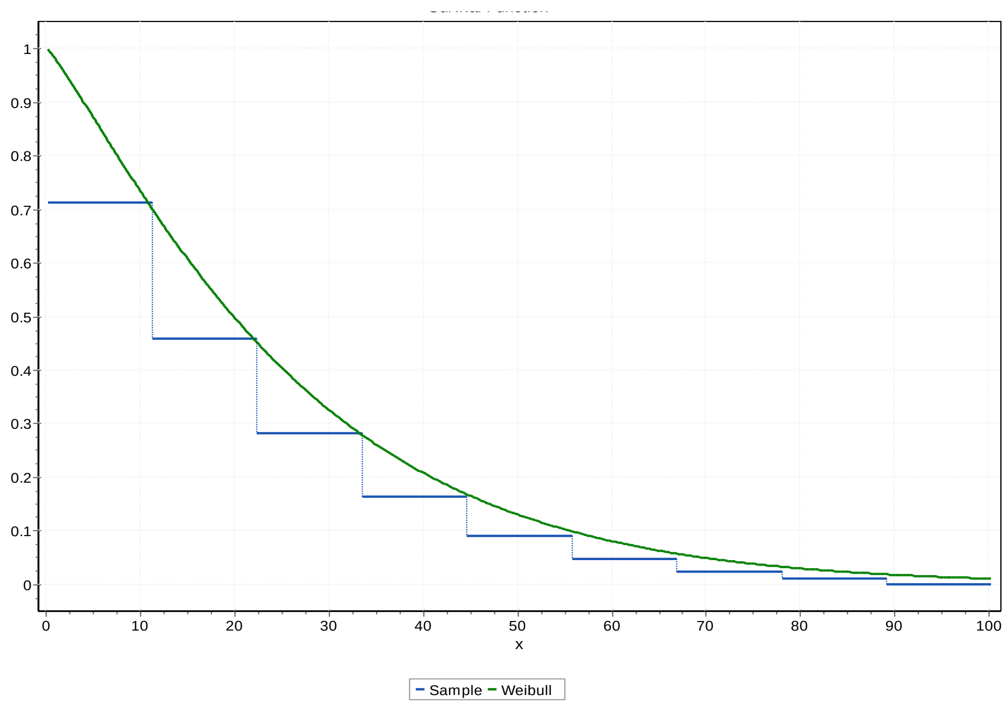


Figure 5-18: Survival function graph for refrigerator type A

5.3.3 Simulation Model Preparation

5.3.3.1 Simulation Model Purpose

The wide purpose of ABM model is to investigate a process for establishing the ROI of ventures related to the internet of things (IoT) in Panda Stores. More specifically, ABM aims to assess the ROI of installing condition monitoring sensors on Panda's refrigerators. This would allow the Panda manager to detect the failure and schedule predictive maintenance before potentially costly failures occur. The scope of this simulation covers refrigerators -related failures at Panda Stores.

5.3.3.2 Process Overview

Figure 5-19 shows a Unified Modeling Language (UML) state diagram of the refrigerators in Panda stores. The agent moves in a cyclic process between working normally, failing and getting a repair. Each type of refrigerators (A, B, and C) moves from working state to failure state based on a different failure probability. Then after some period, a failed refrigerator will be inspected and then decided what type of repair it needs. Finally, it will go back to be working normally after getting fixed.

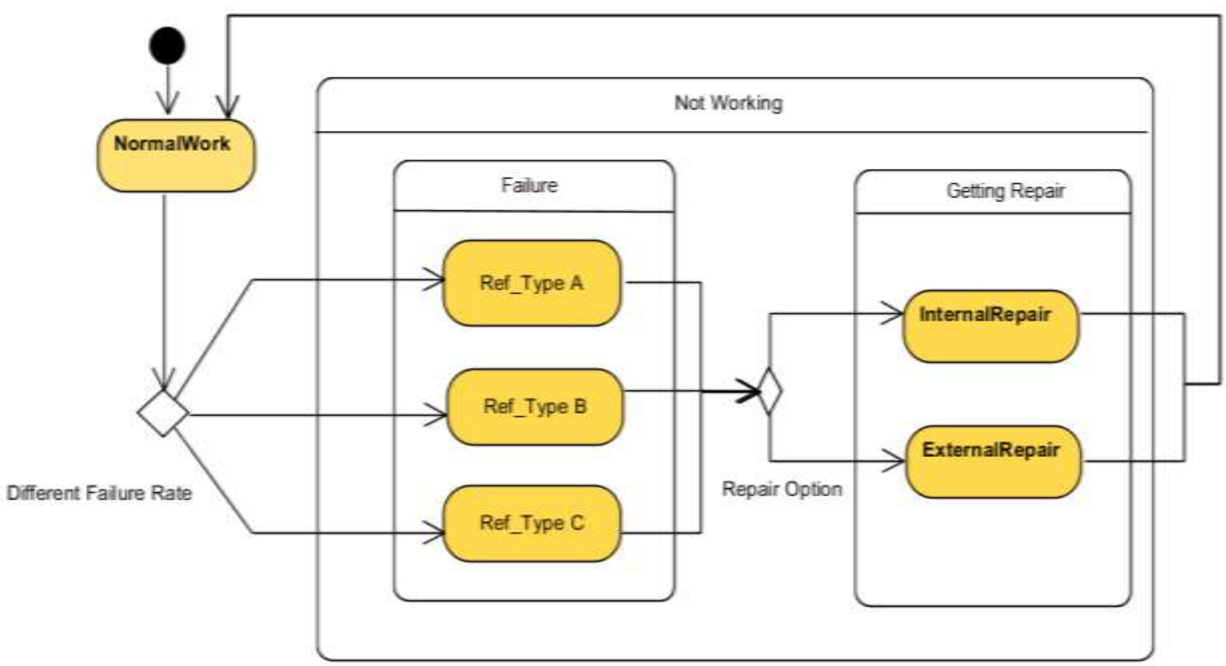


Figure 5-19: UML state diagram for the refrigerators in Panda stores

In order to describe the structure of the system, a UML class diagram shown in Figure 5-20 was developed. This class diagram shows the system's classes, their attributes and the relationships between agents and objects.

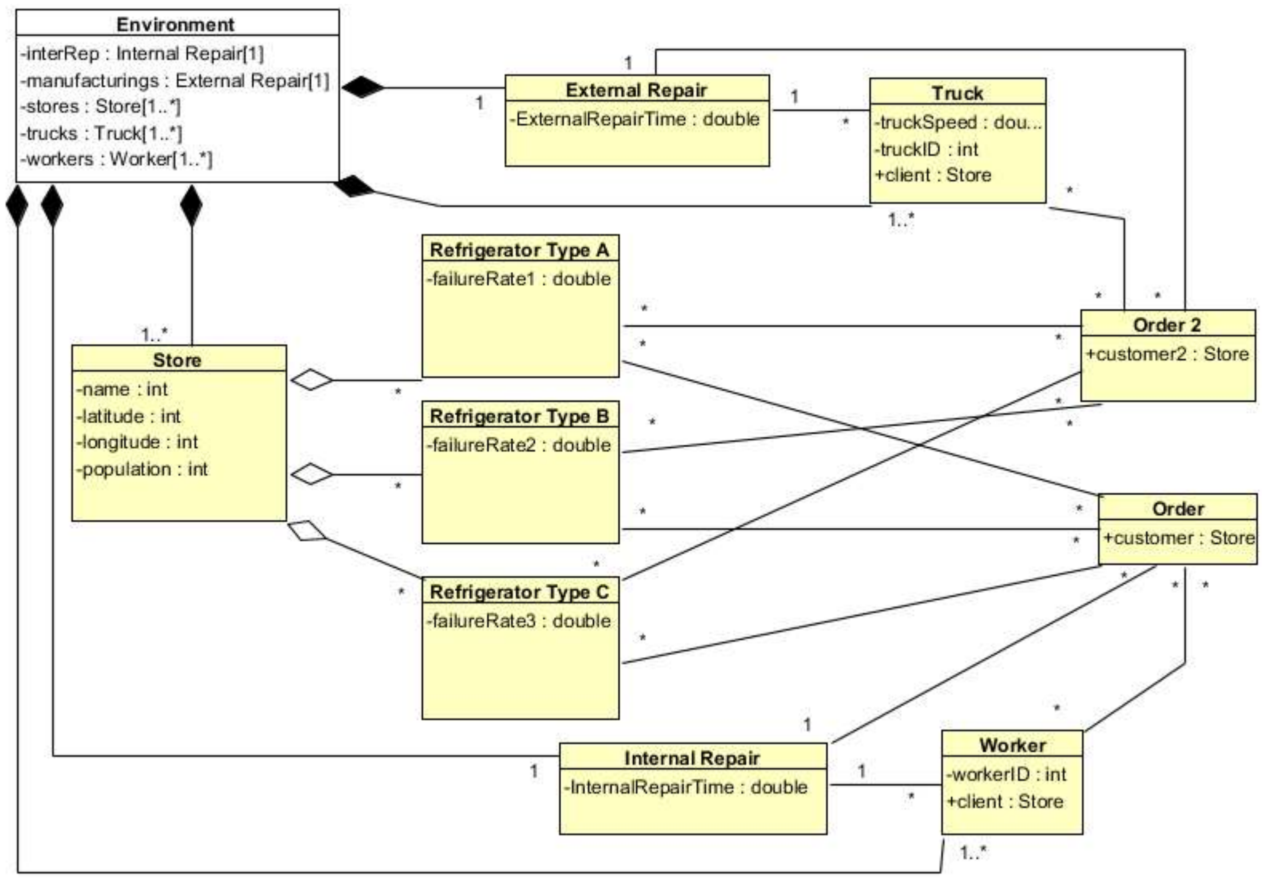


Figure 5-20: UML class diagram displays links between objects and agents

A UML sequence diagram was also developed (Figure 5-21) to show agents communications arranged in time sequence. It shows the sequence of messages exchanged between the agents needed to perform the functionality of different scenarios.

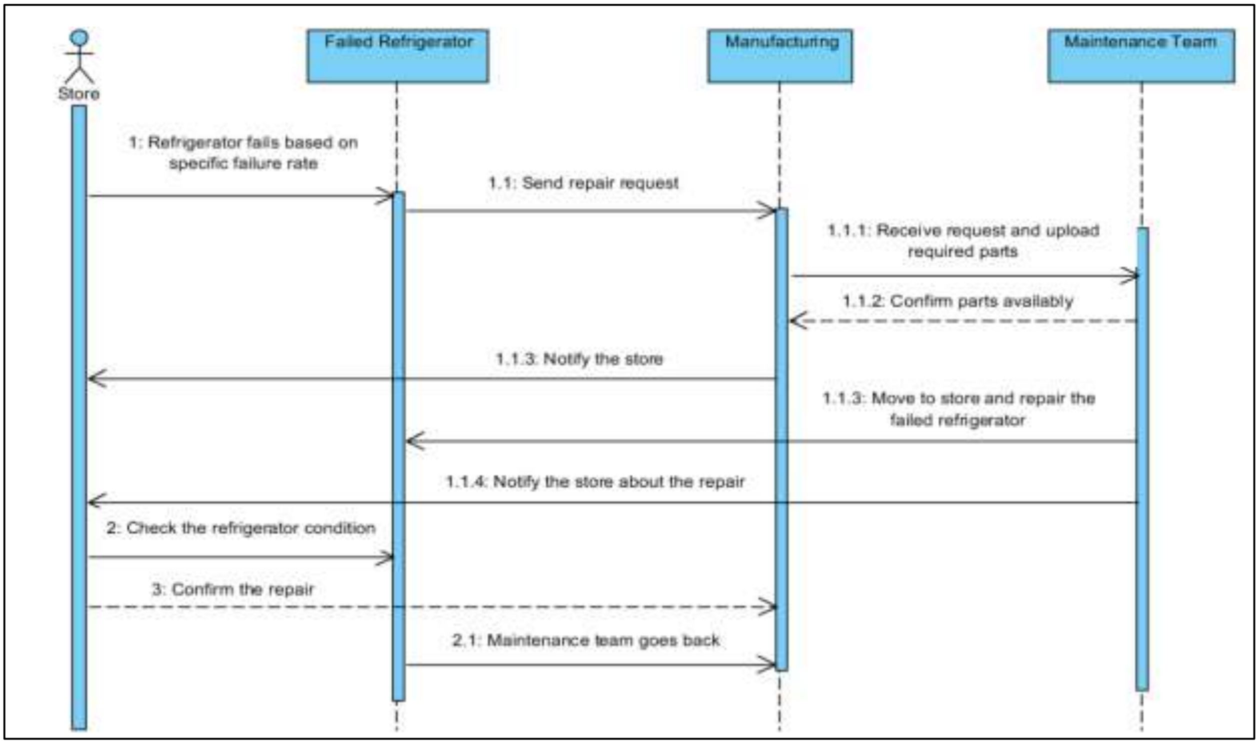


Figure 5-21: UML sequence diagram shows the sequence of messages exchanged

5.3.3.3 Initialization

Table 5-6 summarizes all parameter values in the ABM. A Total of 7,420 refrigerators is presented in the model.

Table 5-6 Values of the different parameters in the simulation

Parameter	Value	Units	Source
Refrigerator Type A Failure	Weibull (5.9,0.043)	n/a	Analysis of Failure Dataset
Refrigerator Type B Failure	Lognormal (-3.7,0.229)	n/a	Analysis Failure Dataset
Refrigerator Type C Failure	Lognormal (-4.79,0.26)	n/a	Analysis Failure Dataset
Replacement Probability	10	%	Panda Refrigerators Specialist
Internal Repair Time	3.9	Hour	Calibration
External Repair Time	8.6	Hour	Calibration
Panda Response Rate	0.8	Rate	Panda Manager
Total Number of Refrigerators	7,420	Refrigerators	Panda Manager
Number of Stores	212	Stores	Panda Manager
Average Number of Refrigerators per Store	35	Refrigerators	Panda Manager
Truck Loading Time	Uniform (2,3)	Hour	Assumption
Truck Speed	60	Mile/hour	Panda Manager
Cost of Internal Repair	1,600	$	Panda Refrigerators Specialist
Cost of External Repair	4,500	$	Panda Refrigerators Specialist
Cost of food waste/ Refrigerator	650	$	Panda Refrigerators Specialist
Cost of Out of Service / Refrigerator / Day	10	$	Panda Refrigerators Specialist

5.3.4 Simulation model

At this time a complete picture of the system is clear, and it is time to develop a simulation model. Discrete-event and agent-based model are used. The hybrid model is programmed in a simulation software called "AnyLogic." The software is capable of merging and combining different types of simulation, discrete-event simulation (DES), agent-based simulation (ABM), and system dynamics (SD), in one model. According to Liraviasl, ElMaraghy, Hanafy, and Samy (2015), AnyLogic is a useful simulation tool to model a hybrid simulation model. This software it is based on Java object-oriented programming language that used to structure the behavior of the individual agents. Also, AnyLogic can imitate any communication that could happen between agents and their environment (Nagadi, 2016). Prior simulation modeling, various assumptions are considered including:

- Workers are always available for internal repair
- Trucks are always available for external repair
- Worker movement time inside the store is neglected in the model
- Loading time with ordered spare parts in the truck requires 2 to 3 hours
- Queue in the model is based on FIFO (first in first out)
- Refrigerators have the same behavior with different parameters values

The following of this section is divided into the agent-based model (ABM), an updated simulation model, Hybrid model, simulation validation, and financial consideration of IoT investments for Panda.

5.3.4.1 Agent-Based Model

The basic principle of the agent-based model is that ABM is used to test the hypothesis that installing condition monitoring sensors on refrigerators in Panda will reduce the costs. The main principle includes comparing results from a base case, where no sensors installed and no predictive maintenance is applied, to simulations with installed sensors and predictive maintenance.

In this research, Panda store is considered as an agent. Stores have its own statechart to represent their behavior. The population of the agent (store) contains 7,420 (refrigerators). Each store has an average of 35 refrigerators. Different states for stores were identified. Figure 5-22 depicts how the statechart is modeled in the software.

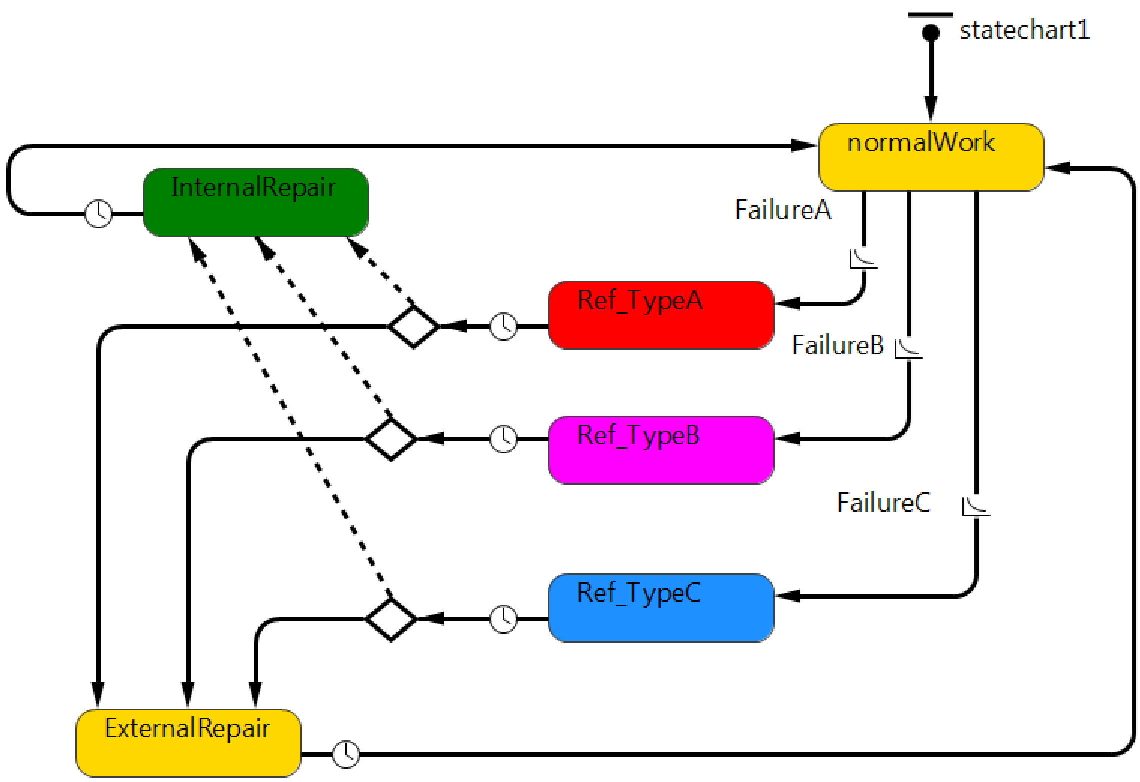


Figure 5-22: Store statechart

Experts from Panda agreed that these states represent the different states that a refrigerator in the store can take. There are transitions along with these states. As mentioned earlier, transitions are based on events. Figure 5-23 shows the different parameters that create these events. If needed, the model provides the option to adjust these parameters during the runtime based on the boundaries provided by the experts.

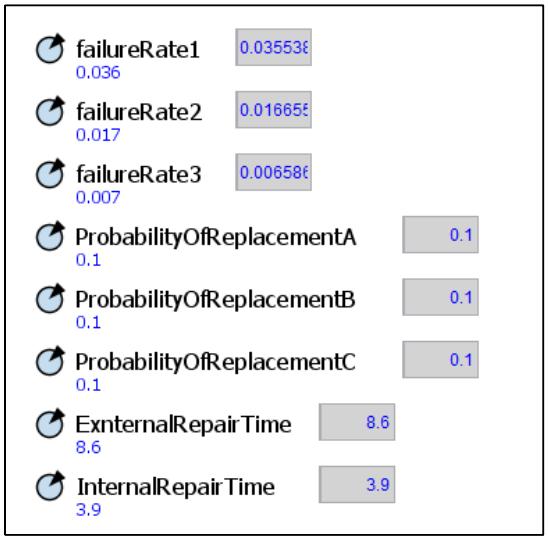


Figure 5-23: Example of different input parameters from AnyLogic

Initially, refrigerators are in the *normalWork* state (Figure 5-22). Each refrigerator type (A, B, and C) move from *normalWork* state to failure state (*Ref_TypeA*, *Ref_TypeB*, *and Ref_TypeC*,) based on a specific failure rate defined in their transition. Each transition is stochastic and depends on its probability distribution which was defined based on the analysis of failure data in section 5.3.2.1 (Figure 5-24). In this case, the refrigerator turns to the failure state; where it is not working and waiting for the service crew to arrive. **A lack of IoT feature is a clear gap in this incident**. There is no automated high-tech data collection for failures and its causes. Thus, failures are not predicted in Panda which causes food waste and unwanted costs.

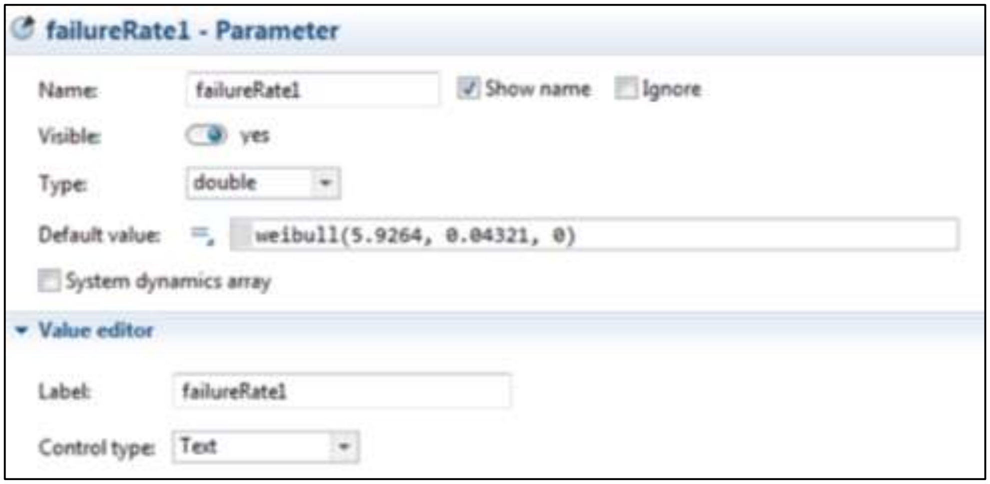


Figure 5-24: The failure rate parameter for refrigerator type A

After the failure occurs, refrigerator specialist decides whether a refrigerator need an internal or external repair (Figure 5-25). Based on Panda specialist, replacement policy (external repair) exists nearly 10% of the times (Figure 5-26). After that, service crew arrives to do the repairing task. Based on Panda expert the internal repair takes from 3 to 5 hours while the external repair takes 6 to 12 hours. By default, after repair, the refrigerator goes to *normalWork* state again.

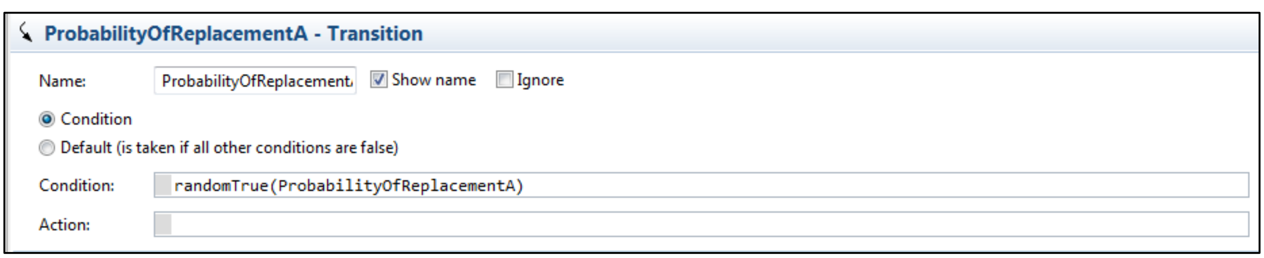


Figure 5-25: Replacement policy transition

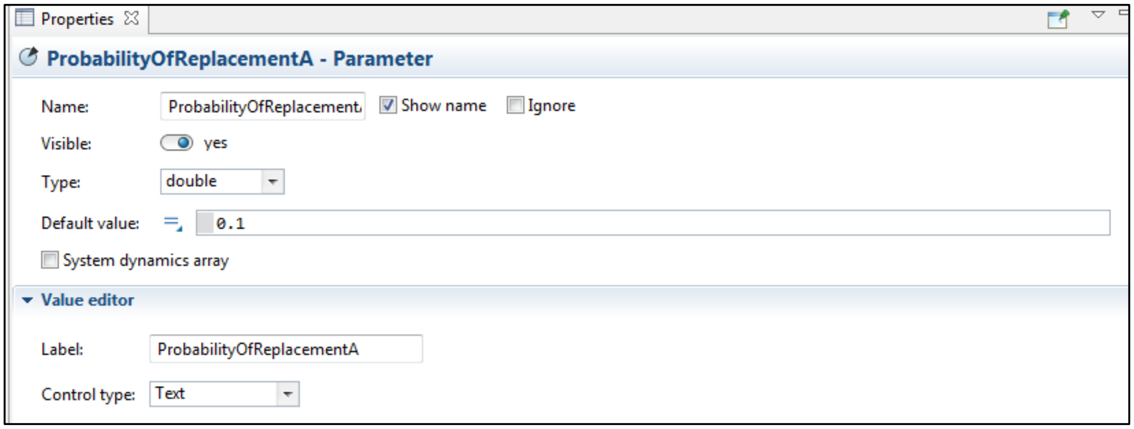


Figure 5-26: Replacement parameter

5.3.4.2 Updated Simulation Model

Panda with the current situation does not have enough information when and why its refrigerators fail. An effective approach to infer refrigerator condition is the use of sensors to collect motion and vibration data. This data can then be transferred to an online platform where data analytics techniques are utilized to realize the evolution of these variables over time. Observed trends help to imminent failure that may be prevented by planning maintenance actions on the offending component (Houston et al., 2017).

Assume that each refrigerator is connected to a sensor that records information about failures. At the same time, installed sensors can send messages to the service team in case of failure. Ideally, each refrigerator (sensor) is connected to a central warehouse unit which is connected to ABM that is able to analyze the real-time data.

Three potential sensors were evaluated: Libelium Waspmote, the Genuino 1000, and Wzzard sensing hardware. While the Genuino sensor is maintained by a solid open source community, the specification of this type of sensor shows that it does not possess the comprehensive power management abilities of those designed primarily for the industrial setting (Houston et al., 2017). Moreover, its lower unit price would be more than offset by extra costs incurred in the process of certifying this sensor. The Libelium Waspmote, on the other hand, has a higher purchase price, and its dimensions would potentially restrict its installation onto the refrigerator. These considerations suggest the Wzzard would be the most appropriate platform in this application (Figure 5-27).

Figure 5-27: Three different types of sensors

The level of complexity of ABM will be increased in order to capture this new situation. Changes are applied to the statechart and sequence messaging diagram of Panda. In this case, when a failure occurs in a refrigerator, a service request will be sent to the control unit.

The updated simulation model is comprised of several agents consisting of a network of regional stores, a single manufacturer, trucks, workers, and orders. The ABM model uses the integrated GIS functionality to locate the stores in the model as well as automatically define the routes based on the roads of Saudi Arabia from the GIS provider. Based on latitude and longitude data (Table 5-5), each Panda store is placed exactly where it is located in GIS map of Saudi Arabia (Figure 5-35). Orders are created by the stores and received by the manufacturer (external repair) and workers (internal repair). These orders are represented by agents and communicate between the stores, the manufacturer and the workers. After receipt of any order, loading the truck is modeled with a process logic embedded within the manufacturing agent. When the truck is loaded, the order is delivered to the requesting store and unloaded and sent back to the manufacturer. In order to simulate this, the following steps have to be performed (Baggio, 2015):

1. Set locations of the stores and manufacturer using the GIS capabilities in AnyLogic. The routes will automatically be created from the same GIS functionality.

2. Establish the process of ordering refrigerators spare parts and communicate the orders between the stores and manufacturer agents.

3. Build the manufacturer's logic containing order processing, truck loading, and unloading, delivery receipt notification and truck return.

In the first step, GIS Map in AnyLogic will be used for map region selection and agent locations as shown in Figure 5-28.

Figure 5-28: Display of the GIS map object

By clicking on the map object, the properties tap allows selecting the routes that will be generated during model execution either from PBF file or OSM server, the criteria for route selection (shortest, fastest), the road type such as a car, bike or walking, and other properties. In ABM model, shortest and OSM (open street maps) are chosen (Figure 5-29).

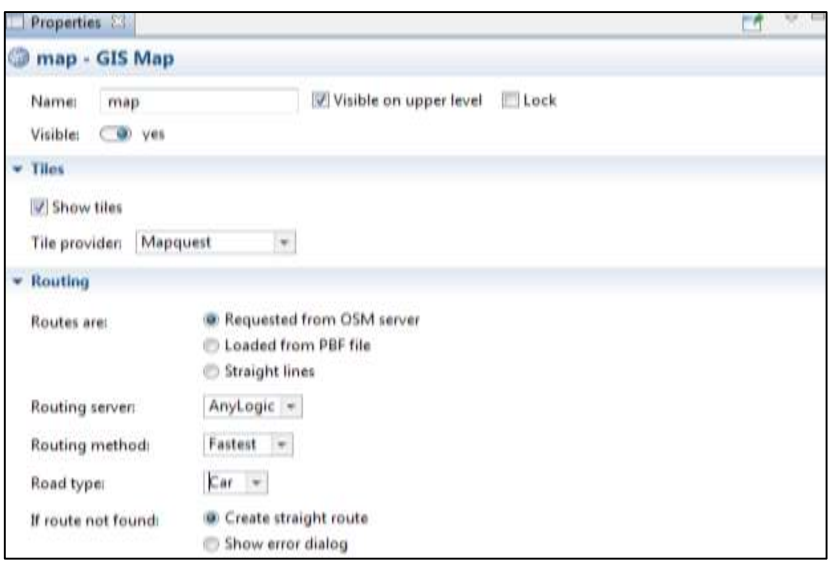


Figure 5-29: Map object properties

Since the coordinates for all of the 212 panda stores is stored in Excel file named “location”, the option “Loaded from database” is selected and the excel file “location” is chosen to identify the exact physical locations for each Panda store in Saudi Arabia map (Figure 5-30). The option “Multiple agents per record” is selected to determine the population of the agent (Figure 5-31). After this step, the statechart of Panda refrigerators demonstrated previously in Figure 5-22 in will be added.

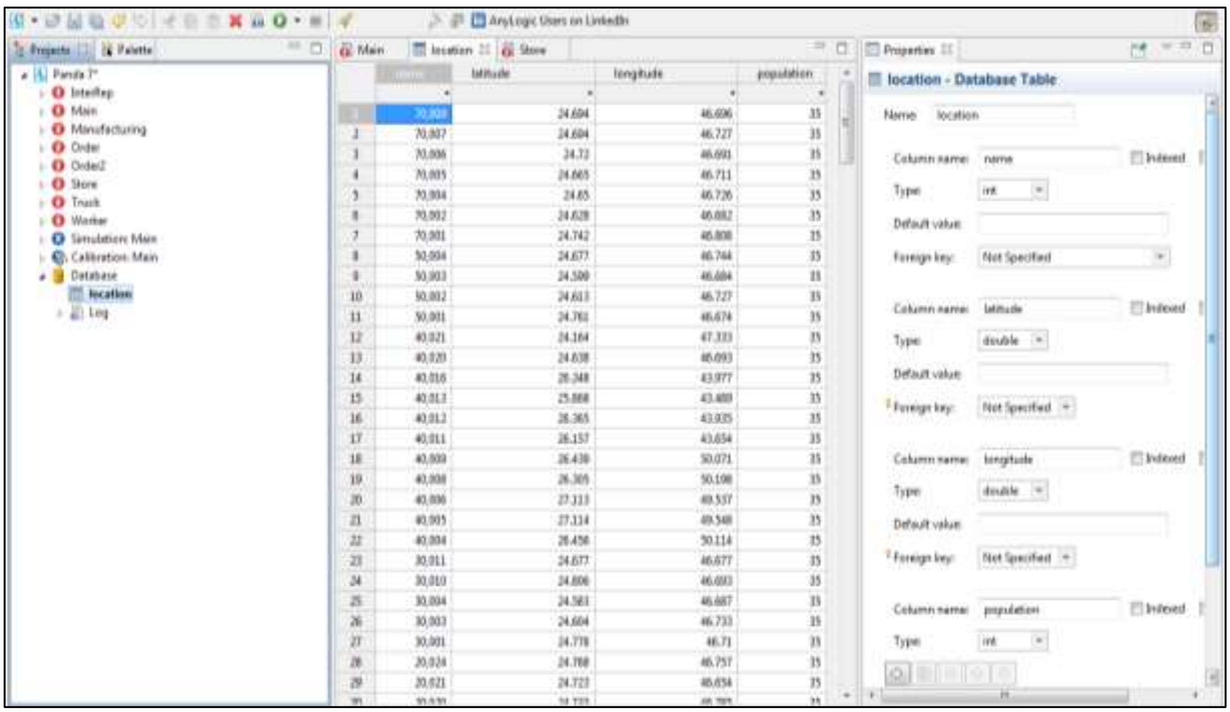


Figure 5-30: Latitude and longitude data for each Panda stores

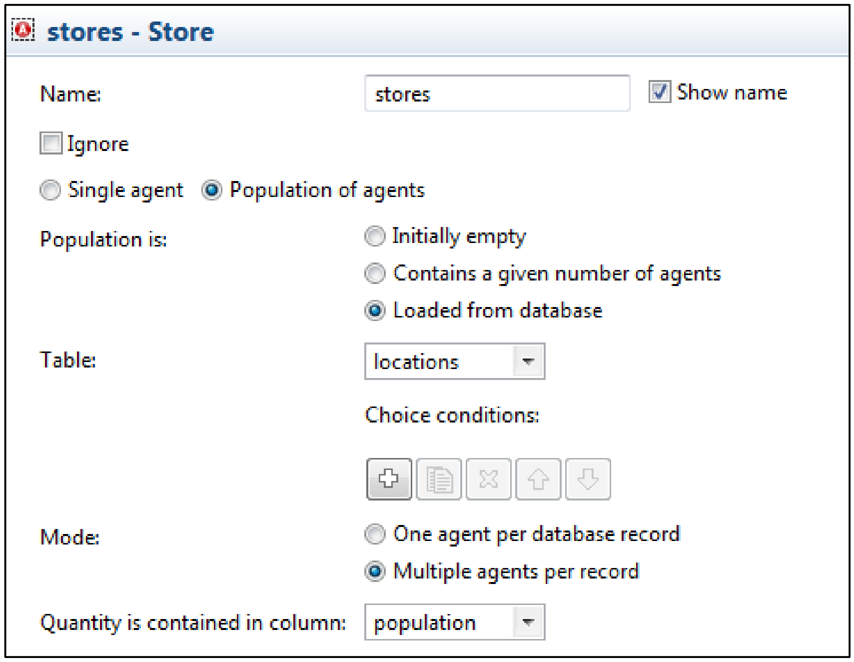


Figure 5-31: Population of agents

❖ New agents in the updated simulation model include:

- Internal repair agent (External repair)
- Manufacturing Agent (External repair)
- Truck agent
- Worker agent
- Order agent
- Order 2 agent

➢ Internal repair agent and manufacturing Agent

The manufacturing agent (external repair) should be linked with the mark on the map. The initial location of the manufacturing will be identified by selecting the option "in the node" and from the drop-down list, Riyadh will be selected (Figure 5-32). The location of the internal repair agent will be the same as the store locations.

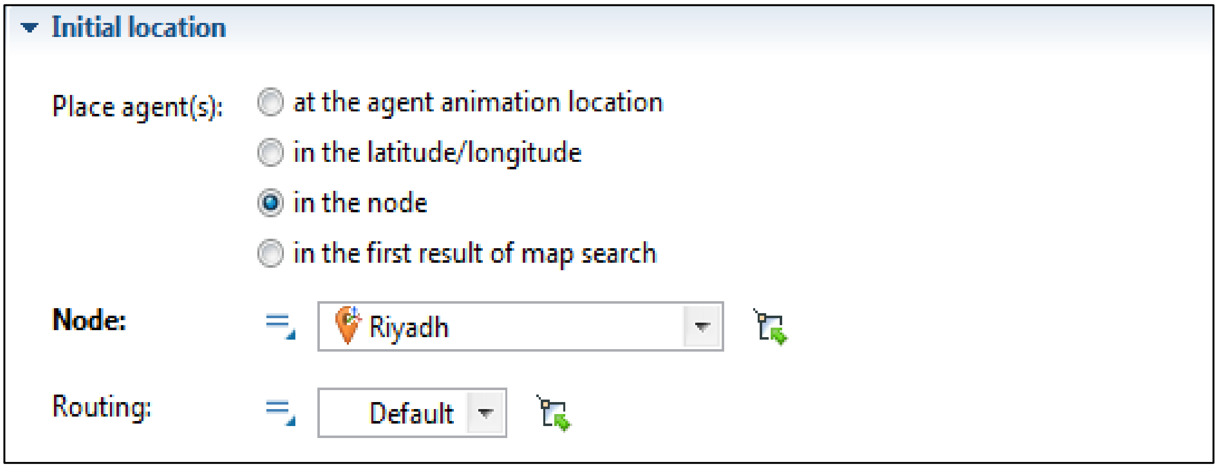


Figure 5-32: Manufacturing agent properties window

➢ Work and Truck agent

It is clear that all trucks in ABM model are owned by the manufacturing agent**.** It is necessary to identify the starting location in the agent population trucks properties, such as in Figure 5-33. The location of the worker agent will be the same as the store locations.

"Client" parameter is added to both agents (worker and truck) as a placeholder (or pointer) for which store has created the order and is requesting this specific order. The "Client" parameter is declared as a type "store" so that the simulation can easily determine which store has requested this specific order. Similar parameters in the "customer" and "customer2" in the Order and Order2 agents are used, and order's customer and order2's customer2 are assigned to the worker and truck's client.

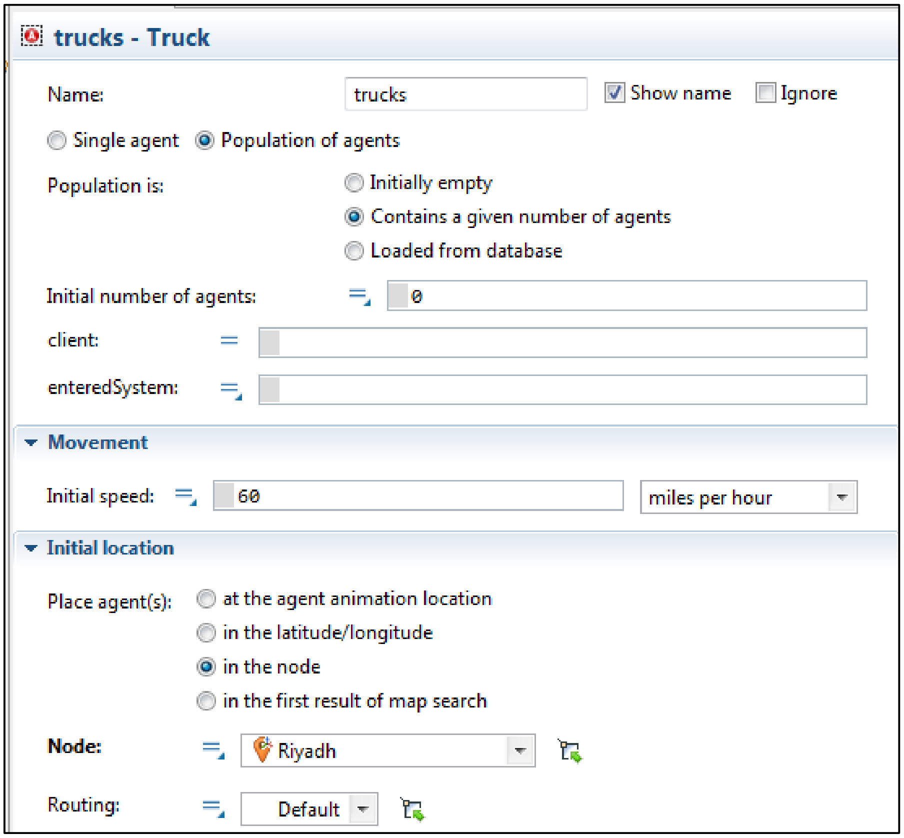


Figure 5-33: Truck agent properties, starting location set to GIS node Riyadh

Order & order 2 agents

Stores should fill out an order when a refrigerator fails. “Order” is created when a refrigerator needs an internal repair while “Order 2” is generated in case a refrigerator needs to obtain spare part (external repair). The parameters “customer” and “customer 2” are declared as a type “store.” This will be valuable as the orders are created by stores and received by the manufacturers (external repair) and internal repair. Also, these parameters are used in the order agent to assign the refrigerator in the store that has created the order to the worker and delivery truck.

It is now necessary to show that trucks are a resource of the manufacturing agent. To do this, a resource pool will be added to the manufacturing agent from the palette Process Modeling Library, that identifies a set of available resources. (Figure 5-34).

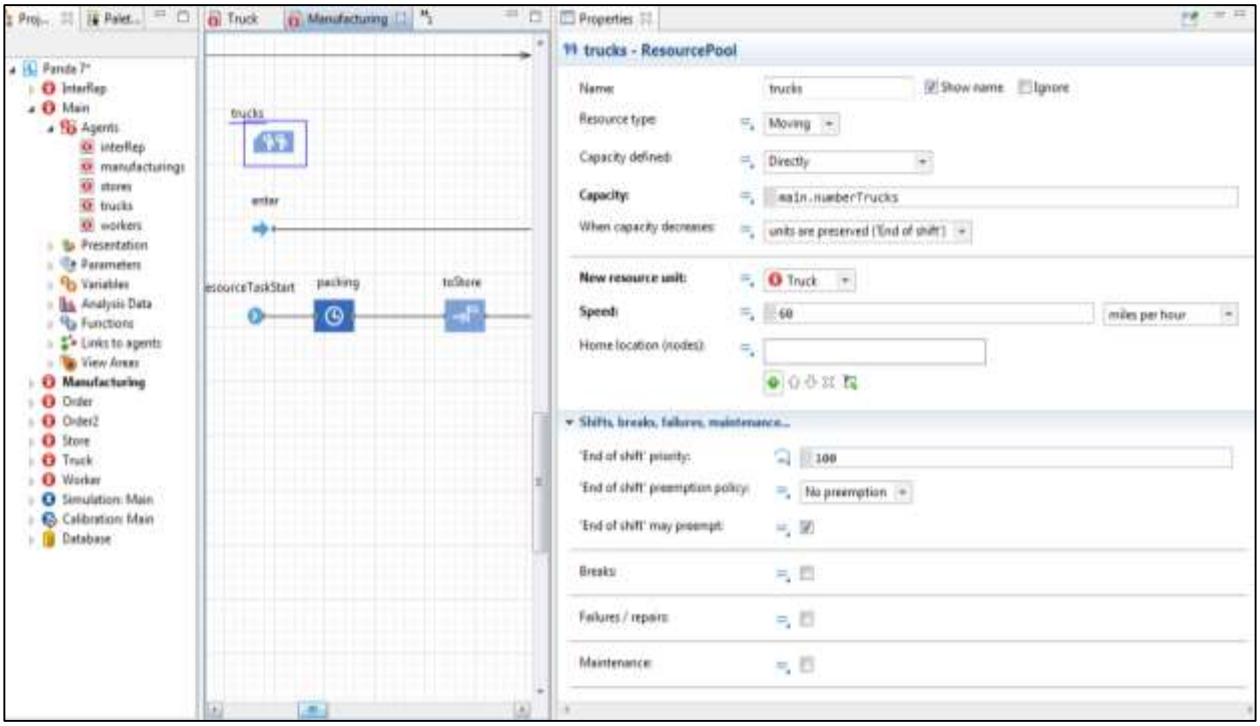


Figure 5-34: Truck agent properties window

The initial data entry can be considered finalized. Initial data includes stores (their coordinates), production (coordinates), trucks (as a resource for manufacturing), created an application for ordering (such as agent type order). Figure 5-35 shows a model run with stores, manufacturing, and truck Agents displayed.

Figure 5-35: Model run with stores, manufacturing, and truck agents displayed

❖ The Stores States and Orders:

As soon as the refrigerator fails, an order has to be filled out and sent to the store management (internal repair) or manufacturer (external repair). First, an order needs to be created and then sent. Figure 5-36 shows an example of a JAVA code used to create “order 2” and send it to manufacturing (external repair).

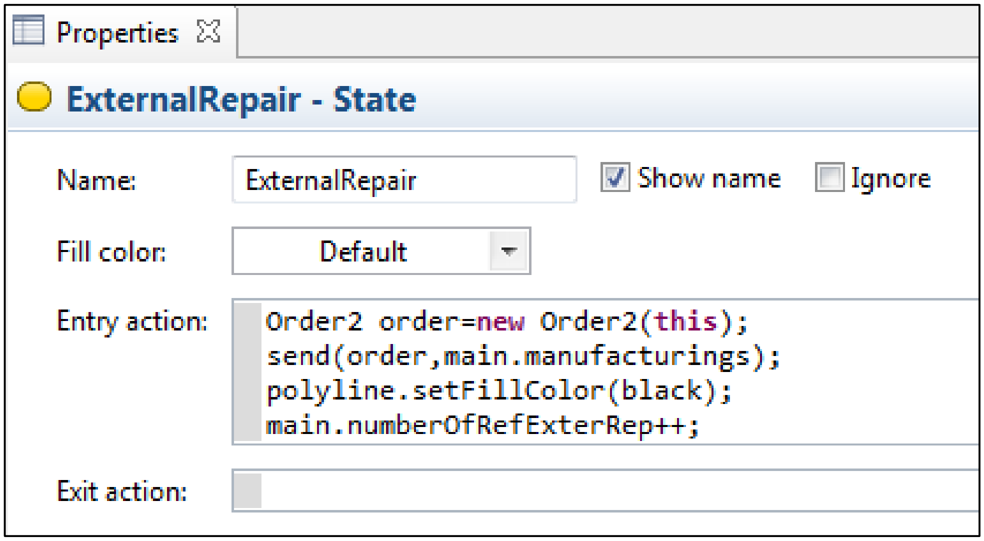


Figure 5-36: Order 2 is created and sent to external repair

In the first line, there is a new order with the parameter *this*, which indicates a store, from which an order is received. The second line of Java code is needed to send - *send* function, which has 2 arguments: what to send (the order) and to whom to send (the manufacturing). To guarantee that the logic operation of a store is reflected, there is a need for another transition from the external repair and Internal repair states to normalWork state. The normal mode of operation is carried out when a message "Delivered!" for internal repair and "Delivered2!" (Figure 5-37) for external repair are received.

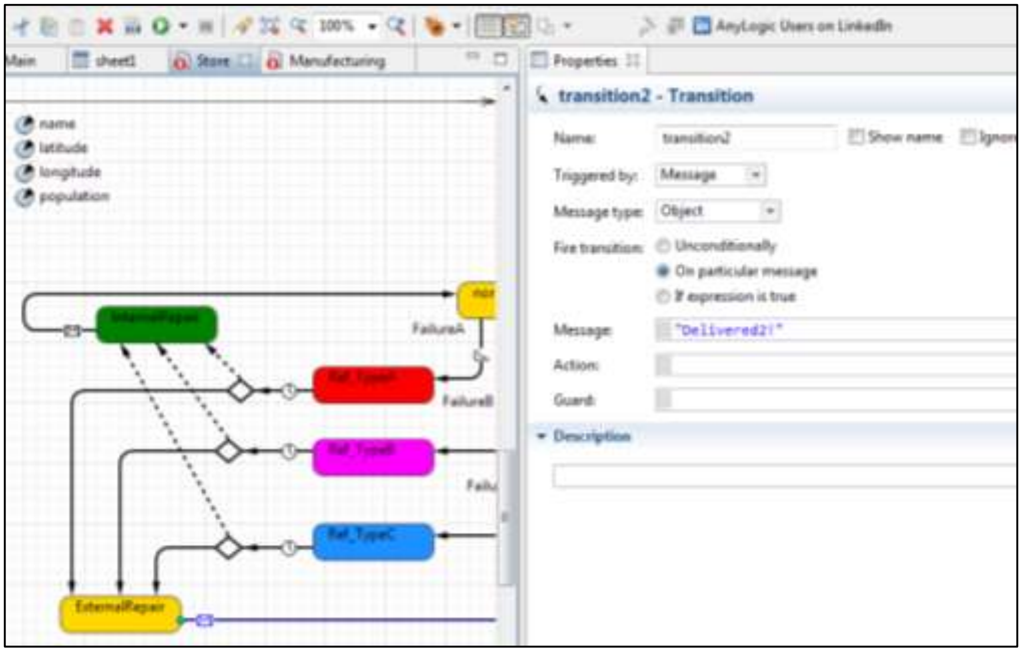


Figure 5-37: Transition from external repair state to normalWork state is triggered by the message “Delivered2!”

❖ Manufacturing /stores and Order Processing

After receipt of the order for external repair, the manufacturing allocates resources (truck) for the execution of the order. The truck is loaded with ordered spare parts of refrigerators, for which it requires 2-3 hours and then they are sent to the store. Upon arrival at the store, the trucks are unloaded. After unloading is completed, the “Delivered2!” message is sent, and the truck returns to the manufacturing agent and becomes a free resource. The same thing happens when a store creates the order for internal repair expect that the worker movement is the store is neglected. Figure 5-38 shows the design of the ordering process for external repair.

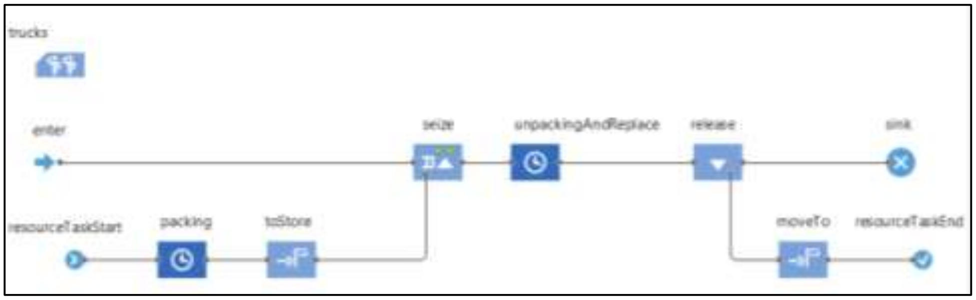


Figure 5-38: Processing modeling logic for the manufacturing agent

Enter block in Figure 5-38, receives orders. The received order enters the queue waiting for resources. **Seize** is responsible for resource capture and connect it with block **enter** (Baggio, 2015). Before, as a resource will be acquired, it must be prepared, which in this case means **packing**. In a parallel process, the trucks will undergo the packing and delivery and eventual return process steps, outlined in the **resourceTaskStart** and **resourceTaskEnd** process. The time delay is specified uniform distribution between two and three hours (Figure 5-39).

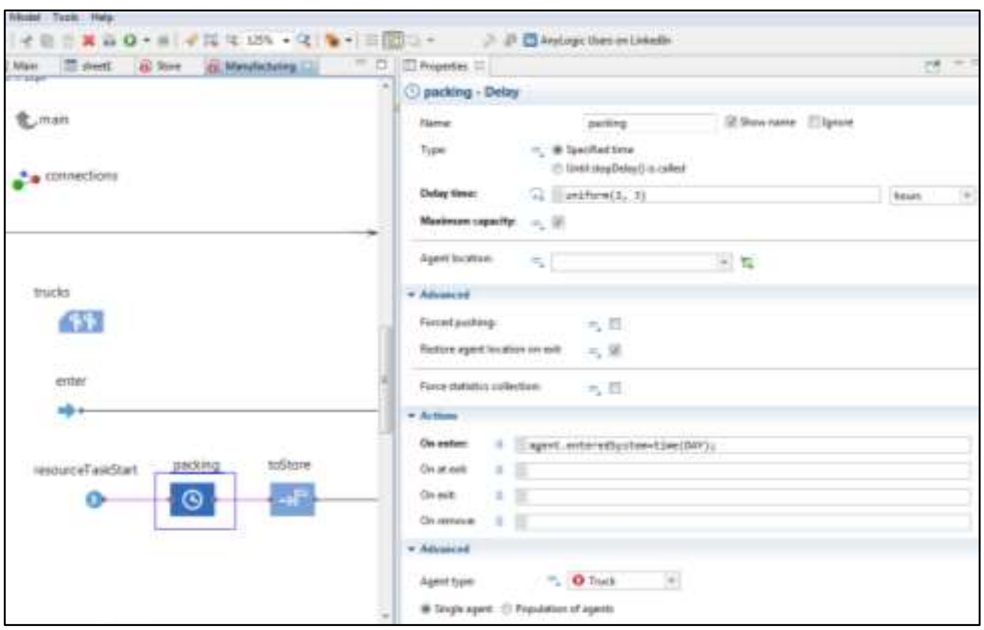


Figure 5-39: Packing delay properties window

When a truck is loaded, it will be sent to the store through **toStore.** In the properties, it is necessary to identify the destination, as shown in Figure 5-40.

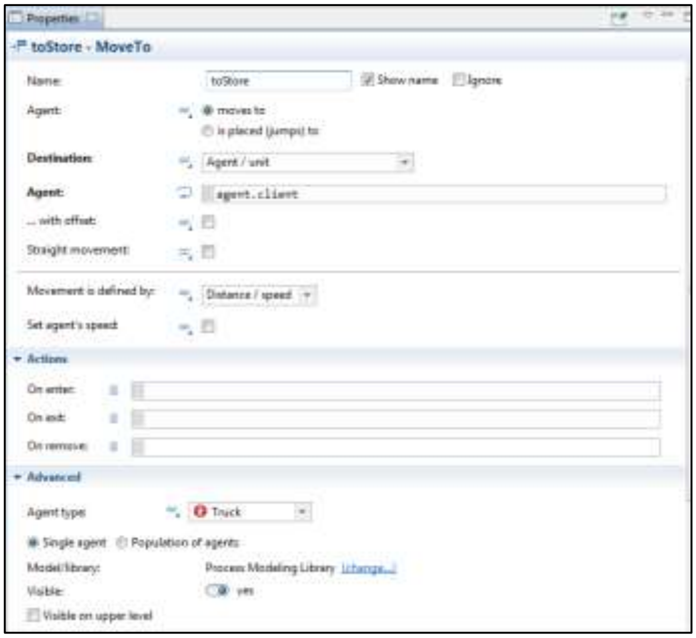


Figure 5-40: Properties of the toStore block

The truck is sent to the unit seize; now this resource should be transferred the information inside the order so that the truck moves to the store that created this specific order (Figure 5-41).

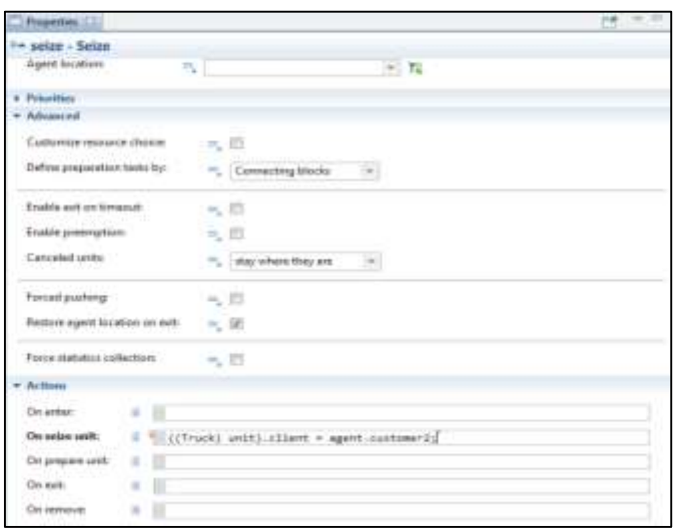


Figure 5-41: Properties of the Seize

In this expression, the value of parameter client, which is stored inside a resource truck, is assigned the value of the parameter customer2 for agent Order 2. As soon as the truck arrives at the store, it must be unloaded. This process is modeled similarly to the process of loading the truck, namely the delay, which in this case is referred to as **unpackingAndReplace**. The properties of this unit are shown in Figure 5-42.

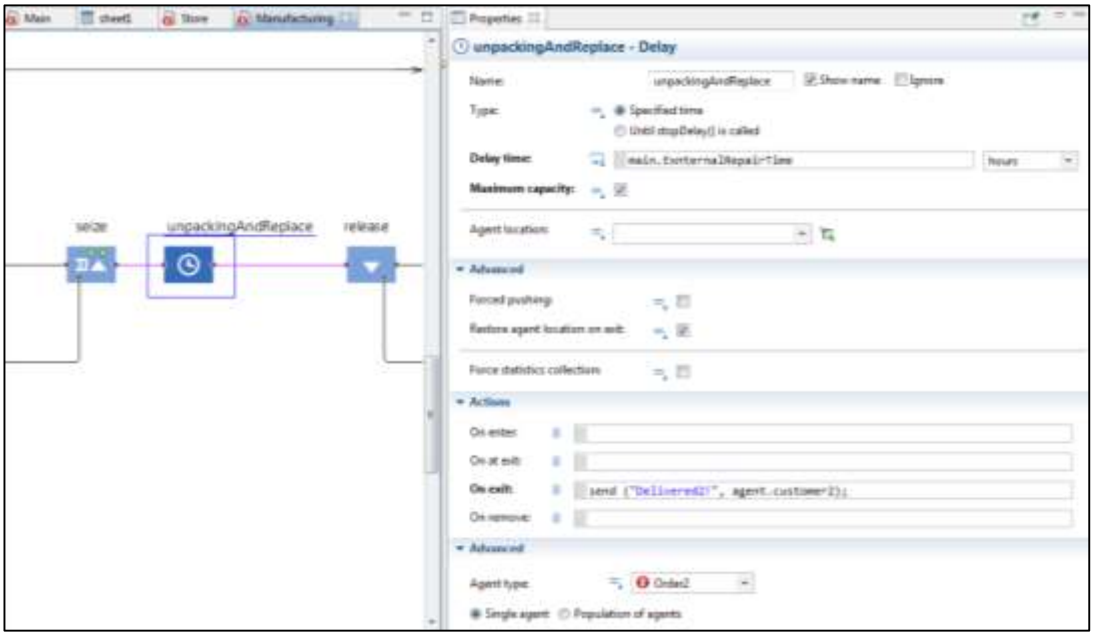


Figure 5-42: Unpacking and replacing delay properties window

When modeling the logic operation of the store, it was pointed out that the transition from the external repair state to normal working state happens when a message "Delivered2!" is received. This message will be sent, as soon as unloading is finished. Inside function *Send,* that has two arguments (that to send, whom to send), is used to send a notification.

After the order is completed, the resource (truck) becomes free (block **release)** and the agent (order 2) is sent to the unit **sink**, where it will be deleted. Since a resource "truck" is available, it must be sent back to the manufacturing, to do this, once again **moveTo** is used, in which to specify a destination of manufacturing agent. Sub-process for the resource must be finalized by the **resourceTaskEnd**, to guarantee that the resource (truck) has returned to common pool resources and was free for the new pick-up. With this last step, the process of orders is complete, the only thing left to do is to make sure that all arriving orders were received at the unit **enter** processing.

All received messages are processed in a standard block (*connections*), that by default, is within each agent (Figure 5-43).

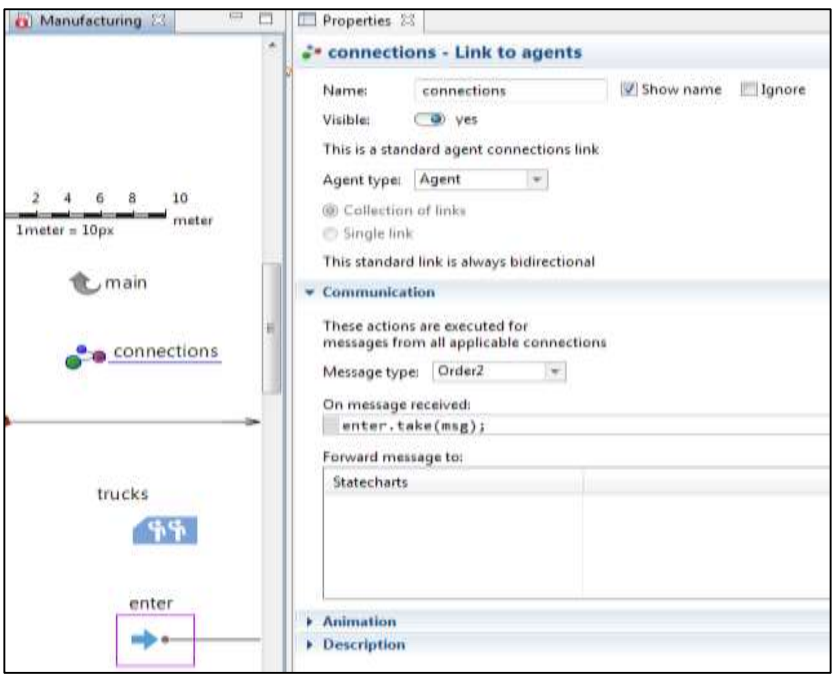


Figure 5-43: The unit "connections" used to put the received order agent into the "Enter" block of the processing logic

In “On message received”, the command *enter.take(msg)* is used. Basically, this command takes the messages (orders) and puts them in the **enter** block of the processing logic. The message type is specified earlier in agent manufacturing**.** These steps are developed for orders which were sent from the store for external repair.

5.3.4.3 Hybrid Simulation Model

A hybrid model was developed to appropriately capture the system of Panda. Figure 5-44 shows the interaction between discrete event model (DES) and agent-based model (ABM). As it is described in the previous section, the store agent and manufacturing agent were modeled separately and then connected via a standard block *(connections).* DES on the right-hand side of Figure 5-44 deals with trucks movement. Trucks move from agent 1 (manufacturing) to agent 2 (store) based on a certain message (trigger) sent by agent 2. Then, trucks move back from agent 2 to agent 1 after a certain time (timeout). Once the truck enters the (queue) module, it goes into a different simulation type (ABM). Depends on the design of the statechart of agents, trucks are moving. AnyLogic software is based on Java. For agents’ interactions with discrete models, java codes have to be inserted properly into the model as it was shown previously.

Figure 5-44: Hybrid Simulation Model

5.3.4.4 Model Animation

The animation of agents visualization is shown in Figure 5-45 (sample of 15 stores). This animation represents the state transition of each refrigerator according to the lapse of time for one year of simulation. Each state of the refrigerators is represented by different color (Table 5-7).

Figure 5-45: Model animation of agents (sample of 15 stores)

Table 5-7: Different colors for each type of agent in every state

State	Color
Normal Work	Gold
Failure Type A	Red
Failure Type B	Magenta
Failure Type C	Dodger Blue
Internal Repair	Green
External Repair	Black

5.3.4.5 Validation

Despite the absence of an agreed process for validation of ABM model, numerous methods have been suggested (Klügl, 2008). Klügl (2008) proposed one such approach for full validation of an ABM. This comprehensive framework includes four key steps:

1. Face validation: this involves the input of human with experience in the subject of the simulation model.

2. Sensitivity analysis: this step is to evaluate the effect of various combinations of parameters on the overall behavior of the agents.

3. Calibration: the aim of the calibration is to set unknown parameters to reasonable values that will produce approximations of the actual system. In many cases, this step may be combined with the sensitivity analysis step.

4. Statistical validation: this step is to demonstrate that the simulation is valid by comparing the outputs with the historical data (Houston et al., 2017).

❖ Calibration and Sensitivity Analysis:

Calibration and sensitivity analysis can be combined into one step (Klügl, 2008). The main concern at this step is to properly calibrate parameters that were not directly extracted from historical data analysis. In this agent-based model, the most critical of these parameters are the internal and external repair time of refrigerators. Sensors installed and predictive maintenance were inactivated for these simulation runs.

Multiple simulations with varying combinations of these parameters were completed over the same period. Ten separate runs were simulated at each combination to account for the stochastic nature of the ABM. Total time that out of service (OOS) of the refrigerators from ABM was then compared to the true value from historical data. OOS Data provided by Panda was available for 480 days (16 months). To ensure unseen data remained for the following statistical validation step, a subset of this data for 365 days (12 months) was taken as the calibration dataset (Figure 5-46).

Figure 5-46: Calibration dataset

Figure 5-47 and Figure 5-48 show how the total refrigerator time OOS output from the ABM was obtained. In the **packing** unit, the Java code "*agent.enteredSystem= time(DAY)*" stores the time in the *enteredSystem* parameter when an entity (worker or truck) received a repair request from the store. In the **moveTo,** the Java code "*main.outOfService.add (time(DAY)-*

agent.enteredSystem);" adds out of service time to *outOfService* data statistics in main. Figure 5-49 shows *outOfService* data statistics for internal repair (worker) and external repair (truck).

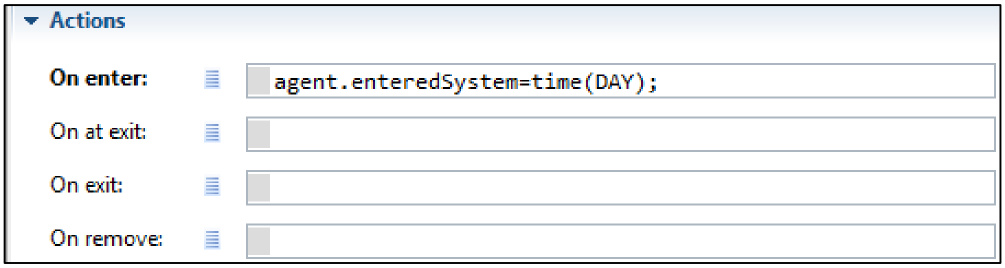


Figure 5-47: Java code to store the time in the enteredSystem parameter

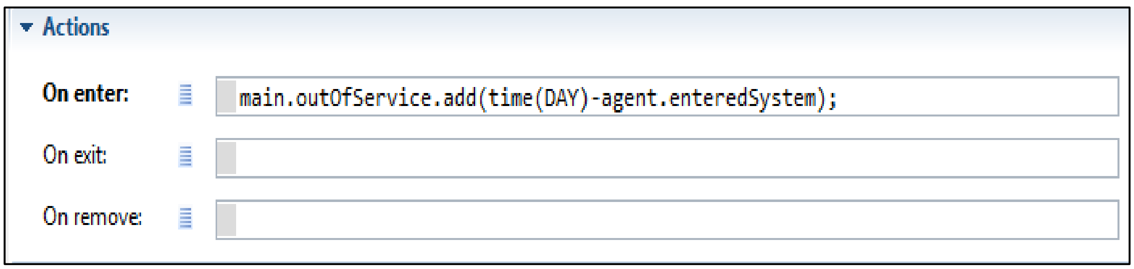


Figure 5-48: Java code to add out of service time to outOfService data statistics in main

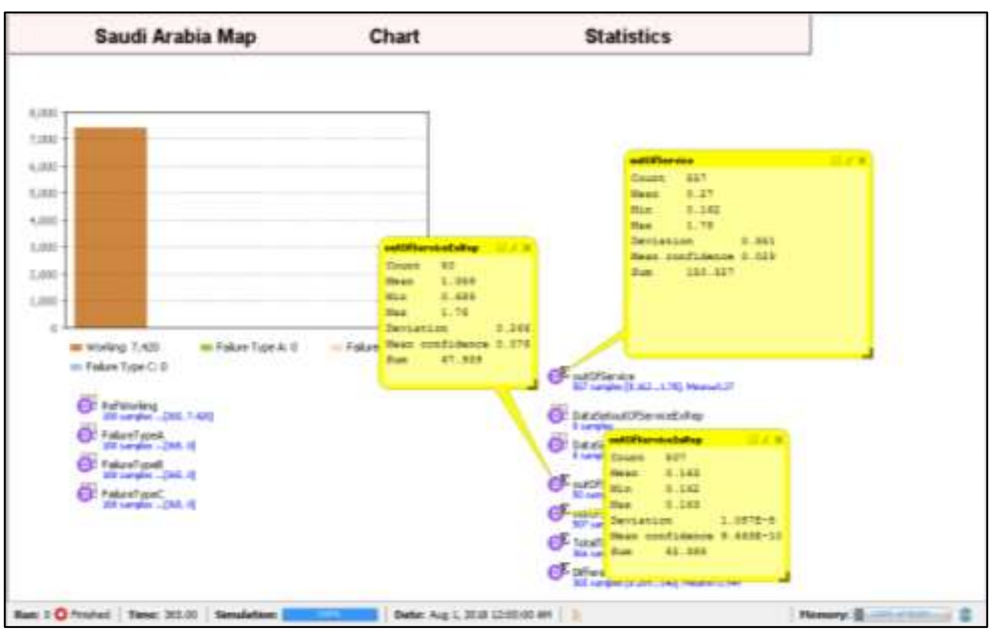


Figure 5-49: OutOfService data statistics for internal and external repair

The calibration experiment was done using AnyLogic software as shown in Figure 5-50. The objective of the calibration is to minimize the absolute difference between the total refrigerator time out of service (OOS) from the ABM and the value from the historical data for each combination of these parameters.

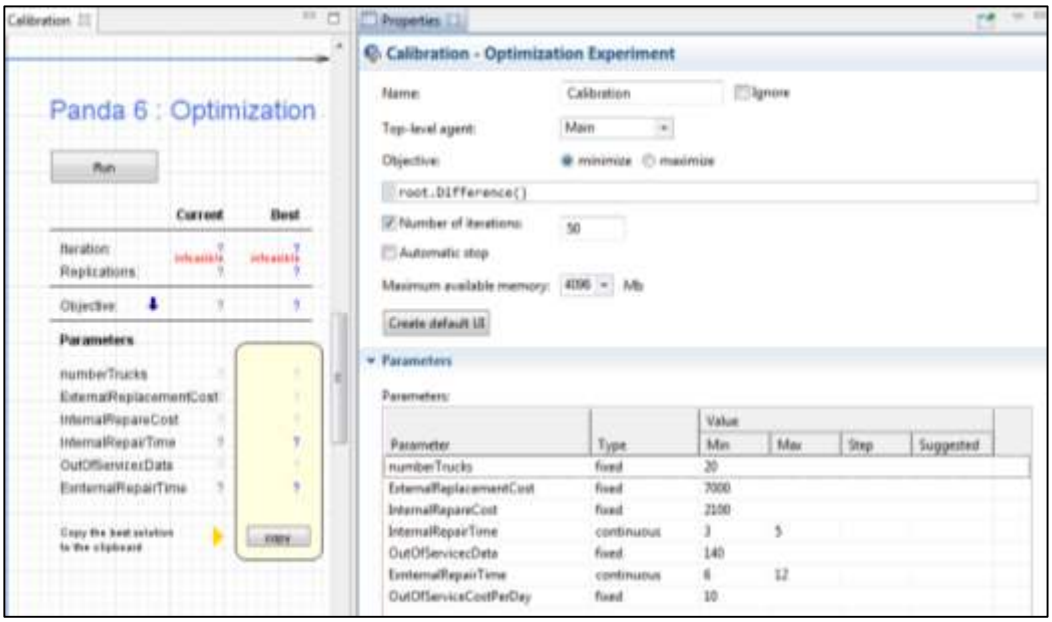


Figure 5-50: Calibration experiment

Figure 5-51 shows the calibration experiment result. As it is shown in the figure, the internal repair time should be 3.9 hours and the external repair time should be 8.6 hours in order to have a difference of 0.215 day between the OOS time output from the ABM and the value from the historical data.

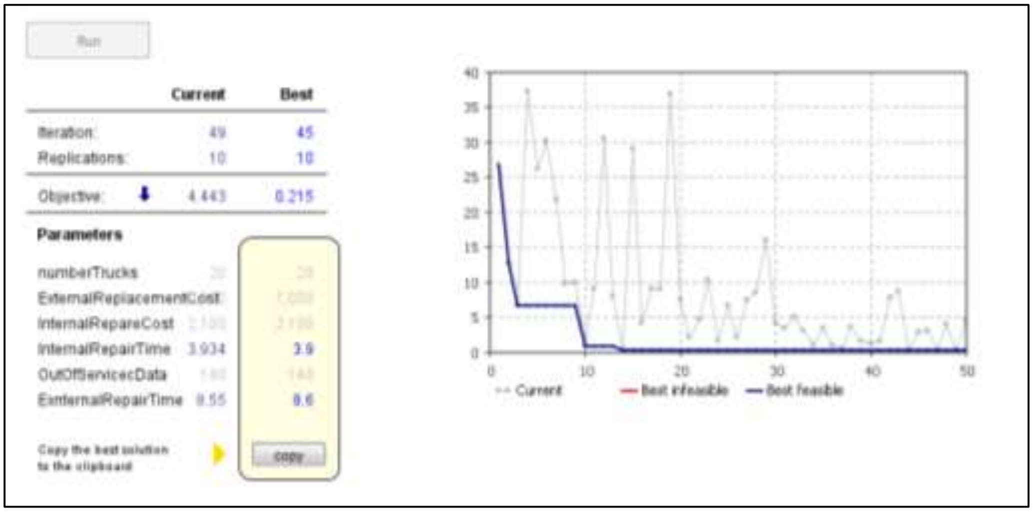


Figure 5-51: Calibration result

The surface plot in Figure 5-52 provides different illustrations of the same surface.

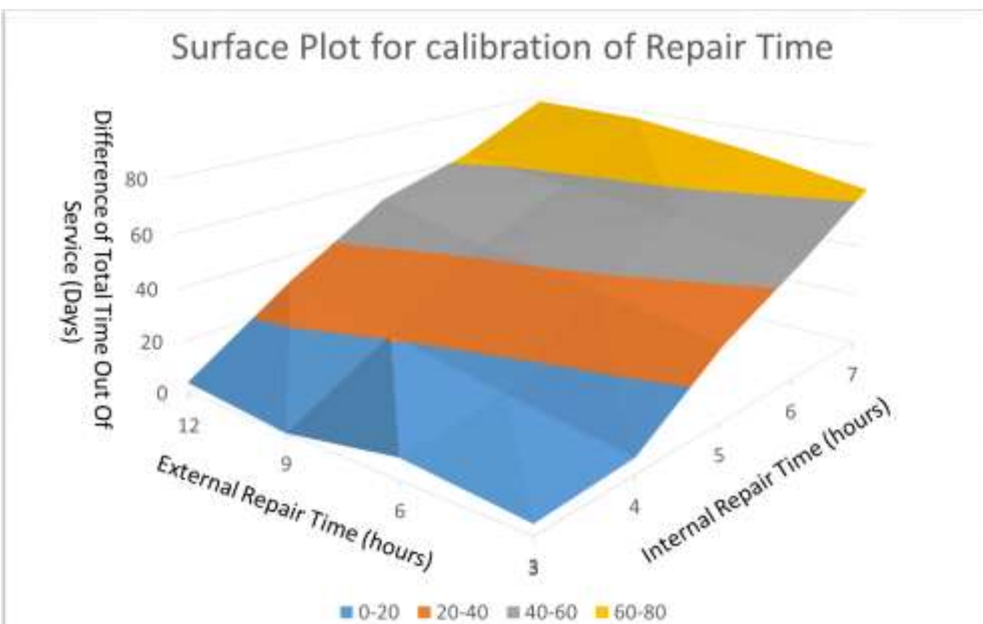


Figure 5-52: Fitted surface for calibration of internal and external repair time parameters

❖ Statistical Validation:

In this final step of the validation, the simulation model output was compared to with the true value from the historical data to confirm that the simulation applies to the system it is describing and not the data which it was calibrated from. A subset of OOS for 480 days was used in this stage of the process. Twenty separate runs were simulated through this period. In the real system, the total time OOS due to refrigerator failures was 178.14 days within this period (480 days). The simulation results give an output of (182.7 ± 4.56) days at the same time. There is a 3% relative difference between the value from the ABM and the true value (i.e., simulation is suitable for the system).

5.3.4.6 Financial Consideration of IoT investments

Panda considers two type of IoT investments:

- Investment A: invest in installing sensors that monitor the temperature of the refrigerators only and receiving alerts when a refrigerator fails, and the temperature goes below a certain limit. In other words, apply the connectivity platform of IoT (level 1 as described in chapter 4). As mentioned before, Panda has an annual cost of 1.4 million dollars due to its refrigerators failure and food waste. Investment A aims to reduce the food waste only while failure cost remains the same.

- Investment B: invest in predictive analytics to predict failure before it happens. In other words, apply the action platform of IoT (level 2). The aim of investment B is not only to reduce the food waste but also costs associated with refrigerators failure (Figure 5-53).

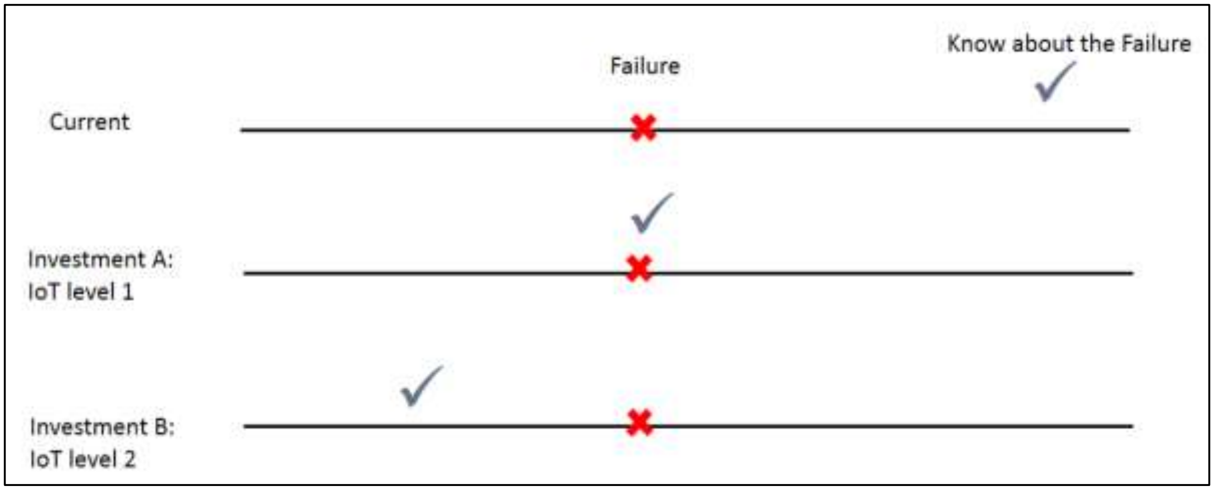


Figure 5-53: Two different types of IoT investments

❖ Cost of the investment:

Investment A: The initial purchase costs of sensors can be determined from the price of Wzzard website (SmartWorx, 2016). Wzzard has a special kit for temperature monitoring only (Figure 5-54). The cost of the temperature sensor is $ 140. The total cost of Investment A= (Number of sensors *Cost of a sensor) + Cost of installation.

One sensor will be installed on each of the 7,420 Panda's refrigerators. The insulation fee is $50 per store (Panda has 212 in Saudi Arabia). This brings the cost of investment A to approximately $ 1,049,400.

Figure 5-54: Wzzard monitoring starter kit-special temperature kit

Investment B: In this type of investment, Panda needs to be able to monitor the health and condition of every refrigerator, so that failures can be identified as they begin to develop, and proper maintenance can be done before failures occur. There are measurable parameters that can be used to predict when a refrigerator need maintenance. Comparing things such as vibration, temperature, and current use of historical readings will raise red flags when the newer numbers exceed acceptable parameters. In this case, a system integrator must install the Wzzard Intelligent Sensing Platform. The Wzzard platform creates a whole connectivity stack between sensors at the network edge and application in the cloud or at the network core (SmartWorx, 2016). Mainly, it uses two pieces of IoT technology: 1) wireless Wzzard Intelligent Edge Nodes. 2) Spectre Network Gateway (Figure 5-55).

Figure 5-55: Wzzard intelligent sensing platform

The Wzzard Intelligent Edge Nodes, shown above, connect to new or pre-existing industry standard sensors, read the data, and wirelessly transmit it to the Spectre Network Gateway. Each node has routing capabilities so that they can form extremely scalable, reliable, highly, and self-sustaining wireless mesh networks. All the Individual nodes need be within wireless range of the gateway, so they can route the data to various nodes until it reaches its destination. Then, the Spectre Network Gateway offers secure network connectivity through either cellular data connections or wired Ethernet (SmartWorx, 2016).

The cost of Wzzard intelligent Sensing sensors is $ 850 with the installation. This brings the total investment in the project to approximately $ 6,307,000. Panda manager suggested Microsoft Azure to be used for data analytics. Data analytics and storage costs as $12,000 per year.

5.3.5 Simulation Model Result

5.3.5.1 Simulation Output

Frequent runs of the ABM model were performed for one year (356 days). Base case simulation model was run where no sensors were attached to the refrigerators. What-if scenarios with predictive maintenance were then performed. For investment A, different values of response rates to the sensor notifications of Panda were tested. The ABM model was run with these responses rate: 0.7, 0.75, 0.80, 0.85,0.90 and 0.99. For investment B (where predictive maintenance applied), different values of responses rates of Panda and various failure rates were tested. From the introduction of predictive maintenance capabilities described in chapter 4, the failure would be eliminated or reduced significantly. In each case, 100 simulation runs were carried out to examine the full spectrum of results that could be reached. Each simulation run is different as various values are drawn from probability distributions embedded in ABM model.

- **Base Model**

Figure 5-56 shows the simulation output of base model where no sensors were attached to the refrigerators. As it is shown, the annual cost due to refrigerators failure and food waste is around 1.4 million, 293 failed refrigerators of type A, 199 failed refrigerators of type B, 65 failed refrigerators of type C, and 507 refrigerators needed internal repair while 50 refrigerators needed external repair.

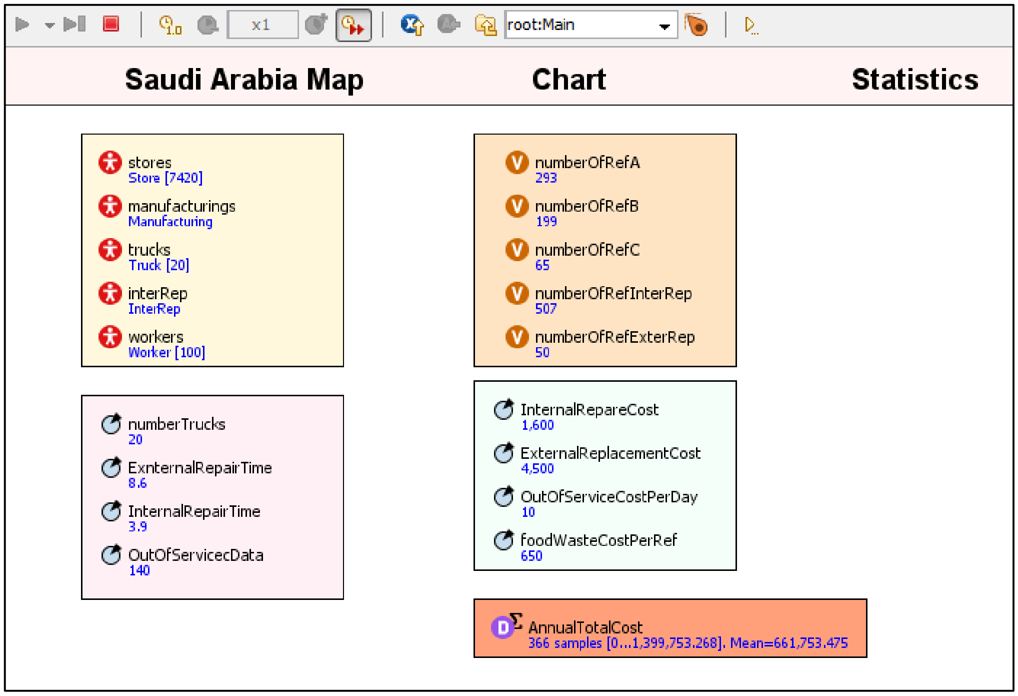


Figure 5-56: Simulation output of the base model - no sensors attached

❖ **Investment A:**

For this type of investment, sensors will be installed only to monitor the temperature of the refrigerators and receive alerts when a refrigerator fails, and the temperature goes below a certain limit. The failure rates for each refrigerator (A, B, and C) are still the same as the base model. Different values of response rates to the sensor notifications of Panda were tested. The ABM simulation outputs with the responses rate: 0.7, 0.75, 0.80, 0.85,0.90 and 0.99 are shown in Figure 5-57, Figure 5-58, Figure 5-59, Figure 5-60, Figure 5-61, and Figure 5-62 respectively. Table 5-8 summarizes the average annual cost for the different response rate of panda.

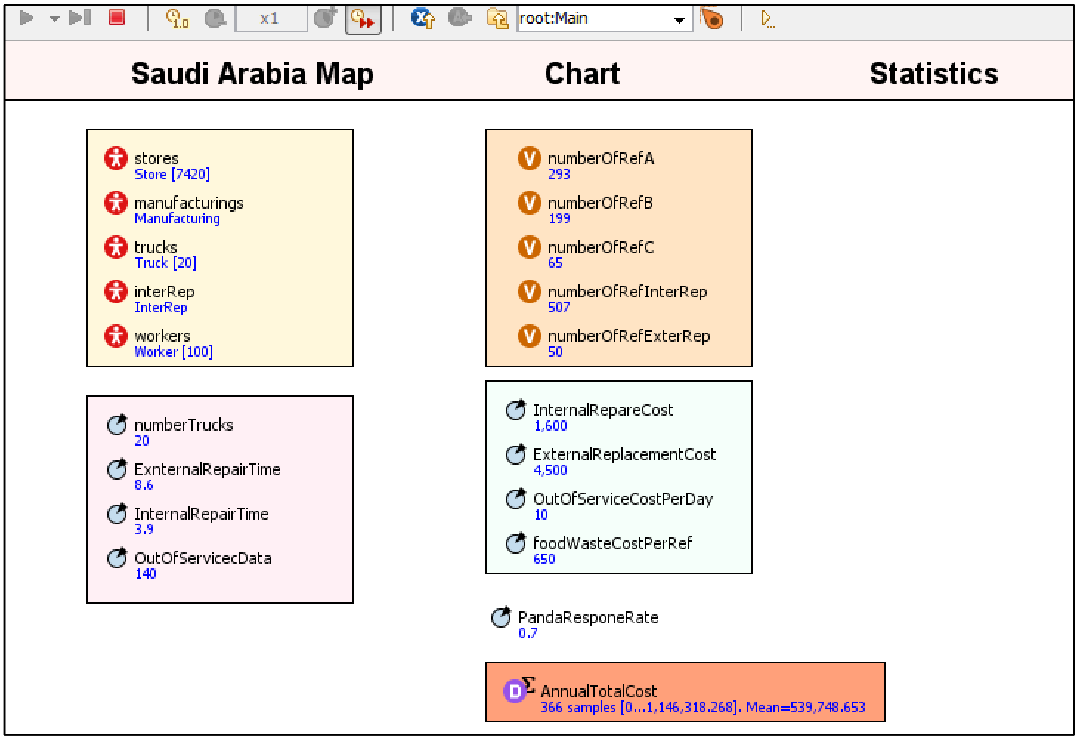


Figure 5-57: Simulation output when Panda response rate is 0.70

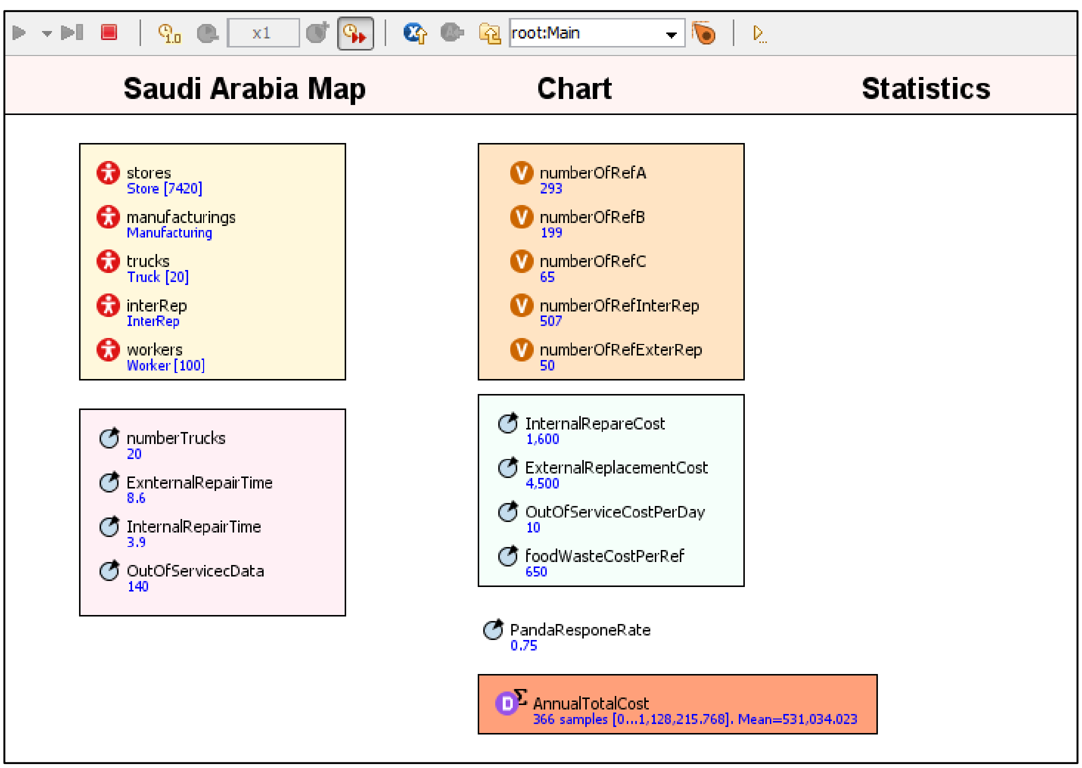


Figure 5-58: Simulation output when Panda response rate is 0.75

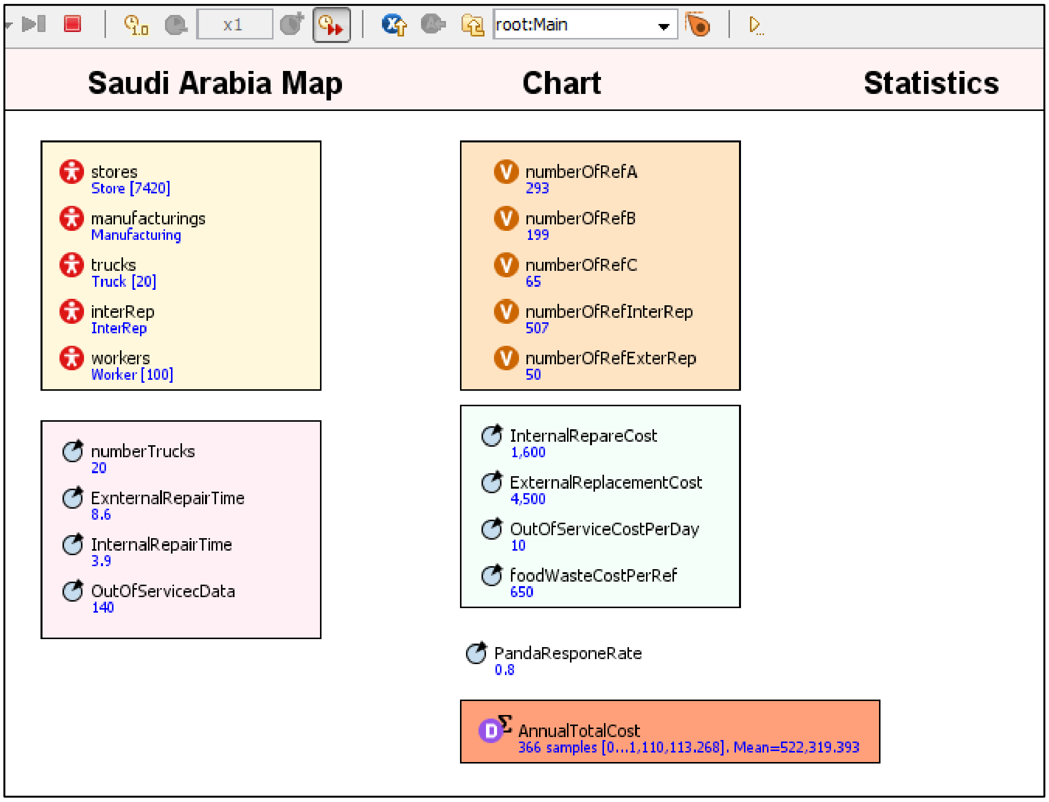


Figure 5-59: Simulation output when Panda response rate is 0.80

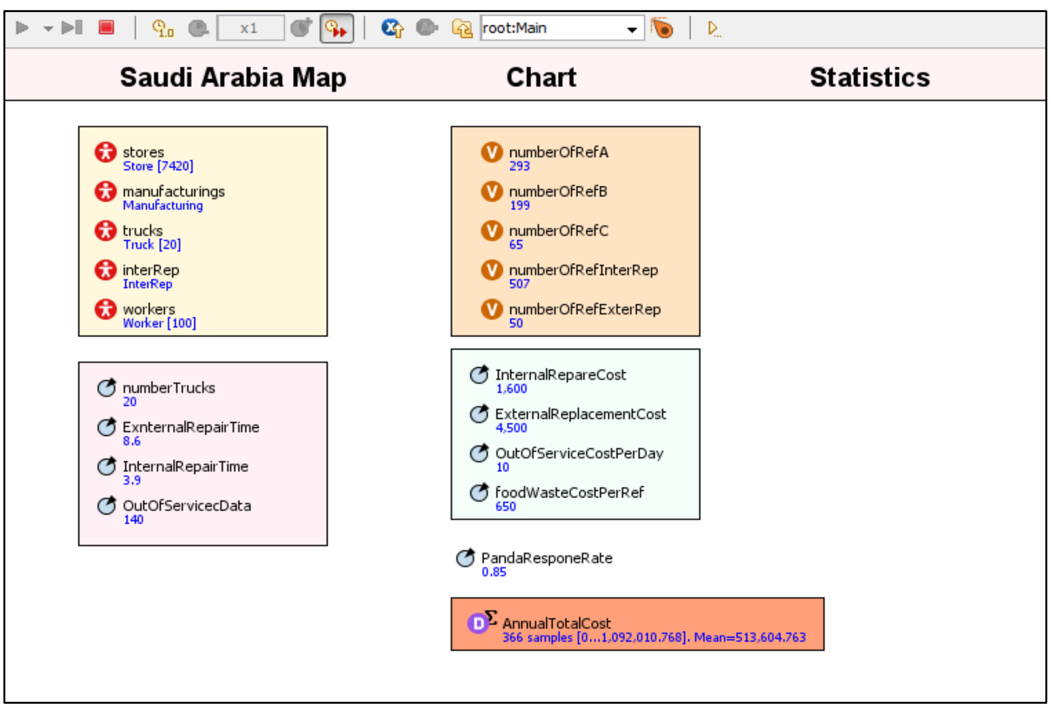


Figure 5-60: Simulation output when Panda response rate is 0.85

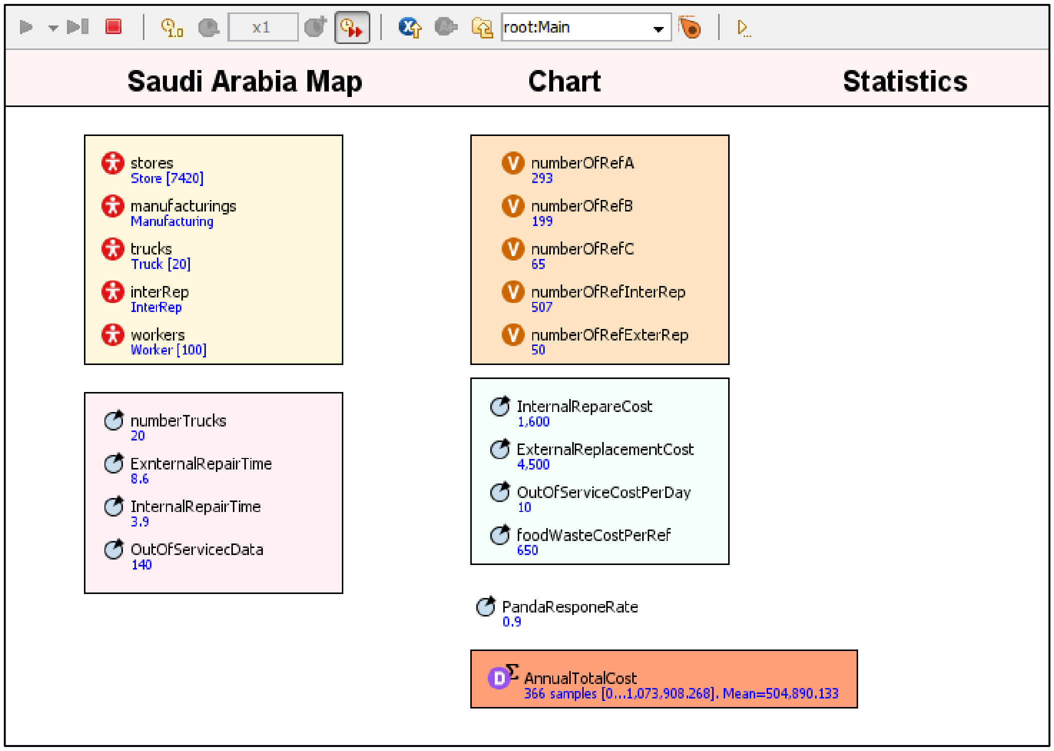


Figure 5-61: Simulation output when Panda response rate is 0.90

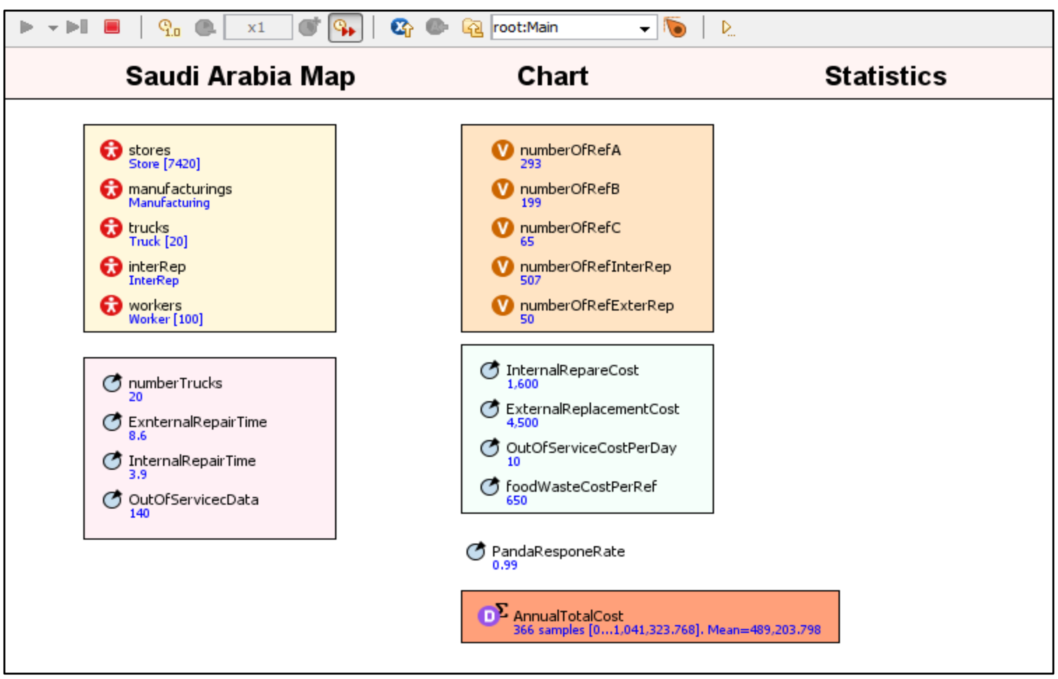


Figure 5-62: Simulation output when Panda response rate is 0.99

Table 5-8: Average annual cost for different response rate of Panda

Panda Response Rate	Annual Cost –Simulation Result
0.7	$ 1,146,318.27
0.75	$ 1,128,215.77
0.80	$ 1,110,113.27
0.85	$ 1,092,010.77
0.90	$ 1,073,908.27
0.99	$ 1,041,323.77

❖ **Investment B:**

In this type of investment, Panda needs to be able to monitor the health and condition of every refrigerator, so that failures can be identified as they begin to develop, and proactive maintenance can be done before failures occur. Different values of responses rates of Panda and various failure rate were tested. From the introduction of predictive maintenance capabilities described in chapter 4, the failure would be eliminated or reduced significantly. The ABM simulation outputs with Panda response rate of 0.80 and failure rate reduced by 80%, 85%, 90%, 95%, and 99% by are shown in Figure 5-63, Figure 5-64, Figure 5-65, Figure 5-66, and Figure 5-67 respectively. Table 5-9 summarizes the number of failed refrigerators corresponding to different failure rates. The average annual cost of different Panda responses rates and failure rates is summarized in Table 5-10.

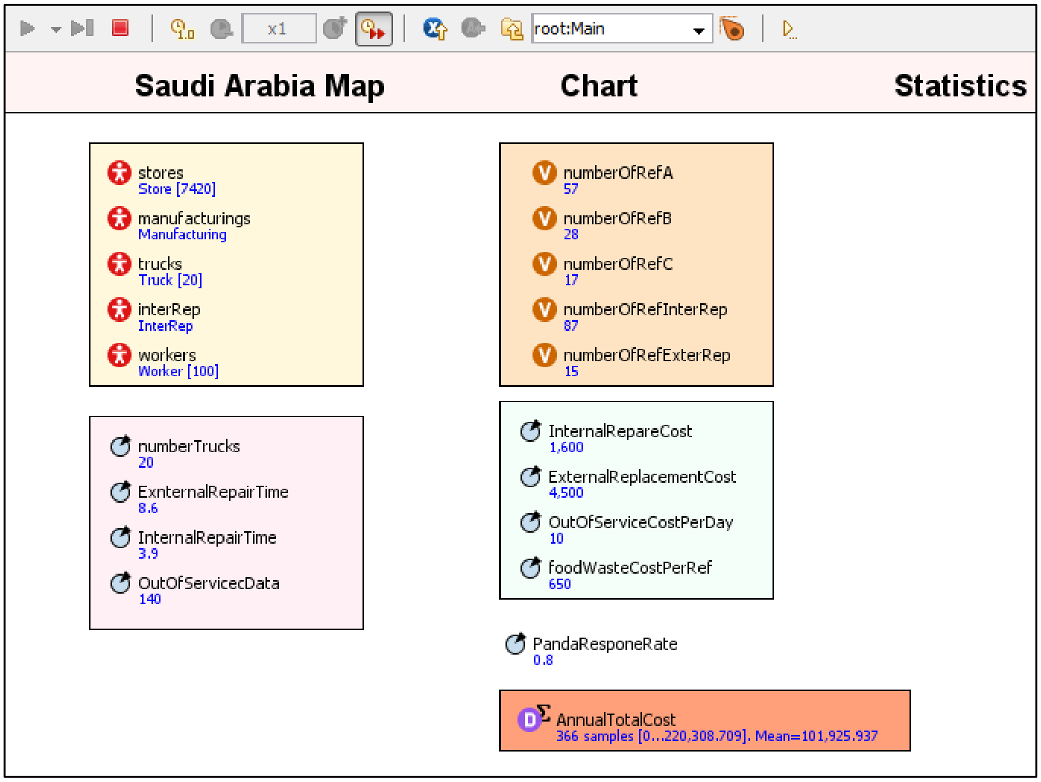


Figure 5-63: Simulation output when failure rate reduced by 80%

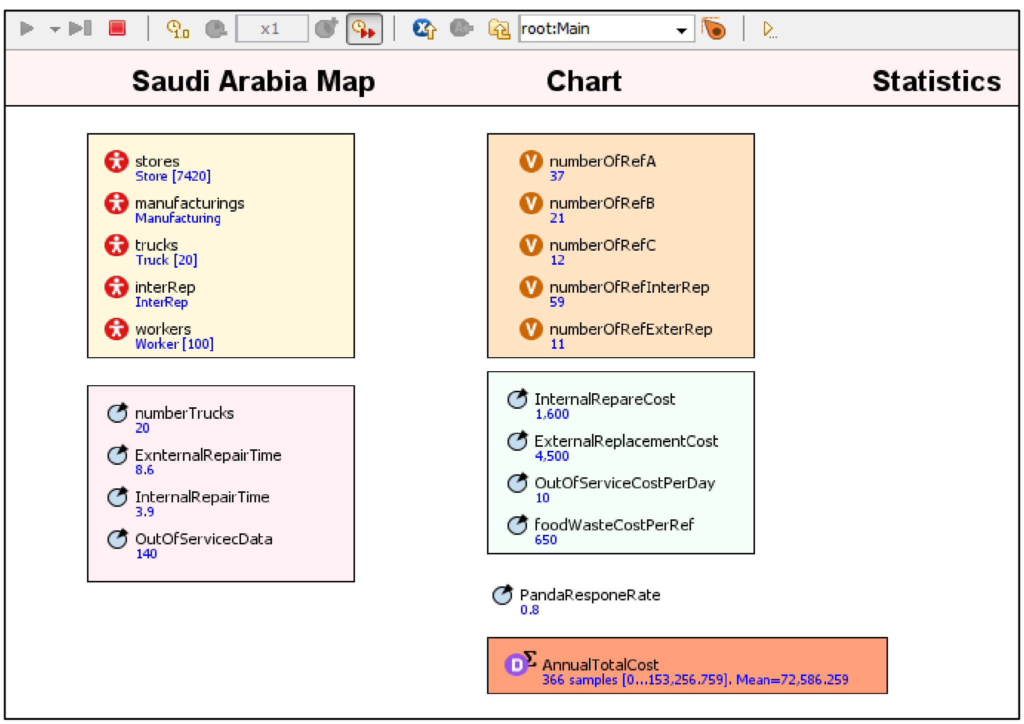


Figure 5-64: Simulation output when failure rate reduced by 85%

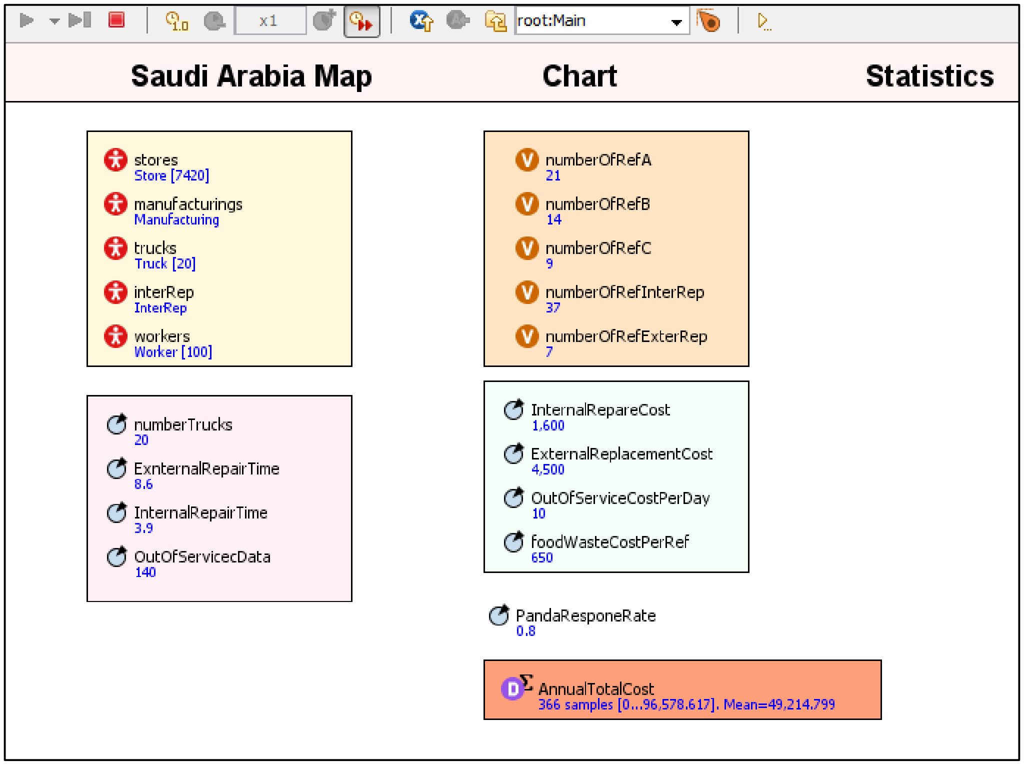


Figure 5-65: Simulation output when failure rate reduced by 90%

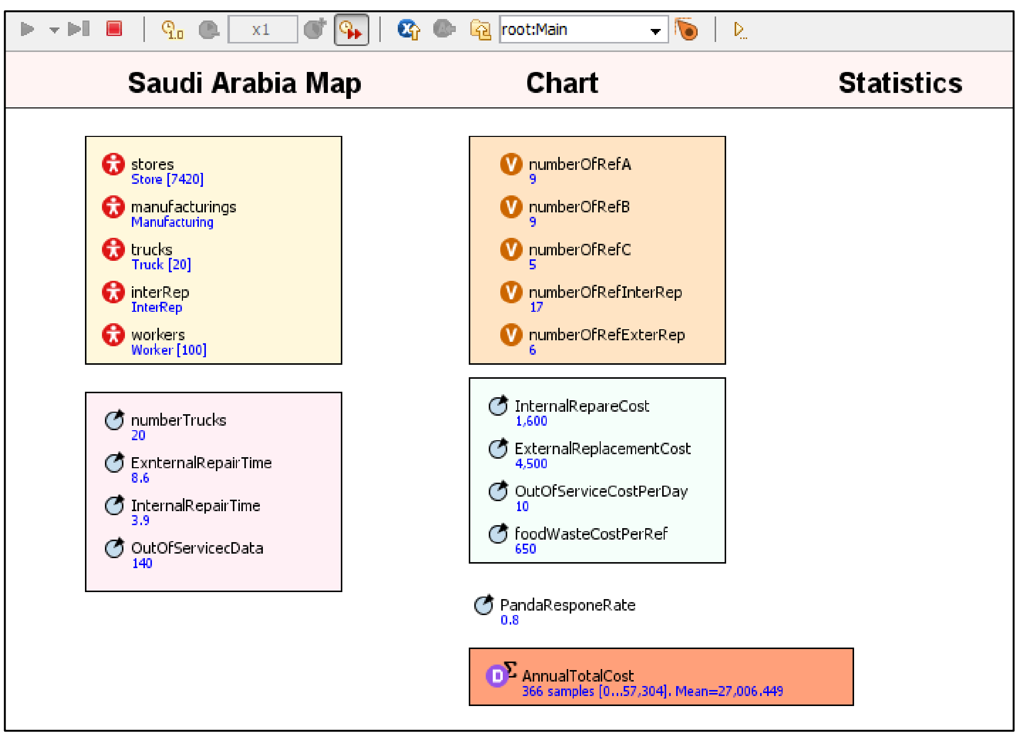


Figure 5-66: Simulation output when failure rate reduced by 95%

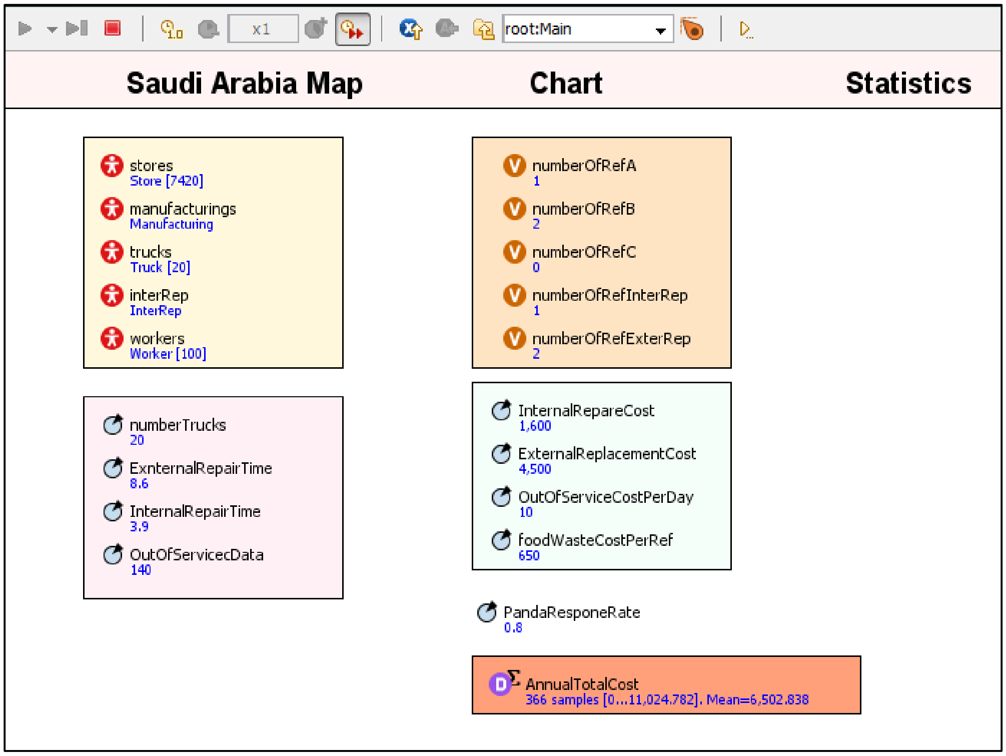


Figure 5-67: Simulation output when failure rate reduced by 99%

Table 5-9: Number of failed refrigerators corresponding to different failure rates

Failure rate reduced by	Failed refrigerators of type A	Failed refrigerators of type B	Failed refrigerators of type C	Refrigerators needed internal repair	Refrigerators needed external repair
80%	57	28	17	87	15
85%	37	21	12	59	11
90%	21	14	9	37	7
95%	9	9	5	17	6
99%	1	2	0	1	2

Table 5-10: Average annual cost for different Panda responses rates and failure rates

Panda Response	Failure Rate reduced by	Annual Cost –Simulation Output
0.8	80%	$ 220,308.71
	85%	$ 153,256.76
	90%	$ 96,578.62
	95%	$ 57,304.00
	99%	$ 11,024.78
0.85	80%	$ 216,993.71
	85%	$ 150,981.76
	90%	$ 95,148.62
	95%	$ 56,556.50
	99%	$ 10,927.28
0.90	80%	$ 213,678.71
	85%	$ 148,706.76
	90%	$ 93,718.62
	95%	$ 55,809.00
	99%	$ 10,829.78
0.95	80%	$ 210,363.71
	85%	$ 146,431.76
	90%	$ 92,288.62
	95%	$ 55,061.50
	99%	$ 10,732.28

5.3.5.2 Return on Investment

To find ROI values from the output of the ABM, it is essential to quantify simulation outputs financially (Houston et al., 2017). The return on investment (ROI) ratio calculates the percentage return (profitability):

Simple ROI = (Cost savings – Investment)/ Investment.

One concern with the simple ROI formula is that it is usually used for short-term investments. Therefore, it does not take into consideration the time value of money so, it is less truthful for calculating ROI for long-term investments. In order to measure the long-term ROI for future years, the following discounted ROI formula is used:

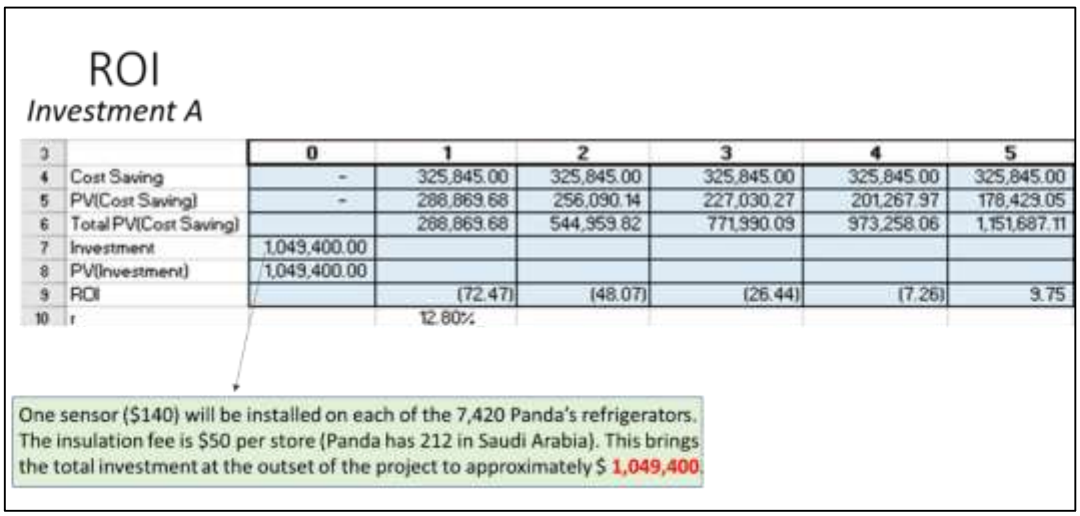
Discounted ROI= (PV cost saving – PV Investment) / PV Investment, where PV = present value

- Investment = (Number of sensors *Cost of a sensor) + Cost of installation
- Cost savings = $\sum_{i=1}^{t}\left(\frac{\text{C Current} - \text{C new}}{(1+r)^{i}}\right)$

Time (t), is measured in years from sensors installation and C represent costs. All the future costs are discounted to their present values. Panda's standard discount rate (r=12.8% per annum) was obtained from its financial statement report (Savola, 2016).

❖ **Investment A:**

Figure 5-68 and Figure 5-69 show how ROI was calculated when Panda response rate = 0.90. The estimated mean returns, which was obtained by subtracting cost savings from Investment, when Panda response rate: 0.70, 0.75, 0.80, 0.85, 0.90, and 0.99 are shown in Figure 5-70, Figure 5-71, Figure 5-72, Figure 5-73, Figure 5-74, and Figure 5-75 respectively. A summary of annual saving rates and multi-year ROI values for different Panda responses rates is shown in Table 5-11.

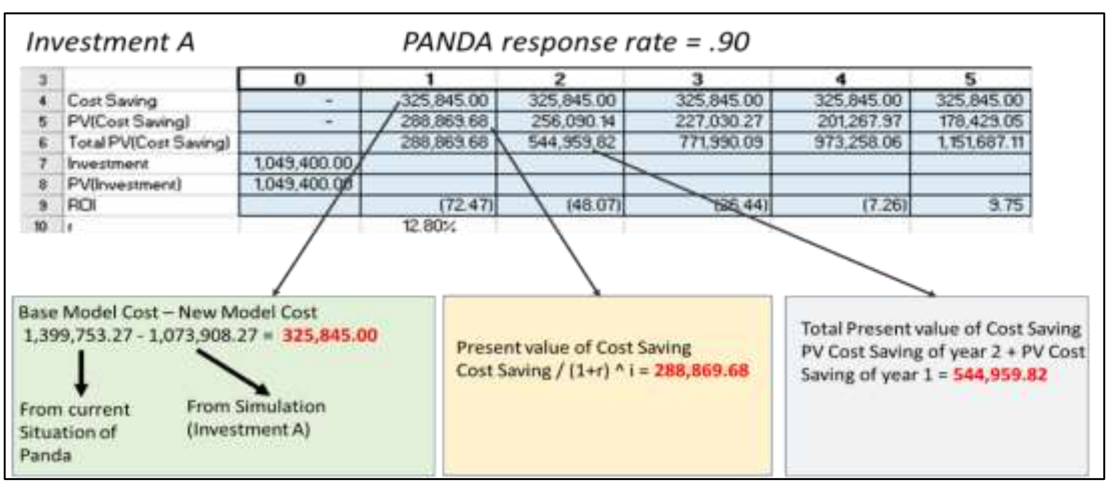


ROI

Investment A

3		0	1	2	3	4	5
4	Cost Saving	-	325,845.00	325,845.00	325,845.00	325,845.00	325,845.00
5	PV(Cost Saving)	-	288,869.68	256,090.14	227,030.27	201,267.97	178,429.05
6	Total PV(Cost Saving)		288,869.68	544,959.82	771,990.09	973,258.06	1,151,687.11
7	Investment	1,049,400.00					
8	PV(Investment)	1,049,400.00					
9	ROI		(72.47)	(48.07)	(26.44)	(7.26)	9.75
10	r		12.80%				

Figure 5-68: Investment A calculation



Investment A *PANDA response rate = .90*

3		0	1	2	3	4	5
4	Cost Saving	-	325,845.00	325,845.00	325,845.00	325,845.00	325,845.00
5	PV(Cost Saving)	-	288,869.68	256,090.14	227,030.27	201,267.97	178,429.05
6	Total PV(Cost Saving)		288,869.68	544,959.82	771,990.09	973,258.06	1,151,687.11
7	Investment	1,049,400.00					
8	PV(Investment)	1,049,400.00					
9	ROI		(72.47)	(48.07)	(26.44)	(7.26)	9.75
10	r		12.80%				

Figure 5-69: ROI calculation when Panda response rate is 0.90

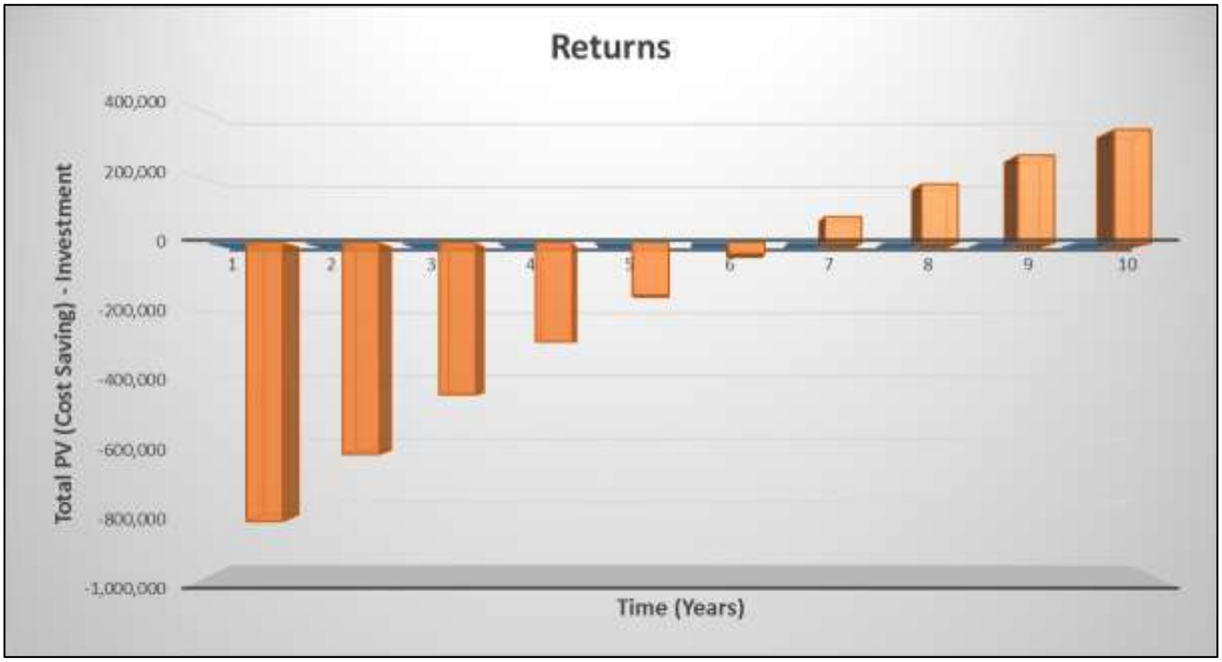


Figure 5-70: Estimated mean returns when Panda response rate is 0.70

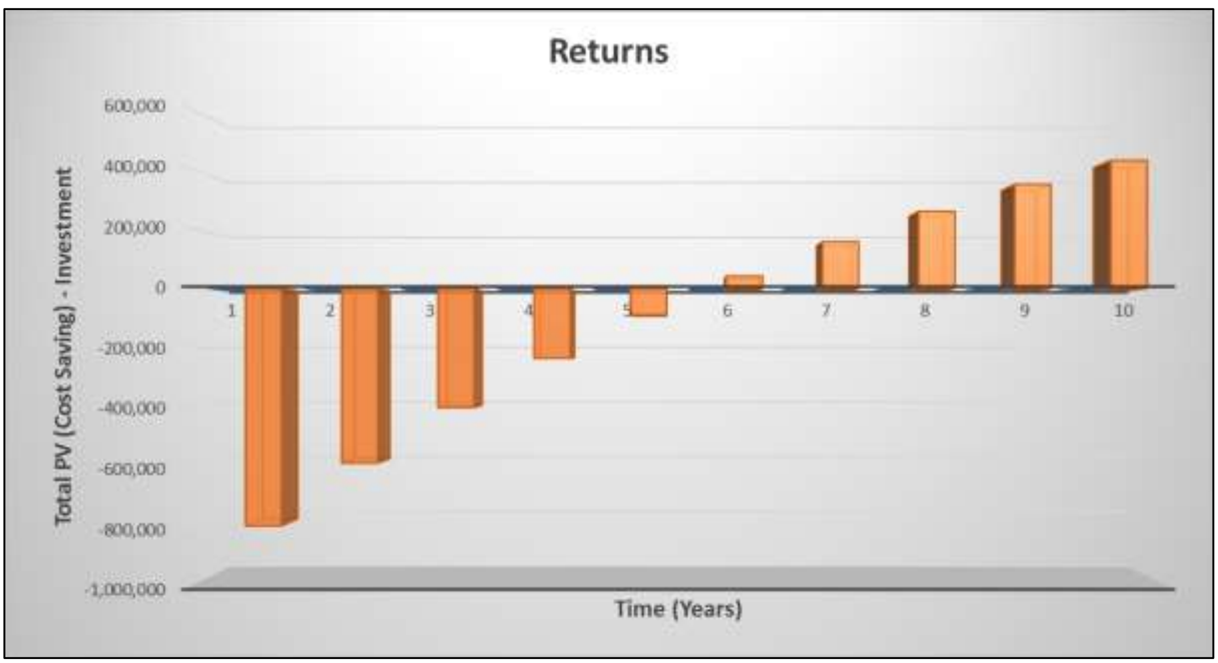


Figure 5-71: Estimated mean returns when Panda response rate is 0.75

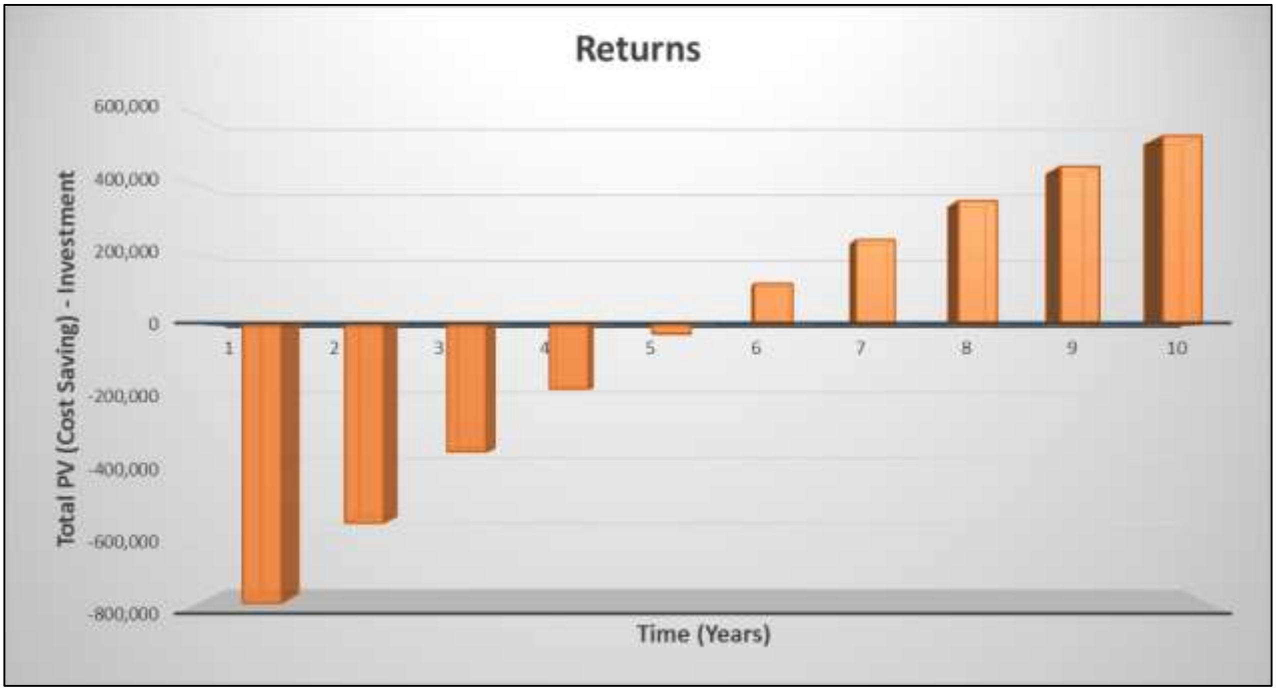


Figure 5-72: Estimated mean returns when Panda response rate is 0.80

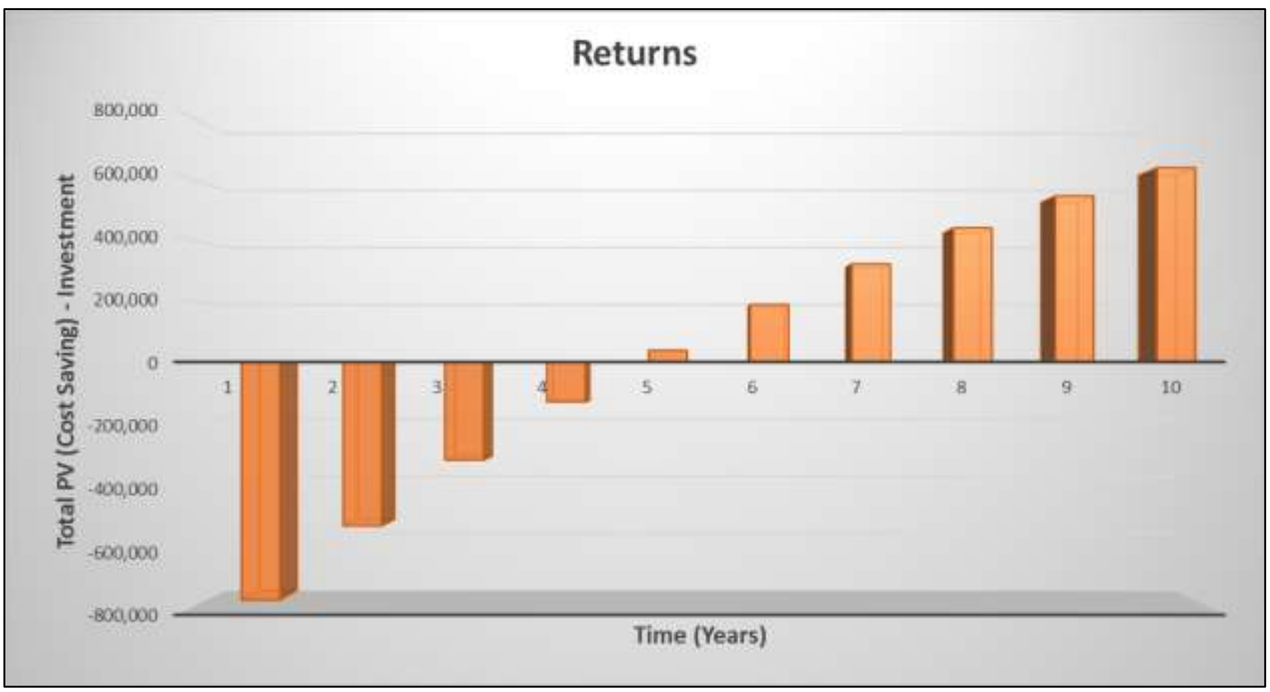


Figure 5-73: Estimated mean returns when Panda response rate is 0.85

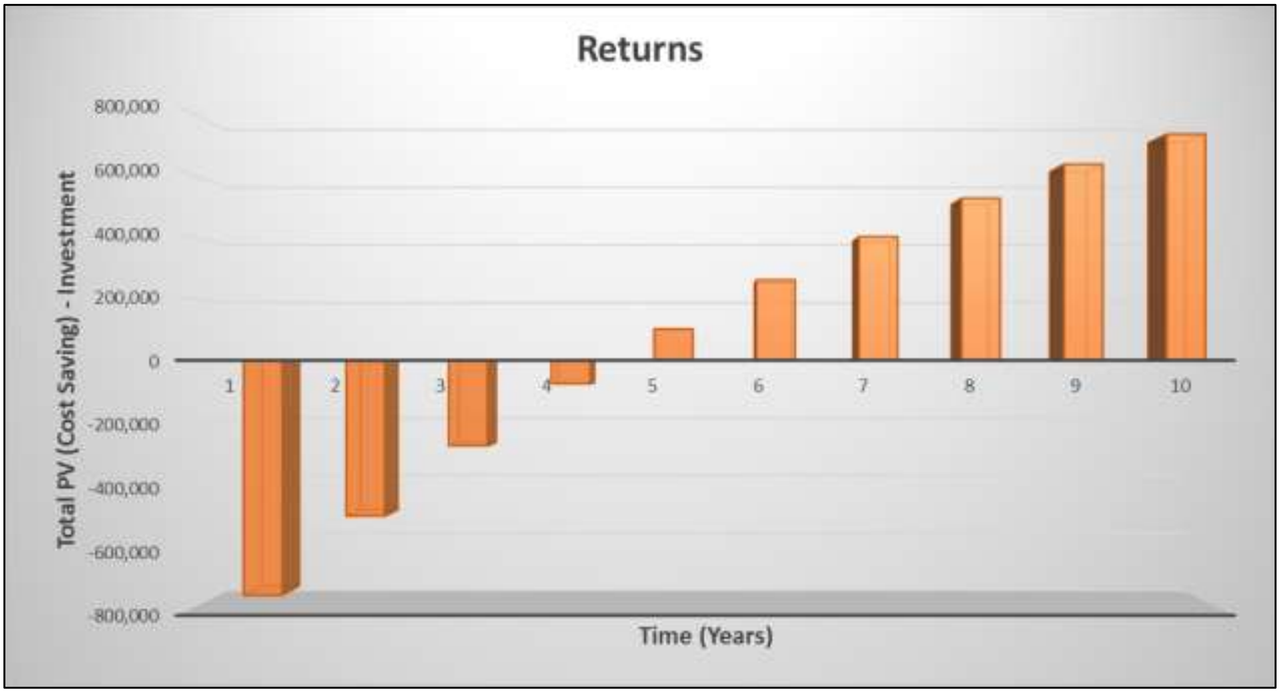


Figure 5-74: Estimated mean returns when Panda response rate is 0.90

Figure 5-75: Estimated mean returns when Panda response rate is 0.99

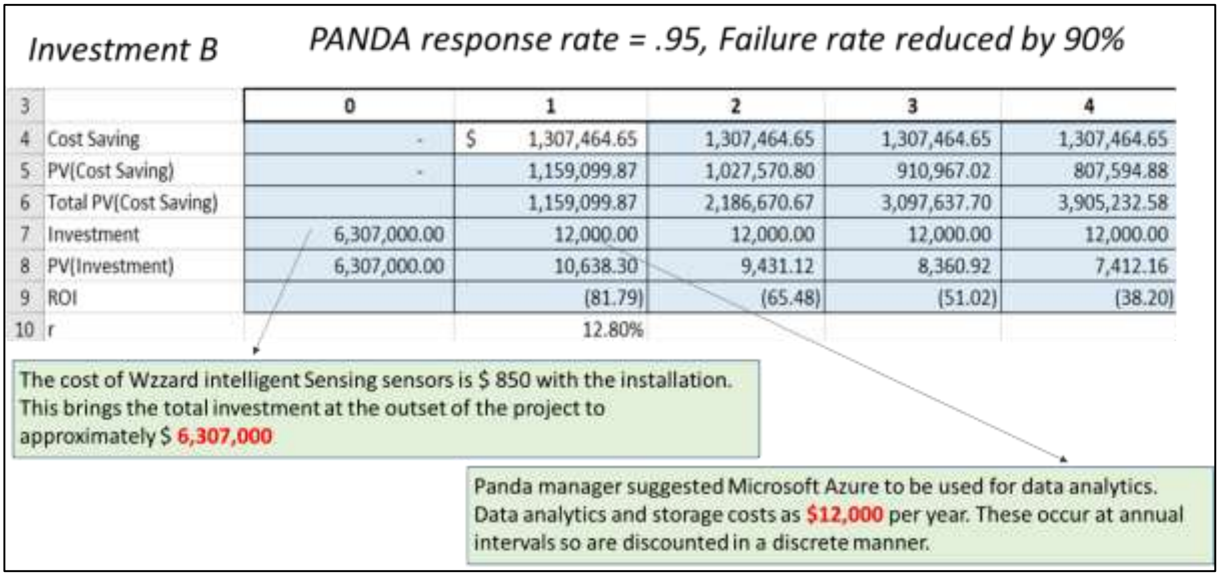
Table 5-11: Summary of annual saving rates and multi-year ROI values for different Panda responses rates

Panda's Response Rate	Saving Rate from Simulation/year	4-year RIO (%)	5-year RIO (%)	6-year RIO (%)	7-year RIO (%)
0.7	$ 253,435.00	(27.87)	(14.64)	(2.92)	7.48
0.75	$ 271,537.50	(22.71)	(8.54)	4.02	15.15
0.8	$ 289,640.00	(17.56)	(2.45)	10.95	22.83
0.85	$ 307,742.50	(12.41)	3.65	17.89	30.51
0.90	$ 325,845.00	(7.26)	9.75	24.82	38.18
0.99	$ 354,809.00	2.02	20.72	37.30	52.00

As it is shown above, a positive ROI could be achieved in year 7 with a response rate of 0.7, year 6 with response rate between 0.75 and 0.80, year 5 with response rate between 0.85 and 0.90, and finally year 4 with a response rate of 0.99.

❖ **Investment B:**

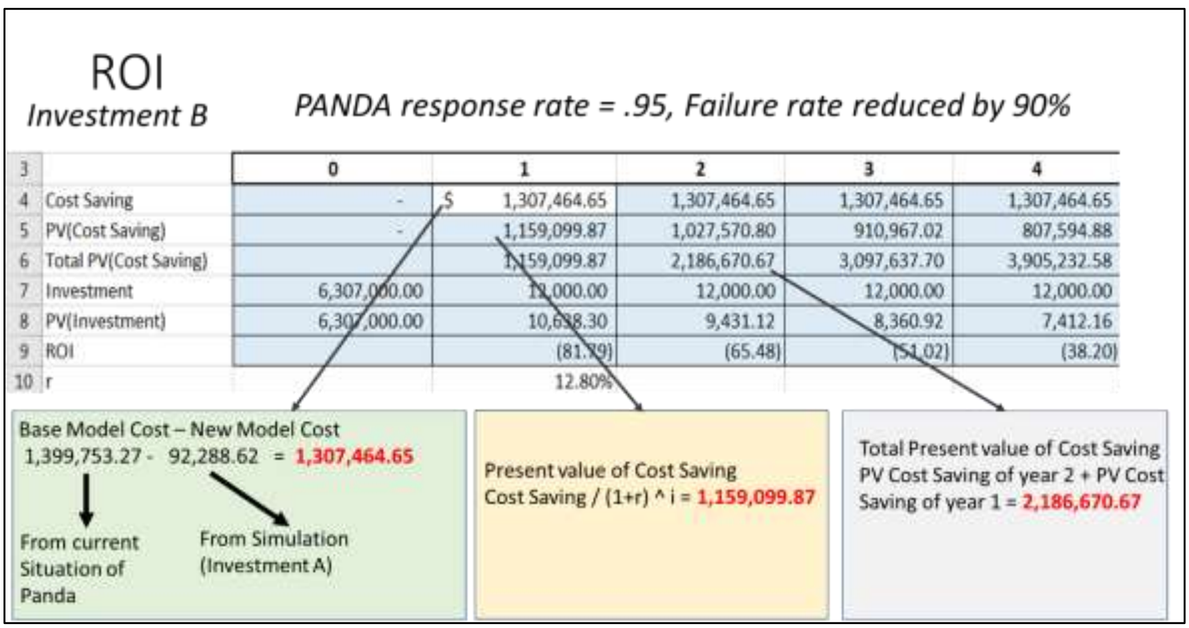
Figure 5-76 and Figure 5-77 show how ROI was calculated when Panda response rate = 0.95 and failure rate reduced by 90%. The estimated mean returns (Cost savings - Investment) when Panda response rate is 095 and failure rate reduced by: 80%, 85%, 90%, 95%, and 99% are shown in Figure 5-78, Figure 5-79, Figure 5-80, Figure 5-81, and Figure 5-82 respectively. A summary of annual saving rates and multi-year ROI values for different Panda responses rates and failure rates is shown in Table 5-12.



Investment B *PANDA response rate = .95, Failure rate reduced by 90%*

3		0	1	2	3	4
4	Cost Saving	-	$ 1,307,464.65	1,307,464.65	1,307,464.65	1,307,464.65
5	PV(Cost Saving)	-	1,159,099.87	1,027,570.80	910,967.02	807,594.88
6	Total PV(Cost Saving)		1,159,099.87	2,186,670.67	3,097,637.70	3,905,232.58
7	Investment	6,307,000.00	12,000.00	12,000.00	12,000.00	12,000.00
8	PV(Investment)	6,307,000.00	10,638.30	9,431.12	8,360.92	7,412.16
9	ROI		(81.79)	(65.48)	(51.02)	(38.20)
10	r		12.80%			

Figure 5-76: Investment B calculation



ROI

Investment B *PANDA response rate = .95, Failure rate reduced by 90%*

3		0	1	2	3	4
4	Cost Saving	-	$ 1,307,464.65	1,307,464.65	1,307,464.65	1,307,464.65
5	PV(Cost Saving)	-	1,159,099.87	1,027,570.80	910,967.02	807,594.88
6	Total PV(Cost Saving)		1,159,099.87	2,186,670.67	3,097,637.70	3,905,232.58
7	Investment	6,307,000.00	12,000.00	12,000.00	12,000.00	12,000.00
8	PV(Investment)	6,307,000.00	10,638.30	9,431.12	8,360.92	7,412.16
9	ROI		(81.79)	(65.48)	(51.02)	(38.20)
10	r		12.80%			

Figure 5-77: ROI calculation when Panda response rate is 0.95 and failure rate reduced by 90%

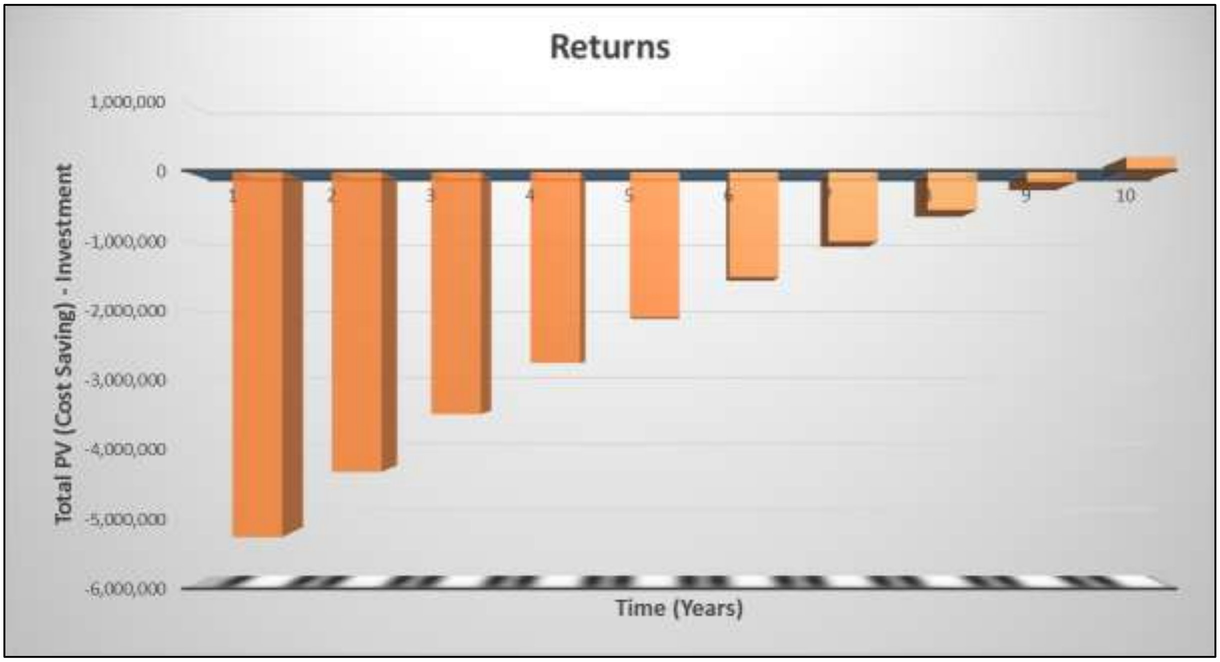


Figure 5-78: Estimated mean returns when Panda response rate is 0.95 and failure rate reduced by 80 %

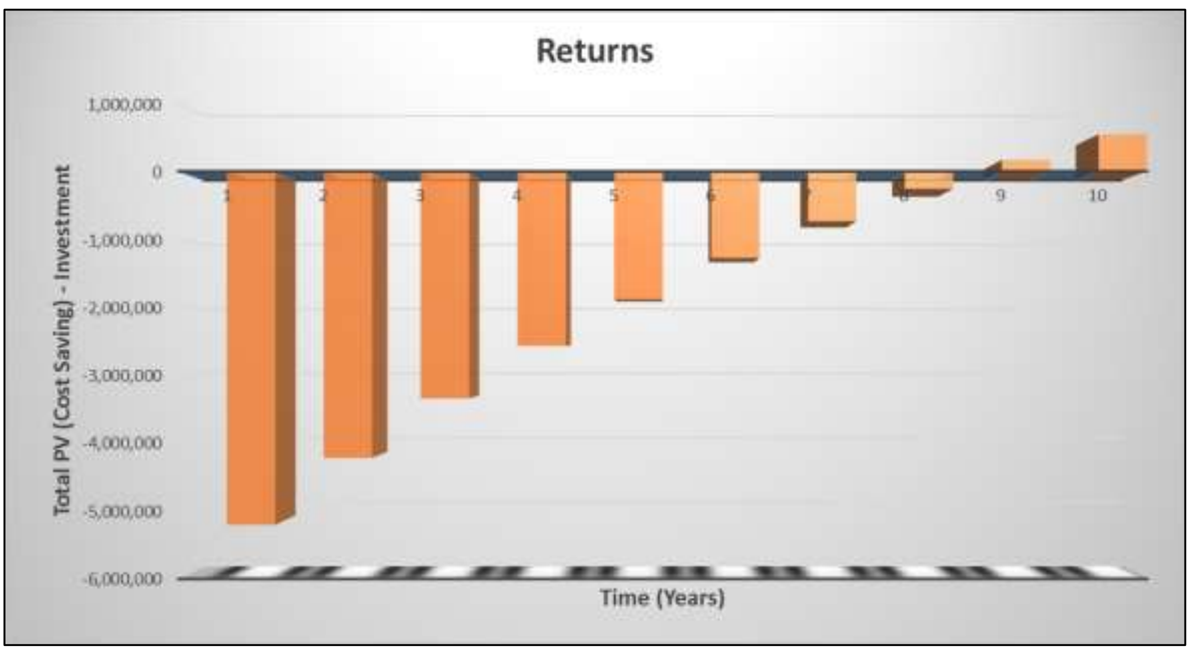


Figure 5-79: Estimated mean returns when Panda response rate is 0.95 and failure rate reduced by 85%

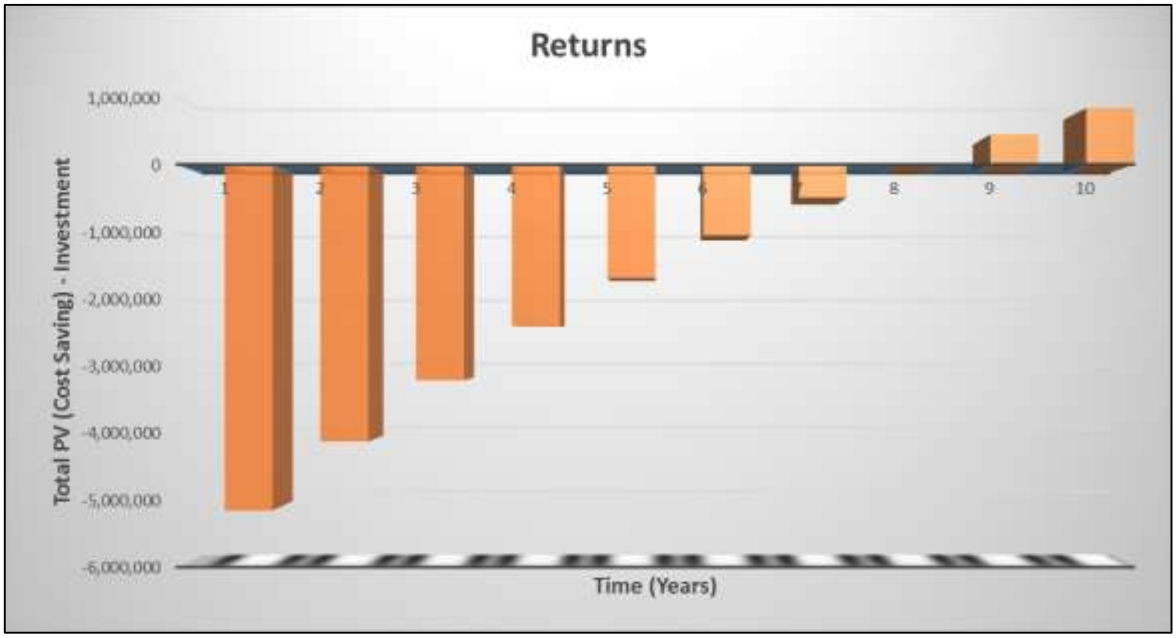


Figure 5-80: Estimated mean returns when Panda response rate is 0.95 and failure rate reduced by 90%

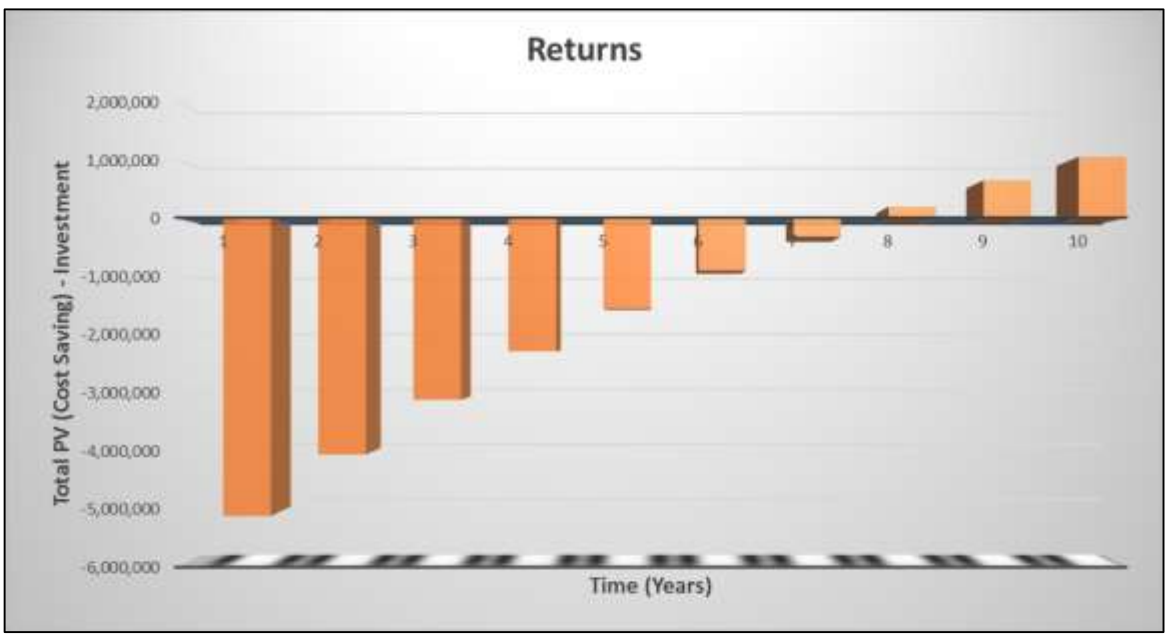


Figure 5-81: Estimated mean returns when Panda response rate is 0.95 and failure rate reduced by 95%

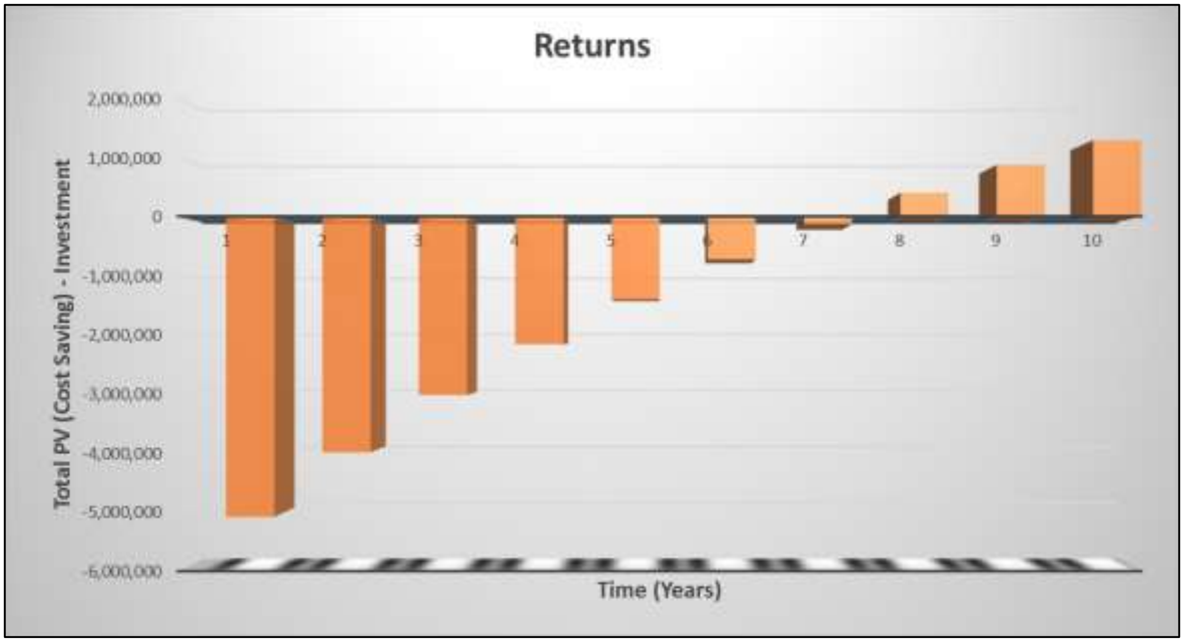


Figure 5-82: Estimated mean returns when Panda response rate is 0.95 and failure rate reduced by 99%

Table 5-12: Summary of annual saving rates and multi-year ROI values for different Panda responses rates and failure rates

Panda Response 0.8	Failure Rate reduced by	Saving Rate from Simulation/year	7-year RIO (%)	8-year RIO (%)	9-year RIO (%)	10-year RIO (%)
	80%	$ 1,179,444.56	(16.86)	(9.72)	(3.38)	2.23
	85%	$ 1,246,496.51	(12.13)	(4.58)	2.11	8.05
	90%	$ 1,303,174.65	(8.13)	(0.24)	6.76	12.96
	95%	$ 1,342,449.27	(5.36)	2.77	9.98	16.37
	99%	$ 1,388,728.49	(2.09)	6.32	13.77	20.38

Panda Response 0.85	Failure Rate reduced by	Saving Rate from Simulation/year	7-year RIO (%)	8-year RIO (%)	9-year RIO (%)	10-year RIO (%)
	80%	$ 1,182,759.56	(16.63)	(9.46)	(3.11)	2.52
	85%	$ 1,248,771.51	(11.97)	(4.40)	2.30	8.25
	90%	$ 1,304,604.65	(8.03)	(0.13)	6.88	13.09
	95%	$ 1,343,196.77	(5.30)	2.83	10.04	16.43
	99%	$ 1,388,825.99	(2.09)	6.33	13.78	20.39

Panda Response 0.9	Failure Rate reduced by	Saving Rate from Simulation/year	7-year RIO (%)	8-year RIO (%)	9-year RIO (%)	10-year RIO (%)
	80%	$ 1,186,074.56	(16.39)	(9.21)	(2.84)	2.81
	85%	$ 1,251,046.51	(11.81)	(4.23)	2.49	8.44
	90%	$ 1,306,034.65	(7.93)	(0.02)	7.00	13.21
	95%	$ 1,343,944.27	(5.25)	2.89	10.10	16.50
	99%	$ 1,388,923.49	(2.08)	6.33	13.79	20.40

Panda Response 0.95	Failure Rate reduced by	Saving Rate from Simulation/year	7-year RIO (%)	8-year RIO (%)	9-year RIO (%)	10-year RIO (%)
	80%	$ 1,189,389.56	(16.16)	(8.95)	(2.57)	3.10
	85%	$ 1,253,321.51	(11.65)	(4.06)	2.67	8.64
	90%	$ 1,307,464.65	(7.83)	0.09	7.11	13.34
	95%	$ 1,344,691.77	(5.20)	2.94	10.16	16.56
	99%	$ 1,389,020.99	(2.07)	6.34	13.80	20.41

As it is shown above, a positive ROI could be achieved in year 10 when failure rate is reduced by 80%, year 9 when failure rate is reduced between 85% and 90%, year 8 when failure rate is reduced by 95% and 99%. The table above also shows that Panda response rate, in investment B, does not have a huge impact on ROI as it has in investment A. For example, a positive ROI could be achieved in year 10 (when failure rate is reduced by 80%) even when Panda response rate changes between 0.7 and 0.95. There is only one situation where Panda response rate makes a difference on when a positive RIO can be achieved. This situation is when a response rate changes from 0.9 to 0.95 (when failure rate is reduced by 90%), a positive ROI could be achieved in year 8 instead of 9.

5.3.6 Conclusion and Discussion

The proposed framework of this study suggests using ABM as a tool to test the acceptance of an IoT business solution. Similar to the first case study, Panda's case study has validated step 3 of the framework which is the main focus of the research. This case study shows a positive outcome in this stage by investigating the potential of using ABM in IoT environment.

A particular application was addressed in the installation of IoT condition monitoring sensors to refrigerators in Panda. The developed ABM was supported by the historical data analysis to present a view of the real system. The results from the case study provide a number of conclusions. The stochastic nature ABM offers an insight into worst and best case scenarios. It is significant to take these potential possibilities and risks into account when understanding the results from the model. The ABM proposes that condition monitoring sensors on refrigerators (investment A) could realize a positive ROI approximately between 4 years (best-case scenarios) and 7 years (worst-case scenarios) following the initial installation. For applying the predictive maintenance capabilities, ABM suggests that investment B could realize a positive ROI approximately between 8 years (best-case scenarios) and 10 years (worst-case scenarios) following the initial installation. These initial results were presented to experienced managers in Panda. Their feedback highlighted that both investments meet Panda's requirements. Since the average cost saving per year of investment B is much higher than investment A, applied predictive maintenance is recommended. The only concern with the predictive maintenance is that it requires a large amount of investment. It was also determined that to realize a positive ROI, Panda firm must ensure that the predictive maintenance strategy is implemented correctly and adopted in its current maintenance system. The next step in to fully graduate this work from its origins in theoretical application to a refined process for evaluating ROI for IoT projects. This case study has highlighted the essential value of this approach and will aid to improve the emerging paradigm between ABM and IoT.

5.3.7 Limitations and Future Work

one of the limitations of this case study is that the failure behavior developed only represents one of some ways to describe this aspect of the system. A more complex behavior could be developed using hidden Markov models (Houston et al., 2017). A major limitation of this case study to the development would be the lack of sufficient data regarding refrigerators failures. An advantage of redesigning the failure behavior using the Bayesian updating approach would be that the sensors themselves could be more rigorously simulated. As Bayesian updating lets one assign failure probability values to the sensor correctly by identifying the refrigerator's condition state, the method would allow ABM to capture this added level of complexity. A further factor to consider in the probability of failure could be to build a new behavior object.

Another limitation is that the predictive maintenance strategy in Panda's case study does not take into consideration the reduction in the frequency of maintenance tasks. The approach to maintenance should be changed if a condition monitoring strategy is to be effective. Future work should cover how a reduction in the frequency of maintenance tasks would affect the overall ROI of the venture.

The complexity of the current ABM model could be further improved. The introduction of more advanced agent decision-making processes can be included. For store agent, it would be interesting to incorporate forecasting ability into the predictive maintenance scheduling. In addition to that, the transportation system could be improved in the model since all the physical locations of the stores are identified in Saudi Arabia map. Moreover, the queueing system for the manufacturing and the internal repair agent could also be enhanced. Application of an advanced queueing theory may generate interesting interactions between refrigerators in Panda's stores and these agents.

Lastly, some of the limitations to ABM model of Panda's case study include the following. The current failure behavior is based on relatively recent historical data, and so it may not continue to apply far into the future. Additionally, the complete replacement of Panda's refrigerators is not accounted for in the agent-based model. Finally, the possibility of the sensor itself failing and needing replacement is not considered. In extending the model, it would be valued to assess how including these longer-term concepts would affect the value added after installing the sensors.

CHAPTER 6: CONCLUSION AND FUTURE RESEARCH

6.1 Conclusion

IoT brings countless benefits to the business. However, firms nowadays face challenges while adapting IoT technology because of the variety of the connected thing in IoT, the absence of structure in the ecosystem regarding roles of the different participants, and the lack of a dominant design of an IoT environment. While business model frameworks are well identified and established for a single organization, most of these frameworks do not consider the interdependencies firms which are developing in the same direction and the opportunities they provide. As a result, a decent representing of business models based on the internet of things (IoT) ecosystems is not yet well recognized.

The objective of this research study is to develop a framework helps to discover the IoT opportunities and challenges for predictive maintenance industry and propose an effective IoT solution. In the era of information, firms should be able to deal with big data issues, especially in this age where the information is growing each minute due to the external and internal interactions between human and objects.

Moreover, the framework of this research introduced a study to test the feasibility of the proposed IoT solution using agent-based model (ABM) in order to identify IoT adoption and life cycle. The paradigm of ABM was utilized to verify the acceptance of the solution by simulating the behavior of the agents. Several earlier studies suggested empirical testing for firm’s business models based on IoT. However, the examples are infrequent because of the limitations access to the company database.

In order to analyze the mentioned problem, a research methodology has been developed. It started by reviewing the literature, analyzing the literature gap, developing a framework, proposing case studies to validate the framework, and finally discussing the results and future studies. The literature showed that there is an absence of a reliable methodology to validate IoT solutions. The need for innovative IoT business models that develop in different industries is crucial. There are numerous reasons cause plenty of research gaps related to IoT solutions. First, there is a small number of studies associated with IoT business models. Second, the existing literature describes business models within a single organization and not across the firm's networks. Lastly, there are unlimited possibilities to connect objects, consumers, and businesses together, which makes this almost unmanageable to create a particular IoT business solution. However, Industrial engineers play a significant role in the development of IoT solutions and test its acceptance through simulation and optimization. One of the important decisions that management must consider upon testing the effectiveness of its IoT business model is the proper validation methodology. This includes a deep understanding of modeling the agents' behaviors.

After reviewing the literature, a conclusion has been drawn about the opportunities and challenges while adapting IoT technology. The interaction between various IoT devices is a part of the key features of the technology. These features can be ultimately modeled by ABM model. However, a comprehensive framework was developed in this study to ensure the reflection of the business requirements in IoT environment.

6.2 Summary of the Framework

This framework was initially adopted from Isaksen and Treffinger model (Isaksen & Treffinger, 2004). The strength of the proposed framework is that it ensures that the IoT technology is driven by considering the business perception of value from the start. This section explains how this framework was applied in IoT environment. As it is shown in (Figure 6-1), the three main steps of the framework are: generating ideas, understanding the challenges, and preparing for actions.

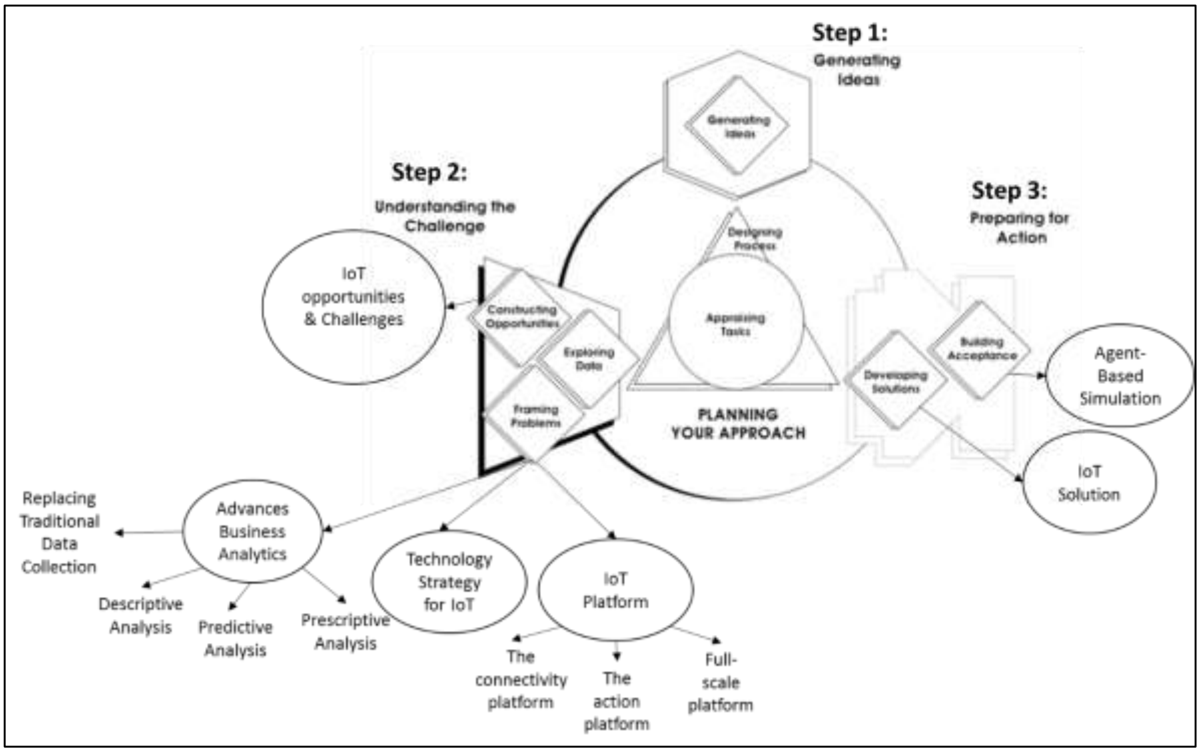


Figure 6-1: Proposed framework for this study

Step one (generating ideas) produces a wide range of potential business solutions and thoughts to respond to the actual strategic concern. The main principle of this step is to challenge assumptions by including all selections. It is not uncommon for a solution that appears unfitting initially to be established into a very operative solution. For IoT environment, this would include listing all the various selections in which all options for providing roaming, all possibilities of providing service ubiquity, etc.

Step two is an investigative step that aims to expose the problems and issues generally to offer an overall perception including conflicting opinions and views. For IoT environment, this covers detailing the different participants from various businesses and industries, the expected services to emerging, the different platforms among industries, etc. This step also squeezes the problem by recognizing the specific requirements that the technology strategy should respond to. It identifies the customers in the selected space and follows to understand what these customers observe as value and what their preferred results are. These specific elements should be addressed in this step to reach the desired objective of the business and therefore to meet and exceed customer needs. For IoT world, it might include a need to make sure zero downtime, need for improve security, need to offer connectivity for remote devices as a differentiator, etc. Step 2 will answer the following questions:

1- What is the IoT technology strategy consideration?
2- Which analytics platforms will be used to obtain value in an IoT environment?
3- What is the level of the technological depth of the internet of things platform?

Step three, which the main focus of this study, not only assesses the IoT potential solutions generated but also examines a suggested solution to be implemented in the future using ABM. It is important to realize the risk and the impact of this step to develop an effective IoT business solution. The output of this step is the recommended IoT solution to be implemented supported by business, financial, and technical feasibility. This step also recognizes how efficiently the selected solution meets both the customer and business needs using agent-based simulation (ABM). As technology progresses towards new paradigms such as internet of things (IoT), there is a need for business executives and leaders for a valid technique to recognize the value of assisting these ventures. Traditional simulation and analysis techniques are not able to model systems complexity. However, ABM presents an attractive simulation technique to capture these underlying difficulties and provide a business solution.

The proposed framework has been validated through two case studies. The first one introduces a hypothetical study of business modeling of IoT using ABM in order to determine its adoption. ABM is utilized to verify the effectiveness of the business model and simulate the behavior of the market in Orlando city (Florida, United States). This case study focusses on a predictive maintenance business model that uses IoT. The physical components of the systems are connected to IoT sensors and RFID tags to collect data that is stored on a cloud-based system. The second case study is addressed to assess the return on investment (ROI) of installing sensors to monitor the condition of refrigerators in Panda. Panda considers two type of IoT investments: A & B. Investment A aims to install sensors that monitor the temperature of Panda’s refrigerators only and receive notifications when a refrigerator fails, and the temperature goes under a certain limit. Investment B applies the predictive analytics to predict failure before it happens. The aim of investment B is not only to reduce the food waste but also costs associated with refrigerators failure. ABM is developed to simulate Panda's refrigerators behaviors and evaluates how returns can be achieved from the two types of IoT investments.

6.3 Contribution to the Body of Knowledge

Upon revising the literature, it appears that there is an absence of integrated dynamic models that validate IoT business solutions. Therefore, this research contributes to the body of knowledge by proposing an integrated framework to resolve the problems associated with the adoption of IoT technology. The substantial phase of the framework is testing the effectiveness of the proposed IoT solution using ABM. To implement it, expert engineers have contributed to the work along with data needed in order to achieve the desired objectives.

Identifying and clarifying the tangible opportunity and its related challenges is not easy. This is true for IoT and many other strategic problems. Because of that, it will be beneficial to use a systematic approach to identify strategic concerns and solve them holistically. This framework contributes as a strategic guidance to analyze internet of things (IoT) solutions and examine its adoption and related challenges. The strength of the proposed framework for recognizing technology strategy concerns is that it guarantees that the IoT technology is driven by considering all the business perception of value from the beginning.

6.4 Limitations & Suggestions for Future Work

In this study, the proposed framework filled a research gap with a methodology that helps to test the feasibility of IoT business solution using a simulation model. The scope of the study covers the interaction between different and various agents. To augment the study in this area, several future research directions are proposed. Also, limitations of the current study are outlined in this section.

One of the limitations of this study is that the framework assumes the capabilities of physical technologies that are able to obtain and analyze real-data and then share it. Due to the absence of a smart technological feature in the chosen facility in this research, another study with more advanced facility is recommended to demonstrate the advantages of the agent-based model in IoT environment more clearly. A deeper understanding of the existing capabilities and potentials of the internet of things (IoT) leads to a better ABM modeling. Moreover, ABM can help in the designing stage of these technologies significantly and support management to determine the needed requirements for its features. Therefore, integrating the technology advancement with ABM is a potential research area.

The lack of an integrated data warehouse that installs the agent behavior within the facility and across the organization level restricts the effectiveness of the framework. A future vision is proposed where the simulation is connected directly to real-time data sources to reduce uncertainties in parameters constantly. In turn, the agent-based simulation (ABM) output can provide extra high-quality data to be examined using data science methods, offering a deeper understanding of the system (Houston et al., 2017). Merging the proper information with the right functionalities gives a chance to develop ABM that is able to simulate the system based on the communication and interaction between agents and events affecting the system performance.

A future research work also should combine various perspectives from computer science, manufacturing engineering, and software engineering. Beginning with conveying the experience of a manufacturing engineer using various concepts such as knowledge acquisition to help a software engineer to design a robust artificial intelligence system that can be integrated with an agent-based model.

Another limitation of this research is that the framework suggests using ABM as the only tool to test the feasibility of IoT business solution. Future work should consider the integration between ABM and data science. As with most advanced technologies, ABM shows limitations that are likely to be the reason to prevent its adoption. Some of ABM limitations can be addressed by integrating ABM with data science techniques. Among the main issue with ABM is the complexity of developing models due to the lack of standardized frameworks. While there are many software packages and free Java libraries available just for ABM, very few provide the capability to develop ABM model without a deep understanding Java programming language. Another common issue is the absence of a commonly accepted technique to verify and validate ABM. These two concern are essential for any simulation to reach accreditation.

Data science should integrate with ABM to improve the intelligence of the agents in the ABM simulation. This can be reached by combining methods such as classifier systems or regression analysis with the decision models of ABM agents. Also, data science can be combined with ABM to validate ABM statistically. Date science techniques such as clustering and regression can be used to decide whether the simulation model output matches the real data output or not. A novel technique in this area is Pattern-Oriented Modelling. In this method, several patterns in the ABM and the real data output are compared to investigate differences and similarities between the system structures on numerous and different scales. Many novel data science methods can be implemented to improve the understanding of ABM output data. This concept of integration between ABM and data science methods can be implemented by applying data-driven ABM Modelling that emphases on using data science techniques in all aspects of ABM, especially in the analysis phase (Houston et al., 2017).

The increasing number of malware programs targeting IoT objects and related security issues is one of the largest obstacles facing IoT technology. The heterogeneous nature of the IoT represents a big challenge in many various scientific and technical areas, among them security. Security becomes a very challenging problem as it exists in each aspect of IoT ecosystem, from objects and data acquisition hardware toward front-end software applications and complex user devices. Future work should utilize ABM to investigate the dynamics of malware spread. ABM must consider a set of varied agents and interactions between them that might allow malware communication and transmission. By applying this, ABM can examine the impacts of defense mechanisms in controlling the malware spread and thus decreasing the effects of attacks in networks.

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