A Hybrid Simulation Framework of Consumer-to-Consumer Ecommerce Space

Oloruntomi Joledo
University of Central Florida

A HYBRID SIMULATION FRAMEWORK OF CONSUMER-TO-CONSUMER ECOMMERCE SPACE

by

OLORUNTOMI JOLEDO
B.S. University of Ilorin, 2004
M.S. Southern Illinois University Edwardsville, 2010

A dissertation submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy
in the Department of Industrial Engineering & Management Systems
in the College of Engineering and Computer Science
at the University of Central Florida
Orlando, Florida

Spring Term
2016

Major Professors:
Luis C. Rabelo
Gene C. Lee

ABSTRACT

In the past decade, ecommerce transformed the business models of many organizations. Information Technology leveled the playing field for new participants, who were capable of causing disruptive changes in every industry. “Web 2.0” or “Social Web” further redefined ways users enlist for services. It is now easy to be influenced to make choices of services based on recommendations of friends and popularity amongst peers.

This research proposes a simulation framework to investigate how actions of stakeholders at this level of complexity affect system performance as well as the dynamics that exist between different models using concepts from the fields of operations engineering, engineering management, and multi-model simulation.

Viewing this complex model from a systems perspective calls for the integration of different levels of behaviors. Complex interactions exist among stakeholders, the environment and available technology. The presence of continuous and discrete behaviors coupled with stochastic and deterministic behaviors present challenges for using standalone simulation tools to simulate the business model.

We propose a framework that takes into account dynamic system complexity and risk from a hybrid paradigm. The SCOR model is employed to map the business processes and it is implemented using agent based simulation and system dynamics. By combining system dynamics at the strategy level with agent based models of consumer behaviors, an accurate yet efficient representation of the business model that makes for sound basis of decision making can be achieved to maximize stakeholders’ utility.

To The Joledos

ACKNOWLEDGMENTS

Special thanks to Dr. Luis Rabelo for his vision and guidance.

Thank you to:

Dr. Ahmed Elshennawy

Dr. Gene Lee

Dr. Richard Ajayi

Dr. Basma Selim

Olorunshola Olaiya

Liz Stalvey

Manuel Gonzalez

Michelle Lores

IAGS at UCF

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS/ABBREVIATIONS

ABM	Agent Based Simulation
DES	Discrete Event Simulation
DESS	Differential Equation System Specification
DEVS	Discrete EVent System Specification
e-SCM	Electronic Supply Chain Management
KPI	Key Performance Indicator
LC	Lending Club
MFI	Microfinance Institution
NN	Neural Network
P2P	Peer-to-peer
SC	Supply Chain
SCC	Supply Chain Council
SCM	Supply Chain Management
SCOR	Supply Chain Operations Reference
SD	System Dynamics
US(A)	United States (of America)

CHAPTER 1. INTRODUCTION

1.1 Background

The internet redefines the way people do business by making products and services accessible to anyone with an internet connection. Social networking sites such as Facebook, and Twitter are transforming the manner in which customers enlist for services. Users are easily influenced to choose services based on electronic word-of-mouth, recommendations of friends and popularity amongst peers (Bachmann et al., 2011; Johnson, Ashta, & Assadi, 2010).

The value proposition offered to customers in ecommerce is the ability to trade with other customers with minimal intermediation. The objective is to provide a responsive system that encourages trust. To meet target requirements, processes are automated to eliminate the middle man and minimize unnecessary overheads. Such business models change industry structure because they often go under the radar of the incumbents until they overtake them.

The proliferation of portable electronic devices such as tablets and smartphones which drive m-commerce is another contributor to this trend. These disruptive techniques have replaced traditional distribution channels and reshaped the customer-supplier relationships (Alt & Puschmann, 2012).

Several studies have been conducted on business-to-business (B2B), business-to-consumer and (B2C) ecommerce but little has been done on the consumer-to-consumer (C2C) business model from a system perspective. In C2C space, consumers sell goods and services to each other. Research in C2C commerce involves business models, practices and strategies, consumer behavior, market dynamics, technology and statistical analysis. C2C applications help individuals conduct their own e-business transactions. Some of such models include social networks, peer-to-peer lending, peer-to-peer commerce as popularized by eBay, Amazon, and Taobao.com.

1.2 Challenges in Ecommerce Hybrid Systems

There are complex, competitive and technology driven environments brought by the Internet and the social networks. To be more competitive, organizations use ecommerce to achieve their goals of just-in-time production, delivery and to improve income. To achieve organizational goals in the midst of conflicting objectives, processes and activities need to be synchronized, coordinated and integrated (Helal, 2008). Organizations face an ever increasing number of challenges and threats – changes in market, competitors, customer demands and security. These systems are characterized by frequent transactions from a varied customer base and consequent reduction in order size while maintaining an element of stochasticity in demand patterns. This means that management faces the challenge of implementing the right strategy. Business processes and system configurations have adverse effects on customer service and order fulfillment (Canetta, Cheikhrouhou, & Glardon, 2013).

The technology dependent business model of ecommerce also means that a blockage or system hack can affect the performance of the system. There is a bigger shift to retaining existing customers than acquiring new customers. A weak link of the business model is that capital investment is initially low and the model is easily replicated (D. Kim, 2013). C2C companies face competitions from large organizations as well as from entrepreneurs who have very little to lose by embarking in the business. In addition, customers do not need to leave the comforts of their homes to find better deals. They can compare the offerings of different companies online and make a hassle free change if they are not getting value for their monies. Other challenges include how to unify a group of consumers according to their needs, preferences and interaction with each other.

Conducting a stakeholder analysis reveal stakeholders range from providers, customers, companies and complementors (J.-H. Wu & Hisa, 2004). These stakeholders include the community, suppliers, alliance partners, shareholders and government - forming a large collection of active objects in the system. These stakeholders seek to maximize their utility. The assumption for this study is that the seller seeks to sell his product at a profit while the buyer seeks to pay the minimum for a particular product. The provider supplies a medium for the realization of customer utility while making a profit in the process.

With the growing popularity of consumer-to-consumer models, decision making on the part of stakeholders can be difficult due to the system's interplaying factors and uncertainty in customer demand. On another hand, risks can include system fidelity, payment fraud and viruses. These characteristics make for a complex system with multi-level abstractions and heterogeneous elements. Simulation serves as a decision support tool but there exist limitations of individual simulation paradigms. It is of the interest of these complex organizational environments to use their knowledge of stakeholder actions and business processes for decision-making. These actions give rise to nonlinear interactions that is difficult to capture using standalone simulation paradigms. Standalone techniques were found to be inadequate for aiding decision making in a hybrid system because most problems do not conform to one modeling paradigm. The complex interactions among different functional areas require modeling and analyzing the system in a holistic way. There is a lack of mechanism to facilitate systematic and quantitative analysis of the effects of users and platform actions on system performance through the understanding of the system behavior.

To study the dynamics of customers in order to support decision-making, simulation provides suitable tools. The complexity of the market and customer behavior requires nontraditional modeling tools to analyze and model. Behaviors are defined at individual level and at the system level. The decision making process is information intensive. Hybrid simulation provides an approach that does not make the assumption of a perfect market and homogeneity. Stakeholders can allocate their resources effectively if they know the characteristics that lead to actions. Simulation helps to incorporate fluctuations in the market into the decision making process.

1.3 <u>Problem Description</u>

Internet based models cause disruptions to traditional business models. New players find it challenging navigating the highly competitive landscape of this complex environment. Due to characteristics mentioned in Section 1.2, the ecommerce system tends towards complexity. There exists several performance risks associated with the business model. These risks include those of minimal return on investment, government regulations and lack of trust. Results from case studies and literary review reveal that the performance of C2C systems remain under explored from a system perspective. Complex interactions exist among stakeholders, the changing environment and available technology. There is a need for an integrated system that will provide a testing ground for managing control actions, anticipating changes before they occur and evaluating the effects of user actions on the system at different managerial levels.

The presence of continuous and discrete type behaviors pose challenges for the use of existing simulation tools in simulating the space. The system is characterized by uncertainty as well as government regulations and external factors. Important factors such as liquidity and different threshold values for consumers remain undefined. Not addressing these issues can result to financial losses and lack of trust that can erode the benefits of the business model. There is a need to systematically map, model and evaluate the viability and performance in order to realize the best tradeoff between benefits and risks.

Decision-making is a function of complex interactions of consumers, suppliers, management, business processes, environment and components. Hence, we suggest hybrid simulation as useful to map real entities into a simulated environment. The main research question to be addressed in this study is: can hybrid simulation-based modeling of the business processes of a risk based consumer-to-consumer (C2C) ecommerce system aid in the assessment of its viability and changing business environment?

1.4 Research Objectives

The main aim of this research is to systematically investigate, through multi-model simulation, the dynamics that lead to success of C2C commerce business model. A secondary objective is to provide a deeper understanding of the operational innovative business model of C2C system. Specific objectives of this research are as follows:

- Develop a framework that will capture the dynamics of this domain.
- Create a comprehensive and scalable hybrid simulation model of discrete and continuous approaches that will enable the evaluation of the viability of ecommerce business models

- and use developed simulation model to test factors critical to the success of the consumer-to-consumer ecommerce case. Using discrete-continuous characteristics of the system, the model will enable management test policies before implementing them.

- Map and develop a systematic model to capture operations and interrelationships of the business model.
- Integrate elements to capture the risk of stakeholders within the simulation environment.

1.5 Proposed Framework

This study proposes the use of a hybrid of agent-based modeling and simulation as well as system dynamics integrated with industrial engineering supply chain concepts to analyze the ecommerce space. Thus, the study will demonstrate how hybrid simulation can be used to explore management decisions in this environment. By viewing the problem from a supply chain perspective will help to identify the efficiencies in the business model and will help to understand the different elements, stakeholders, suppliers and transactions in the system while taking into consideration estimations of customer purchasing behavior.

To achieve the research objectives, a literature review is carried out and an approach for hybrid simulation is constructed. System dynamics (SD) is a system thinking approach proposed to model the business dynamics and policies on a system level. The system dynamics paradigm abstracts away from individual objects – aggregates of stocks and flows – while incorporating feedback loops. SD is practical way to map mental models and business models that incorporates learning (Petrovic, Kittl, & Teksten, 2001). Agent based simulation is applied to study behaviors of individual agents (consumers) as they interact with each other and the environment. The knowledge gained will allow us construct necessary tools for making decisions and implementing systems behaviors in order to mitigate risks.

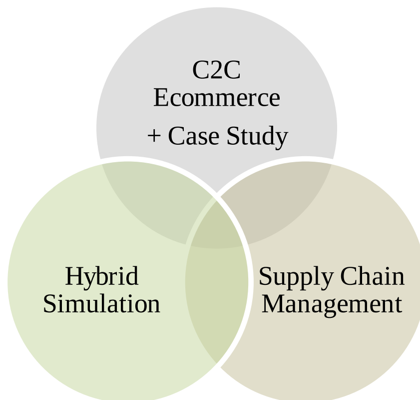


Figure 1: Scope of Study

1.6 Potential Contributions of this Research

Many real-world problems would benefit from combining different simulation paradigms. Past research focused on simulating the supply chains and operations of various industries with no particular emphasis to ecommerce. This study anticipates making the following contributions to the body of knowledge.

First, to create a feasible, systematic generic framework that consists of a hybrid simulation approach that will aid in assessing the viability of new business models. The business processes of this model have not been clearly mapped in literature. Moreover, the developed framework will extend the applicability of hybrid simulations to ecommerce systems and will improve decision support.

Second, results from this study will enable stakeholders evaluate system performance with a goal to maximize their returns. To our knowledge, this research is the first to demonstrate the computer modeling and simulation of a peer-to-peer case study as an effective way to assess viability of a business. So far, very few studies have applied simulation approach, and in particular, hybrid simulation, to understand the dynamics of consumer-to-consumer commerce.

1.7 Thesis Outline

This study is organized as follows: CHAPTER 2 presents a review of existing literature in the areas of ecommerce, hybrid systems and simulation modeling for ecommerce, while inferring gaps in the literature. These topics constitute the building blocks of the framework developed in subsequent chapters. CHAPTER 3 describes details of the methodology used to address the research questions and specifies the way the data is collected for analyses. CHAPTER 4 expounds on the proposed framework. CHAPTER 5 details the case studies of a leading P2P company. CHAPTER 6 implements the framework and validates the results of the framework using the case study. Last but not least, CHAPTER 7 gives the conclusion, recommendations based on results of the study and suggests some directions for future study.

1.8 Definitions

Adverse Selection: describes a situation when sellers and buyers in a given market have different (often limited and asymmetric) information, thereby ensuring that one party bear a higher risk than the other.

Credit Rationing: a sub problem under information asymmetry occurs when some qualified borrowers are not able to obtain loans even when they are willing to undertake higher than market interest rates.

Ex Ante: "before the fact/event" as in the *expected* return used to predict a given outcome.

Ex Post: "after the fact/event" as the use of *historical* returns to predict a given outcome.

Information Asymmetry: decision relating to when everyone does not have the same information is presented by George Akerlof for which he won a Nobel Prize. Example, a seller of a used car can know more than the buyer thereby taking advantage of buyer's incomplete knowledge.

Moral Hazard: tendency for a borrower to use received loans irresponsibly or take unnecessary risks. This can be mitigated by monitoring the borrower.

Risk Aversion: a risk-averse investor is wary of risks and often considers only risk-free prospects and eschews uncertain outcomes.

CHAPTER 2. LITERATURE REVIEW

This chapter presents a review of extant research on hybrid systems, ecommerce, and simulation modeling for ecommerce. Academic articles are reviewed from a number of journals. Texts used in this review were either conceptual modeling or quantitative modeling oriented, in order to understand the practical needs as well as the theoretical development in the area. In addition to ecommerce, search keywords such as agent based simulation, discrete event simulation, system dynamics, were used.

The main objective of the literature review is to (i) present an overview of hybrid systems (ii) give a background of ecommerce and e-business frameworks and application of hybrid simulation for decision making; (iii) understand the research trends both from industry and academic perspectives; and (iv) present the important work done on simulation for ecommerce. In addition, this review will present the place of the current research in the overall academic trends and show the gaps in current simulation study.

2.1 Simulation and Modeling

A model is a simplified representation of real life. Modeling and simulation is a tool to analyze, identify root causes and operation, test different hypotheses and create new knowledge about a system. According to (North & Macal, 2007), *modeling is an act of artful approximation*. Any system that can be described quantitatively using a set of equations or rules can be simulated. Models enable us to understand the structure and behavior of complex systems and test various hypotheses. Simulation is appropriate to model complexity and uncertainty by mapping the real world to the world of models, choosing the abstraction level and the modeling language. After finding the solution from a simulation study, results are mapped to the real world.

Ecommerce systems are classified as intelligent systems (Bucki & Suchanek, 2012). A system (simulation) can be discrete or continuous. In continuous simulation, the system evolves as a continuous function represented by differential equations while in discrete simulation, changes in the system are represented as separate events to capture logical and sequential behaviors. An event occurs instantaneously (such as the press of a button or failure of a device) to cause transitions from one discrete state to another. A simulation model consist of a set of rules (such as equations, flowcharts, state machines, cellular automata) that define the future state of a system given its present state (A. Borshchev & Filippov, 2004).

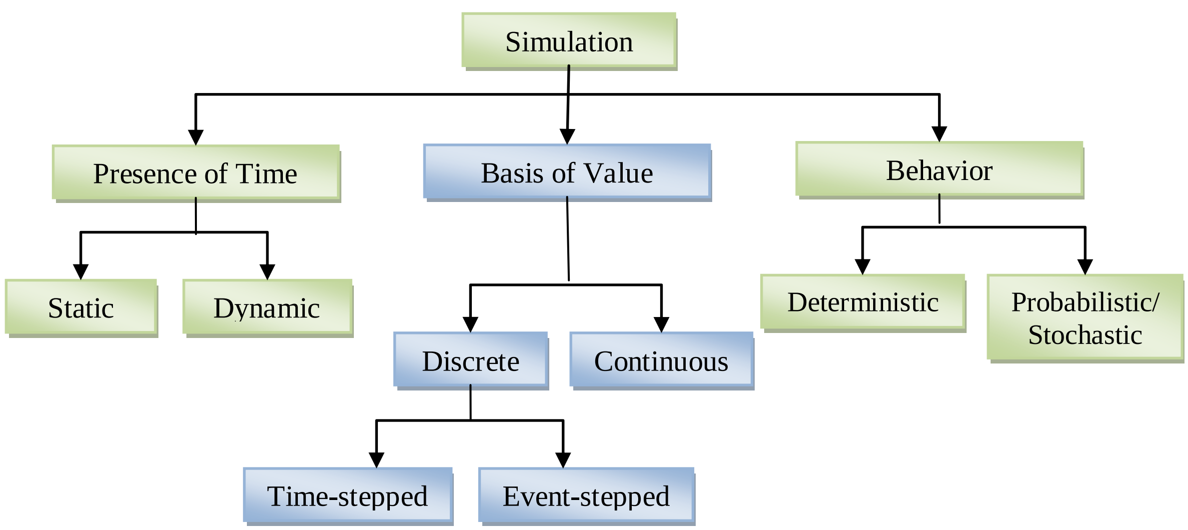


Figure 2: Simulation Taxonomy (modified from Sulistio et al., 2004)

There are different ways to classify simulation in terms of model structure. Sulistio, Yeo, & Buyya (2004) proposed a taxonomy that encompasses different approaches. The presence of time is irrelevant in the operation and execution of a static simulation model (e.g. Monte Carlo models). For the case of a dynamic model, in order to build a correct representation of the system, simulated time is of importance to model structure and operation (e.g. queuing or conveyor system).

Dynamic systems can be classified as either continuous or discrete. In continuous systems, the values of model state variables changes continuously over simulated time. In the event that the state variables only change instantaneously at discrete points in time (such as arrival and service times), the model is said to be discrete in nature. Discrete models can be time-stepped or event-stepped (or event-driven). In discrete-event models, the state is discretized and "jumps" in time and the steps time-step used is constant. State transitions are synchronized by the clock i.e. system state is updated at preset times in time-stepped while it is updated asynchronously at important moments in the system lifecycle in event-driven systems.

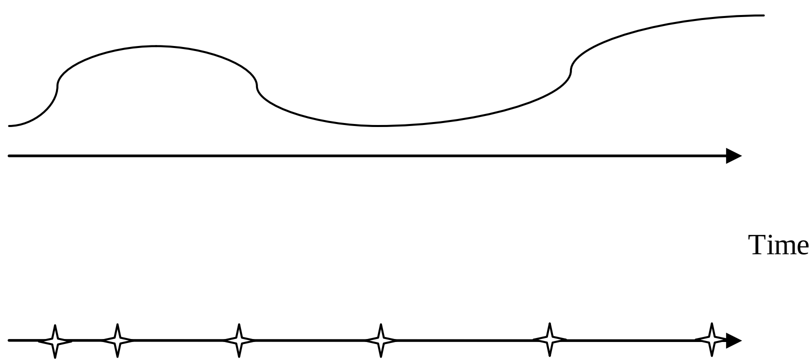


Figure 3: Continuous vs. Discrete Events

Deterministic and probabilistic (or stochastic) properties refer to the predictability of system behavior. Deterministic models are made up of fixed input values with no internal randomness given the same output for same corresponding input. Hence, the same set of inputs produces the same of output(s) in the system. In probabilistic models however, some input variables are random, describable by probability distributions (e.g. Poisson and Gamma distributions for arrival time and service times). Several runs of stochastic models are needed to estimate system response with the minimum variance.

2.2 Decision Making

An organizational system is influenced by operational-level (physical such as number of employees, number of parts) and context-level (such as skill level, policies) variables which interact with each other in a bidirectional manner by taking feedback into consideration to capture complex behaviors of the system. Complex models take into consideration dynamics of change. A business system is constantly faced with the ability to make decisions under pressure. Such decisions are strategic, tactical or operational in nature. Strategic decisions have long term significance. They address the vision of the organization, management policies, appropriate strategies to manage and allocate resources and selecting the right product and investment mix that embodies the vision of the business. Tactical decisions build on strategic decisions to encompass planning, acquiring and allocation and specifying details of work to be carried out as well as how to improve business processes. Operational decisions are more granular, often made on a weekly or monthly time frame. They further build on tactical decisions by specifying execution details such as performance measurement plans, order management, inventory control and scheduling.

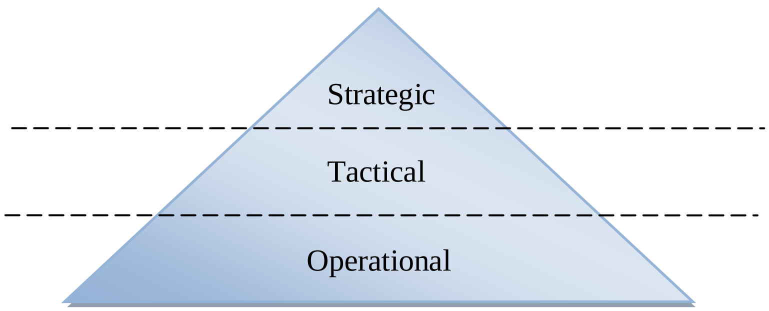


Figure 4: Decision Levels

Various approaches have been employed in past studies to optimize decision making in a business system. Approaches in operations research often find limited use to in real life due to their simplifying assumptions. Artificial intelligence techniques can model quantitative and qualitative parameters in complex systems but are difficult to build and verify (Rabelo, Helal, Jones, & Hyeung-Sik Min, 2005). Models work within reasonable margins of errors for general decision making. Lyons *et al*. expressed disagreement with the notion that realistic models are complex, making their output difficult to understand thus defeating the purpose of creating models. The choice of a particular approach to decision-making depends on the type of decision to be made and the stage of the process (Lyons, Adjali, Collings, & Jensen, 2003). The hybrid simulation approach provides decision-makers with a reliable system analysis that considers different types of system variables.

2.3 <u>Hybrid Systems</u>

Hybrid systems are complex systems made up of subsystems with time-discrete behaviors and subsystems with time-continuous behaviors interacting together to perform a function that can't be performed by individual subsystems alone. Thus requiring analysis at various aggregation levels. The corresponding simulation model is made up of continuous and discrete sub-models and interfaces between them. In hybrid simulation, discrete and continuous components interact either by discrete event causing a sudden change in continuous variable or continuous threshold scheduling a discrete event. These heterogeneous hybrid systems arise in manufacturing, aviation, automobile engineering, computer systems, traffic control, control systems, to list a few.

In order to model a hybrid system, each subsystem is modeled in its own environment and combined to execute overall system objective. The two main approaches to developing hybrid simulation are hybrid state machine (Maler, Manna, & Pnueli, 1992) and the DEVS&DESS formalism (Ziegler, 1976). A formalism provides a generic means or template for easily specifying a system. The statecharts is a visual formalism that is an extension of conventional state-transition diagrams. The state machine or statechart is used to express complex behavior by depicting the sequence of states undertaken by objects during their lifetime in response to events (Harel, 1987). Nodes represent states and arrows represent transition between states in the state diagram. In Figure 5, if event α occurs while the system is in state *A*, the system transfers to state *C*, if condition *P* is true at the time. α(P) is the triggering event that cause a transition to state C when condition P is true at the instance of occurrence. Event *y* takes the system to A from B. Using the concept of state transition, Maler et al. (1992) extends the formalism of discrete event state diagram by implementing continuous behavior thus allowing changes in variables to be modeled by differential/integral equations.

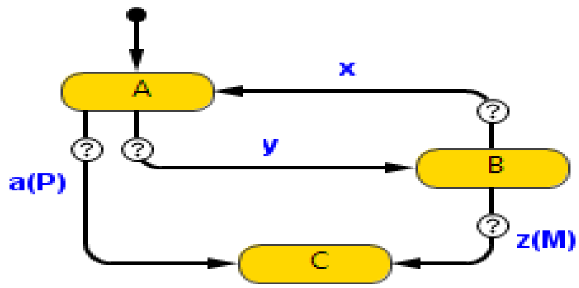


Figure 5: State Diagram

Statecharts react to discrete events and are associated with active objects. Statecharts specifies the state space of objects and events causing the transition as well as describes the corresponding result of a state change. Reactions to occurrences of events are done using Java codes. Continuous behaviors can be incorporated into a discrete model by defining variables using algebraic-differential equations and linking the values of the variables to objects in the model. When a variable reaches a certain value, a change event is created to enable transitions. Mathematical equations can be defined for some states. On executing the states, the equations are solved to cause continuous reaction in the system.

Another approach for specifying and describing the dynamics of a hybrid system is the Discrete EVent System Specification and the Differential Equation System Specification (DEVS&DESS) combined formalism. The DEVS formalism, originally developed by Zeigler (2006) is based on set theory for discrete event system modeling. It is made up of sets of inputs X, outputs Y, states S, internal transition function δ_{int}, external transition function δ_{ext}, output λ, and time advance ta, represented by:

$$DEVS = (X, Y, S, \delta_{ext}, \delta_{int}, \lambda, ta) \tag{2.1}$$

The set Q of the total states of the system contains a state pair and the time elapsed e, since the system entered that state:

$$Q: \{(s, e) \mid s \in S, 0 \leq e \leq ta(s)\} \tag{2.2}$$

The associated time advance of each state $s \in S$ is computed by the time advance $ta(s)$ which is a non-negative real number indicating the length of time the system remains in a state when no input events occur.

In DESS formalism, the state transition function in DEVS is replaced by the rate of change of the state variables. The rate of change of the state variables dq_i is a function of input variables x_i. The continuous model is thus given:

$$\frac{dq_1(t)}{dt} = f_1(q_1(t), q_2(t), \ldots q_n(t), x_1(t), x_2(t), \ldots . x_n(t))$$

$$\frac{dq_1(t)}{dt} = f_2\big(q_1(t), q_2(t), \ldots q_n(t), x_1(t), x_2(t), \ldots . x_n(t)\big), \ \ldots\ldots$$

$$\frac{dq_1(t)}{dt} = f_n\big(q_1(t), q_2(t), \ldots q_n(t), x_1(t), x_2(t), \ldots . x_n(t)\big) \tag{2.3}$$

DESS formalism is made up of sets of input ports and values X, output ports and values Y, states Q, f the rate of change function, and output function λ:

$$DESS = (X, Y, Q, f, \lambda) \tag{2.4}$$

The DEVS&DESS formalism is therefore a combination of the discrete (*disc*) and continuous (*cont*) variables and functions from the DEVS and DESS formalisms as well as the state event detection condition predicate D:

$$DEVS\&DESS = \langle X^{disc}, X^{cont}, Y^{disc}, Y^{cont}, S^{disc}, S^{cont}, \delta_{ext}, \delta_{int}, D, \lambda^{discr}, \lambda^{cont}, f \rangle \tag{2.5}$$

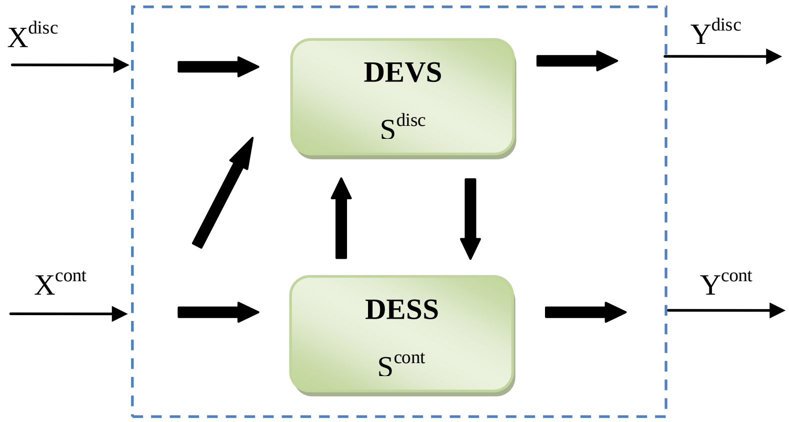


Figure 6: DEVS&DESS Model (modified from Zeigler, 2006)

The degrees of abstraction of hybrid models enable micro and macro analyses of business systems. In the micro (lower) layer, a short period of time such as distances of hours, minutes and seconds are observed. In contrast, long periods of time such as distances of years, months and weeks are observed at the macro (higher) level (Jacob, Suchan, & Ferstl, 2010). The use of a hybrid framework should be justifiable by providing distinguishing between components of system that require discrete and continuous analysis. Linkages between individual simulation methodologies must be specified for seamless integration into the hybrid system. Kirandeep Chahal, Tillal Eldabi, & Terry Young (2013) give the following guidelines for collecting information needed to link individual simulation models:

- What data is exchanged between models?
- How are models mapped to each other?
- How do models interact over time to exchange information?

Simulations can interact with each other either through cyclic or parallel modes. Simulations run separately and exchange information between consecutive runs in a cyclic manner on completion of individual runs in cyclic mode. In parallel mode, models are run in parallel and exchange information during runs. Once the different simulation modules are built, they can be integrated and its synchronizations managed by a hybrid simulation controller (Rabelo, Sarmiento, Helal, & Jones, 2015). The controller is tasked with the responsibilities of managing data, monitoring simulation time and managing customizability to the overall model.

2.4 Overview of Ecommerce

Electronic Commerce or ecommerce comprises the use of networks and internet technology for exchange of goods, services, money or anything of value. As cited in Bucki & Suchanek (2012), according to the structural model, the components of an ecommerce system are the customers, the environment, internet, web server, local area network, customer relationship management (CRM), enterprise resource planning (ERP), payment systems, delivery of goods, after sales services and network of suppliers. Depending on the movement of goods and services as well as relationship of business and consumer, ecommerce models include the types depicted in Figure 7.

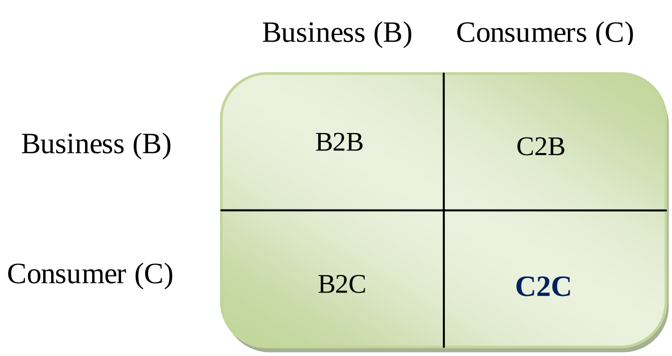


Figure 7: Types of E-Commerce Systems

Traditional or regular commerce is referred to brick-and-mortar. Technology collapses nonessential infrastructures characteristic of brick-and-mortar business models. Internet-based emarket places (IEMPs) are inter-organizational information systems that allow the integration of firms with supplier and consumers. The scope of Internet-based emarket places encompasses buying/selling related information exchange, facilitating negotiation, settlement and after-sales services.

Social commerce is a sub-category of e-commerce that combines shopping and social networking. With the rising popularity of social commerce, new players shape market trends. Chingning Wang & Ping Zhang (2012) present a social commerce framework that is composed of people, management, technology and information with consumers relying on peer-generated information content. Web 2.0 tools in the form of web services, blogs, interactivity, peer review, allow users to jointly create and manipulate content and enhance collaboration. Collaboration through Web 2.0 is known as crowd sourcing. Web 2.0 include open standards application such as tagging, bookmarking, user-generated content allows collaboration. “Web 2.0” or “Social Web” enables close interaction, collaboration and coordination among consumers. The major activities of social commerce modified from Liang & Turban (2011) is presented in Figure 8.

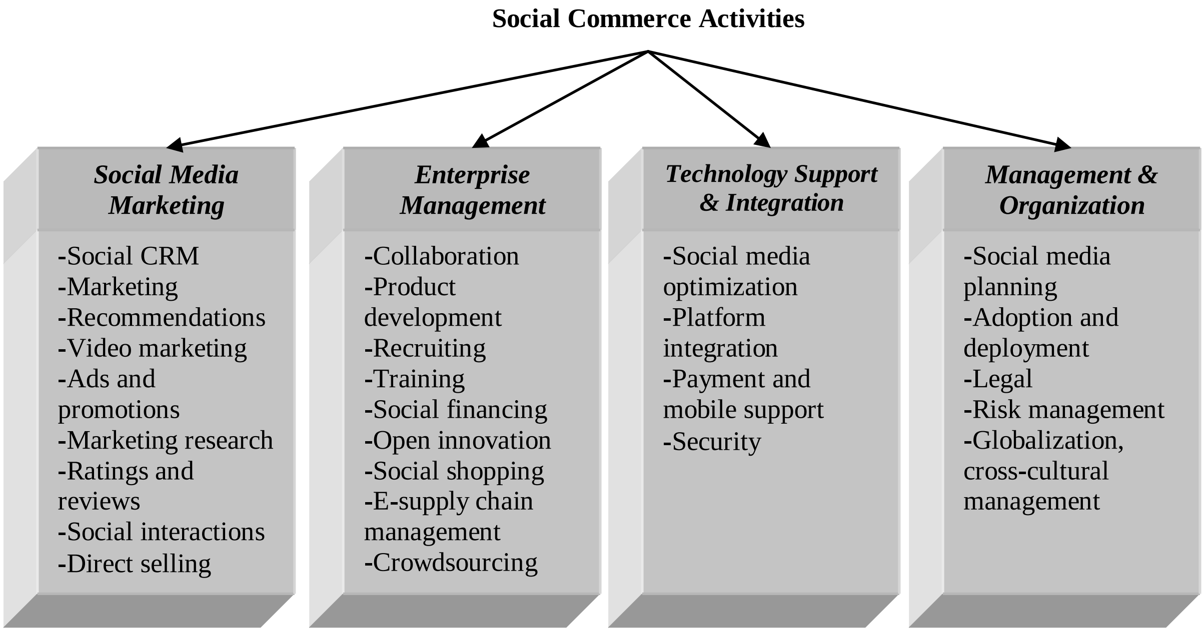


Figure 8: Activities of Social Commerce

A *platform* is a market or environment that connects distinct sides of a network. The growth and size of C2C platforms have been bolstered by different revenue generating mechanisms in the form of transactions cost. *Transaction costs* are a major component of ecommerce. Costs involved in engaging in a transaction include search costs, negotiation costs and enforcement costs. Transaction costs arise because: 1. bounded rationality costs resulting from consumers having limited amount of time and resources to seek out the services and goods they need, 2. Sellers have more information hence information asymmetry, and 3. Opportunism. Compared to 'Web 1.0', ‘Web 2.0’ tools have reduced the costs needed to share information with a wide range of users, thereby making the market more efficient. Transaction costs usually factor in geography and distance; information search and cost of undertaking certain checks to prove the quality of the customer (Johnson et al., 2010).

Eliminating intermediaries such as retailers and wholesalers is called *disintermediation*. Eliminating middlemen result in better efficiencies. Direct channels make the supply chain more agile and responsive – passing value directly to the customers. Companies must know the roles that intermediaries play and decide if they can play those roles themselves or even eliminate the roles. If analysis shows that they can do this, then disintermediation makes sense. *Aggregators* collate information from a lot of sites in order to save the customer time and resources associated with search. When high transaction costs occur, aggregators come in when complexity sets in.

Selling directly to customers is not without its challenges. *Channel conflict* is a concern for companies that adopt ecommerce e-strategy. Such conflict exists with supply chain participants. There are different frameworks and lenses used to analyze ecommerce viz transaction costs, peer-to-peer (P2P) architectures and network effects. Architectures are a source of competitive advantage in ecommerce. In purely P2P architecture, every client is connected to every other. This makes for robustness against failure. Issues of vulnerability can arise in the event of super node/server outage (Sethi, 2014). The value of a network increases as more users join it. This is concept is known as *network effects* and is a defining characteristic of ecommerce. Due to low costs, customers enter the network with ease leading to exponential growth. The users bring other users from their network. As one more user joins the network, other users often benefit. This concept can be observed in Facebook, Twitter and Instagram. As the network grows, the system can now charge more for its services because it becomes more valuable.

2.4.1 E-Business Models

A business model is the method by which organizations build and use resources to offer superior value than competitors while making profit in the process (Afuah & Tucci, 2000; Pateli & Giaglis, 2004). According to Afuah & Tucci (2000) a business model is composed of profit site, customer value, scope of operations, price, revenue sources, connected activities, implementation, sustainability and cost structure. The business model portrays the present way in which the firm makes money and its future plan of making money. The business model highlights the organization’s system of inputs, activities and outcomes (L. Chen, Danbolt, & Holland, 2014). Timmers (1998) defines a business model as “an architecture for product, service and information flows, including a description of the various business actors and their roles; a description of the potential benefits for the various business actors; and a description of the sources of revenues”. Mahadevan (2000) also describes a business model as a blend of the value stream, revenue stream and logistical stream.

Value is the amount buyers are willing to pay for a product or service. The value chain is the set of activities performed to create and distribute goods and services. Value chain analysis identifies activities that create value (Porter, 1998). The steps include 1. Define strategic business unit 2. Identify critical activities 3. Define products 4. Determine its value. Porter argues that organizations should focus on processes that define their purpose. The business model of C2C ecommerce is dependent on fees being charged on money transactions. It derives a significant part of its revenue from internet transactions. The ability of e-businesses to create value depends on these value drivers: efficiency, complementarities, lock-in, and novelty (Amit & Zott, 2001). Amit proposed that innovation and value creation revolves around a firm’s business model.

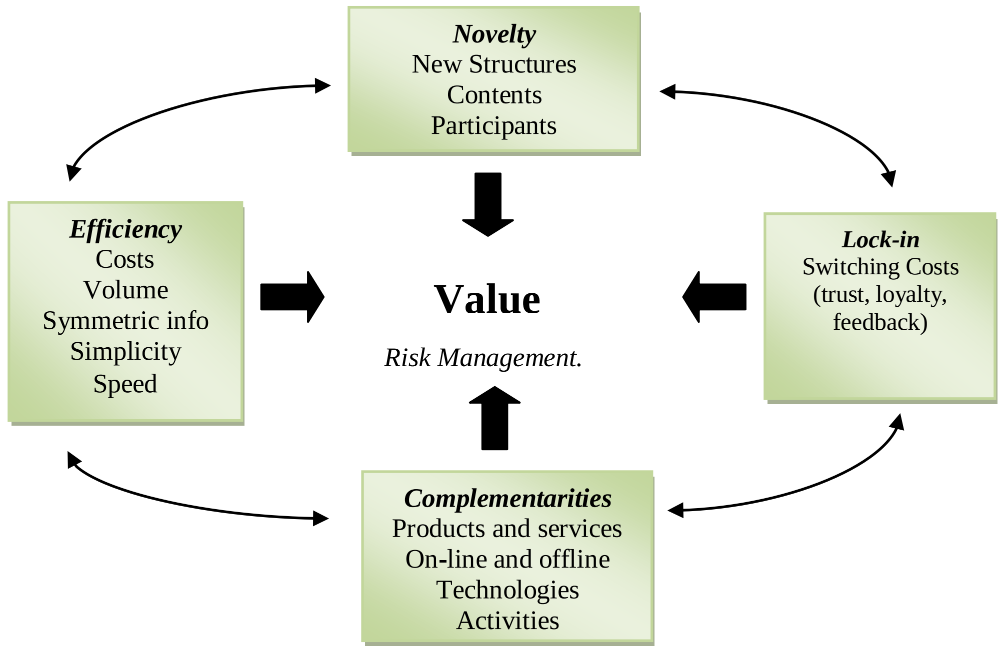


Figure 9: Sources of Value Creation (adapted from Amit & Zott, 2001)

E-business is conducted over a computer-mediated network using the internet to manage and transform business processes. E-business creates business processes and strategies to enable organizations realize their ecommerce potential. The core components of e-business are enterprise resource planning (ERP) and supply chain management (SCM). ERP system is a single system made up of financial, manufacturing, distribution human resources, order management system and shared data. E-business models include advertising, e-tailing, e-procurement, information management, sales support, service and online action.

2.4.2 Business Models and Business Process Modeling

Additional e-business processes include electronic marketing, electronic search, electronic procurement and payment, electronic authentication, electronic processing, electronic shipping, and electronic customer support to e-mail acknowledgment. Understanding the effects of these processes of the business operations and costs, its supplier and customer relationships, and its competitive industry position constitute significant measurement challenge.

According to Grieger (2004), business processes are supply-chain business processes linked across intra- and intercompany boundaries. The internet is used to implement business processes. Business processes are represented as a sequence of steps that define the set of activities to be executed and the control flow among them (Schmid & Rossi, 2002).

Organization goals are achieved by synchronizing and integrating its processes. A business process is a collection of activities with a set of connecting links that accomplish these organizational goals. Increasing competition encourages organizations to release new products to the market at record speed while decreasing costs and increasing profits. This led to the popular adoption of Business Process Reengineering (BPR) as a tool for organizational management to improve productivity. BPR involves redesigning business processes to achieve better quality, higher efficiency and to gain competitive advantage (Vuksic, Stemberger, & Jaklic, 2002). Even with the high adoption rate of BPR, many studies argue that there is a corresponding high rate of failure of BPR projects due to the inability to predict outcome of such changes and the inability to effectively capture business processes (Paul, Hlupic, & Giaglis, 1998). Vuksic et al. (2002) developed a business-to-business ecommerce simulation model to evaluate potential benefits and effects of BPR. Evaluation of alternative solutions through simulation helps to reduce risks associated with the re-engineering process from a dynamic context. Inherent behavior can be discovered from data that business processes are to manipulate (An & Jeng, 2005).

An enterprise is made up of multiple business processes. Business process modeling (BPM) consists of a combination of methodologies, methods, technologies and principles to improve business processes that helps to map current and future processes in order to improve organizational performance and efficiency by managing and optimizing the business processes. BPM is a structured approach used to describe a collection of related activities, information and flow of an organization's business operations which achieves desired goals, drive business results and create value. However, integrating simulation with business process management techniques is yet to find widespread use. Januszczak & Hook (2011) proposes a business process simulation standard to enable organizations benefit from the predictive and prescriptive features of simulation. In a business simulation study, capturing information about business processes to define scope, requirements, benchmarks and scenarios – usually done with Business Process Modeling and Notation (BPMN). In addition, UML and flow charts, System Dynamics, IDEF, Petri Nets, DES and knowledge based techniques are several techniques that can be used for business process modeling (Vuksic et al., 2002).

The internet enables real-time communication along the supply chain. Electronic supply chain management (e-SCM) revolves around such electronic technology-enabled relationships (Boonyathan & Al-Hakim, 2007). The authors describe how to integrate the SCOR reference model with IDEF0 to model the dependencies between activities of the e-SCM. IDEF0 is a process mapping tool used to describe and model a system in a structured graphical form, analyze the process and identify business process improvement opportunities. Each activity is specified by the inputs, controls, outputs and mechanisms. IDEF0 helps describe what an organization does but SCOR helps to specify the logic in sequencing activities.

2.5 Simulation for Ecommerce Decision Making

The structure of a system determines its behavior over time. Ecommerce system is a complex, interactive and stochastic system that deals with various people, infrastructure, technology, and trust. In addition factors like uncertainty, competition, demand and economic landscape. These markets are non-linear, experiencing explosive growth and continuous change. Developing representative models comprise of detailing system stakeholders and pertaining underlying processes. Decision makers must consider these factors when analyzing the system and procuring optimal strategies to a given problem.

2.5.1 Agent Based Simulation

The adoption of agent based simulation (ABM) by simulation practitioners gained traction in 2002. ABMS builds on discrete event simulation and object-oriented programming (North & Macal, 2007). Agents can be vehicles, equipments, projects, ideas, organization or investments. Behaviors in ABM are sometimes defined as rules and can be specified by stock and flow diagrams or process flow charts inside the agents. Adaptability is modeled using rule sets that include probability functions. ABM simulation output is often use for explanatory, exploratory or predictive purposes. Such simulation finds apt use in markets characterized by non-linearity and complexity.

ABM uses a bottom-up approach to model customer and market (system) behavior. Different techniques can be used within agents to determine a decision making outcome of complex rules – multinonimal logit modeling, neural networks, swarm intelligence, optimization methods, linear programming and the likes, thus allowing the agents to learn throughout the simulation. A system modeled by a collection of interacting entities called *agents* that are capable of making decisions independently based on a set of rules. Internal rules represent the cognitive decision process. The most important features of agents is the ability to collaborate, coordinate and interact with themselves and also with the environment to achieve a common goal (Lättilä, Hilletofth, & Lin, 2010) – i.e. the characteristics of autonomy, social ability, reactivity and pro-activeness. *Autonomy* refers to an agent's ability to act without direct intervention of external forces. *Social ability* is the capability of interacting with other agents. *Reactivity* is the ability to perceive and respond to changes in its environment. *Pro-activeness* is the ability to initiate a desired response rather than simply reacting to events.

Agents exist in different capacities. Users can obtain and compare products, vendors and services with the ability to negotiate, retrieve, gather information and monitor transactions (Alshammri, 2009). Agents have been used in asset management, trading and contract modeling. This improves customer shopping experience and reduces the complexity associated with the trading process.

Research on consumer behavior spans the space of psychology, marketing, sociology, economics and engineering. In their paper, Zhang & Zhang (2007) adopts ABM to model consumer purchase decision making using consumer traits and interactions in the market. ABM is used in social science fields to study individuals and groups in dynamic and adaptive systems (B. Wang & Moon, 2013).

Similarly, Smeureanu, Ruxanda, Diosteanu, Delcea, & Cotfas (2012) cites maximizing and optimizing business performance as critical to profitability of a dynamic supply chain management business. It is important for companies to be able to respond quickly to market opportunities. Webservices and intelligent agents can be used to represent and model the distributed and interoperable nature of the collaborative economic environment. Smeureanu *et al.* adopts flexible agent search, the use of location and economic model that considers bankruptcy risk as a variable to evaluate future business partner.

Complex Adaptive Systems (CAS) are dynamic systems that consist of a network of interacting actors that adapt to constantly changing environments. The problem with modeling CAS is that non-linear interactions are often too complex to model with traditional analytical techniques. Agent-based simulations offer new opportunities to examine complex systems. Zhong *et al.* applied ABM to online trading between two strangers by modeling the problem as that of a Prisoner's Dilemma (Zhong, Zhu, Wu, & Wang, 2012). Due to the enormous population of online traders, traders might never deal with the same buyer more than once and this can result to failure of the electronic market model. However, the reputation system keeps the model veritable. Finding answers to some what-if-scenarios regarding to behavior including cooperation, reliability and so on of traders can be difficult. To model the agent based system, the authors utilized an open source modeling framework called the Recursive Porous Agent Simulation Toolkit (RePast) which is well suited for social networks and interactions. Mean Trader Profit is selected as the performance metric for the experiments while the Smoothing Constant and Probability of Imitation are key system variables.

The application of software agents in ecommerce is thus: when consumers shop online, agents can autonomously mediate purchase for consumers. Agents can be involved in all aspects of trade – gathering information, comparing price, making decision and processing payments - thus, saving consumer time. Weng (2007) reports some other applications in mobile agents in e-business applications. One of such is agents searching electronic catalogs for best prices of interested products or using agents to traverse various sites for automated bidding and auction monitoring.

Twomey & Cadman (2002) describes correlation between aggregated variables which result from system behavior. The ABM system for their study was built on a high level of fidelity that captures the internal workings of agents (beliefs, desires and intentions). To investigate market dynamics, behaviors are described by rules and interactions with other agents which often give rise to self-organization in multi-agent simulation. ABMS is applicable when the goal is for adaptive and emergent systems. According to Roman & Kateřina (2012) ABS model is "applied to coordinate, control, and simulate the architecture of decision support system, used in e-commerce".

Bădică, Ganzha, & Paprzycki (2007) considers a situation of multiple item transactions. They conceptualize transactions thus: *Pre-contractual* phase consisting of need identification, product brokering, merchant brokering and matchmaking. *Negotiation* phase in which agents negotiate based on rules of market mechanism (protocol) and strategies. *Contract execution* phase made up of order submission, logistics and payment. And, *Post-contractual* phase which includes managerial information and product or service evaluation.

Lopez-Sanchez, Noria, Rodríguez, & Gilbert (2005)'s study seeks to understand dynamics of the role the internet plays in the content, marketing and distribution of digital contents. The authors implement this by creating a tool (called SimwebAB) using RePast to help make competitive business strategy decisions. The foundation of SimwebAB is rooted in multi-agent simulation paradigm with market data from survey and allows stakeholders to test scenarios affecting their business landscape. Market stakeholders are represented by agents that act autonomously to promote their interests and interact with each other.

Guttman, Moukas, & Maes (1998) describes the roles of agents as mediators in electronic commerce systems in the context of the traditional marketing consumer buying behavior model (CBB). Guttman et al. (1998) presents a simplification of the stages that guide consumer buying behavior. In the need identification stage, consumers become aware of an unmet need. The product brokering stage utilizes information to determine what to buy. The merchant brokering stage helps to determine who to buy from. The negotiation stage determines terms of transaction. The purchase and delivery stage detail the purchase, payment and delivery options. Finally the service and evaluation stage determines the post-purchase services and customer satisfaction enquiry.

Software agents or intelligent agents (IA) developed in Java can perform tasks based on programmed knowledge and received message (Carlsson & Turban, 2002). In an electronic market, IAs are delegated the tasks to collect, analyze information, negotiation, execute transactions and get feedback for services provided. Liang & Huang (2000) develops architecture for organizing intelligent agents. The authors group agents into three levels – market, contract and activity. The process include scanning the environment for messages, processing messages based on knowledge and taking actions based on the messages processed.

Agent-based model (ABM) combines elements of complex systems and multi-agent systems. Multi agent systems merge the study of negotiation and software agents. There are two main multi-agent system paradigms – the multi-agent decision system (MADS) and the multi-agent simulation system (MASS) (Siebers & Aickelin, 2008). MADS embeds agents or a simulation of embedded agents with a focus on decision making. Participating agents make joint decisions as a group using an auction or augmentation. The MASS uses the multi-agent system as a model to simulate real-world scenarios. MASS is a collection of interacting agents which are characterized by heterogeneity and diversity. A distinguishing perspective of the ABM and MAS is thus: while the former seeks insights into the behavior of agents obeying rules, later solves problem from intelligent agents perspective.

M. He, Jennings, & Leung (2003) extends Liang and Guttman et al. (1998)'s study. They describe some of the B2C and B2B applications of agents from the consumer buying behavior perspective (CBB) for needs identification, product brokering, buyer coalition formation, merchant brokering, negotiation, purchase and delivery. Decision making can be made by explicitly reasoning about opponent's behavior using game theory, finding a current best solution using fuzzy constraints or via argumentation.

In simulating customer purchase decision-making, Zhang & Zhang (2007) combines a robust agent based simulation and multi-agent simulation (MAS) to model emergent market dynamics between market participants and environment. The authors group the data that affect consumer purchase decisions into demographic, behavioral and psychographic data. Psychographic data such as interest, attitude, and opinion (IAO variables) affect consumer decision yet is challenging to incorporate in models. They develop motivation function to control agent buying behavior and was programmed using Netlogo.

Dn Chen, Jeng, Lee, & Chuang (2008) develops a multi-agent model to facilitate buyer collective purchasing (BCP) behavior consisting of product description, buyer invitation, needs synthesis and negotiation to capture consumer behavior. This model is applied to consumer-to-business (C2B) ecommerce to explore the role of agents. The Analytic Hierarchy Process algorithm was then employed to synthesize common needs from buyer group. The BCP behavior proposed by Chen *et al* is given in Figure 10.

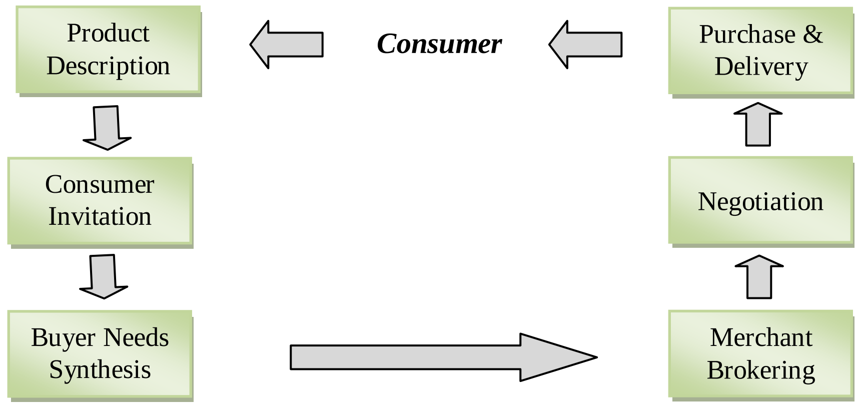


Figure 10: Buyer Collective Purchasing Model

Generally, in ecommerce, a decision support system (DSS) is a computer application used to enhance a user's decision making capability (Roman & Kateřina, 2012). A multi-agent approach to viewing products, applications and services as autonomous entities cooperate and coordinate together with the goal of solving a problem. Incorporating agent-based simulation into the architecture can enhance the purchasing prediction behavior of consumers. Roman *et al* proposed a DSS architecture made up of 4 layers: interface, process, knowledge and simulation layers. The interface layer supports interaction and collaboration between facilitator and control agents. The process supports implementation of functions and processes to solve a particular problem.

2.5.2 System Dynamics

System dynamics (SD) was developed in the late 1950s by MIT professor Jay Forrester. Forrester applied SD to model problems in industrial corporations and later found application of the approach in economics, crime, health, biological sciences field (Forrester, 1961; Sterman, 2000). SD is based on system theory and has been used to model business processes, epidemic, supply chains and growth of cities from a macroscopic view of the system. System theory considers an organization as a separate social system acted upon by the environment.

System dynamics uses the laws of physics (especially laws of electrical circuits) to describe and investigate the dynamics of economic and social systems. SD helps in the study of complex behaviors from a deterministic systematic view point through the use of time delays and causal (feedback) linkages for flows and feedback dynamics, trend and system-level behavior. System behavior is described as a combination of interacting feedback loops. Objects and people in the system interact via feedback loops with a change in a certain variable affecting other variables. A negative feedback loop moves behavior towards a goal while a positive loop is self-reinforcing. To find out how a system reaches equilibrium, it can be modeled using the source, inflow/outflow, stock, sink, variables and feedback-loops (Lättilä et al., 2010).

Diffusion of a product or service into the marketplace has been modeled using the Bass model represented by Equation 2.6. This model can guide the amount of new products to be produced by helping to forecast demand, set cost of advertisement and discounts. The rate of change of adoption of a product is proportional to potential adopters.

$$\frac{dN(t)}{dt} = g(t,N)[N_T - N(t)] \qquad (2.6)$$

Where $N(t), g(t,N), N_T$ are the number of adopters, coefficient of diffusion at time T and the total number of potential adopters. The change in time *dt* is both infinitesimal and finite time-step. Although SD is better known as a continuous time methodology, the time-step can in fact be made as small as possible to mimic the discrete modeling methodology and can be numerically solved by Runge-Kutta-4th order simulation (Ossimitz & Mrotzek, 2008).

The interest of SD is not in the implementation of individual events but in aggregate terms. Several studies adopt SD to model the overall structure of the organization at strategic and tactical management levels as well as capture financial, global environment (Rabelo, Eskandari, Shaalan, & Helal, 2007; Rabelo, Eskandari, Shalan, & Helal, 2005). SD is a non-data driven system thinking approach that targets top management. This is convenient since detailed data or business process activities are not always available. SD is a continuous simulation methodology whose models are more intuitive than discrete-event simulation. This methodology lends its expertise to dynamic problems of strategic importance for long horizons. System dynamics had been be used to understand and analyze a supply chain (such as to understand the bullwhip effect) and its control policies.

Speller et al. (2007) developed a system dynamics model to capture dynamic value chain system of “the traditional production/assembly supply chain system with service components added to it”. The first step is made up of generic, causal-loop diagrams and subsequently a detailed stock-and-flow model. Taylor series approximations were used to generate a linear system of differential equations to capture the behavior of the system with time. These behaviors are analyzed and make long-range predictions of interest using the eigenvalue technique. The combination of the SD model, Taylor series approximations, eigenvalues and elasticities analyze the value chain incorporating production and service as major contributors to growth.

Operation Research and other management science methodologies for solving complex problems with large number of variables, nonlinearity and human intervention have been found to be insufficient. SD was one of the very first responses to the inadequacy of these approaches. Based control engineering tools and models used to analyze the stability of mechanical and electrical control systems, Forrester developed a set of tools and a powerful method for modeling and analyzing complicated problem situations (Tustin, 1953).

SD is mainly built upon traditional management of social system, cybernetics and computer simulation. A formal business process model enables the simulation of target business operations. SD modeling capture physical laws governing the system using subjective thinking with an assumption of dynamic behavior of entities in the system (An & Jeng, 2005). Due to complexity of system characterized by nonlinearity and time delay, the system may not be solved analytically. Available numerical method for ordinary differential equations such as Euler's first order finite difference, Runge-Kutta second and fourth order finite difference method can be employed to solve the system numerically. As pointed out previously, a solution for the system of ordinary differential equation is continuous. However, discrete states and time can be represented by scaling about the measurement points along the time units e.g. hours, days, weeks.

2.5.3 Discrete Event Simulation

For the purpose of completeness, the use of the third simulation paradigm (discrete event simulation) in business process modeling is presented in this section. This section gives an overview of DES and relevant literature in the context of how it relates to SD and ABM organizational implementations. In DES, the system is modeled from a microscopic point of view as a sequence of operations being performed across entities as it evolves over time. State variables capture desired behavior, events that change associating variables and its logic. DES is widely used in logistics, service, manufacturing and business processes to detect scheduling conflicts, improve system performance and analyzes alternatives. State variables change instantaneously at separate points in time.

The EAS (entity, attribute and set) structure is as follows. Entities are system elements that flow through the model and consume resource's capacity. Entities are passive objects that travel through blocks of the flowchart forming queues, are delayed, processed or utilize resources, split, combined etc (A. Borshchev & Filippov, 2004). Some entities are permanent (never leaves the system) while others are temporary. Attributes identify entities. For a given for a business process model, attributes can be defined as price and volume traded of a security, wealth of an investor, buy or sell attribute of an order. Sets are made of buy and sell orders. Entities and resources are passive with no behavior, only carrying data and defined by process charts (A. Borshchev, 2013). Other components of a DES are variables that give information about the system, resources used by entities to perform an action or provide a service; queues that signal consumption rate of resources; activities performed by resources over entities; and events that occur (García, Barcelona, Ruiz, García-Borgoñón, & Ramos, 2014). Generally, DES is appropriate for tracking the status of entities and resources for different operating conditions of the system

DES helps address the effects of uncertainty in a system. The state of the system is assumed to be unchanged in DES. Supply chain discrete-event simulation models are often larger in size, take a long time to build and are harder to validate. In (F. Persson et al., 2012), the authors proposed dynamic SCOR mapping template in Arena as a tool to speed up the simulation of supply chain analysis. While event-based simulations have commonly been used for system planning and analysis in manufacturing, Jacobs, Levy, & Markowitz (2004) applies it to financial analysis. Jacob *et al.* created the JLM Sim tool, using asynchronous-time, discrete-event simulation, to enable investors model the market with user inputs. Service and arrival times are represented by a probability distribution. They can be staff, loan officers, cashiers, computer memory or transport. The events incorporated in the simulation include initialize, reoptimize, and review order. Reoptimization is done by choosing a portfolio from a mean-variance efficient frontier based on the investor's risk aversion. Some limitations highlighted by the author include the limit to the number of investors/securities that can be simulated due to PC resources constraint which he proposed the use of distributed simulation to enable multiple PCs over the internet.

Data is generated by sampling fitted probability distributions of activities, expected events, arrival rates. Processes are stochastic and because inputs to the model are random, outputs will also be random, interpretable using statistical techniques. To accurately predict response times, DES can be employed to dynamically model interactions within elements of the system, system variability, scheduling, congestion, nonlinearities and stochasticity in demand and supply.

Hook (2011) describes how DES can be used with business process modeling (BPM) software. The author demonstrates the way business processes are modeled by using DES to deliver business value to an organization by incorporating additional information to business process models. Components of simulation parameters used for business process management include scenario metadata and context, process descriptions, events, resource model, activity parameters and tool extensions (Januszczak & Hook, 2011). In addition, Hlupic, de Vreede, & Orsoni (2006) links the applicability of DES tools to business process modeling and simulation because:

- Business process models can be modified to provide decision support tool for continuous improvement.
- Business processes are time-ordered interrelated events

- Stochasticity exist in key process parameters
- There exist dynamic interdependence among process activities

As a support to decision-making, García et al. (2014) proposes an application of model-driven engineering to integrate the definition of business processes with DES that generates a simulation model from BPMN. This bridges the gap between the business analysts and the simulation modelers. On the other hand, DES simulation is inappropriate for problems in which state variables interact continuously or when emphasis is to be placed on behavior of entities instead of associated events. Another limitation of DES is that data demands are not always available at higher management (strategic) levels.

2.5.4 Multi-model Simulation

A model is an abstraction and simplification of a real problem. Assumptions are often stated explicitly and irrelevant details pave way for details considered important to the problem. Systems can be modeled as physical or mathematical models. Mathematical models represent a system using logical and quantitative relationships that can be manipulated to study the model reaction (Law, 2009). Mathematical models can be either analytical or simulation. Analytical models include linear and integer programming and other operations research tools. Because many real life problems are complex in nature, using analytical methods can often be impractical. Hence, simulation presents an approach to dynamically study the system.

Modeling large systems strictly with DES means that complexity of model increase exponentially with the size of the model. The use of an integrated simulation model is cheaper than building and analyzing separate models which can lead to redundancy. Adopting hybrid techniques can improve decision making process.

Hybrid simulation combines features of discrete-continuous simulations. Each simulation paradigm is made up of a set of assumptions. Lorenz & Jost (2006) proposes the Purpose-Object-Methodology framework that helps to match a problem to the paradigm. The *purpose* describes the motivation of solving the problem, the *object* is the real world problem to be studied and the *methodology* refers to the techniques and methods (simulation method) of how the problem is to be solved. This framework for identification is summarized in Figure 11 and the one-on-one equivalence for the different paradigms is given.

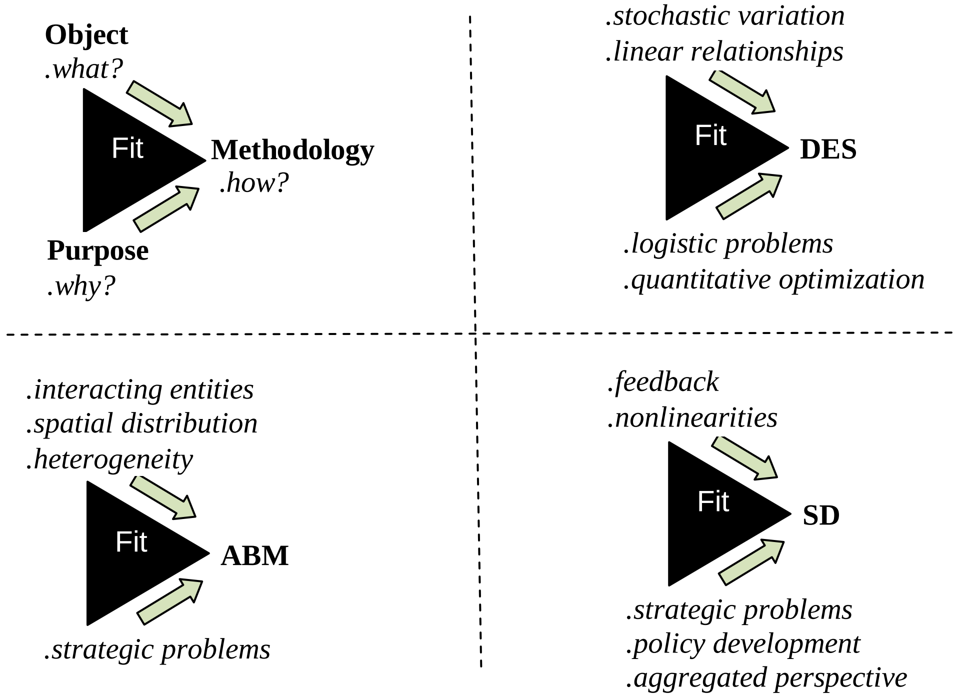


Figure 11: Selecting best fit methodology (modified from Lorenz & Jost, 2006)

A survey of literature indicates that DES has been used with more frequency to model supply chains than other simulation methods except for, the bullwhip effect which has been better modeled using SD (Tako & Robinson, 2012). States change in discrete steps in DES while changes are continuous in SD. SD is has been studied in literature to be better suitable for modeling at a strategic level and DES at an operational or tactical level.

Variables interact with each other in hybrid systems. This interaction can become problematic if initiator variable is not in sync with receiver variables. In SD, time is advanced in preset intervals that capture significant changes in the system. In DES, time is advanced based on scheduled events. For example, as illustrated in Alvanchi, Lee, & AbouRizk (2011), system productivity variable can be initiated secondly in the SD model and received via a request in the DES model on a minute basis. Update rates and types of variables should be clearly defined to minimize conflicts using a meaningful/critical variable update threshold to minimize cross model interactions.

According to Alvanchi, hybrid modeling framework is the set of provided basic elements and concepts to capture and describe complex behaviors in the system. Such modeling framework is useful in the conceptual design stage of hybrid model development. Interests in integrating continuous and discrete models have led to a number of approaches to implement hybrid system. Lee, Zhou, & Hsu (2004) proposed a Petri net (PN) framework with associated state equations to model hybrid dynamic systems. Tako *et al* performed a study of 127 papers that use DES and SD approaches and discovered that 2% of surveyed papers used DES-SD hybrid simulation in logistic and supply chain management context (Tako & Robinson, 2012). Tako et *al* makes the argument based on surveying literature that most SCM operational (daily), tactical (1 month to 1 year), or strategic (2-5 years) issues are better modeled either by DES or SD.

Different modeling paradigms can be used in different parts of a simulation. For example, discrete communicating agents can contain system dynamics models; agents can be modeled in an SD environment; and agents can be modeled as interacting in a discrete event flowchart (A. Borshchev & Filippov, 2004). DES and ABM model individual objects in a system. These objects are subject to variations (stochastic) while SD models an aggregate of the objects in which variations are minimized by the effect of averaging (deterministic).

Table 1 and Table 2 provide some guidance on selecting between simulation paradigms in addition to modeler judgment.

Table 1: Differences between simulation approaches

	DES	**SD**
Scope	Narrow, operational	Global, strategic
Abstraction Level	Low, middle	High
System Behavior	Stochastic	Deterministic
Perspective	Analytic	Holistic
Time Advance	Unequal time slices	Equal time steps
Data Source	Numerical & inference	Broad
State Change	Discrete	Continuous
Processes	Discrete	Continuous
Control Parameter	Holding (queues)	Rates (flows)
Resolution	Individual entities, attributes, events	Homogenized entities, Emergent
Outputs	Point predictions, detailed performance	Understanding structural source of behavior modes, location of KPIs

SD and ABS are commonly used to explain effects of socio-technical phenomena. The approach taken however is different. There are different approaches to ABMS and SD simulations. ABMS takes a bottom-up perspective to system modeling while SD takes a top-down perspective. As summarized in Lorenz & Jost (2006), *"...SD is particularly well suited to studying systems containing a complex web of feedback loops, while discrete system simulation is preferred when the system contains a high degree of uncertainty. A key strength of ABS is its ability to incorporate spatial as well as probabilistic aspects of the system."*

Table 2: Differences between simulation approaches (modified from Lorenz & Jost, 2006)

	SD	**ABMS**
Abstraction Level	High	Low, middle, high
Approach	Exploratory	Explanatory
Unit of Analysis	Structure	Rules
Perspective	Top-down	Bottom-up
Basic Building Blocks	Feedback loop	Agents
Entities	Undistinguished	Distinguished
Intelligence	No	Yes (specified by modeler)
Mathematical formulation	Integrals	Logic, algorithms
Processes	Continuous	Discrete
Origin of dynamics	Levels	Events

Discrete event simulation can address the effect of demand fluctuations and variations in delivery times on system performance while agent based simulation address the effects of rules used by on the behavior and profitability of the system (North & Macal, 2007). In developing a decision support prediction enrollment model for optimal resource allocation for university management, Robledo, Sepulveda, & Archer (2013) develops a network model framework consisting of SD for high level simulation and ABM for low level simulation. Wang *et al* used hybrid modeling and simulation to evaluate deployment of strategies that enable managers forecast innovation deployment outcomes to aid decision making. This is one of the many practical ways in which hybrid simulation is used in nontraditional applications (B. Wang & Moon, 2013).

Macal (2010) describes how the Susceptible-Infected-Recovered (SIR) model can converted to an ABS model from the SD formulation. In the individual-based ABS SIR model, Macal factors in stochasticity by updating the state of the agents dynamically while keeping other parameters constant. This was done by identifying, isolating and translating probabilistic elements of the SD model into probabilities used in the ABM model.

Rabelo *et al* present an approach that integrates analytical hierarchy process (AHP), system dynamics, discrete-event simulation to model activities of the global supply chain of a manufacturing company (Rabelo et al., 2007). The supply chain operations model is adopted as guide to develop the DES model. The SD model estimates demand for products, services, quality levels, reactions of customers, investment decisions, overhead costs, and new products. Results from the SD model are exported to DES to study performance of the service facilities and to estimate the associated costs. Costs, units and services are fed back to the SD model to re-evaluate overall performance of the system. AHP is then used to rank best outcome using tradeoffs and management expertise to increase decision makers’ confidence to maximize shareholder value. Rabelo, Helal, et al. (2005) also applies SD-DES models in a distributed approach to combine the two different simulation paradigms. DES is applied to model production decisions while the business decisions done using SD. They demonstrate that the objective of developing hybrid models is to provide management with a reliable decision and performance tool that helps to dissect the interaction and interdependencies in an integrated enterprise system.

As an extension to the created SD-DES model, Helal, Rabelo, Sepúlveda, & Jones (2007) specify an approach that maintains the integrity of individual simulation paradigms while enabling reusability of already created models. The SDDES formalism is proposed to better model management and communications with a synchronization mechanism to coordinate and synchronize interactions among simulation paradigms. The formalism is a made up of a standardized structure that take in data inputs, outputs, formatting and timing in defined modules at the controller's interface. A module is represented thus,

$$m = (T, X, Y, P, TB) \tag{2.7}$$

Where m is the current SD or DES module, T is the type of module (SD or DES), timing of data exchange is based on TB the time bucket, P is the set of all variables in the current module and X is a set of module inputs. X is defined as,

$$X = \{(m, v, s, op_s, U_m) \mid m \in M, v \in aP, s \in M - \{m\}, op_s \in OutPorts_s, U_m \subset P_m\} \tag{2.8}$$

m is the current SD or DES module, v is the input variable, s is the source module from which v is obtained, op_s is an output source through which v is obtained, P_m is a set of variables of current module, aP is the set of all variables in all other variables, U_m is the set of variables in the current module that take in the input value and is specified by

$$U_m = \{(ip, u, t, f) \mid ip \in \mathrm{In}Ports_m, u \in P_m\} \tag{2.9}$$

ip is an input port in current module, u is the variable in the current module that uses the input variable, $t,$ is the timing of reading the input variable to be used by u, f is data preparation action performed by the controller before sending input data to requesting module and $\mathrm{In}Ports_m$ is the set of input ports in current module.

Thus, the set of module outputs Y is given by,

$$Y = \{(m, op, v, D) \mid m \in M, op \in OutPorts_m, v \in P_m, D \subset M - \{m\}\} \tag{2.10}$$

op is an output port in the current module, v is the output variable leaving at the current output port, $OutPorts_m$ is the set of all output ports in the current module and D is the set of module that receive the current output variables from the current module. D is defined as,

$$D = \{(m_d, V_d) \mid m_d \in M - \{m\}, V_d \subset P_{md}\} \quad (2.11)$$

m_d is a module receiving an output of module , V_d is the set of variables in which use the received value and P_{md} is the set of all variables in the receiving module.

The different simulation approaches provide insight into different issues. Each approach provides a view of the complex problem. The features of simulation paradigms are thus: whilst SD is use feedback loops to model cause and effect relationships in the system – providing a top-down view of the problem, ABM enables study interactions among participants while DES provides an approach that allows for individual analysis of the system. Adopting hybrid simulation incorporates important features inherent in the problem space.

Analyzing hybrid simulations with different behaviors in isolation and consolidating findings can result in redundancy and inconsistency. Jacob et al. (2010) presents an approach for developing hybrid simulations of business systems using a structural model containing time-discrete and time-continuously simulation coupled submodels. Submodels can be coupled using continuous to discrete converters or discrete-to-continuous converters to transform state variables from one form to another. Due to inherent characteristics of these simulation approaches, time-discrete simulation is used to model business system micro-level submodel while time-continuous system dynamics submodel models the system at a macro (strategic) layer and micro (operational) layer submodel components coupled directly or indirectly using converters.

(A. Borshchev, Karpov, & Kharitonov, 2002) used hybrid state machines to model complex interdependencies between discrete and continuous time behaviors. High level architecture (HLA) standard, developed by the US Department of Defense (DoD), is used for distributed simulation to synchronize and aid communication of the complex system simulation components. To model hybrid systems, continuous behavior is represented using algebraic-differential equations associated with a state of a state machine. The Run-Time Infrastructure (RTI) is an interpretation of the HLA interface. A HLA simulation (called federation) is made up of federates, run-time infrastructure (RTI) and object model template (OMT). A federate is a simulation program that can be run independently. The RTI serves as a communication channel among different federates while the OMT defines the structure and information of the shared data inside the federation (Kuhl, Weatherly, & Dahmann, 1999). A calendar federate can also be present to regulate time and date with the federation. In a hybrid simulation federation, individual submodels can be implemented as separate federates that is adaptable to future changes (Alvanchi et al., 2011).

With a goal to develop simulations that are reusable, maintainable and interoperable, Sung & Kim (2011) proposes a framework for distributed hybrid simulation systems by using HLA for interoperation between existing simulators for continuous and discrete event model. The time management services of HLA/RTI are employed for time synchronization between existing heterogeneous models without modifications to the independent models (Figure 12).

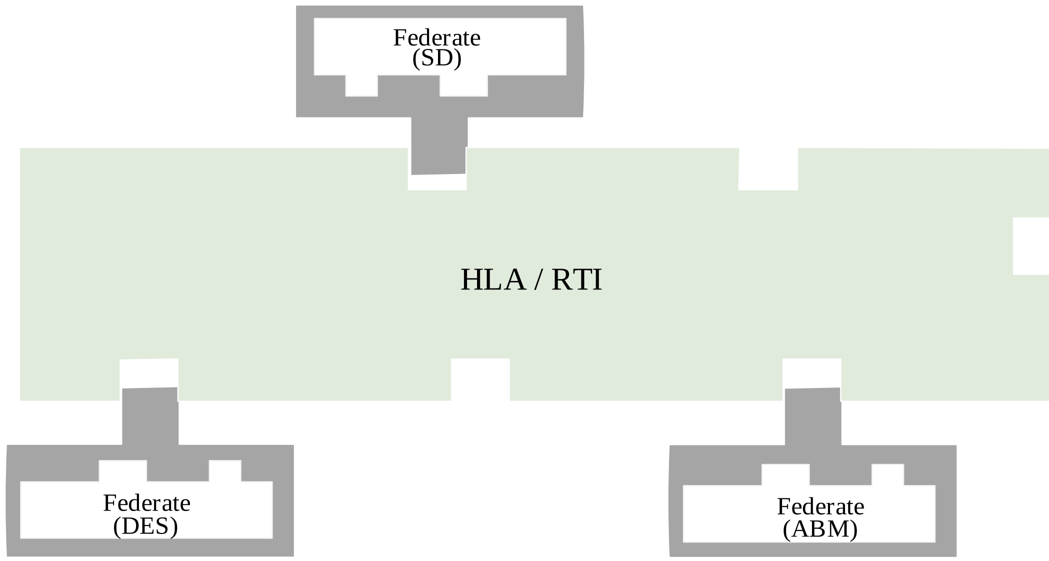


Figure 12: Hybrid Simulation Configuration using HLA/RTI

Similarly, Jacob et al. (2010) proposed an integrated coupling mechanism for hybrid dynamical systems using continuous to discrete (C2D) and discrete to continuous converters. Transformation from continuous to discrete and vice versa occurs when the value of a state variable crosses a set threshold. An output of DES becomes input of the continuous model. Data is converted using converters using an event-function mapping table. Continuous signals triggers event when they reach a threshold level. Transitions in the time-continuous model often precede multiple changes of same state variable in discrete model. To address the resulting time lag, aggregation of values is beneficial to couple the submodels.

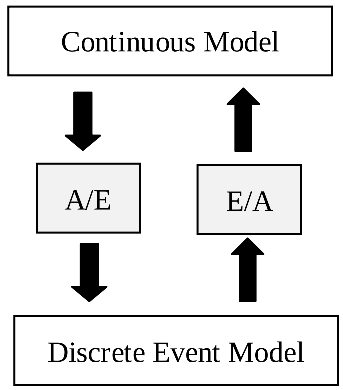


Figure 13: Analog/Event (A/E) and Event/Analog (E/A) Conversion

Once submodels have been developed and interaction prepared, the submodels must be synchronized. Helal et al. (2007) proposes the time bucket (TB) approach in which time is advanced in steps in SD and events in DES. Synchronization of submodels is managed using the controller to integrate and facilitate interaction between the submodels as specified in the proposed SDDES formalism. Integrated Definition (IDEF) modeling techniques are used to specify the functions of the controller. The controller is responsible for managing data, time and participation of the modules.

2.5.4.1 Hybrid Engine Architecture in AnyLogic

AnyLogic (http://www.anylogic.com/) has the capability of creating mixed discrete-continuous simulations of DES, ABMS and SD models in the same interface. Discrete and continuous objects interact through the use of state charts. Objects are made up of properties and methods. After defining the problem context, the modeling paradigm which best captures the nature of the problem is evaluated. AnyLogic is an object-oriented programming (OOP) language which allows reusability, extensibility and maintainability. Object classes can be added and extended using Java.

AnyLogic implements hybrid state machine proposed by (Harel, 1987; Maler et al., 1992). Continuous behaviors are described by a system of algebraic-differential equations associated with a state of a state machine (A. V. Borshchev, Kolesov, & Senichenkov, 2000). The Unified Modeling Language for Real Time (UML-RT) is extended to incorporate continuous behavior. Once the model is specified using UML-RT, the hybrid engine executes it. The canonical form of the differential and algebraic equations as well as the formulas is given respectively as:

$$\frac{dx(t)}{dt} = f(x, y, t) \tag{2.12}$$

$$g(x, y, t) = 0 \tag{2.13}$$

$$h(x, y, t) \tag{2.14}$$

The hybrid engine consisting of the discrete engine and the equation solver is specified by Figure 14. At each time step, the discrete engine invokes the equation solver and provides it with the current equation system and a stop time. The equation makes periodical callbacks to the discrete engine to make sure the current combination of variable values satisfies the pending change event conditions. Once the condition is satisfied, the solver solves for the time when the condition becomes true then returns control to the discrete engine.

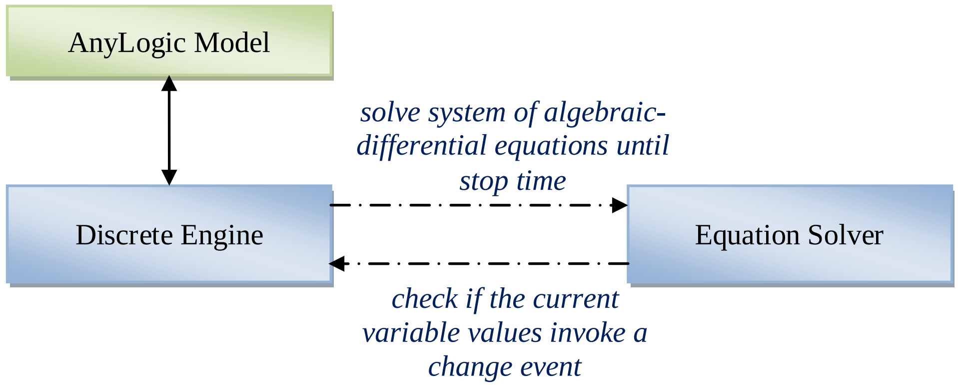


Figure 14: Hybrid Engine Architecture

2.6 Success Factors

There has been a range of ecommerce success factors proposed in literature. Central to the success factors are customer satisfaction and trust with other factors bearing a relationship to the two factors. Outputs of the model include the number of executed transactions, return on investment, downtime, customer feedback, profit, stability, security and key performance factors. Transaction processing feature of e-businesses means an increased risk for users. Drivers or barriers to the diffusion of e-commerce range from factors such as trust in online systems to the choice of logistics strategies of online sale of goods (Ghezzi, Mangiaracina, & Perego, 2012). The internet dis-intermediates or shortens the supply chain of the e-business leading to better responsiveness and lower costs. However, new forms of intermediation such as infomediaries and meta-mediaries arise to target information overload and transaction cost inefficiencies (Mahadevan, 2000). In addition, issues of security and privacy in e-commerce business have to be dealt with also.

The following section reviews literature on ecommerce critical success factors and performance measures. As defined by Manchala (2000) trust, which is a fundamental concept in managing commercial risk, is the assurance that someone or something will act in the way you expect. There must be trust among vendors, customers and transaction intermediaries. Manchala defined risk of a transaction to include transaction cost, transaction history, and indemnity. Transaction history includes behavior in past transactions and complaints. Trust actions models which includes a combination of verification and authorization can be implemented based on required efficiency.

In order to improve a business process, the measures and targets for a simulation must be clear. The choice of measures drives the final outcome. Ecommerce influence business performance and can be measured by *critical success factors (CSF)* as presented by (DeLone & McLean, 1992, 2003). The Delone and McLean's Information Systems (IS) Model is a theoretical model for measuring IS success (DeLone & McLean, 1992). The study presents a framework for measuring performance of information systems (IS). Success is measured by factors including system quality, information quality, use, user satisfaction, individual impact and organizational impact.

Many studies adapt and extend the IS Model to comprehensively identify the CSF of ecommerce. Later in the present study, a causal loop diagram will be presented on the relationships between arbitrary CSFs. On an organizational level, ROA (accounting), ROI and Tobin's q ratio (market based) are used as a measure of performance of the firm. In comparing critical success factors explanatory power firm performance, Sung (2006) showed that security, privacy, and technical expertise were more significant in Korean firms while evaluation of ecommerce operations, technical expertise and ease of use were more explanatory in USA firms. Lyons et al. (2003) describes the customer choice (cognitive) model that uses understanding, utility, acceptability and adoption as decision making sectors that influence purchase decision of a product.

An exploratory and empirical study was conducted by Wang, Huang, & Lee (2005) to determine the critical success factors (assessment indicators and impact factors) to achieve successful ecommerce implementations as it relates to Chinese electronic industry. The impact factors given by Wang *et al* include leadership, strategy, management, organization, technology, customers and suppliers factors. The backward regression model proved that leadership, strategy and organization factors were significant to success. Ecommerce assessment indicators include marketing costs, sales cost, average same revenue, gross profit rate, customer satisfaction, value and market share.

Murphy (2000) presents performance problems associated with ecommerce systems and the advantages of performance assurance. He defines performance assurance as a system life cycle methodology that ensures the system meet performance requirements while reducing risks. He encouraged the use of performance assessment throughout the ecommerce project life cycle with emphasis to the early stages of project. Dynamic modeling proved to be a reasonable approach for modeling bottleneck hopping, scheduling priorities, workload time scales and congestion.

2.7 Supply Chain Management in Ecommerce Simulation

Supply chain management encompasses all activities including order generation, order taking, order fulfillment and distribution of products, services or information. A role of SCM is to transfer information to all departments in minimal time as can be done using e-commerce. A supply chain comprise of key functions such as production, marketing, customer service, accounting and finance, shipping and distribution of goods to customers. A supply chain is a network of suppliers, manufacturers, distributors and retailers that partner together to achieve specific goals. The supply chain operations reference (SCOR) model is a step-by-step engineering approach that helps to achieve standardization of processes across the network, reengineering processes and benchmarking practices. It is a strategic tool for describing, communicating, implanting, controlling and measuring complex supply chain processes to achieve competitive advantages (Li, Su, & Chen, 2011). The SCOR model is a reference model to map, benchmark and develop the operations of supply chains (F. Persson et al., 2012).

SCOR, first released in 1997, was developed and endorsed by the Supply Chain Council and is currently in its 11th version. SCOR uses a simple "building block" approach and a common set of definitions that is used to improve supply chain operations. The SCOR model is made up of:

1. Modeling tool using standardized processes as building blocks
2. A set of key performance indicators (KPIs)
3. A benchmarking tool

SCOR provides a basic process modeling tool, an extensive benchmark database, and defines a set of supply chain metrics to a company. SCOR is used to study the static operations of a supply chain which does not include possibilities for dynamic analyses. There is also a need to study the dynamic effects e.g. changes in production rate, poor quality in raw materials. Supply chain management (SCM) is an important strategy for achieving competitive advantage across different businesses (Chan & Chan, 2005).

The SCOR model serves as a base for research with a framework that helps to evaluate supply chain order fulfillment, measure the effects of the customer, employees and leadership (Li et al., 2011). To define the supply chain, the SCOR model is organized around five management processes: Plan -> Source -> Make -> Deliver -> Return *[-> Enable]*.

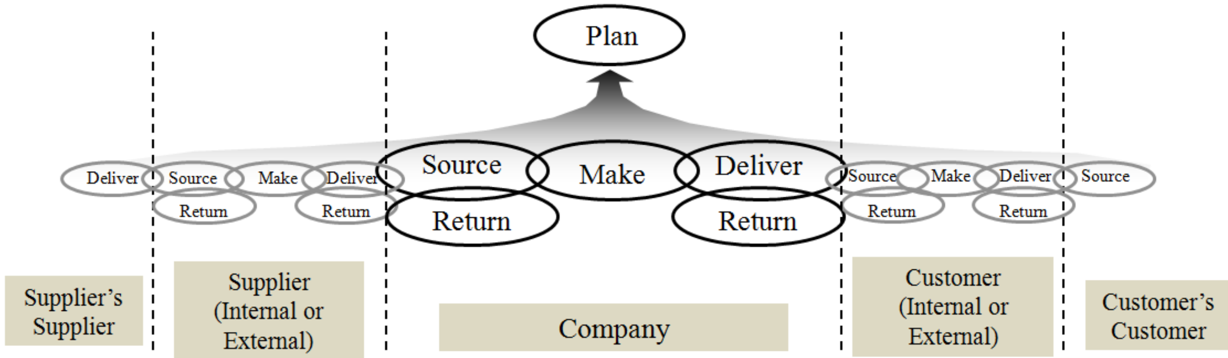


Figure 15: SCOR

Process elements have four different structures for four product-business environments. The four different environments are Make-to-Stock, Make-to-Order, Engineer-to-Order, and Retail. As mentioned in the previous section, the internet business model should reflect how a firm intends to make money long term using the internet. The structure of the model details the processes, network, characteristics, interdependencies, functional units, interactions, information and material flow. Efficiency of the supply chain depends on collaboration and coordination between suppliers and customers. SCOR is a business process reference model that helps to describe business activities, operations and tasks for satisfying internal and external customer demands. Supply chain activities captured by SCOR includes customer interactions, products and market interactions (Kirchmer, 2004).

In order to develop business process simulation models of a supply chain, an understanding of the overall SC is critical. The structural model created from the SCOR model is used to define the simulation process logic, decision logic, resource allocation, entity definitions and interactions among process, resources, entities and resources (Cope, 2008).

A typical SCOR project comprise of the following project: understand the scope; investigate solutions; identify solutions; design solutions; and plan and launch change projects. Level 1 consists of five different process types: source, make, deliver, return and plan. *Source* involves the procurement of goods and services for production. *Make* transforms products to finished state. *Deliver* transports and distributes finished products to customers. *Return* involves returning products to suppliers and from customers. *Plan* coordinates demand and supply across other processes. (Hermann, Lin, & Pundoor, 2003) describes a simulation model of a supply chain executed in Arena that is made up of three levels. Level one is the simulation model. Level two was made up of sub-models corresponding to consumers, producers and traders while level three has sub-models corresponding to process elements. Supply chain planning activities and performance measures calculations were implemented via Excel VBA routines.

2.7.1 Supply Chain Management Metrics

Every business deals with issues of achieving high quality service while reducing their costs and increasing efficiency of the supply chain. Success is defined by measuring supply chain performance which can be determined by increase in sales, increase in profits, decrease in throughput times, reduction in inventory, number of unique customers and higher fill rates. SCC performance measures address reliability, responsiveness, flexibility, cost and asset management.

Managing customer demands involve balancing customers' requirements with firm's resources. It ranges from forecasting demand and synchronizing it with distribution, production and procurement (Gimenez & Ramalhinho-Lourenco, 2004). Order fulfillment involves the management of activities to deliver order to the customer. Gimenez & Ramalhinho-Lourenco (2004) called for more empirical research (case studies and business models) about the implementation of e-fulfillment. The impact of the internet can be classified into internal, downstream and upstream. Internal effects impact the focal company while downstream effects impact the relationship with customers while upstream effects impacts relationships with suppliers.

The internet makes the supply chain more responsive. Kim (2004) develops a framework for supply chain performance metrics to examine the impact of e-commerce implementation on SCM in the healthcare industry. These metrics are applicable to ecommerce as well as to other industries. The performance metrics fall into process, delivery, resources and customer service categories. Kim believes that the goal of supply chain should be customer satisfaction**.**

Longo & Mirabelli (2008) built a simulation model to support decision making in supply chain management. Longo *et al* propose the use of their simulator with Design of Experiment (DOE) to plan the experiments and also with Analysis of Variance (ANOVA) to study how supply chain input parameters like lead times, inventory policies, echelons, number of items, stores, distribution centers, demand forecasts affect supply chain behavior.

Through simulation Chan & Chan (2005) identified four performance measures. These measures include inventory level, order lead time, resources utilization and transportation cost. The authors classify performance measures into numerical (qualitative) measures and nonnumeric (quantitative) measures. Qualitative measures include customer satisfaction, flexibility/responsiveness of the supply chain, supplier performance and information flow integration. Quantitative measures include cost minimization and profit maximization measures, customer responsiveness measures such as fill rate maximization and time minimization as well as productivity measures such as capacity utilization and resource utilization measures.

2.8 Gap Analysis

The nascent consumer-to-consumer ecommerce space resulted from penetration of the Internet. This area involves liquidity, value chain, supply chain, risk, and pricing schemes that has not been researched in Industrial Engineering. The purpose of this study is to develop a comprehensive framework to model the business processes of ecommerce. This research draws on previous work in the area of ecommerce and hybrid simulation. Processes are complicated and need support in decision making. No literature comprehensively addresses the application of hybrid simulation in ecommerce.

With an increasing global market, organizations must be agile – responding quickly and adequately to situations that arise. Business processes can be viewed as a system consisting of customers, activities, and technology. Simulation-based methodology is ideal for gaining understanding of complex and uncertain systems. DES best fits problems of narrow scopes and finds application in tracking entities and resources. Some disadvantages of DES are that estimates of variables and the corresponding correlation rely on statistics. Stability is difficult to study under DES (Rabelo, Helal, et al., 2005).

A systematic approach to ecommerce that provides a holistic view, with the consideration of system feedback, is beneficial. Standalone simulations are inadequate to model such a system behavior. DES approach proves to be more granular than aggregate while SD models are more suited for studying long term effects of policies in the system. By using a hybrid approach, the advantages of individual simulation paradigms can be harnessed to model different types of system behaviors.

Table 3: List of Papers

Authors	Ecommerce/ E-Business	Supply Chain Management	Business Process Modeling	Discrete Event Simulation	System Dynamics	Agent Based Simulation
Afuah, A., & Tucci, C. L. (2000)	x					
Alshammri, G. (2009)	x					x
Alt & Puschmann, 2012	x					
Alvarado et al., 2007		x				
Alvanchi, A., Lee, S., & AbouRizk, S. (2011)				x	x	
Amit & Zott, 2001	x					
An, L., & Jeng, J.-J. (2005)			x		x	
Bădică, C., Ganzha, M., & Paprzycki, M. (2007)	x					x
Borshchev, A., & Filippov, A. (2004)				x	x	x
Carlsson, C., & Turban, E. (2002)	x					x
Chen, D., Jeng, B., Lee, W., & Chuang, C. (2008)	x					x
Eriksson, H.-E., & Penker, M. (2000)			x			
García, M. T., Barcelona, et al. (2014)			x	x		
Grieger, 2004	x	x				
Guttman, R. H., Moukas, A. G., & Maes, P. (1998)	x					x
Helal, M., Rabelo, L., Sepúlveda, J., & Jones, A. (2007)		x			x	x
He, M., Jennings, N. R., & Leung, H. (2003)	x					x
Hlupic, V., de Vreede, G., & Orsoni, A. (2006)			x			
Hook, G. (2011)			x	x		
Kirandeep Chahal, Tillal Eldabi, & Terry Young. (2013)				x	x	
Liang, T.-P., & Huang, J.-S. (2000)	x					x
Lopez-Sanchez, et al. (2005)	x					x
Macal, C. M. (2010)					x	x
Rabelo, Eskandari, Shaalan, & Helal, 2007		x		x	x	
Rabelo, L., et al. (2015)		x		x	x	
Roman, Š., & Kateřina, S. (2012)	x					x
Schmid, H. A., & Rossi, G. (2002)	x		x			
Tako & Robinson, 2012		x		x	x	
Vuksic, V. B., Stemberger, M. I., & Jaklic, J. (2002)	x		x			
Wang & Moon, 2013					x	x
Winch, G., & Joyce, P. (2006)	x				x	
Zhang, T., & Zhang, D. (2007)	x					x
Zhong, Zhu, Wu, & Wang, 2012						x

Business model has been well defined in literature but only a limited number of research has been carried out from a scientific point of view. Business process models can be developed using graphical tools such as UML, BPMN, Flow charts. A disadvantage of using such tools is the lack of ability to provide analysis of the processes. The models provide static representation of processes that do not show dynamic changes in the system and are unable to demonstrate the effects of stochasticity on the system. In order to address issues of agile and flexible organizations, business processes (or management, operational or support processes) can be simulated from a continuous improvement standpoint. Simulation provides a way to dynamically analyze the process being described.

A number of frameworks have been proposed for combining different models (Alvanchi et al., 2011; Helal et al., 2007; Rabelo et al., 2015). Hybrid simulation research faces a number of challenges which can be summarized as a lack of modeling framework, working philosophy and practical methodology for combining the various approaches, time advancing and communication architecture. Based on the review of literature, it can be argued that the lack of modeling elements and concepts that aid seamless definition, description and conceptualizing the model and its interactions remain a deterrent to hybrid model development for complex systems.

2.9 Chapter Summary

This chapter reviewed from existing literature, the definitions and technical aspects that are necessary for the conceptualization of a methodology to analyze the consumer-to-consumer ecommerce space. Reviewing existing literature can be a time consuming phase. Applications of hybrid simulation were also presented in this review. Many of the works reviewed focused exclusively in a sole area or a few of the sole areas reviewed above, as a result, this study can fill the systematic and quantitative gaps in the literature.

CHAPTER 3. RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the research methodology and design used to address the research objectives specified in Chapter 1. Research methodology explains the design and feasibility of procedures used to collect and interpret data (Leedy & Ormrod, 2013). The methodology is a set of individual methods or techniques that explains what data is collected, when and how it is collected and what techniques (quantitative or qualitative) were used to unlock meaning of the data. The motivations for selecting the methodologies and an overview of the approaches adopted for the process implementation are presented. Figure 16 shows the high level process map for the research methodology used in this study.

3.2 Methodology Outline

A scientific study is based on empirical or measurable evidence that include an iterative process of observation, measurement, experiment and hypothesis testing. This study begins by formulating a question that encapsulates the subject of interest. In planning the study, a literature survey was performed in the identified research area. Gaps were identified in literature and the research problem was redefined as highlighted in Chapters 1 and 2.

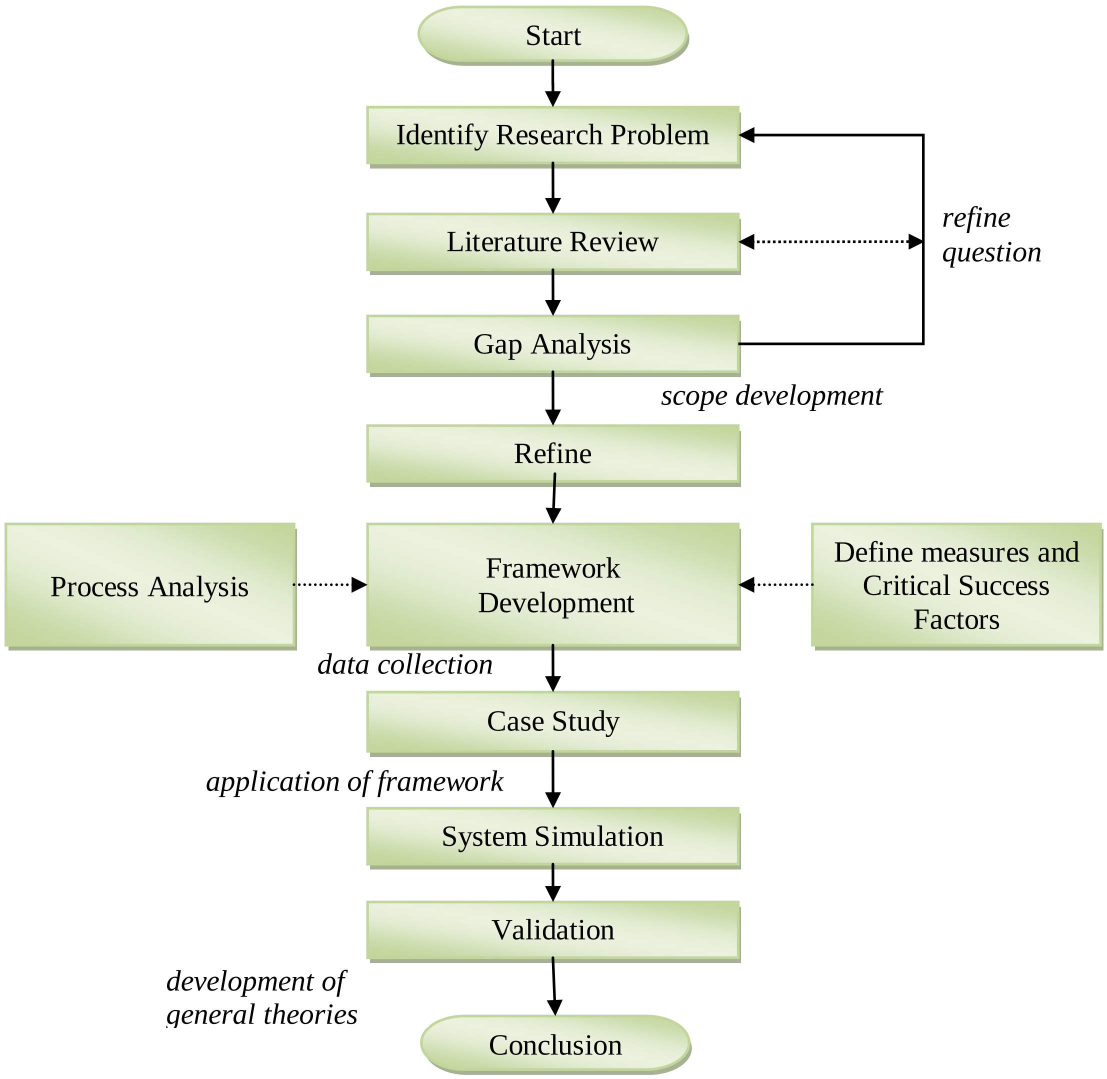


Figure 16: High Level Research Methodology

3.2.1 Research Problem and Literature Review

Development of an industrial engineering approach to tame the complexity of consume-to-consumer ecommerce business process innovation from a supply chain management perspective is the subject of interest of this study. A systematic search was performed in academic literature to establish the need and capture different technical aspects of the problem.

The literature review presented the definitions and building blocks necessary for the conceptualization of the problem. The literary study sought to expose research trends and to present existing body of knowledge pertinent to the subject of interest including how they were conducted. Emphasis is placed on the future research recommendations proposed by experts to identify perceived gaps that form the foundation of the developed framework. In line with the identified characteristics of the ecommerce system, the applications of the concepts of modeling and simulation, corresponding critical success factors and individual modeling paradigms were presented in this review. Additionally, the applications of different simulation paradigms to ecommerce problems were investigated.

3.2.2 Gap Analysis

The research process builds on past research hence the review of literature became an iterative process to ensure the problem is adequately captured. The gap analysis helps to identify the areas of importance that are under explored by other researchers. It is evident from literature that there is no integrated engineering-based approach for capturing the business processes in order to evaluate its successful implementation. For example, the evaluation of viability of ecommerce has not been adequately addressed in literature using traditional statistical tools or dynamic simulation tools. The current effort proposes integrating theories from engineering economics, operations management and simulation and modeling to be incorporated into the approach.

3.2.3 Refine Question

While refining the question, the broad scope of the otherwise over ambitious initial problem is narrowed. The literature review demonstrates that there is a need for a holistic engineering model for evaluating the behavior of ecommerce business processes and aid in dynamic and stochastic decision making. The boundaries of the present study will address the following: *Firstly*, to effectively model consumer-to-consumer commerce with the aim of aiding decision making and *secondly*, to analyze the business model (and processes) of C2C ecommerce and how the business cycle can be stabilized against risks. By iteratively refining the question a roadmap for implementing the study can be specified.

3.2.4 Framework Development

The generic conceptual C2C framework is developed to manage system complexity, assess viability and evaluate system behavior. To decompose the problem, system boundaries are considered to identify strategic and tactical problem solving opportunities. Viewing this space as a complex system characterized by uncertainty and varying system behaviors, the proposed steps to accomplish the research goals include:

i. Identify all the stakeholders in the system
ii. Identify the factors (internal and external) that influence the system
iii. Evaluate the competitive landscape of the business model
iv. Define the system as a supply chain
v. Specify system performance metrics
vi. Specify interactions between system components
vii. Model the behavior of the system, and

viii. Analyze the results of the model implementation

Figure 17 illustrates the characteristics of the system leading to the development of the proposed framework that enables the implementation of a solution.

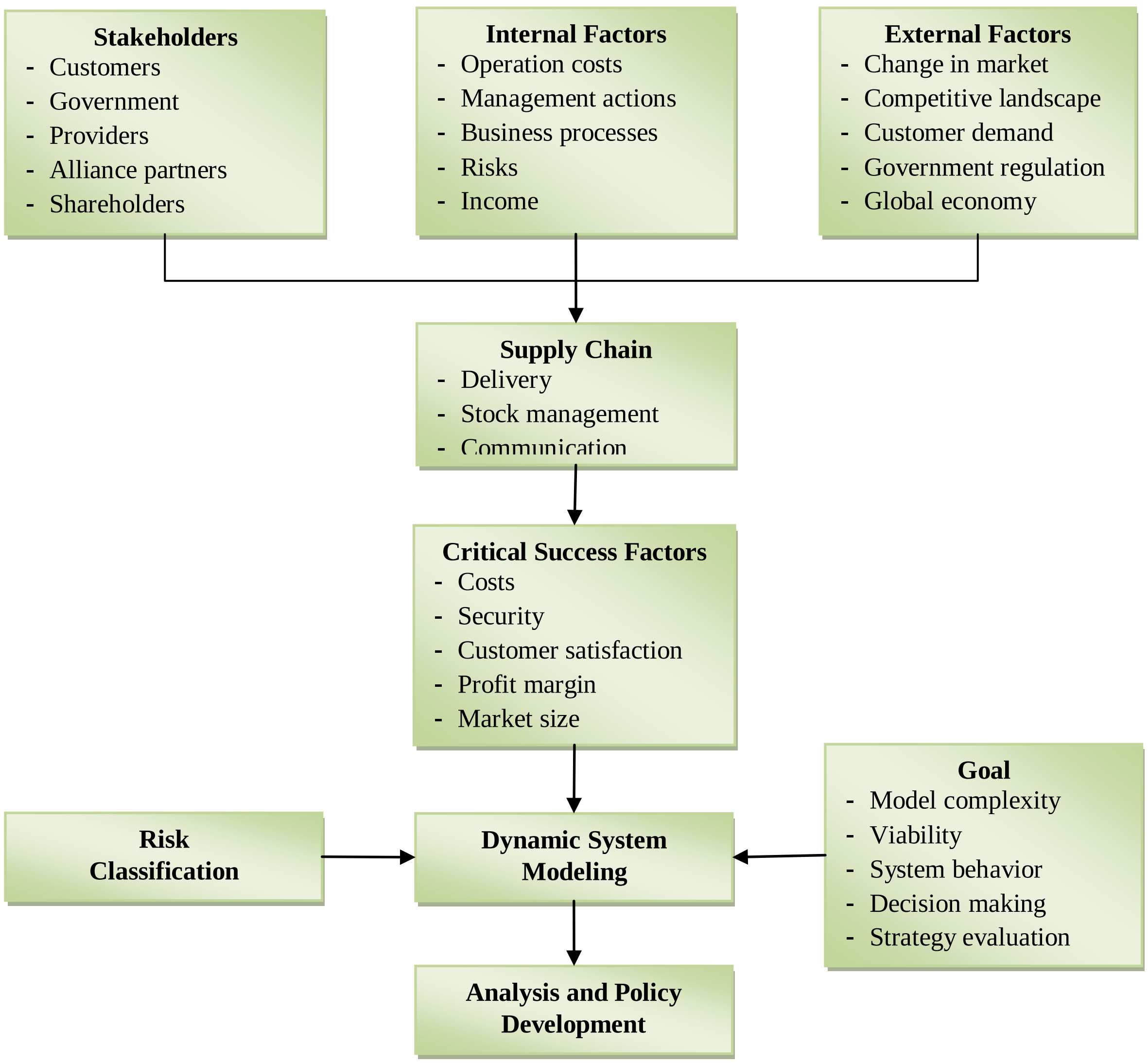


Figure 17: Framework Development

As identified from literature, organizations face an ever increasing number of challenges and threats which include changes in market, competitors, customer demands and security. These system risks can be used to generate a mechanism for risk classification assignable to system characteristics. The needs of the stakeholders are then integrated into the developed framework since they define what brings value to the system.

The ecommerce system is influenced by internal and external factors. Internal factors include the cost of operation; management actions and policies; processes involved in delivering value to the customers; risks associated with implementing the business model; and generated income. External factors are uncontrollable but it is imperative that the organization responds in ways to adequately manage them. These factors include the change in market, activities of competitors, customer demand, government regulations and the global economy.

Managing the supply chain of the system exposes the inefficiencies associated with achieving organizational goals. The C2C ecommerce space is mapped in order to identify the suppliers, clients and communication requirements of the system. Based on the information gotten from this, the modeling of system complexity is applied for dynamic analysis.

Starting with the desired system state, performance indicators influence the achievement of the system goals. The factors of interest are summarized as costs, security, customer satisfaction, profits and market share. Once these critical success factors are defined, the complexity of the system which take into consideration all the system characteristics hereby identified can be then be modeled and results analyzed for policy development.

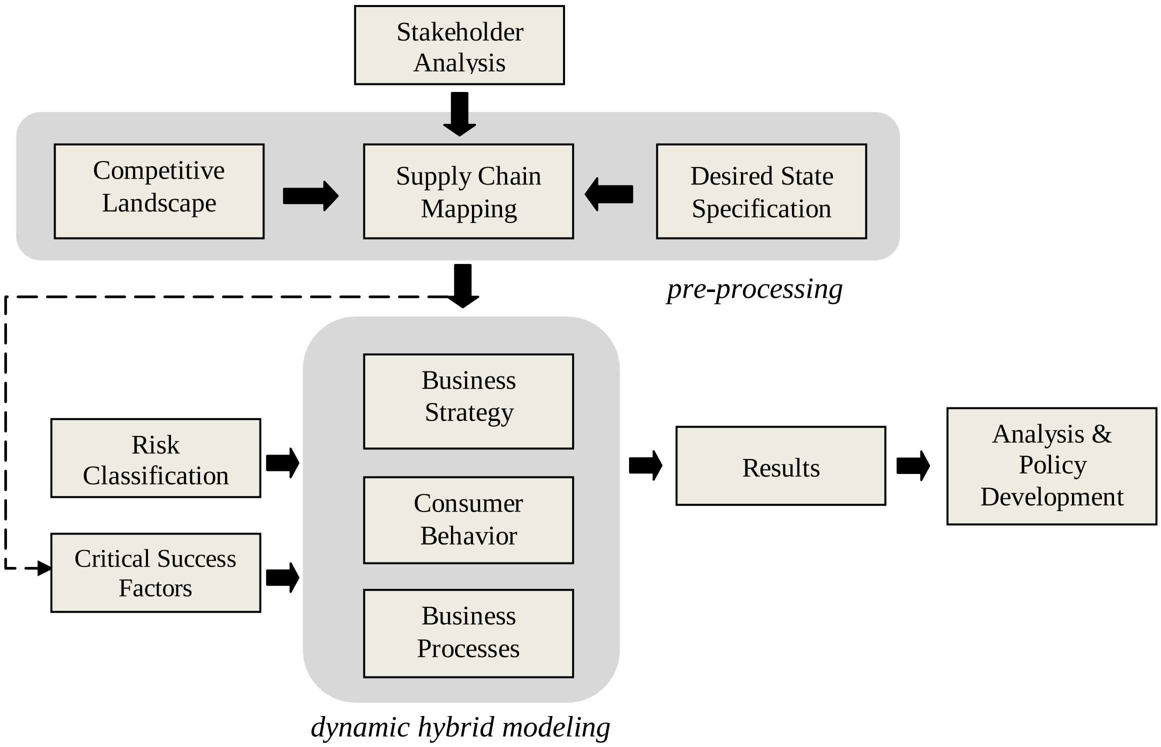


Figure 18: Framework Mapping of System Characteristics

The resulting developed framework is explained in detail in Chapter 4 while a case study is presented in Chapter 5. Implementation of the framework as applied to the case study is then presented in Chapters 6.

3.2.5 Case Study

Case study research methodology helps to capture information from a given event or problem in order to be able to apply it to other cases. According to Turner & Danks (2014), "The utilization of case study research is an effective way to identify the strengths and opportunities for the improvement of organizational procedures, policies, processes or programs.

Case study research provides evidence of new emerging theories and helps to make sense of real world problems".

The case study is used in implementing the proposed framework. The steps to design a case study research include 1) determining the research question; 2) selecting the case(s); 3) preparing for data gathering; 4) data collection - clean data by reducing sample size, formal analysis of confidence levels and retrieving quantitative and qualitative data with the goal of understanding interactions between different components of the system; 5) analysis of data and 6) interpretation and presentation of results. According to Nilson (2010), the case study method helps to solve open-ended, high uncertainty problems that have multiple respectable solutions by analyzing issues and formulating workable solutions. A limitation of the case study method, however, is that findings from particular events cannot usually be generalized to the whole populace due to uniqueness of each problem.

The present study adopts Lending Club (https://www.lendingclub.com/) as representative study of the dynamics of C2C ecommerce space. The case study is used to identify suppliers, consumers and processes of the business model as well as related internal and external factors. Data is utilized from Harvard Business case studies, company 10-K, prospectus, blogs and company website. The case study will help select and define boundaries and core areas of interactions in the system.

3.2.5.1 Lending Club

To describe the online consumer-to-consumer (social) lending in the context of ecommerce, liquidity, pricing models, and risks, hybrid modeling will be used. An industry overview and an introduction to the operations of peer-to-peer (P2P) lending platforms are presented in Chapter 5. Growth in the industry partly resulted from investors being discouraged by stock market returns and lower interests provided by banks. Results from business case studies and literature review indicate that the success of P2P lending business process innovation has not been proven. As an example is the number of lenders and qualified borrowers that can effectively meet the mutual needs of the customers. . Because this form of lending is insecure, lenders are exposed to a risk of default by the borrower. The platforms have to deal with uncertainties that pervade all aspects of its operations. Any unplanned downtime, outage or system hack can have long term effects to its operations and credibility. There is room to define how the industry perceives the model and in what environment in which it can be successfully executed. Important factors such a liquidity, profitability and the different threshold values for investors and loaners must be defined. There is a need for a peer-to-peer lending model that will aid in effective decision making in which the business processes is assessed for risks. The case presents a snapshot of the company as at December 2014

3.2.6 Modeling System Characteristics

In line with the characteristics of the system, the proposed framework is implemented from a hybrid system perspective. Such an implementation provides a testbed for analysis of management and stakeholder actions and also for evaluating performance of the system under different conditions. Hybrid simulation finds extensive applications in research and practice in part because most real life systems are hybrid in nature. Conventional simulation and optimization models are not sufficient to address inherent characteristics of behavioral- and business-type problems. Hybrid modeling helps to overcome the weaknesses of individual methodologies and harness on their corresponding strengths to create more realistic models. Use of hybrid non-classic models can be used to analyze business policies and performance providing a complementary tool in decision making.

3.2.7 Verification and Validation

Validation of the initial models is accomplished through the use of historical data. Data on existing C2C systems is utilized to build and validate the model in order to garner insights. The data was used to develop rules and simulation parameters. According to Law (2009), "Validation is the process of determining whether a model is an accurate representation of the system, for the particular objectives of the study". Also, sensitivity analysis helps to determine the model factors that have significant impact on the desired performance measures. While verification ensures that computer program's syntax is correct, validation ensures that the model's range of accuracy is satisfactory.

3.3 Conclusion

This chapter outlines the methodology adopted to create the decision-making framework. The framework takes into account the system characteristics and risks of the system. The problem can be implemented in an integrated manner using different industrial engineering tools. The next chapter provides details of the reference framework and the steps taken to address the research question.

CHAPTER 4. RESEARCH FRAMEWORK

4.1 Introduction

This study presents a simulation-based framework for decision making in C2C commerce. The main purpose of the proposed framework introduced in Chapter 3 is to offer an approach designed to test management policies and to determine how customer behavior gives rise to aggregate results. This chapter delivers a conceptual architecture to create a hybrid simulation that incorporates decision making at different management levels, by taking into consideration human components characteristics. To achieve the research objectives, techniques from engineering management and industrial engineering are employed.

For the purpose of study, platform refers to the ecommerce platform where transactions take place. The platform also provides the technological tools needed to execute a trade. The system refers to the simulation or the aggregate of modules being studied while customers (sellers and buyers) are referred to as players. We expound on the framework to quantify the effects of player characteristics in the system and its effects on aggregate behavior.

4.2 Proposed Framework

The proposed conceptual framework consists of an integrated and systematic approach to characterize and model ecommerce system for desired analyses. The framework consists of evaluating the current situation of the system and identifying the participants present in the system. The proposed framework is mapped to identify the problem, corresponding hybrid components, and in addition, how individual models interact with each other. The choice of the design is motivated by the research objectives outlined in Chapter 1. A good starting point is to decompose objectives to sub-objectives in order to determine the behavior of the system and subsystems. Figure 19 presents the basic components of the developed generic model for the proposed framework. The framework can be rearranged to make up of the following modules: (a) stakeholder identification; (b) supply chain mapping; (c) system characterization; (d) risk classification; (e) simulation design; (f) dynamic hybrid simulation and (g) policy and analysis.

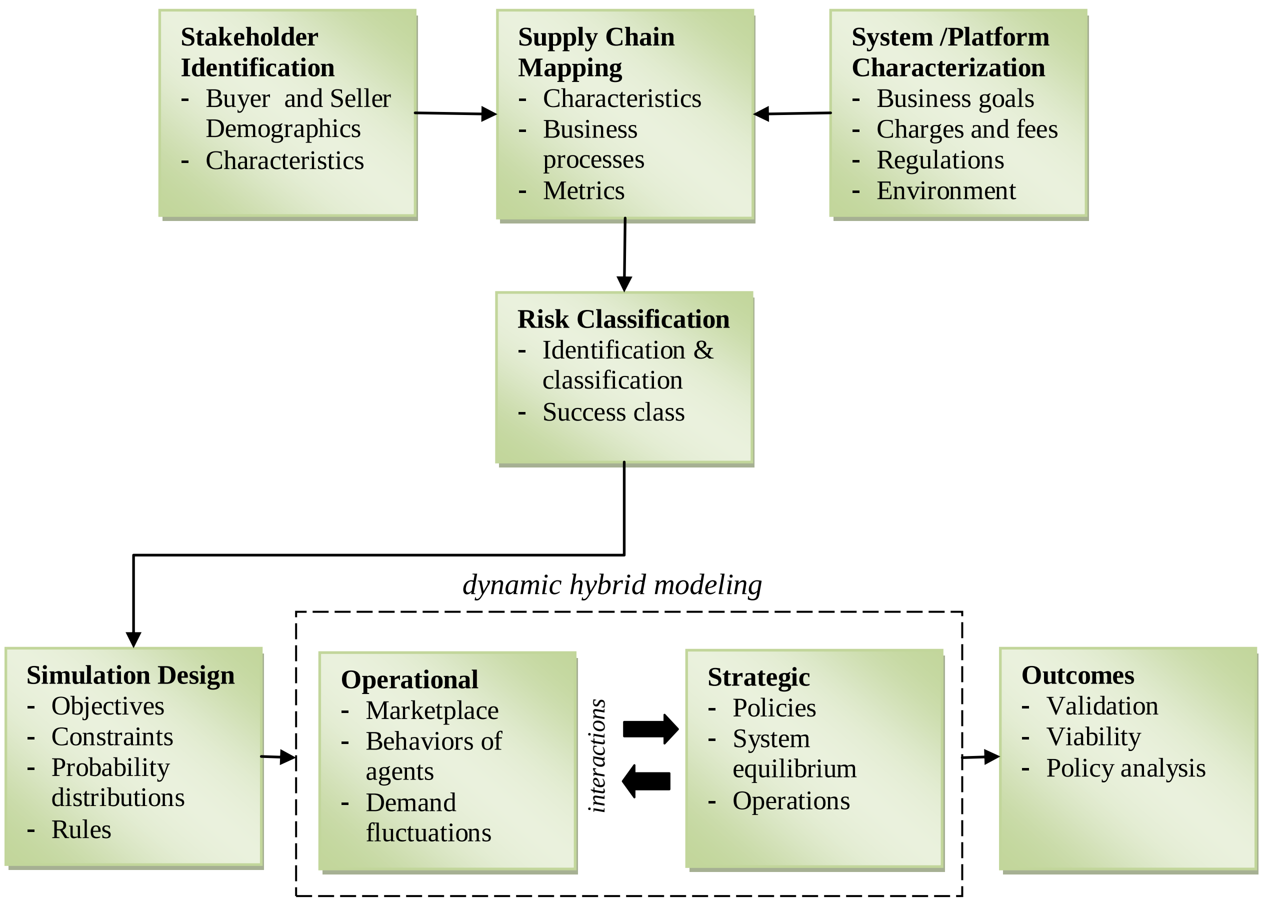


Figure 19: Generic System Framework

Each module has well-defined functions with inputs and outputs to interact with each other. Modules (a) through (c) describe the specification of the environment as it relate to the system goal. The proposed framework presents an approach to model the discrete and continuous components of the system, taking into consideration long and short term effects of policies and characteristics of the system. The proposed implementation flow of the modules representing system characteristics is presented in Figure 20.

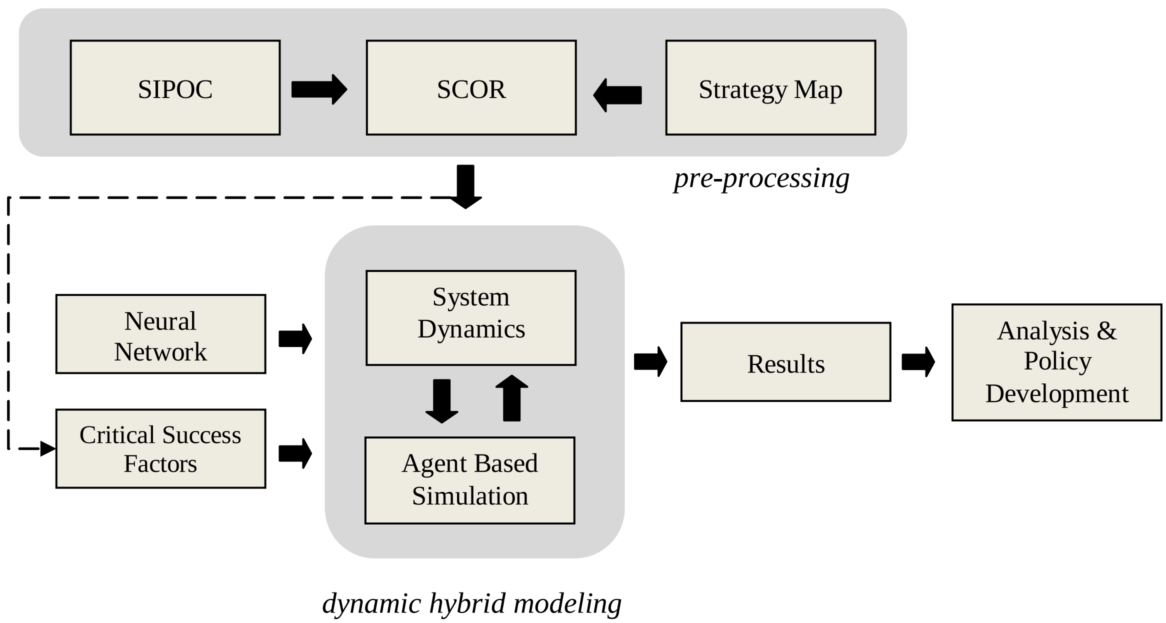


Figure 20: Proposed Framework Implementation Flow

4.2.1 Stakeholder Identification

A stakeholder is an individual or entity that affect or is affected by the realization of an organization's objective. This module is used to identify high level requirements of the system. The players are identified in the stakeholder identification module along with their interactions with the system and intended behavior. In the case of ecommerce platforms such as ebay.com and amazon.com, the players are buyers, sellers, workers and managers. In peer-to-peer lending, the players are lenders and borrowers who sell and buy loans respectively. According to Eriksson & Penker (2000), modeling a business's surroundings involves answering such questions as:

How do the different actors interact? What activities are parts of their work? What are the ultimate goals of their work? What other people, systems, or resources are involved that do not show up as actors to this specific system? What rules govern their activities and structures? And, Are there ways actors could perform more efficiently? Answering these questions will help to determine actions or event steps required by actors from the system in providing a starting point for modeling business processes.

4.2.1.1 SIPOC

The SIPOC tool can be used to identify suppliers, inputs, processes, outputs and controls within the system. SIPOC is a tool for identifying basic elements of a process from its suppliers through to its customers. These elements include boundaries, supplier inputs, process inputs, steps, customers and outputs.

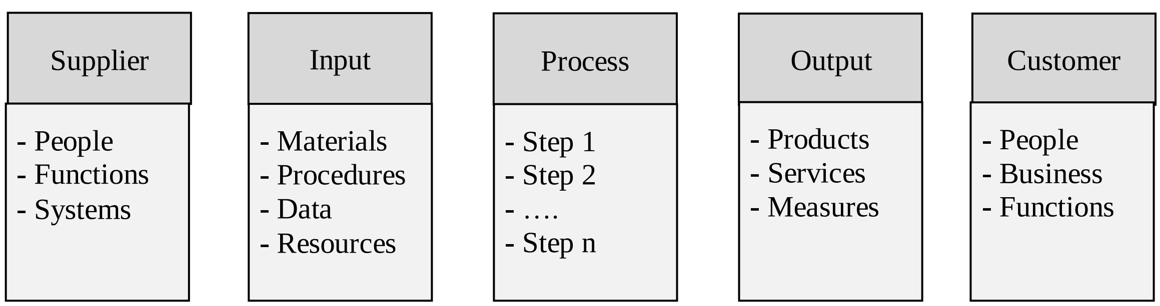


Figure 21: The SIPOC Tool

The *suppliers* provide input to the process. The *inputs* represent materials, information or resources needed by the supplier in completing the process. A *process* is a series of activities that transform a set of inputs into a specific set of outputs in order to provide value to the customers and shareholders. $Y = f(x_1,x_2,x_3,\ldots,x_n)$ represents the output(s) which is a function of input *x*'s with $f(x)$ being the transformation of inputs into the outputs. The *output* element in the SIPOC tool gives the products and services from the process. The *customer* receives the outputs of the process.

4.2.2 System Characterization

The system characterization module specifies the external and internal factors pertinent to performance of the ecommerce platform. The behavior of the platform is affected by its environment. Government regulations can stymie or foster its growth. Past performance on its platform will determine actions to be taken and how problems will be addressed. The principal function of the platform is to meet the needs of systems, thus creating value for its customers. The charges enforced by the platforms are minimal in comparison with those associated with brick-and-mortar stores. In the characterization module, charges and transaction fees associated with providing services are identified and factored into how it affects business performance. This ensures that the true benefits of using the platform are revealed on completion of the final transaction related to a trade.

4.2.2.1 Strategy Map

A business concept is made up of the core strategy, strategic resources, and customer interface and value network. The strategy map helps specify key overall objectives and customer value propositions, depicts the cause and effect linkages among stakeholders, external customers, internal business operations and strategic competencies. It helps to translate knowledge-based technology related processes into tangible operational terms (Kaplan & Norton, 2001).

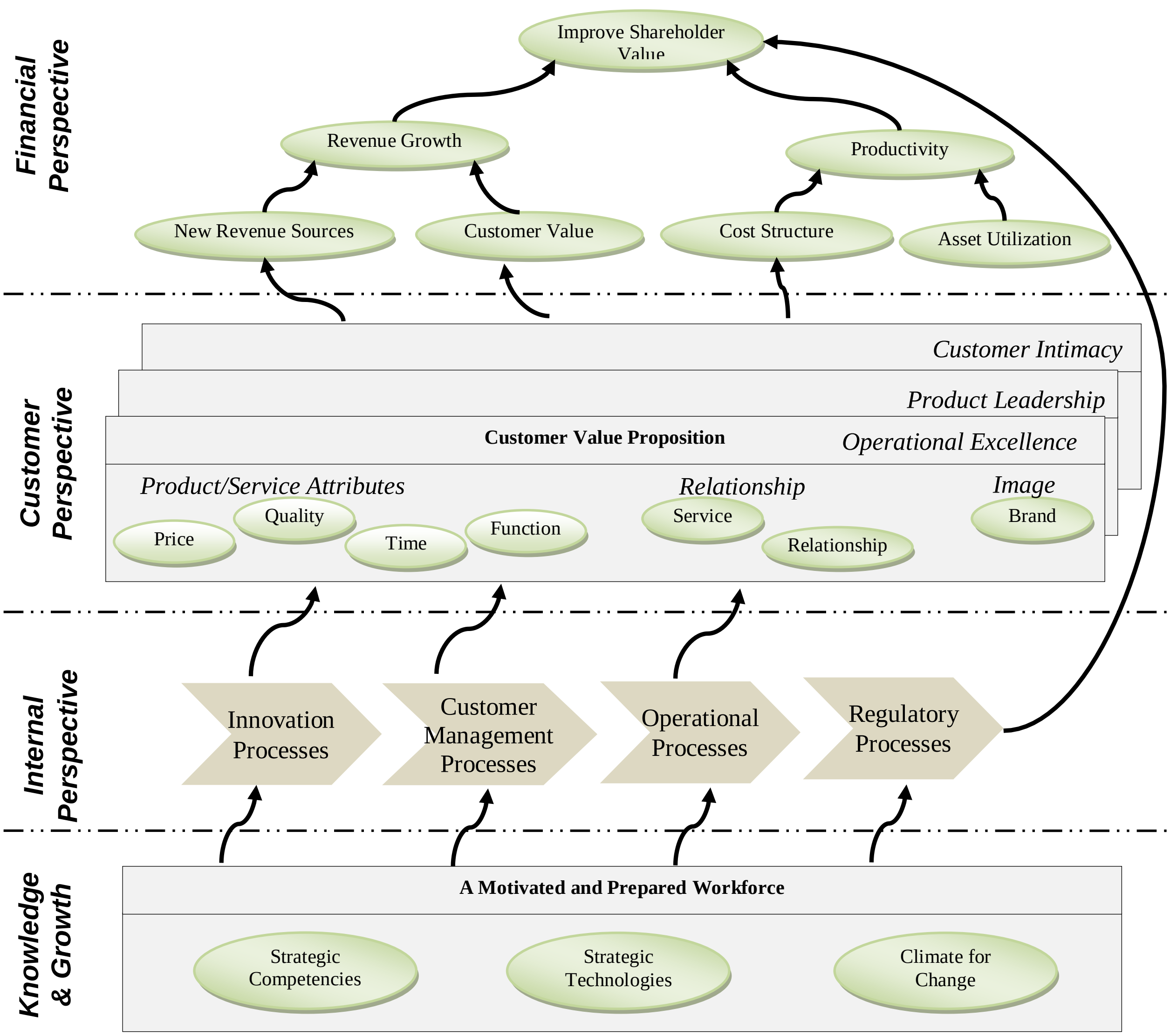


Figure 22: Strategy Map (adapted from Kaplan & Norton, 2001)

The strategy map is made up of four perspectives which are financial, external, internal and learning and growth perspectives. The financial perspective is made up of growth and productivity factors that help increase shareholder value. The External perspective consists of product leadership, customer intimacy and operational excellence to strengthen customer value proposition. The internal perspective emphasizes innovation, customer management, operational and regulatory processes. The learning and growth perspective consist of competencies, technologies and organizational climes.

The extension of the strategy map to incorporate tangible (quantitative) measurements to the various objectives and their cause-and-effect linkages can be achieved using the Balanced Scorecard (BSC). BSC is a strategic management system for achieving long-term goals. According to Kaplan & Norton (2001) "The balanced scorecard retains traditional financial measures. But financial measures tell the story of past events, an adequate story for industrial age companies for which investments in long-term capabilities and customer relationships were not critical for success. These financial measures are inadequate, however, for guiding and evaluating the journey that information age companies must make to create future value through investment in customers, suppliers, employees, processes, technology, and innovation". Short-term and long-term performance and objective measures across the four perspectives. Measures of interest in ecommerce span transaction costs, transaction volumes, process cycle-time, service time, inventory costs and financial ROI to capture supplier and customer profitability. The balanced scorecard provides a framework to assess and develop strategy, develop strategic objectives and performance measures to translate strategies to actions, provide a way to measure performance of key performance drivers and it is also an effective tool to ensure continuous improvements in the systems (H.-Y. Wu, 2012).

4.2.3 Supply Chain Mapping

The supply chain mapping module can be implemented to receive inputs from the SIPOC, Strategy map and BSC which feed into the SCOR and in turn into the simulation design.

4.2.3.1 SCOR

This study employs the supply chain operations reference (SCOR) model, an industry standard approach, to define, design the e-supply chain of ecommerce. The SCOR model is a supply chain management tool that will be used to capture and map the supply chain in order to describe the business activities. The supply chain module is responsible for extracting the business processes of the system. The supply chain of C2C ecommerce then defined using the SCOR model to determine requirements and benchmark using metrics already defined in the model.

The SCOR model helps to understand complexities of the supply chain structure of an organization, measure performance and identify priorities and processes. The model fuses concepts of business process reengineering (BPR), benchmarking and best practices into a single framework. Business process reengineering defines the supply chain “as is”. Benchmarking compares the supply chain “as is” with best performers. Best practices analyze the best means to convert the “as is” status of the supply chain to the desired target status.

Standardization allows the organization capture complexities and clear communication in order to achieve competitive advantage across supply chain processes. As introduced in Chapter 2, there are four levels of standardization of the Plan-Source-Make-Deliver-Return processes of the SCOR Model that details the roadmap that a company takes to SC improvement (Figure 23).

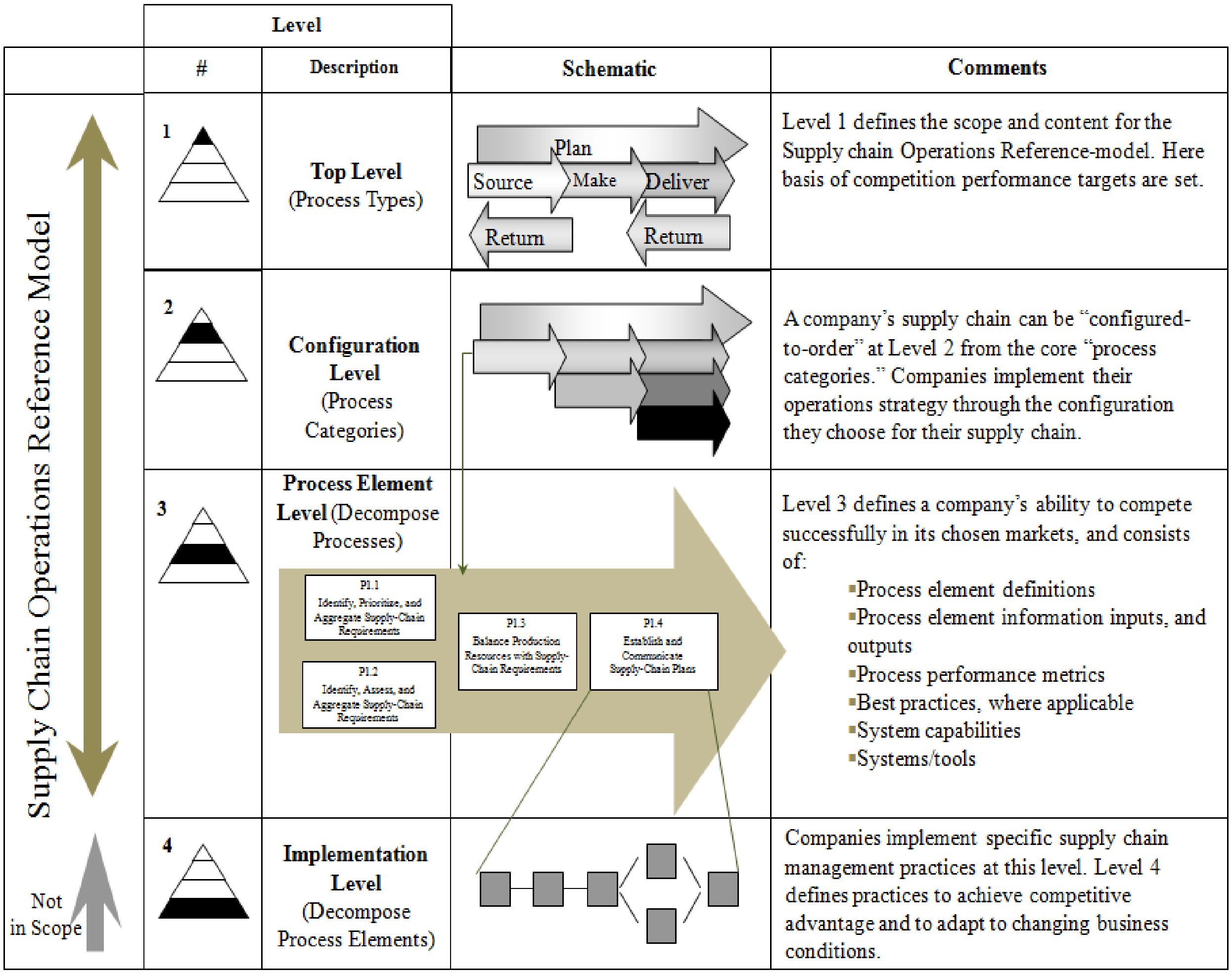


Figure 23: SCOR Levels of Process Detail

Top level (Process Types) defines the scope and content of SCM processes at a high (strategic) level. The Configuration level (Process Categories) categorizes the SC processes into planning processes, execution processes and enable processes. Process element level (Decompose Processes) decomposes and details Configuration level into sub-processes, providing the organization with information needed to plan and set goals through detailed practices - and identifying strategic processes within each element. Implementation level

(Decompose Process Elements) is organization specific and deals with the implementation and not defined within the industry standard model.

The SCOR model is used as a building block to guide the simulation. The framework is used to create hierarchical simulation models that capture activities of a supply chain in as much granularity as desired. Simulation of the supply chain helps to describe complex and dynamic system, help to interpret results and give an insight into the cause and effect relationships in the system. Once a process is captured in the standard process reference form, it can be implemented to achieve competitive advantage, it can be described and communicated and it can also be measured and controlled. The use of the SCOR module is instrumental in defining the elements needed for the characterization of the hybrid system, allowing for quicker and simpler model building.

4.2.4 Classification using Neural Networks

There a lot of algorithms within the machine learning space including Support Vector Machines (SVMs), Artificial Neural Networks (ANN), amongst many. Classification problem uses inputs to classify the performance of the system into groups or categories. Neural Networks is proposed in this study for risk classification. The classification module specifies how users in the system are screened using characteristic attributes that are of interest to the system. Artificial Neural Networks have been successful in solving image classification problems, natural language processing, speech detection and CAT classifications by predicting some output values using a combination of input values. ANN is used to extract data patterns for model building using specified criteria contained in the data.

Machine learning techniques extract knowledge from data set. Different model representations are constructed using these techniques to explain the data. The idea of neural networks is loosely based on the neurons in the brain and the synapse that connect them. There exist nodes that have connections between them. To get a neuron to do something, a trigger is applied to a node with some input and that triggers other nodes to which it is connected to. Let the training set be represented as S. A given output space Y can be predicted using the input space X. Having a testing data of inputs and corresponding outputs can be used to train a model to predict what a future output will be. Nodes can take a sum or average of connecting nodes.

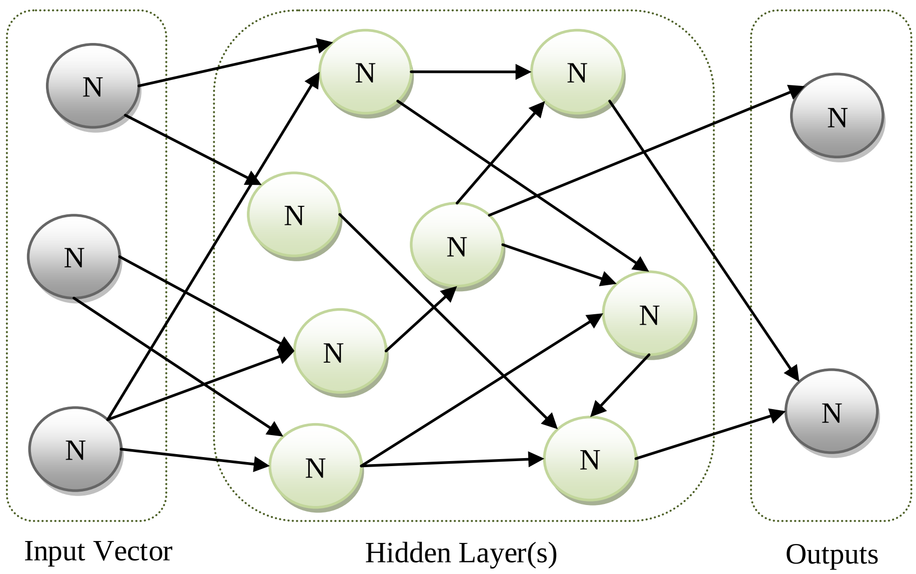


Figure 24: Neural Network

Neural Networks are made up of three components: the architecture or model, the learning algorithm and the activation function. Data is fed into the neural network using comma delimited files (CSV). Data has to be normalized in the CSV files – example, to feed a consumer's age of 21 into the NN, you normalize by (taking the inverse of the upper limit e.g. 1/21). Information is transformed for easy analysis and assessment. The training data is used to determine the weights of the NN in order to produce the desired output. The procedure and corresponding mathematical equations is represented thus. Connections have different weights indicating their importance. Using the connection weights and transfer functions, takes its inputs and produces outputs. Neural networks learn the weights of connections and new weights are calculated using the old weights, input values, error and learning rate.

$$W_{j,i} \leftarrow W_{j,i} + \alpha \times a_j \times \Delta_i \tag{4.1}$$

$$\Delta_i = (T_i - O_i) \times g'(\textstyle\sum_j W_{j,i}\, a_j) \tag{4.2}$$

There are 2 activation functions at the intersection between layers: sigmoid function (Eqn. 4.3) and the hyperbolic tangent function (Eqn. 4.4).

$$f(x) = \frac{1}{1+ e^{-x}} \tag{4.3}$$

$$f(x) = \frac{e^{2x}-1}{e^{2x}+1} \tag{4.4}$$

The NN can be trained as a sort of optimization problem by viewing it as a function having many parameters.

$$f(w1, w2, w3, \ldots.) = Output(\, or \, = Error) \tag{4.5}$$

The goal is to minimize the error by choosing different combinations of *Wi* values that will give a minimal error. This can be done using gradient descent (GD) using derivatives and calculus techniques. The gradient is the instantaneous slope (derivative) at the error curve. GD can be done by backpropagation, resilient propagation or manhattan propagation algorithms. The Mean Squared Error (MSE), Root Mean Squared Error (RMSE) or Arctan Error can then be used to calculate the error which is then used to calculate the gradient. The gradient descent optimizes a nonlinear function by distributing the errors of the output neuron across the weights of the NN. The capacity of the NN to represent information accurately is dependent on the number of hidden neurons and weights.

Other machine learning techniques like Support Vector Machines (SVM) seek to optimally separate the classification surface. In their study, He, Shi, Wan, & Zhao (2014) used an SVM algorithm developed in MATLAB to predict customer attrition for commercial banks. They compared their results in SVM to a Logistic Regression model and found that prediction is optimal using the radial basis function (RBF) kernel function to transform nonlinear classification into linear classification of imbalanced features (contained in the customer data) the SVM model.

4.2.5 Simulation Design

The simulation model, consisting of reusable components, is created using the SCOR model to guide the modeling process. The modeling processes are then converted to AnyLogic using the basic structure provided by SCOR. The model objectives, inputs (factors) and outputs (responses) determine the model scope. In the simulation design module, system constraints are defined. The scope and level of detail of the simulation-based study is determined. Based on the characteristics realized in the simulation design phase, the approach to simulation is determined and defined. In this module, the data is also fit to probability distributions to determine which best represents the factors being studied. Once the system processes are identified, the process map can show the relationship with simulation models.

The simulation model is a set of rules (differential equations, statecharts, process flow charts, schedules) that indicate how to obtain the next stage of a system. Rules are statements defining operations, constraints and definitions that specify how overall system behavior is controlled. Existing standalone models have underlying assumptions that do not fit requirements of common decision making situations in the business systems. The steps for conducting a simulation study, based on Law (2009) , are depicted in the flow chart in Figure 25. Data must be representative of model, unbiased, in appropriate type or format and void of measuring or rounding errors and conducted under known conditions.

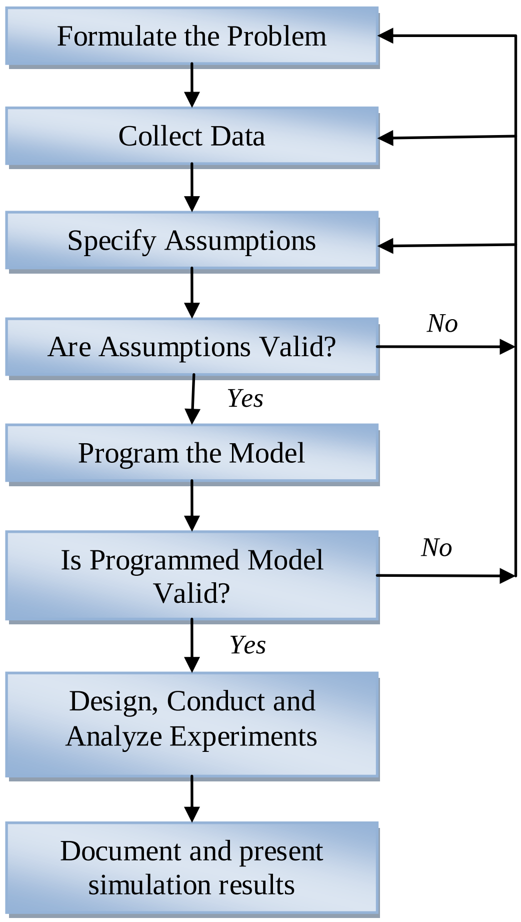


Figure 25: Approach to conducting a simulation study

At inception, conceptual modeling and development abstracts the simulation model from a real system that may or may not already exist by choosing what to model. Due to time and knowledge constraints, a simulation study must decide the level of abstraction that will provide an acceptable representation of the system being studied (Robinson, 2012). A simulation makes assumptions about the real system and chooses what details to include in the model.

Simulation models are developed for the particular set of objectives of the study. Hybrid simulation methodology is adopted using agent-based modeling and simulation and system dynamics in addition to risk management in order to evaluate the performance of C2C ecommerce. The simulation methodology offers an approach that targets dynamic policy design that incorporates the scopes and planning horizons of management. Static models do not account for changes in the system over time and cannot model variability. Therefore, hybrid simulation is employed to extend this into a dynamic framework. Dynamic analysis enables us to study the long term implications of policies, activities and behaviors on the system. Decision makers need a methodology that allows for timely and efficient updating to reflect changes in the environment (Cope, 2008).

4.2.6 Hybrid Simulation

Hybrid simulation models are developed in AnyLogic, an object-based program. The multi-method model architecture is given thus. Seller consumers come into the system with goods to sell. These consumers require different returns threshold. Buyer consumers have different highest price which they can pay for goods offered on the platform. Consumers are modeled as agents whose behaviors elicit response. The dynamics of price agreement are modeled in the agent based system. The platform acts as a service system. The system is loaded based on the number of customers that come into the system. The environment is modeled in a

SD with agents living therein. The population of consumers is disaggregated to individual level using agents.

In the simulation of business processes, interaction between system players can be modeled using statecharts. Update to the system state is driven by events. Communication can be modeled as discrete events of information exchange.

The steps feeding into the hybrid system is as listed:

1. Analyze current situation of the system
2. Collect and analyze information
3. Develop causal loops from brainstorming sessions (address communication, knowledge etc)
4. Design a stock and flow model
5. Design agent based model to reflect:

   - Participants. Firms of interest, customers, suppliers and allies.

   - Relationships. Either electronic or primary relationships.

   - Flows. Money, information, product or service flows.

4.2.6.1 System Dynamics

In order to study the business processes and relationships of the supply chain of C2C ecommerce space are studied using system dynamics. Sterman (2000) defines system dynamics as, "*a perspective and set of conceptual tools that enable us to understand the structure and dynamics of complex systems. System dynamics is also a rigorous modeling method that enables us to build formal computer simulations and use them to design more effective policies and organizations*". The steps for modeling a problem in system dynamics is given in Figure 26.

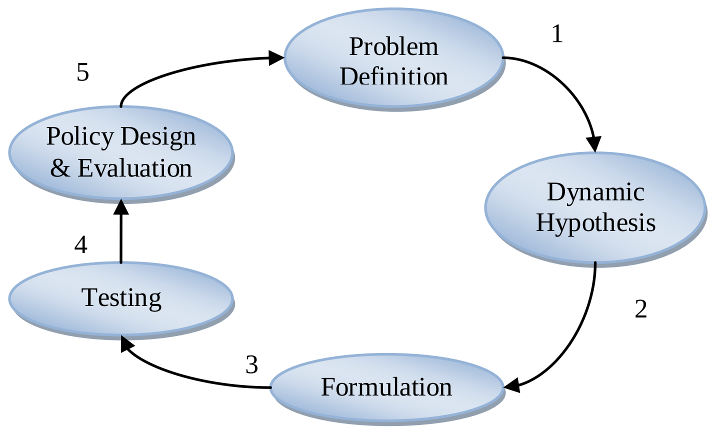


Figure 26: Iterative Steps to Modeling process (adapted from Sterman, 2000)

System state variables vary continuously over time in continuous simulations. Cause-and-effect diagrams help to illustrate relationships and interactions among state variables. The rate of change of the variables with respect to time is represented by a set of mathematical equations. Building a model involves identifying parameters which are related to the analysis, defining causal relationships and defining stock and flows of the parameters before the model is mapped into the mathematical formulas.

Stocks are state variables that characterize the system state while flows represent the rate of change of stocks over time. A causal diagram is made of variables which are connected by arrows to indicate the causal influences among variables. SD model can be applied to organizational environment for calculations of costs, profits, investments and productivity. Figure 27 shows a hypothetical state of interest rate being determined by default rate. The polarity of the causal links indicates how a change in the dependent variable affects the independent variable. For example, the positive polarity of the causal link indicates that an increase in interest rate results in an increase in default rate than what would otherwise have been and vice versa. A negative causal link would mean that an increase in the cause will result in a decrease below what would otherwise have been ceteris paribus.

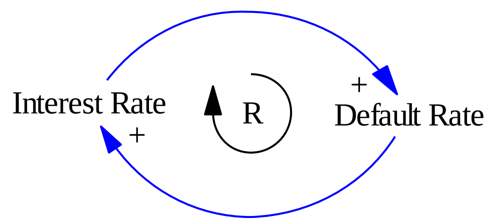


Figure 27: Causal Links

The polarity of a loop can be determined either by counting the number signed links in the loop of by tracing the effect of a change around the loop. In Figure 27 if interest rate increases, default rate is hypothesized based on literature, to increase. The link from default rate back to interest rate also shows that a high default rate will cause the institution to hike up its interest rates for loans in order to cover the costs of granting the credit. The loop is positive because feedback reinforces the original effect.

Causal loops diagrams (CLD) depict feedback loops and a different way to view the world, understand delays and unintended consequences of one's actions. Causal loops modeling provide qualitative insights into the behavior of the system while stock and flow offers quantitative modeling. The application of stocks and flows is based on known causal relationships and their directions, ability to estimate causal relationships and projected changes that can occur in causal variables. Stocks and flows (shown in Figure 28) track the accumulation of resources in the system. Stocks can be consumer population, cash, and debt while flows are the rate of change of stocks such as population change and rate of change in cash flow. Stocks characterize the state of the system and acts as memory and a source of delay. Delay in stock accumulation occurs when change is not instantaneous. New system states (stocks) are calculated by adding the impact of flow rates.

Figure 28: Stock and flow - Iterative Steps to Modeling process + feedback

The system can be mapped into integral and differential mathematical description and solved using a computer simulation. Dynamic behavior of a system is modeled over discrete time periods. Derivative equations help to determine the rate of change of variables. The system can be represented with Equations 4.6 and 4.7. The value of the stock can be calculated by accumulating the difference between material inflows and material outflows over a given period of time.

$$Stock(t) = \int_{to}^{t} [Inflow(s) - Outflow(s)]ds + Stock(t_o) \quad (4.6)$$

$$d(Stock)/dt = [Inflow(t) - Outflow(t)] \quad (4.7)$$

The integral in 4.6 describes the stock-flow principle wherein a new $Stock(t)$ is the difference between the $Inflow(s)$ and $Outflow(s)$added to the initial $Stock(t_o)$.The equivalent differential equation gives the net rate change of a stock. Corresponding behaviors can be exponential, oscillation and goal seeking. The three common variables used in SD modeling are levels, auxiliaries and constants. Levels are initialized at the start of the simulation and accumulate their value over the simulation run. Auxiliaries are computed at each time step. Constants are initialized at the start of the simulation and do not change values during the course of the run. Since the primary goal of SD is system behavior, models are deterministic devoid of intrinsic randomness.

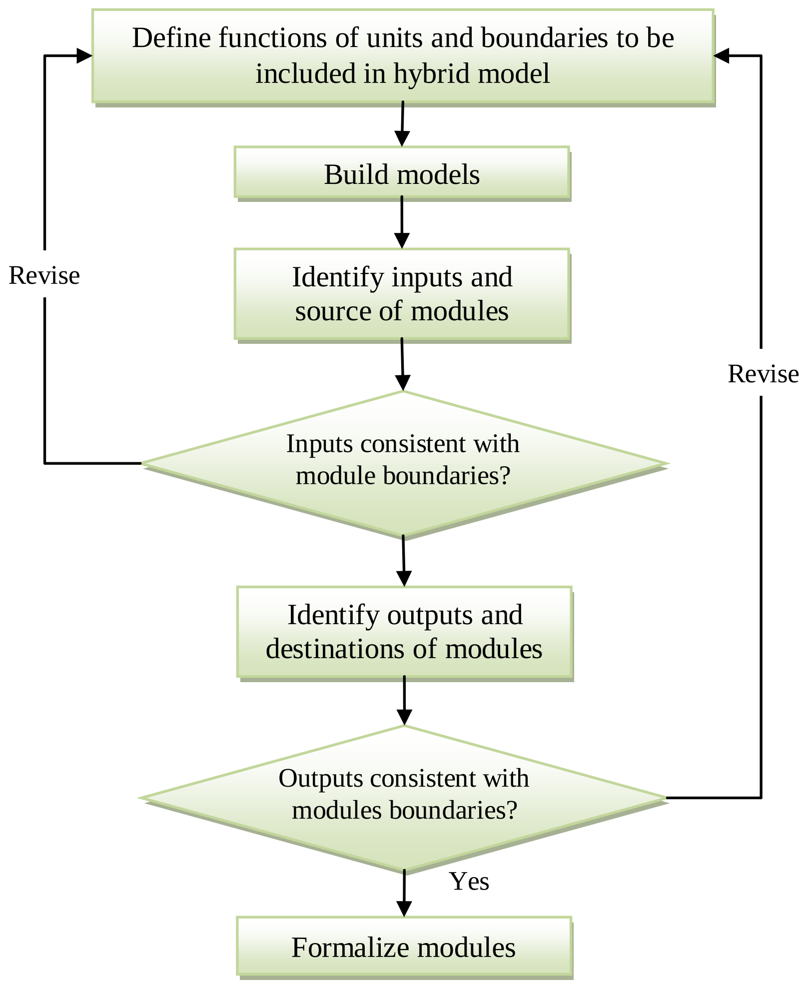


Figure 29: Modules Definition (modified from Helal, 2004)

System Dynamics helps to identify variables and causal loops of a system which are then fed to the ABMS model. The Stock Management Model (SMM) forms the base to modularize SD models and standardize the building of SD models (Sterman, 2000). The SMM provides a guide to building SD modules. Figure 29 gives the process for building SD modules. Input (predictor) variables are received through input ports from other modules while output variables are sent via output ports to other modules.

Key success criteria for ecommerce strategies were generated from relevant literature and case studies. The important factors are defined from literature and given in Chapter 2. From the review of critical success factors of ecommerce (DeLone & McLean, 1992; H. Wang et al., 2005), the following are identified and the relationship presented in a causal loop diagram of important factors that impact success (Figure 30).

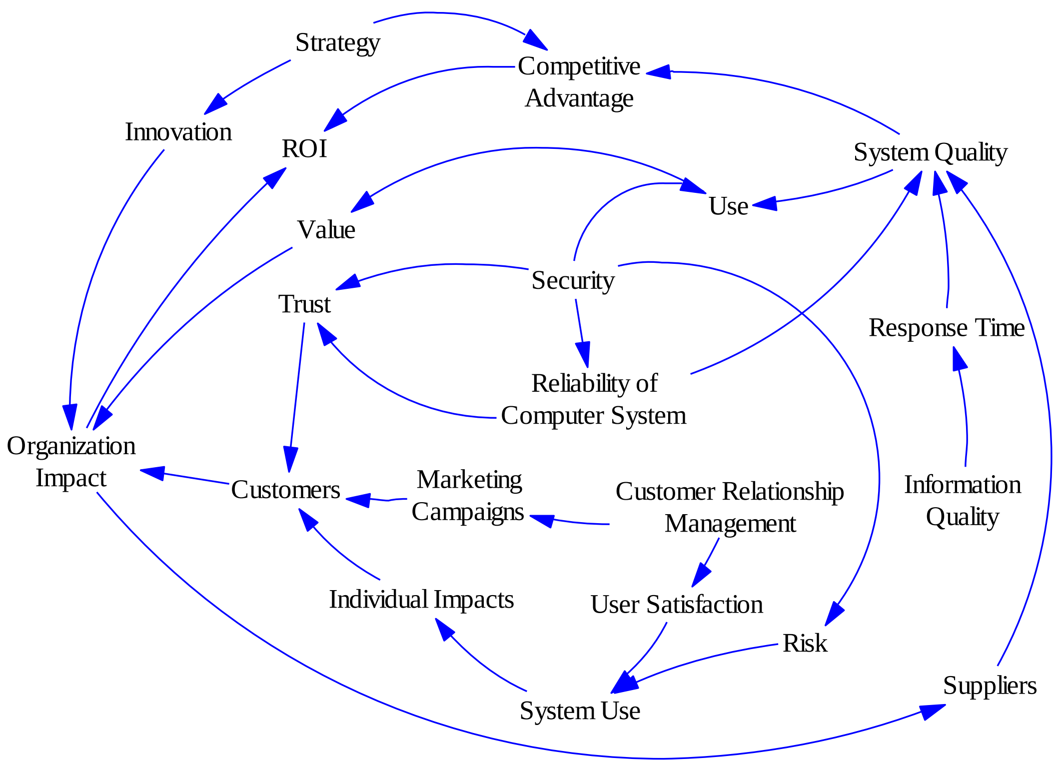


Figure 30: A Generic Causal Loops of Ecommerce Success Factors

4.2.6.2 Agent Based Simulation

ABMS is used to gain understanding into how a system works, its key variables, interractions and dependencies. Agents make decisions in complex adaptive systems. Agents have set attributes and behavioral characteristics. Attributes include defining features such as age, sex, income, history, risk aversion and preferences for the case study introduced in Chapter 3, (Figure 31). Behavioral characteristics of an agent can include operations and planning. In a multi-agent framework, we start by determining who the players are. In C2C ecommerce, these players include buyers, sellers, employees and industry regulators. Agents have states which determine its behaviors. States represent variables associated with the agents' current situation (Charles M. Macal, 2010). Agent simulation helps to capture the behaviors of complex interacting components.

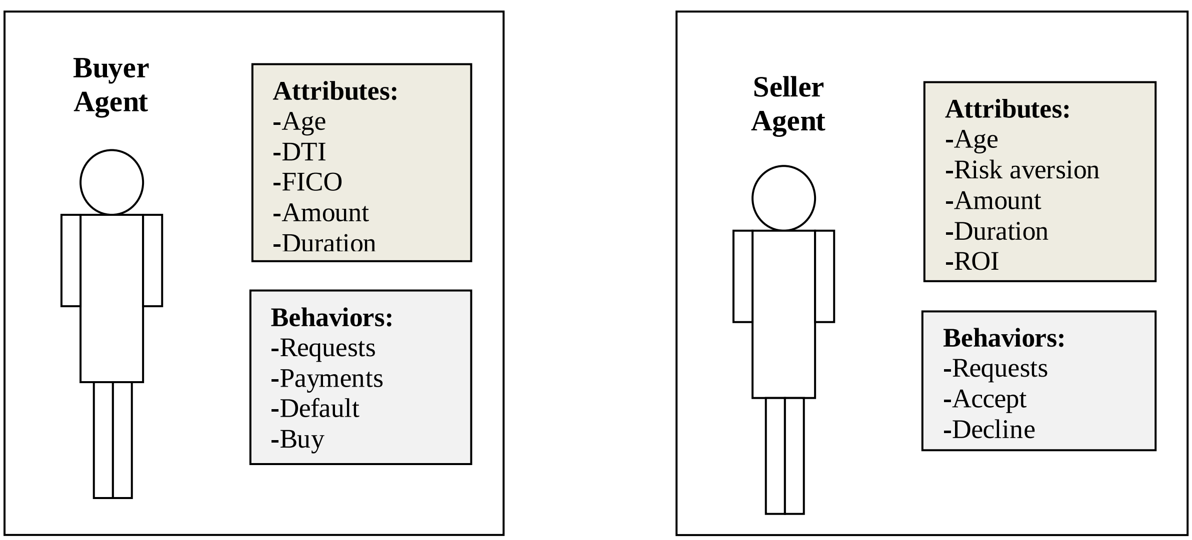


Figure 31: The Basic Structure of Customer Agents

The approach to ABMS is that of incremental discovery, design and development (North & Macal, 2007) in which models can be built and tested in phases to provide insights. To develop the initial simulation scenario and determine the initial agent behavior selections, basic information is collected from the case studies. ABMS can help study how a system evolves over time. Agent-based simulations are implemented by using an object-oriented framework, allowing for detailed modeling of the different elements. The simulation of this business model and the environment will combine several agents, define their relationships, and observe their resulting interactions over time.

There are different types of agents: resource/system-agents, process agents, market agents, and decision-maker agents. Decision-maker agents are agents that make decisions. These agents include the common representations of discrete-events such as queues and clocks, finite state machines, differential equations, and others. They also include constructs to make decisions such as expert systems, neural networks, and other mechanisms from operations research. We have to investigate the most important actors in the business model and their interactions (e.g., messages, reporting, hierarchies, and collaborations) with other agents.

The simulation model is defined as

$$ABSM = \{A_t, M(A_{t-1})_t, I\} \tag{4.8}$$

A_t represent the set of agents in different states at a given time t, $M(A_{t-1})$ is the set of mechanisms operating on the agents at time t, and I is the agent interaction protocol. The ecommerce system is made up a variety of players. Players can be customer agents that can either be seller or buyer agents, provider agents and product agents. The transacting entities include customer, vendor, broker, intelligent agent, intermediaries, servers etc. The provider agents have the capacity to send out advertisement to the market which consumers can remember when making decisions. Potential buyer behaviors include buying best offer, buying cheapest offer, being loyal to provider, following the herd and satisfying exact requests.

Statecharts are state machines used to graphically represent behavior of agents during their lifetimes. Resource/system agents utilize differential equations, continuous models, and discrete-event flows in order to simulate their behavior, aging, and availability/serviceability. They represent important systems. Process agents are agents that utilize mainly discrete-event flows such as discrete-event simulation using discrete-event lists and/or state charts. They can have environments and are important to represent the different phases of the life cycle or the different steps of a complex process. Other agents can be an active part of the phases and collaborate with other agents using that specific phase/environment.

The agent based simulation model of this study comprises of:

i. Objects: C2C Ecommerce environment, the space where the simulation takes place
ii. Agents: consumers and employees
iii. Parameters: such as gender, age, probabilities, inter arrival rate, etc
iv. Messages: to be exchanged amongst agents
v. Message Sequence Diagram

An "Agent" in AnyLogic is a unit of model design that can have behavior, memory (history), timing, and contacts. Agents can represent people, companies, projects, assets, vehicles, cities, animals, ships, products. AnyLogic has classes for developing agents as it has all necessary properties to define variables, events, state charts, system dynamics stock and flow diagrams. The performance metrics are interest rates and profit made from transaction costs. Design of an agent typically starts with identifying its main drivers and interface with the external world. The decision-maker agents can use ports as agent interface points. In case of large number of agents with dynamic connections, agents can communicate by calling methods of each other or through the environment.

ABMS is adopted to help determine the interrelated effects of the online platform, the supply chain structure, the market rules, external environment and corporate behavior on the profitability of p2p. Buyers determine if they are going to commit their scarce resources to fund a loan. Borrowers decide if they will accept the interest rates set by the platform. The market rules can include: fund or don't fund. The corporate behavior include is dependent on information gotten from its business environment. This information can be used to set regulations and inform investment choices.

4.2.7 Outcome Identification

To manipulate and interpret data, the research tools apply statistics and computer software. Specifying distributions consistent with data ensures that results of the simulations are reliable and applicable to decision making. The implementation of the framework is also presented and sensitivity analyses are performed to determine the robustness of results. If the research objectives are accomplished, the process concludes and if not, the research problem is revaluated and redefined.

In the Outcome Identification module, the identified performance metrics are analyzed. There is a forecast of potential customer performance – this is a random event. Once results have been generated by the simulation, experiment helps to analyze the effects of various factors on the system, identify unnecessary factors to reduce model complexity. Depending on the question being studied, simulation experiments often integrate simulation modeling, scenario analysis and design of experiments.

4.3 Implementation of Agent Based Simulation

The simulation implements a normative and pseudo-behavioral model where by the agents begin by seeking to optimize utility. Market participants learn using data mining techniques, particularly neural network in this study. The risks of different agents are also implemented using neural networks.

The assumptions of our ABM model is that of

1. Rationality: clear objectives and able to optimize behavior
2. Homogeneous: identical in characteristics
3. Seeks equilibrium

A prototype was developed to evaluate concepts in the framework proposed in the previous sections. How to construct…. The modules are interfaced. The buyer and seller agents enables users y. The environment is first built. In addition, a platform for agents to communicate and interact is created. Different agents in the system are specified. There are x types of agents which play different roles in the model. Explain each e.g. the decision making agent has knowledge of what is going on in the entire environment. Other agents have knowledge of what goes on in their specific environment. DM receives information from other agents and communicates between agents. Before running the model, attributes and behaviors can be parameterized using survey data or field research.

The system architecture is thus: agents are created from the company's database and placed in the SD environment which describes the organization behavior. The SD components model change in external conditions. The decision maker is also tasked with the responsibility of assigning different states. Agent properties and decision making parameters are set to ensure that model meet system objectives.

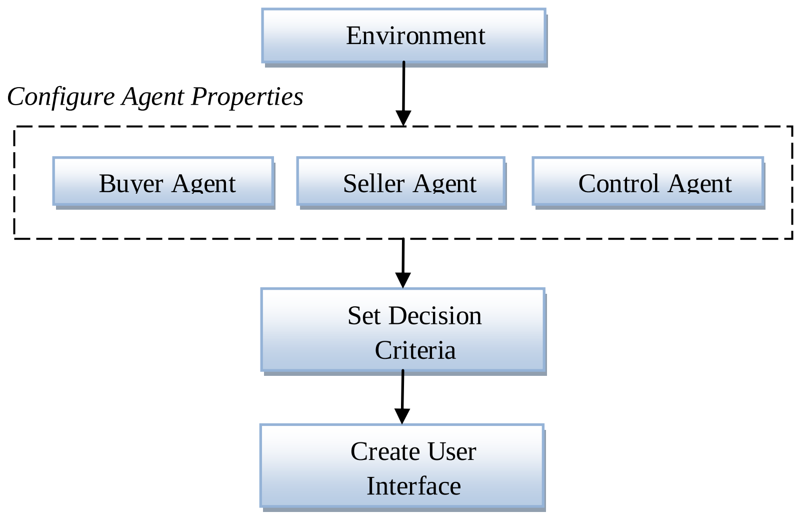


Figure 32: Agent Modeling Implementation

The environment affects interactions between entities. In the description of the system, we depict all agents and interactions. Heterogeneous agents are specified using data on demographics and preferences. In addition to adverts, agents also belong to a network of trusted friends that can influence his choice via word of mouth. In the model topology, the buyer is connected to the borrower and the system and act based on the available local information. To create an ABS model, there is a need to identify, model and following elements (C M Macal & North, 2010): agents with attributes and behaviors; agent relationships and methods of interaction and agents' environment. The sequence of actions includes:

- Providers advertise
- Customer and provider receive adverts
- Buyer tries to satisfy buyers

- When period elapse, success or failure

4.4 Summary

This chapter provides an overview of the proposed framework, a supply chain modeling and analysis framework integrated with a dynamic hybrid modeling module consisting of agent based modeling and simulation and strategic level system dynamic, and a risk evaluation component. Furthermore, it is recommended that the resulting framework be subjected to periodic adjustments with respect to feedback acquired about the system. The framework demonstrates the integration of a hybrid of simulation paradigms to aid decision making. We present a background for implementing this framework using a combination of BCS, Supply Chain Management, Hybrid Simulations, and Neural Networks. Validation is done by comparing the simulation results with case study. Sensitivity analysis helps determine the relative importance of underlying assumptions. The next chapter is dedicated to the peer-to-peer Lending Club case study.

CHAPTER 5. CASE STUDY ANALYSIS

5.1 The Rise of Online Peer-to-Peer Lending

Transformation in the financial industry as a result of the financial crises, changing customer behaviors, constant innovations based on information technology, the Internet, and financing services offered by non-banks is here to stay. Lenders can now pool their resources together online and make them available as loans at a premium to borrowers who need it. Online peer-to-peer (P2P) lending is the process by which lenders pool their resources together and lend it out to prime borrowers through a platform at a lower rate without the direct mediation from financial institution. By diversifying resources to fund borrowers of different credit grades, lenders can reduce volatility of returns in their portfolio. P2P lending is a customer-oriented banking that passes cost savings of eliminating the middle man in the system to the users (borrowers and lenders). Loans are offered directly to borrowers without underwriting discounts. The 21st century customer is more informed and demands more transparency. In a perfect world void of information asymmetries, traders would deal directly with each other without intermediation from banks and financial institutions. P2P lending increases the efficiency of the financing process by reducing the rigor experienced from traditional banking.

Forrester Research (http://www.forrester.com/) forecasts that US ecommerce sales will approach \$370 billion by 2017, up from \$262 billion recorded for 2013, an amount that is equivalent to 9% compound annual growth rate (CAGR)[1].This study focuses on profit oriented online P2P lending platforms, where lenders raise interests for loans they provide, and the platforms create revenues by charging service fees (Bachmann et al., 2011). Non-commercial or

[1] https://www.internetretailer.com/trends/sales/us-e-commerce-sales-2013-2017/

charity driven platforms are excluded here, since it can be assumed from literature, that that the behavior of agents in such environments is different than in P2P lending with commercial background.

Adoption of peer-to-peer (P2P) lending sites occurred in tandem with the proliferation of Web 2.0. Web 2.0, encompassing social networking sites, blogs, wikis, user reviews, enables interaction and collaboration among users via dynamic content creation. For-profit P2P model, which is the focus of this study, was virtually nonexistent pre-2005. CircleLending Inc. was incorporated in the early 2000s in the United States (U.S.) and became Virgin Money US in 2007 after acquisition by Virgin Group. Before pulling out of the US market in 2010, Virgin Money specialized in facilitating private loans and mortgages between friends and family.

Zopa (http://www.zopa.com/) was launched in 2005 in the United Kingdom (U.K.) and its now defunct U.S. platform two years later. Zopa, which operated a depository model, connected interested borrowers with lenders by acting as a clearinghouse, screening borrowers and requiring lender diversification (Sahlman & Kind, 2006). Risk diversification is done by requiring that loans be spread across several borrowers. Zopa had a partnership with credit unions which enabled acceptance of lender funds and in turn giving lenders federally insured deposits (CDs). The lender funds allowed the credit union to then issue low interest loans to borrowers.

Prosper.com was launched in the U.S. in 2006 while the following year Lending Club (https://www.lendingclub.com/) launched its platform. Since the P2P lending was still in its inception, there was no standard operational model across the companies. Although players take slightly different approaches in their modes of operation, the underlying principle is largely similar. Prosper Marketplace Inc. (http://www.prosper.com/) used an auction-type model to link lenders to borrowers (Sahlman & Kind, 2006). Borrowers post the amount they wish to borrow and the highest interest rates they are willing to pay while lenders filtered through profiles of borrowers and bid to fund the loans by indicating the lowest interest rate they are willing to receive on their investment.

Lending Club facilitates loans to consumers and businesses in an approach similar in some ways to that of both Prosper and Zopa. Lenders had the option to select the loans (via the purchase of Member Payment Dependent Notes) they wanted to fund and this promotes the notion community-building. LC charges a 1% service fee on principal, interests and fees on the loans facilitated therefore reducing the effective yield on the notes below the stated interest rates. Based on the grades and terms of the loan, LC also charges 1.11% to 5.00% fee for originating the loan. Interest rates are set by considering economic conditions, inflation, demand for and availability of funds, loan default rate and rates offered by competing platforms. Rates are assigned to loans based on the sub-grade (A1-G5) category in which the borrower falls into. Borrowers pay anywhere between 6.03% - 26.06%[2] in interests based on their risk profile. Although Lending Club had a late entry in the P2P industry, registering its notes with the securities exchange commission (SEC) cemented its position as the leader of the innovative business model. By filing with the SEC, investors were provided a secondary market in some states in form of a notes trading electronic platform called FOLIO*fn*, to liquidate their purchased loans (notes). Figure 33 gives a breakdown of P2P loan mobilization in millions of US dollars across P2P companies worldwide in 2013 and 2014.

[2] As given in Lending Club's April 2014 Prospectus

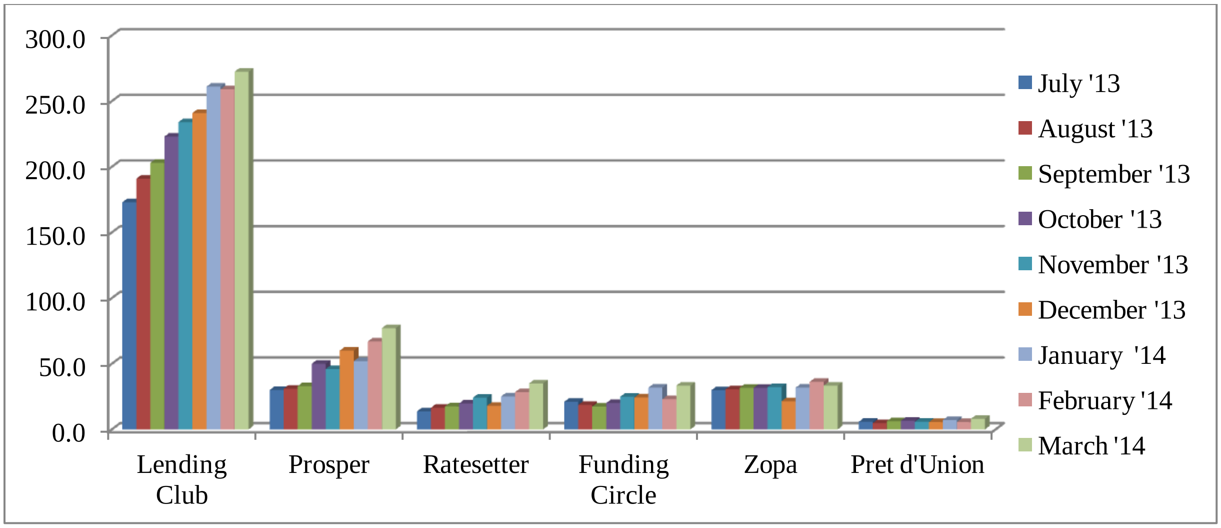


Figure 33: Graphical representation of P2P lending funds mobilization ((in millions U.S. dollars) from June 2013 to March 2014

Source: http://www.wiseclerk.com/group-news/

Figure 33 presents some lending platforms that have arisen to meet the demands for unsecured loans. Although the rate of new entrants is seemingly high, most companies have had a challenge maintaining profitability in this industry. Several companies have entered the market, failed or had to pull out. Companies are faced with regulations from the SEC, solution to secondary market for loans and importantly, the ability to manage risks and make profitable loans. For banks, the acquisition cost of small loans is about the same as that of acquiring large loans. This means that banks would rather focus on acquiring larger loans. Banks have traditionally catered to small loans by offering credit cards. Small loans are targeted by payday loans, pawnshops and Rotating Savings and Credit Associations (ROSCA). In ROSCA, members of a group contribute to a general fund on a regular basis and member funds are subsequently pooled and distributed as loans to each member. This is popular in different parts of the world. In West Africa, employees usually join corporative societies and have their monthly salaries automatically deducted in participation. A snapshot of the industry attractiveness and dynamics is given in the Porter Five Forces diagram of Figure 34.

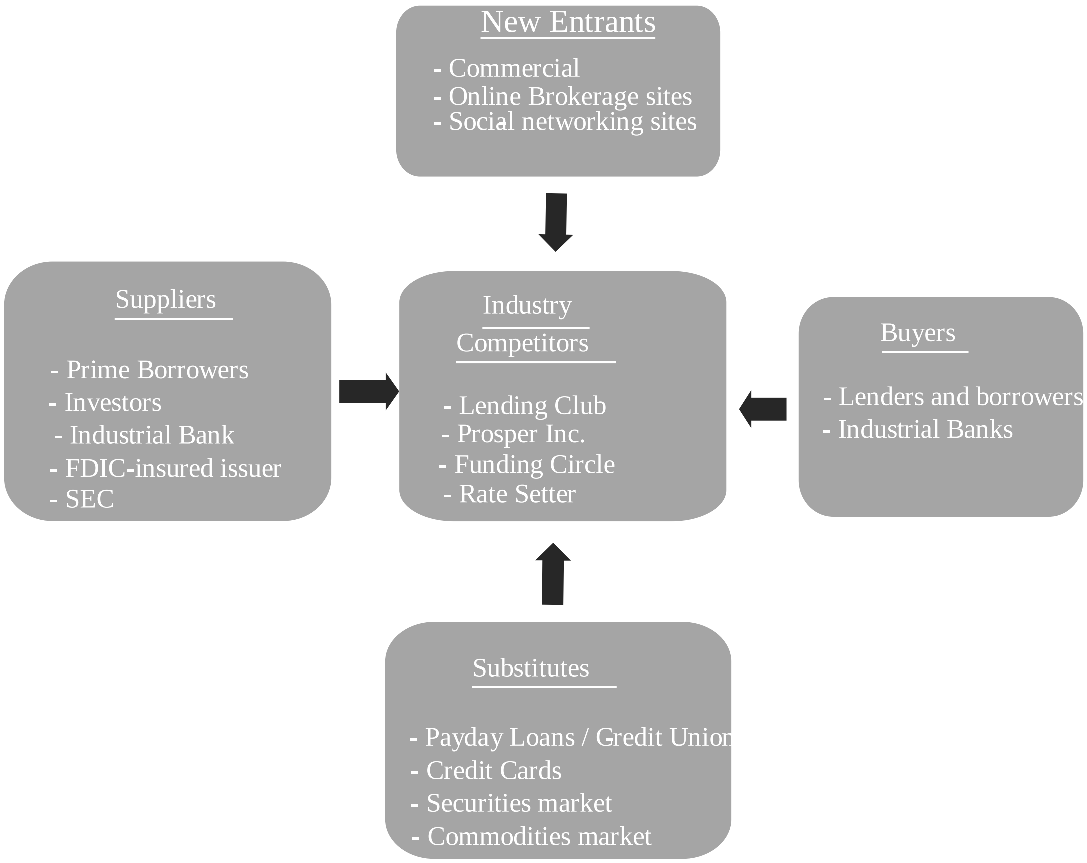


Figure 34: Porters Five Forces of P2P Lending

One of the main threats for existing platforms is the possibility of major financial institutions as new entrants. These institutions can harness their reputations and resources to better meet the demands of the ever changing needs of customers. Even though some structures have been put in place to reduce risks, P2P lending still suffers from a great risk when compared to traditional lending.

5.2 Overview of Microfinance

Existing literature reveals the similarity and influence of microfinance on P2P lending. Microfinance refers to loans of less than $10,000. It has its origins in not-for-profit financing business models adapted for developing nations; hence it has not enjoyed as much interest in academic finance circles. Borrowers of microfinance institutions (MFIs) are usually members of a lending group and repayment is high because members of a group monitor each other thereby saving the institution the cost of monitoring.

Grameen Bank, the premier microfinance bank, was founded by Muhammad Yunus in 1983. Its business model, which aims to create economic and social development for the poor in Bangladesh later earned Yunus a Nobel Peace Prize in 2006. In the Grameen business model, borrowers form a group of five and seek a loan from the bank. The first two members of the group receive a loan and if they successfully repay their loans, the next two members are offered loans and subsequently the last member. A default from any member of the group means all members are denied future credit. Grameen targets moral hazard through shame and ostracism. Group lending (joint liability contract) is the lending innovation accrued to Grameen (Sengupta & Aubuchon, 2008).

However, lenders are often limited to information provided by borrowers which results to significant asymmetry which can in turn lead to adverse selection and moral hazard (Akerlof, 1970). The main challenge in microfinance is in addressing information asymmetry problems of non-bankable community (Everett, 2011). Adverse selection issues include not lending to borrowers with a high risk of default. Adverse selection and moral hazards make it difficult to gauge a borrower's risk characteristics. The case of Grameen bank has shown that unsecured loans can be successful if the right checks are put in place. Joint liability ensures that group takes over underwriting, monitoring and enforcement of loan contracts. However, monitoring can prove to be challenging in an online environment since participants can be long distances from each other.

In another study, microfinance institutions were found to charge rates lower than market rates to promote social equity. Low rates are as a result of efficiency in screening and monitoring borrowers and the use of joint lending mechanisms. Interesting to note is the high rate of repayment (greater than 90%) of these institutions. Sengupta *et al* argues that group formation does not work well in the US because of the impersonal nature of the market, diverse poor population, availability of other forms of credit and the problem of social security. Peer-to-peer lending companies target different user markets. Zopa, promotes social investing (as opposed to equity investing) in socially responsible borrowers while expecting lower risk-adjusted returns (Brau & Woller, 2004) while other MFIs target women as opposed to men.

5.3 Consumer-to-Consumer Lending Research

P2P companies are the banks for the 21st century. The proliferation of social media has bolstered the adoption of peer-to peer lending business model. Consumers are open to this new form of financing yet in spite of the numerous benefits of P2P lending, research applied to this area is still in its infancy. Johnson, Ashta, & Assadi (2010) proposed that P2P lending was 'more of an aspiration than a reality' because relationship links exist between lenders and borrowers hence the system cannot exactly be classified as being peer-to-peer. They argued that only Virgin

Money was truly peer-to-peer because there are zero links and the players already know each other.

Information collected on borrowers enables the platform to assess credit risks. Banks use mostly hard credit information as indicators to screen their loan applicants. Hard credit information is the credit profile information of borrowers. This runs the gamut from credit grade, financial ratios like debt-to-income ratio, number of credit inquiries, number of outstanding loans and number of public records (Lin, 2009). Soft information represents demographic characteristics and intermediation. In his study, Lin finds that business loans are more risky while debt consolidation type loans are more likely to be funded. He also indicates that African Americans and borrowers under the ages of 25 were less likely to be funded on p2p sites while women were more funded over men. In P2P lending, default may be taken as missed number of scheduled payments within a period (Crook, Edelman, & Thomas, 2007).

In their study, Ryan et al. (2007) explores factors that determined fundability of loans requested by borrowers on the Prosper platform. When Prosper Marketplace Inc. entered the P2P lending industry, they placed emphasis on the groups borrowers belonged to. By regressing *Percent Funded* on hard and soft factor variables, Ryan *et al*. found that credit grade had a significant effect on the loan fundability. An endorsement from a group leader in addition to trustworthiness gave a reputation boost to a borrower that led to fundability.

Results of Emekter, Tu, Jirasakuldech, & Lu (2015) showed consistency with other studies. They find that credit grade, DTI ratio, FICO score, loan duration, credit grade, and revolving line utilization were significant factors in loan defaults using the Cox Proportional Hazard test. To be profitable, they recommend that Lending Club pursue loans to high network borrowers with high credit scores.

In his thesis on Zidisha, a P2P lending non-profit organization, Majois & Van Damme (2013) finds that Dutch auctioning does not necessarily help to drive down interest rates. A repeat borrower who has had success repaying past loans is considered lower risk. Van Damme finds, in his linear regression analysis that maximum rate and lending period were the greatest determinant of interest rate while interest rates declined on the Zidisha platform with lending period.

Most of the analyses done in current literature have been on Prosper.com loans. For example, Krumme & Herrero (2009) studied static and dynamic characteristics of a P2P network using 350,000 loan listings from Prosper.com. They found that social factors such as participation in member groups and a descriptive profile are correlated with financial indicators. They also found evidence of suboptimal lending decision, minimal learning and herding behavior in the network. It is well documented in literature that the higher the loan grade, the easier it is to get funded.

Redmond & Cunningham (2013) constructed a network comprised of Prosper members and their loans. His focus was to investigate arbitrage and money laundering strategies for members who acted as both lenders and borrowers that constituted 5% of all members on the platform. This network was explored via breadth-first-search (BFS) algorithm, a process that lead to the discovery that certain network based features indicated the presence of arbitrage. The authors confirm that C2C lending among peers is influenced by network effects. Also, implementing time-respecting subgraphs reveal that arbitrage was not lucrative in early Prosper Marketplace model due to high default rates of borrowers.

Shen, Krumme, & Lippman (2010) investigate social factors on bidding behaviors in the Prosper auction platform finding strong evidence of herding behaviors. They found that lenders did not make good decisions concerning risk and returns but followed the crowd. Lenders depend on social factors to evaluate investment opportunities since they lack complex risk assessment models utilized by banks. Shen *et al* modeled the effects of social influence such as group ratings and endorsements from friends and group leaders. Lenders tended to follow the crowd because they may believe that others had better information on the borrower than they did. Lending Club has eliminated social factors such as friendship, endorsements and groups. Lenders adopt lending strategies that meet their profitability goals hence choosing loan amount, interest rates and loan characteristics that maximize their profitability.

Lending platforms have two main streams of revenue: fixed fee (new borrower) and transaction fee. Haewon Yum, Byungtae Lee, & Myungsin Chae (2012) states the value proposition of P2P lending as (i) lower credit borrowers attracted to p2p due to social collateral and (ii) lower interest loans. Traditional performance measurements in banking include return on assets (ROA) and return on earnings (ROE). Performance drivers are leading indicators while outcome measures are lagging indicators. *Wu* identified critical and influential factors to improve banking performance to be customer satisfaction, sales performance and customer retention rate (H.-Y. Wu, 2012). This means, financial institutions must align their strategies to key performance indicators in order to sustain competitive advantages. Wu's model is not limited to measuring productivity of banking industry by only output, costs and performance but the review of an organization's financial (quantifiable) and nonfinancial (unquantifiable) goals (Kaplan & Norton, 2001). P2P electronic marketplaces create value by reducing information asymmetries between lenders and borrowers.

Thomas (2000) surveys some of the techniques used to decide for or against granting credit to consumers. The classical method involved using the 5Cs of credit. Decision in 5C is based on *character* of requester, how much *capital* is requested, *collateral* in case of default, free capacity and economic *conditions* of the market.

Research by Lin et al (2013) on P2P lending found that borrowers with friends on the lending platform were more likely to have their loan requests funded and at lower interest rates than borrowers without friends. A healthy friend network serves as information cue of a borrower's credit quality (Lin, Prabhala, & Viswanathan, 2013). However, the anonymous environment of the internet limits trust. In spite of the similarity between P2P lending and MFIs, literature has shown that traditional solutions to issues of trust in MFIs are not available in online P2P lending because it presents "*different set of challenges in risk management for lender"* (Haewon Yum et al., 2012). Lenders must be able to trust both the borrowers and the intermediary – online marketplace (Dongyu Chen, Lai, & Lin, 2014). The intermediary must be able to enforce fair rules, procedures and outcomes in the marketplace and provide security and protection of transactions.

The risk of default is can be mitigated by joint liability. In Prosper Inc's early business model, groups were created to minimize risk. In a study done on Prosper loans, it was found that nearly half of borrowers with low scores (E and below) default on their loans (Krumme & Herrero, 2009). Everett (2011) shows in his study that screening, monitoring and enforcement effects performed by peers in microfinance groups exist in online social lending as in his case study of Prosper.com, especially if real-life social sanctions are enforceable. Loan defaults are costly to lenders and increase rates charge. Relationship banking uses soft information to tackle information asymmetries as regards to borrower credit-worthiness. Everett found that borrowers exhibit a lower default rate while the benefit is transferred to the borrower in form of lower interest rates.

Credit scoring is the evaluation of risk associated with lending (Crook et al., 2007). This help to distinguish between good and bad loans. Scoring classification is commonly done through logistic regression using maximum likelihood method to estimate parameters. Other methods of classifying loans into good and bad loans include discriminant analysis, linear programming, neural networks (NN), genetic algorithm (GA) and support vector machines (SVM). According to Crook *et al.,* the use of SVM in classification is showing the most promise.

Passing the Basel 2 accord impacts the credit scoring process. At loan origination, lenders use soft credit information to access the riskiness of a borrower. These are information generated from his or her social network in the peer-to-peer lending community. (Lin, 2009) reports that relational aspects of online social network help to mitigate information asymmetry in the lending process. Interestingly, structural aspects such as degree of centrality of borrower's social network do not affect the risk of default.

Investment risk is as important as expected return (Bodie, Kane, & Marcus, 2011). Risks affect the expected performance of a portfolio. Risk management enables the company align their business goals with those of stakeholders. Realized rates or returns are observed after the fact. In their study, Vyas *et al.* presents why risk management is important (Vyas & Singh, 2011). They highlight that credit risk (as a result of dealings of banks with customers) is the biggest risk faced by banks. Figure 35 illustrates a chart of the different kinds of risks associated with financial companies. Risk is defined as 'the volatility of a corporation's market value'. The authors highlight an approach to implement risk management in financial firms using standards and reports, position rules, investment strategies and incentive schemes.

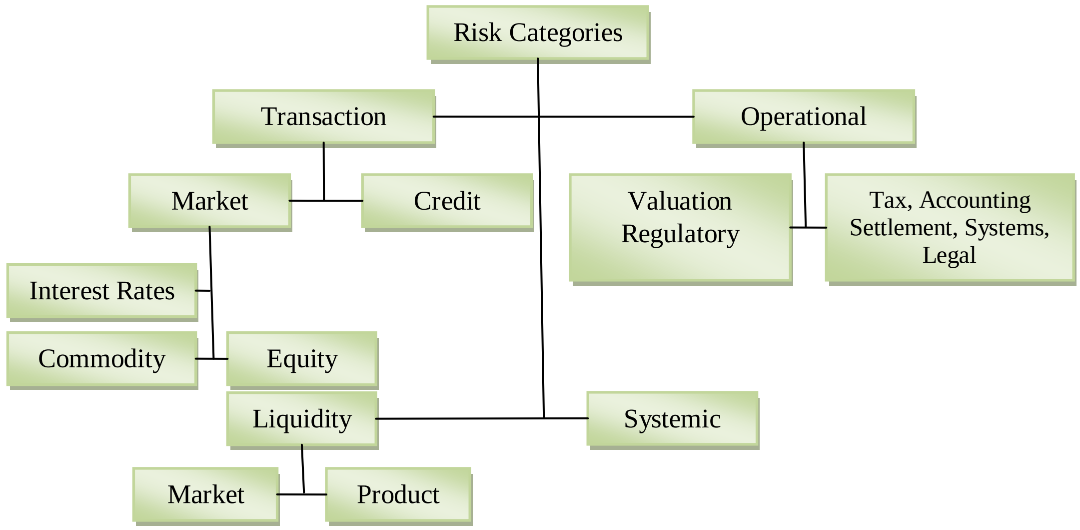


Figure 35: Financing Risks (recreated from Vyas & Singh, 2011)

The main objective of risk management is to preserve assets and projected profit. Various software such as Governance Risk Controls (GRC) provide an integrated view of risk undertaken by financial institutions, monitor profitability with respect to risk policy and regulatory body reporting and measuring the risk (Žigić & Hadžić, 2012). Value at risk (VaR) is a risk analysis approach to calculate how much financial value that the firm can lose over a period of time at a given confidence level.

Greiner & Wang (2010) proposes the use of Elaboration Likelihood Model (ELM) to explore trust-building mechanisms in C2C P2P lending. Credit information serves as mechanism to reduce uncertainty and enhance trustworthiness.

5.4 <u>Lending Club</u>

5.4.1 Borrower and Lender Activities

To avoid the need for individual licenses and provide loans nationwide in the U.S., borrower loans are made from WebBank (Magee, 2011). WebBank, an industrial bank based in Utah, furnishes the loan proceeds in exchange for corresponding promissory notes from the borrower. LC provides WebBank with the aggregate of funds received from lenders in exchange for the assignment of borrower's promissory notes. LC then collects monthly payments from borrowers and distributes proceeds to lenders after deducting a service charge of 1%. Uninvested funds are put in a Wells Fargo In Trust For (ITF) account and do not earn interest. FDIC covers funds in ITF account for up to $250,000 on all accounts in an institution. Upon issuing a loan, LC charges borrowers origination fee ranging from 1.11% to 5.00%[3]. Investors are charged 1.00% on principal and interests.

Notes are risky and speculative. When a payment on a loan is late by 30 days, it becomes delinquent and a collection agency can be involved. Expected principal and proceeds is decreased by collection fee and service fee. LC treats notes as indebtedness for income tax purposes. Potential borrowers interested in a loan fill out an approval form to specify the amount requested and the purpose for the loan. Borrowers are evaluated based on certain pre-conditions they have to meet such as their credit history and capacity to repay.

Figure 36 illustrates lender and borrower activities on the LC platform in 2014. Lending Club requires a FICO score greater than 640 and at least 1 year of credit history. The borrower should also have no ongoing delinquencies, concerns of bankruptcies, inquiries from collections, or unpaid taxes. The borrower’s capacity to pay is evaluated by a debt-to-income ratio of less

[3] LC Prospectus April 2014

than 25%. If the borrower meets the pre-conditions, other information is used to determine the best interest rate per Lending Club's pricing model. Borrowers have to be able to accept the loan conditions, which depend on the current economic conditions. On approval, the borrower's profile is created indicating requested amount and reason for request. Lenders can access borrower profile and decide which of them they would like to fund.

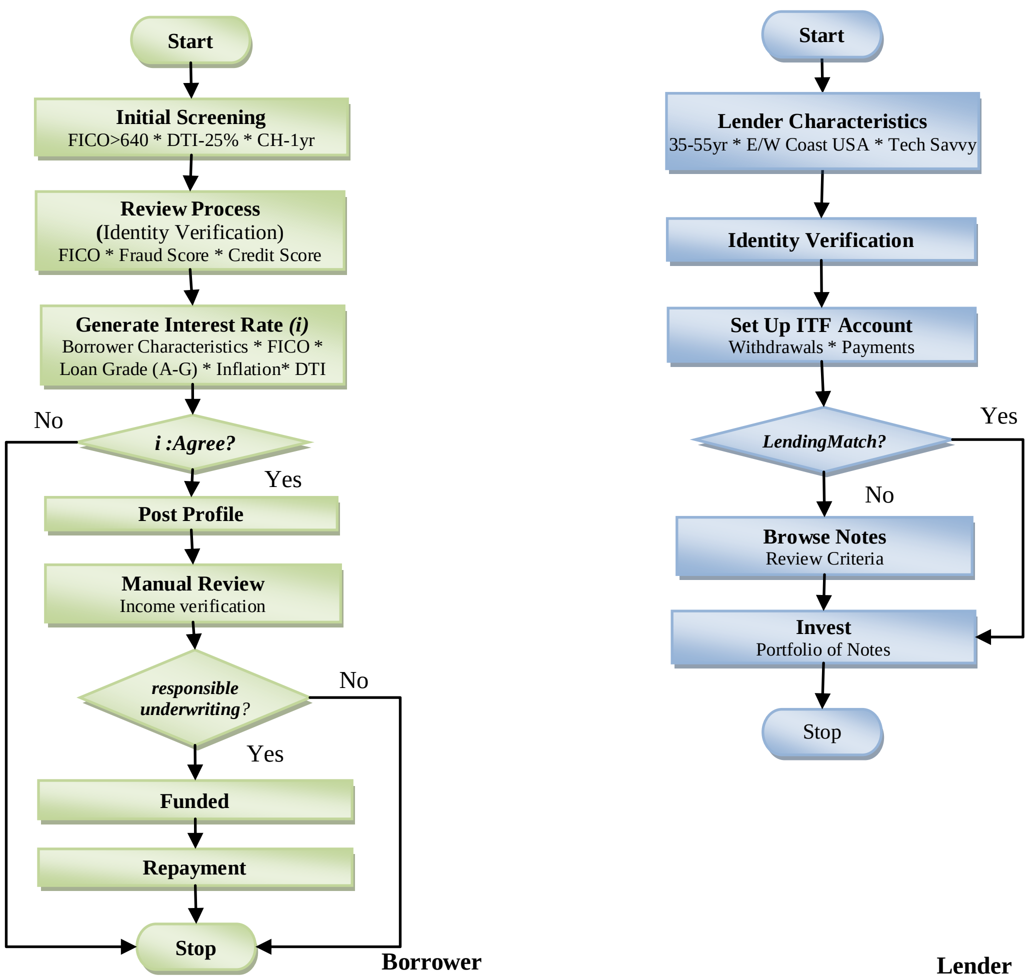


Figure 36: Flow Chart of Borrower and Lender Activities

Source: Adapted from (Joledo, Bernard & Rabelo, 2014)

Pre-approved borrowers are usually approved for a 36 month fully amortizing loan. After a consensus of loan amount and interest rate, borrower profiles are posted on the platform as pending approval phase. Lending Club then ensures proper underwriting to identify inconsistencies or potential frauds. After successful income and identify verification, the lenders can setup a secure and seamless way, via an in trust for (ITF) account with Wells Fargo, to fund loans. With only a 1% service fee throughout the life of the loan, lenders had the flexibility to choose as many loans as they wish to fund or go with Lending Club's proprietary search-engine generated portfolio, known as LendingMatch. Figure 36 illustrates borrower and lender activities of LC.

5.4.2 Business Model

Lending Club targets consumers with good credit to minimize default rate. They advertise and broadcast the company's purpose through both traditional and social media outlets. National news agencies like CNN, FOX, NPR etc. have all covered its business model and the emerging P2P lending industry in general. Lending Club has strong and active presence on social media. Its Facebook page and a twitter account is used to communicate important company information as well as industry trends to interested persons. The target audience, typically composed of people interested in investment opportunities, is able to spread such information to their family and friends. This continuing growth in awareness, brand promotion and subsequent building of credibility is desirable to promote company growth over time.

The lender is able to invest in a borrowers loan via notes that are anywhere between 36 to 60 months. Lenders interested in cashing in or reselling their notes do so using FolioFn secondary market within the company's online platform. Lending Club loans are not available nationwide. Some or all services are available to investors and borrowers. Current earnings come from lender and borrower fees. Lending Club charges the lender a 1% service fee and the borrower a 0.75% to 2% fee. Lower operating costs mean that the company is able to charge their customers small fees. They are able to maintain an operating to expense ratio of less than 2%, whereas traditional banks usually have an operating to expense ratio of around 5% to 7%[4].

The approach to loans and investment on the online platform is an example of business model innovation. The advantage of having an online platform is that customers can get a loan or become investors from their home computers. Customers get quicker processing times than their local banks. Investor base is comprised of institutional investors, retail investors and individual investors. For individuals interested in investing but lack familiarity with how to go about it, Lending Club has develop a proprietary tool called LendingMatch that is able to match up risk tolerance with a set of open loans. Lending Club performs all the underwriting and processes the loans further simplifying the role of the borrower and the lender

Lending Club's success can be traced to distinguishing elements of its business model. The business model is developed using lessons learned from research in microfinance and strategic management. According to Gary Hamel, a business concept is made up of the customer interface, core strategy, strategic resources and value network (Hamel, 2002). The structure of P2P lending takes into consideration how to link borrower and lending activities, how risk assessment is to be done, and the possibility of inclusion of a secondary market to monetize loans. P2P lending targets a virtual market in which direct costs of economic transactions are decreased by circumventing or dis-intermediating banks (Joledo, Bernard, & Rabelo, 2014).

The customer interface element of the business model (illustrated in Figure 37) describes how the company reaches its customers. This is made up of the following sub-elements.

[4] The Official Lending Club blog"

Fulfillment & Support describes channels employed to reach customers. This is done via the Internet, word of mouth, social media, search engine marketing and public relations. Consumer transactions are performed through the website. Borrowers are able to monitor as their loans become funded until the entire amount is accounted for.

Information & Insight describes knowledge collected and utilized from customers. Lender applications are collected to evaluate their worthiness. Each borrower is given a rate based on the grade or sub-grade and term life per their application. Lenders are then given access to approved borrower's profiles.

Relationship Dynamics describes the nature of interaction with customers. Interaction is done online or via phone calls. Lenders make decisions on who they want to fund based on the borrower's profile. Customers are processed through the firm's platform. Being the broker and servicer of the loans, Lending Club interfaces directly with the borrower and lender, but gives some transparency to the lender of the borrower's situation.

Pricing Structure details how and who Lending Club charges for its services. The pricing structure is both on flat- or percentage-based service along with amortization fees. A flat 1% fee is applied for the lender and between 0.75% to 2% fee for the borrower, depending on the size of the loan [9]. Interest rates are based on borrower's credit history and pricing model. Borrowers are charged a small fee for processing the application for general information such as background check and credit check.

The core strategy element of the business model describes the essence of how Lending Club chooses to do business. It is made up of three sub-elements:

Lending Club's business mission is to make credit more affordable to consumers and businesses by replacing the high cost and complexity of bank lending with a faster, smarter way to borrow and invest (A. Ryan, Jackson, & Tufano, 2010).

Product or Market Scope describes where the company competes. Lending Club started as a Facebook app in 2006. Lenders are able to invest in 30 states while borrowers can source for loans in 52 states of the US.

Basis for Differentiation describes how the company competes differently. Lending Club uses algorithms and automation to give fairer interests in an “eBay of loans” manner. Interest rates are set via a pricing model, instead of an auction as done by its main competitor Prosper Inc. To reduce rate of default, the platform is picky in screening applicants. Risk management is done using the 5cs of credit philosophy i.e. collateral, credit/character history, capacity (debt-to-income), capital and condition (Hamel, 2002).

The strategic resources enlist specific resources related to the company. These are:

Core Competencies is what the firm knows how to do well. For example, Lending Club uses analytical processes to quickly verify the borrower risk and match them with lenders based on the borrower’s conditions.

Strategic Assets sub-element of the strategic resources element describes what the firm owns. It is strategically located around Silicon Valley giving access to state of the art technology. The lendingclub.com website is user friendly while the LendingMatch proprietary loan matching search engine helps connect lenders to borrowers.

Core Processes describes what the employees of the organization do. Core processes are focused more on activities rather than assets. Lending Club’s organization Structure is managed by the CEO, COO, Director of Product Strategy and Vice President of Technology. Business activities undertaken include extensive approval, due diligence, underwriting processes of promissory note loans.

The value network element describes the connections that benefit all stakeholders. This is made up of s*uppliers* including investors and lenders, Wells Fargo and the Fair Isaac Company to provide FICO scores. *Partners* include WebBank and Automated Clearing House (ACH) while WebBank is also a *coalition*.

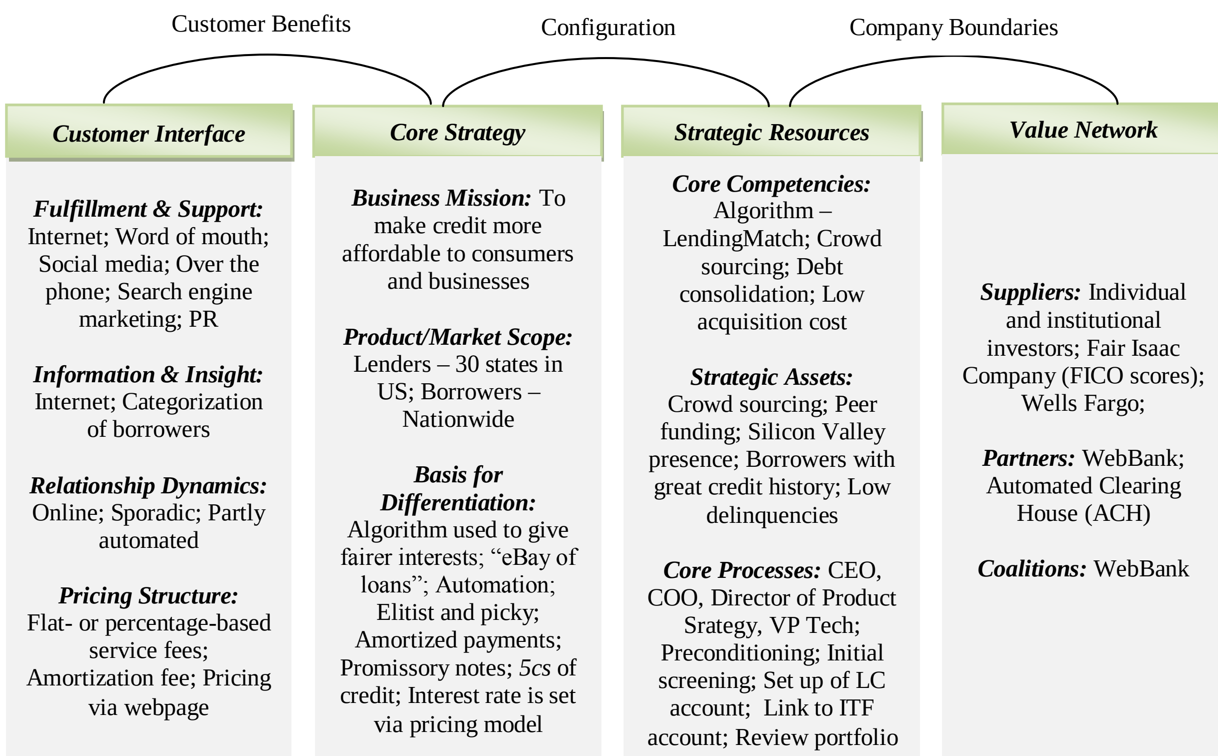


Figure 37: Lending Club Business Model

5.4.3 Strengths, Weaknesses, Opportunities and Threats (SWOT) Analysis

Analysis of the basis of competition can be done using the SWOT analysis. The SWOT tool is used to evaluate LC’s strengths, weaknesses, opportunities and threats that could affect its competitive position in the short and long run. The SWOT analysis can help to understand what strengths can be best likely to be translated into opportunities and at the same time ensuring the acknowledged inherent weaknesses can be mitigated to prevent a threat from impacting the execution of the company's business strategy (Joledo, Bernard, Cisneros, & Laval, 2013).

P2P lending is an emerging alternative to the traditional lending practices. LC is faced with the task of differentiating itself from commercial lenders in areas of external pricing, internal costs, and customer satisfaction. Its strengths include that low leverage ensures it passes along savings to both the borrower and the investors via low rate-based fees. The loan approval and underwriting processes ensures a low borrower delinquency rate. In addition, since their online trading platform enables the option to purchase fractionalized notes, LC can offer flexible and diversified loans that lead to a high customer satisfaction. The well-designed and easy-to-use website and social utility applications are transparent with their customers about its business practices and performance to improve the trust and brand reputation.

In analyzing LC's weaknesses, there were some distinct areas of improvement to point out in effort to leverage new opportunities for early market share leadership, and avoid potential threats anticipated in the future. First, given its startup status in a new unprecedented P2P lending market, it has limited financial credibility to demonstrate its viability to prospective members as it currently has a fairly small customer member base, short history of loan performance and default rates, and limited accounting resources to support the anticipated disclosure filing with the SEC. Second, the reliance on the WebBank partnership for its national loan origination exposes a weakness in its issuing competency. Lastly, its inability to offer returns on idle deposits and its investor's income being taxed as ordinary income, makes it difficult to attract investors who prefer long-term tax benefits and money market account returns from typical stock investment brokerage firms.

Despite the notable strengths and tremendous opportunities, Lending Club's weaknesses and anticipated unknowns threatens its potential future business viability and execution. There are also the threats of Information Technology (IT) cyber-security attacks on the P2P websites that compromise the reliability and performance of the automated trading platform as well as the integrity of the member's confidential information. Similarly, any datacenter outage, IT webserver crashing, or even a software bug in their pricing algorithm, could impact the reputation of the platform from ever getting off the ground and scaling to the loan mass markets. In addition, with such a small market footprint, any negative publicity of potentially dissatisfied customers, whether true or not, could taint their brand image similar to the Ponzi schemes that have already tainted the unsecured promissory note market. Furthermore, there is always the threat of an Intellectual Property (IP) lawsuit against their proprietary software platform that could both hamper their legal costs and slow down market acceptance.

On the external front, Lending Club and P2P lending is exposed to overall negative economic conditions as well as potential identify theft of the members that could lead to either default rates by the borrowers or huge losses by the investors. However, a positive economic environment could increase a borrower's ability to repay loans sooner than maturity dates that actually lowers the net return for the investors. Of note is the rising rates of treasury bills and inflation typically leads to higher returns of bonds and CDs that could threaten current and new investor activity. Furthermore, the slim chance of commercial credit card companies lowering their rates will also threaten new borrowers from resorting to Lending Club for credit consolidation.

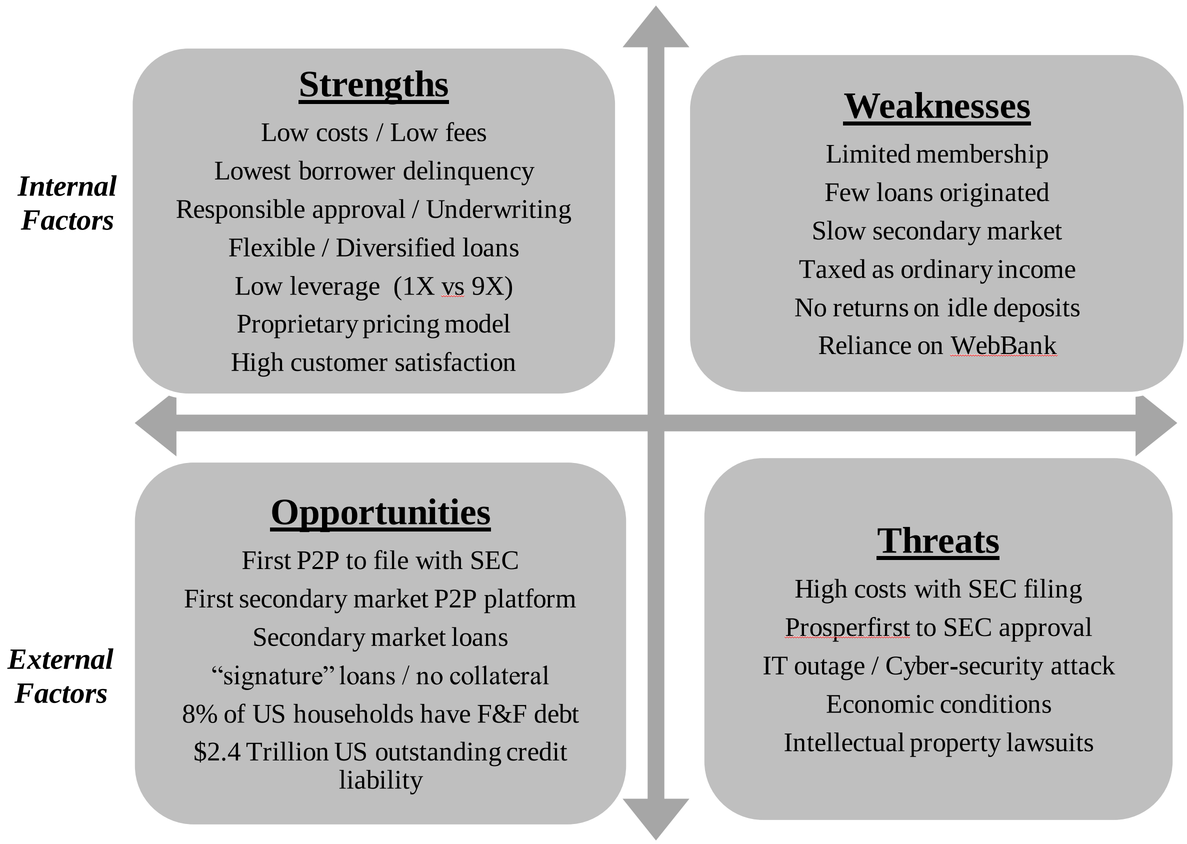


Figure 38: SWOT Analysis for Lending Club

5.4.4 Activity Chain Mapping for Lending Club

The activity map, as illustrated in Figure 39, shows the interactions among suppliers, distributors and customers. The lender has a dual role of being the supplier and the customer while the borrower is also the customer. WebBank serves as lender and assign loans at closing. The advantages of virtual companies such as Lending Club is low capital investment, flexibility and speed. Cost reductions are due to lower overhead achieved by avoiding of retail branches and utilizing automation technology for the transactions and approval processes. Lending Club's overall strategy is that of low cost of loans and quick response to the demands for loan. Activities of the supply chain involve cost cutting, financing, marketing and operations. Information about the borrower's income, credit grade, debt-to-income ratio, is available to the lender to enable him make educated financing decisions. Lending Club's notes are lower risk hence potentially a stable alternative to higher performing stocks that are more volatile and tied to uncertain economic conditions. The risk of the 3-year note commitment is mitigated by having employing a secondary market to liquidate the notes.

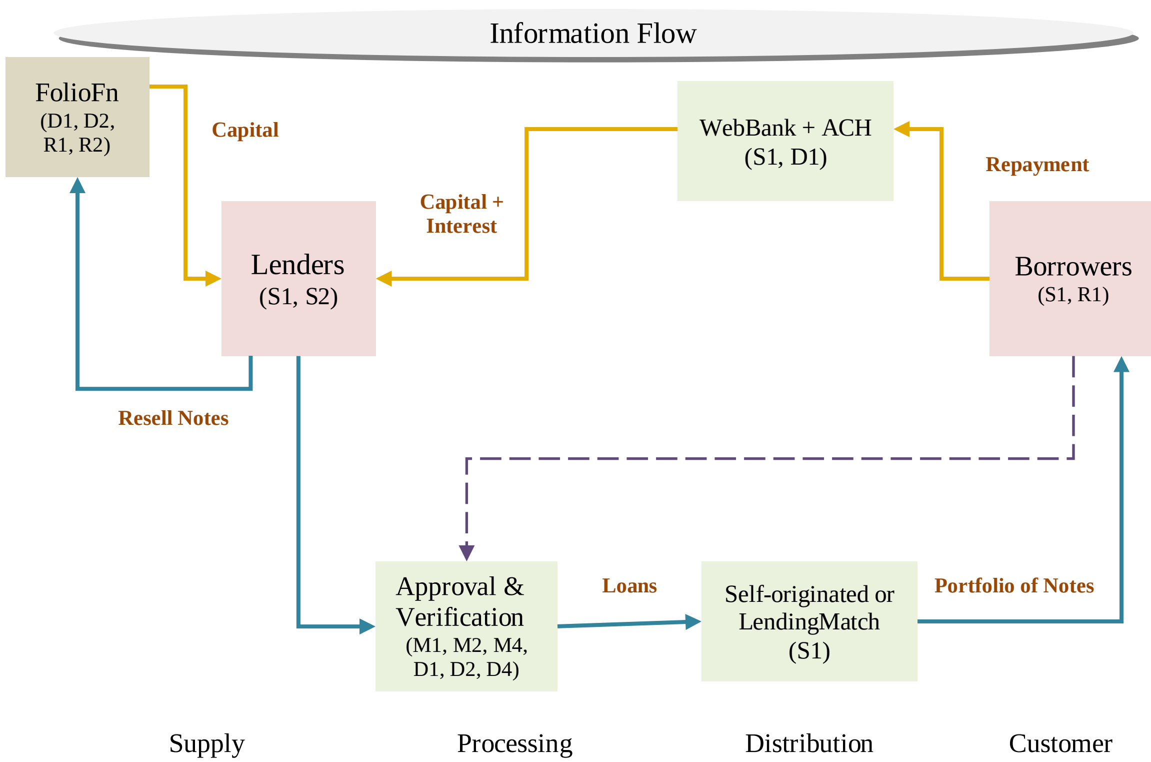


Figure 39: Activity Map for Lending Club (2014) with SCOR processes

5.4.5 Balanced Scorecard and Strategy Map

Lending Club's fundamental goal is to create an attractive alternative to conventional banking while offering great interest rates to consumers is reflected in all perspectives of its balanced scorecard as shown in

Table 4.

Table 4: Proposed Balanced Scorecard

Perspectives	***Strategic Objectives***	***Strategic Measures***
Financial	Optimal Interest Rates	Low Rates for Borrowers
	IPO	High Rates for Lenders
	Financial Growth	Market Capitalization
	Low Overhead costs	Profit; Automated processes
	Secondary Market	Activity in FolioFn
Customer	Brand	Brand perception
	SEC Regulation	Business model viability
	Nationwide Presence	Orders originating nationwide
	Product Leadership	Diversify product offerings
	Apps	Apps to find optimal rates
	IOT	Interoperability with devices
	User Experience	Easy to Use Platform
	Low Default rate	Well screened borrowers
	Customer Loyalty	Number of active traders
Internal	Transparency	Prevent information asymmetry
	Innovation	Innovative business solutions
	Secure Trading Platform	HTTPS
	Automation	LendingMatch
	Employee Satisfaction	Employee retention
Knowledge & Growth	Recruit the best	Innovative business solutions
	Strategic Competencies	Multifunctional Skilled Workforce
	Technology leadership	Disruptive technologies

Source: Adapted from (Joledo et al., 2013; A. Ryan et al., 2010)

One of the prevalent themes is the need to get optimal interest rates from its pricing model that will be both beneficial to lenders and borrowers. The company must adopt knowledge management and transparency in order to establish its brand, build its customer base and reduce loan default rate. When disruptive technologies emerge, they often change the status quo. In order for Lending Club to disrupt the financial industry, it must continually fine tune its business model. The strategy map provides a picture of how Lending Club's operation determines loan rates for consumers. Competitive interest rates filters to the bottom line hence can be used as a gauge of the effectiveness of the company's strategic plan.

The *financial* perspective illustrates how Lending Club will be perceived by its investors. Every element in the scorecard ultimately seeks to increase efficiency and profitability of this new business model. This filters downward to the customer perspective. Loan offerings must be competitive in order to strengthen the company's presence. This will drive achievement of financial target and will consequently increase profitability. The *internal* perspective illustrates all the processes at which Lending Club must excel at internally to drive value. A focus on transparency, innovation and employee welfare would ensure customer loyalty and strengthen the company's brand. The *learning* perspective describes the skills that must be cultivated in its people to drive internal processes. The proposed strategy is prescribed for top management and should be deployed to various strategic business units for customization to suit specific needs of departments. Success of the objectives is measured by metrics highlighted in the subsequent SCOR model.

Lending Club's fundamental goal is to create an attractive alternative to conventional banking while offering great interest rates to consumers is reflected in all perspectives of its strategy map as shown below in Figure 40.

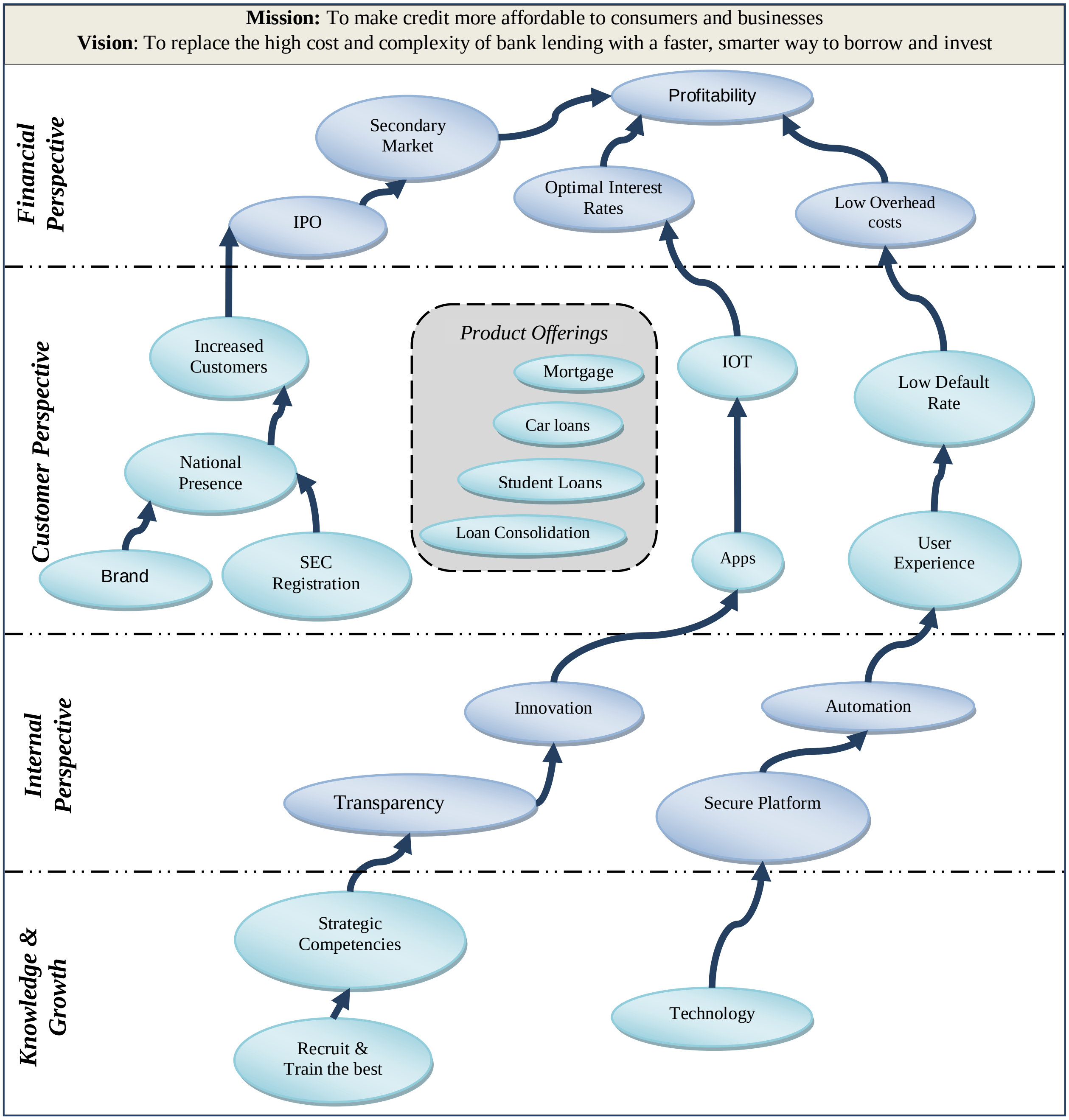


Figure 40: Strategy Map

5.5 <u>P2P Lending Risk Management</u>

To perform risk management is derived from threats identified from the SWOT analysis given in the previous section. Regulations from the SEC posed the highest threats to the business model. The risk of data center outage, cyber security attacks and other software related issues pose a medium threat. A summary of other threats is given in the risk register of Table 5, adapted from Joledo et al. (2013)

In finance and credit, the issue of trust is vital. Lenders must have some amount of confidence that their monies will be repaid. Institutions must put in place control mechanisms that ensure borrowers repay is important in peer lending since there is no collateral and borrowers feel they are once-removed from lenders because transactions are done over the internet. Acceptance of the peer lending model by companies such as Google Inc fosters trust and increase customer adoption. A good predictor of whether a borrower will pay back borrowed money in the future is whether he has paid back money in the past. P2P lending targets information asymmetry by making available to the lenders, hard and soft borrower characteristics, needed to make an informed decision on whom to lend out money to.

Table 5: Lending Club's Risk Register

Priority	Risk Statement	Likeli-hood	Impact	Risk Score	Consequence	Mitigation Plan
1	Unfavorable SEC Regulations	Medium	High	High	No issuing loans during waiting period; Investors consider competitors	Transparency with customers; Seek external capital to weather storm of no revenue; keep operating costs low
2	Threat of new entrants	Medium	High	High	Current business model at risk;	Create differentiated strategies to acquire market share
3	IT cyber security attack	Low	High	Medium	Compromise member's confidential information & platform performance	Invest in enterprise firewalls & anti-virus software at datacenter
4	Data Center Outage	Low	High	Medium	Web server crash and customer have no access to web platform	Failover systems, backup UPS, & spinning reserves on peak traffic
5	SEC fines on non-securities business model	Medium	Medium	Medium	Millions of dollars in fines to affect cash flow and potential bankruptcy	Limit impact with external capital and filing first to SEC to shape regulatory process
6	Dissatisfied customers	Low	High	Medium	Negative publicity to prevent membership growth and trust	Make historical data transparent to investors and strive for high customer satisfaction
7	Economic conditions impact borrower	Medium	Medium	Medium	Higher default rates could impact note attractiveness	Improve credit risk engine to filter out high risk borrowers
8	Computer bug in pricing model	Low	High	Medium	Impact performance and customer satisfaction	Invest in software quality assurance to identify flaws
9	Intellectual Property lawsuits	Low	Medium	Low	Lending platform requires software license & damages	File patents on software & build strong legal team
10	Identity theft of members	Low	Medium	Low	Increased default rates	Enhance borrower member registration verification process
11	Rising federal interest rates	Medium	Low	Low	Higher rates on risk-free rate, bonds, and CD's, reduce P2P attractiveness	Continue to improve performance of platform & lower fees to both members
12	Earlier loan payoffs	Low	Low	Low	Lower rate of return for investors	Lower default rate & reduce fees to investor

5.6 Data Analysis

Real data of LC business model is available via its platform. Data on arrival patterns and arrival intervals are generated stochastically according to the data collected for years 2013 and 2014. There were 235629 accepted loan requests during this period. Table 6 summarizes descriptive statistics for variables relating to the funded (accepted) borrowers within the time period.

Table 6: Snapshot of Borrower Profiles

	Minimum	Maximum	Mean	Std. Deviation
funded_amnt	1000	35000	14870.16	8438.32
int_rate	6.00%	26.06%	13.78%	4.32%
annual_inc	3000	7500000	74854	55547
dti	0	39.99	18.04	8.02
delinq_2yrs	0	22	.34	.89
inq_last_6mths	0	6	.76	1.03
mths_since_last_delinq	0	188	33.40	21.78
open_acc	0	84	11.67	5.26
revol_bal	0	2560703	16508.09	21462.89
revol_util	0	892.30%	55.69%	23.10%
total_acc	2	156	26.01	11.89
out_prncp	0	35000.00	12037.48	8139.02
total_pymnt	0	42270	3808	4314
total_rec_prncp	0	35000.00	2713.90	3942.73
total_rec_int	0	9350.20	1093.20	1031.96

Variables of interest include loan amount, interest generated based on user characteristics, annual income of the borrower, debt-to-income ratio (*dti*), home ownership, number of delinquencies in the past 2 years, revolving utilization ratio, verification status of the user, number of accounts open in the last 2 years, the term of the loan (36 or 64 months).

The loan status includes Charged Off, Current, Default, Fully Paid, In Grace Period, Late (16-30 days) and Late (31-120 days). Figure 41and Figure 42 present a visual representation the data. Each variable is illustrated per the count of accounts by Loan Status. Only completed loans are considered i.e. those that have been fully paid or charged off. On extracting these two categories, the data is thus reduced to 17301 data points for easier manipulability.

Taking a sample of 1000 accepted transactions, a correlation study was conducted between variables. The Pearson Correlation coefficient estimates the degree of linear relationship and the direction of the relationship that exist between two variables. Table 7 displays the correlation coefficients between the variables. The annual income (*annual_inc*) is moderately correlated with the amount of loan requested (*loan_amnt*) with a coefficient of 0.414.

A score of -0.296, indicates a fairly negative correlation. A high score on the *annual_inc* variable would predict a low score on the *dti* variable and vice versa. An absolute value of correlation of about 0.40 is considered moderate indicating that although the relationship between two variables is not very strong, a linear relationship does exist between the two variables.

A small correlation, such as -0.046 that exists between the *dti* and *loan_amnt,* can be interpreted that no relationship exists between the two variables. Hence, there would be a large amount of random scatter on a bivarate plot. A negative correlation of -0.607 between delinquencies experienced by the borrower in the last two years (*delinq_2yrs*) and months since he was delinquent (*mths_since_last_delinq*) also indicates that a high score on the one variable would predict a low score on the other variable.

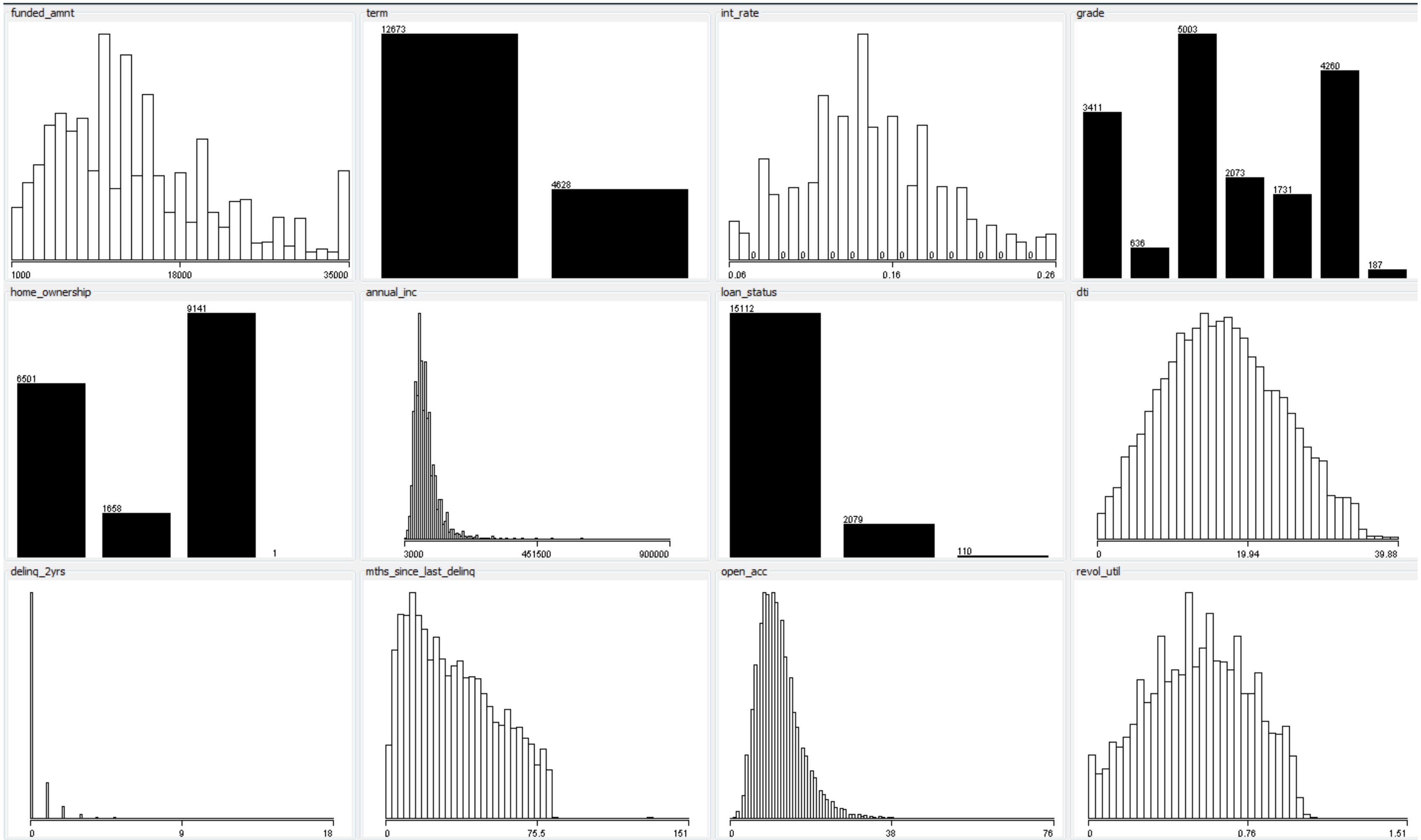


Figure 41: Visualization of Data

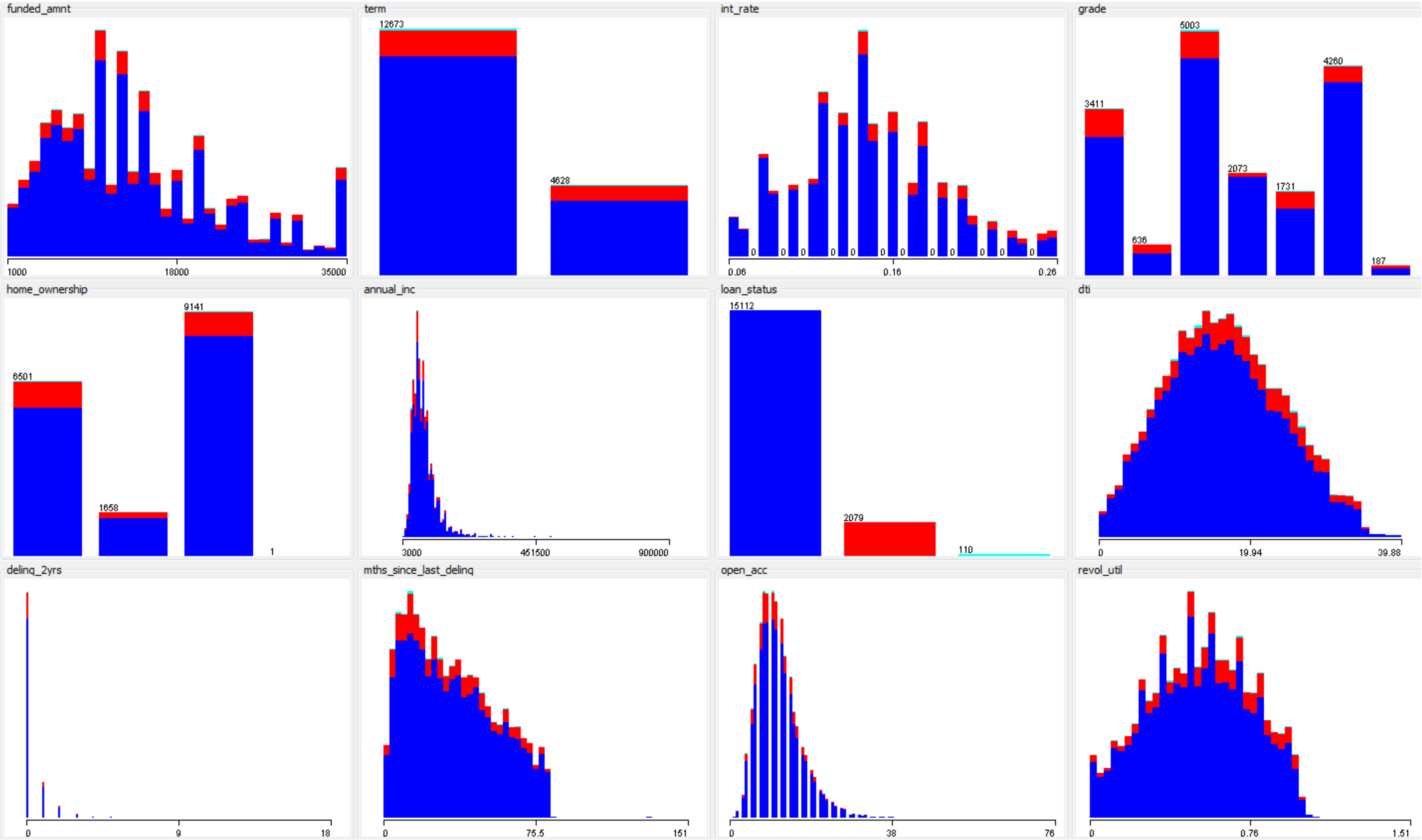


Figure 42: Variables by Loan Status

A positive correlation of 0.645 such as exists between number of open accounts (*open_acc)* and the total number of accounts (*total_acc)* for a given lender indicates a strong correlation in predicting a high score on the another variable. A correlation close to 1.0 would result in negligible scatter on a bivarate plot, hence signifying a large correlation.

The Pearson Coefficient and p-value should be interpreted together. While the coefficient helps to quantify a correlation, the p-value helps to assess whether a correlation statistically significant (real). A low p-value (generally less than 0.05) indicates the correlation is statistically significant, and that the calculated Pearson Coefficient can be used. On the other hand, a higher p-value (generally greater than 0.05) indicates the correlation is not statistically significant and cannot be relied on.

The ANOVA was performed on the FICO scores for both the rejected (*FICO_r*) and accepted (*FICO_a*) samples. The p-value of less than 0.05 confirms that the mean differences between the FICO scores are statistically significant. It can be deduced that there is no overlap between *FICO_a* and *FICO_r*. This is illustrated in Figure 43 and Figure 44. As is expected, for the accepted users' data, it is observed that most of the borrowers have very high FICO scores while the scores of the rejected users are concentrated at the lower end of the spectrum with a lot of outliers.

Table 7: Correlation Coefficients

		loan_ amnt	emp_ length	annual_ inc	dti	delinq_ 2yrs	inq_last_ 6mths	mths_since_ last_delinq	open_ acc	revol_ util	total_ acc	int_ rate
loan_amnt	Pearson Correlation	1										
	Sig. (2-tailed)											
	N	1000										
emp_length	Pearson Correlation	.093**	1									
	Sig. (2-tailed)	.004										
	N	956	956									
annual_inc	Pearson Correlation	.414**	.099**	1								
	Sig. (2-tailed)	.000	.002									
	N	1000	956	1000								
dti	Pearson Correlation	-.046	-.007	-.296**	1							
	Sig. (2-tailed)	.145	.840	.000								
	N	1000	956	1000	1000							
delinq_2yrs	Pearson Correlation	-.006	-.027	.069*	-.025	1						
	Sig. (2-tailed)	.844	.404	.029	.429							
	N	1000	956	1000	1000	1000						
inq_last_6mths	Pearson Correlation	.007	.041	.059	-.001	.007	1					
	Sig. (2-tailed)	.820	.208	.063	.978	.825						
	N	1000	956	1000	1000	1000	1000					
mths_since_last_delinq	Pearson Correlation	-.028	.037	-.026	-.032	-.607**	.046	1				
	Sig. (2-tailed)	.529	.415	.562	.479	.000	.308					
	N	503	476	503	503	503	503	503				
open_acc	Pearson Correlation	.204**	.054	.164**	.262**	.071*	.133**	-.039	1			
	Sig. (2-tailed)	.000	.095	.000	.000	.025	.000	.379				
	N	1000	956	1000	1000	1000	1000	503	1000			
revol_util	Pearson Correlation	.069*	.010	-.008	.210**	.033	-.088**	-.118**	-.132**	1		
	Sig. (2-tailed)	.028	.761	.792	.000	.298	.005	.008	.000			
	N	999	955	999	999	999	999	503	999	999		
total_acc	Pearson Correlation	.207**	.149**	.264**	.144**	.117**	.152**	-.002	.645**	-.109**	1	
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.966	.000	.001		
	N	1000	956	1000	1000	1000	1000	503	1000	999	1000	
int_rate	Pearson Correlation	.147**	.012	-.120**	.067*	.036	.168**	-.069	-.044	.280**	-.148**	1
	Sig. (2-tailed)	.000	.718	.000	.035	.258	.000	.121	.168	.000	.000	
	N	1000	956	1000	1000	1000	1000	503	1000	999	1000	1000

. Correlation is significant at the **0.01 level (2-tailed). *. Correlation is significant at the **0.05** level (2-tailed).

One-way ANOVA: FICO_a, FICO_r

Method

Null hypothesis	All means are equal
Alternative hypothesis	At least one mean is different
Significance level	$\alpha = 0.05$

Equal variances were assumed for the analysis.

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Factor	1	1839090	1839090	769.15	0.000
Error	1998	4777346	2391		
Total	1999	6616436			

Model Summary

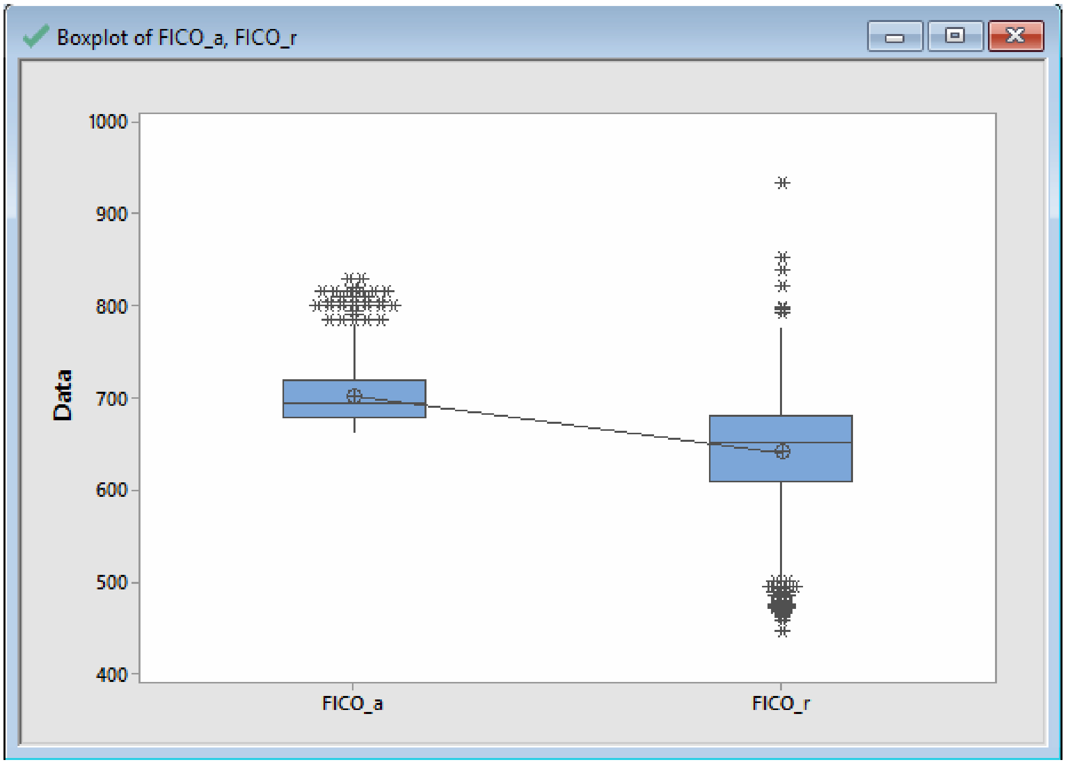
S	R-sq	R-sq(adj)	R-sq(pred)
48.8985	27.80%	27.76%	27.65%

Means

Factor	N	Mean	StDev	95% CI
FICO_a	1000	701.790	31.340	(698.757, 704.823)
FICO_r	1000	641.14	61.64	(638.11, 644.17)

Pooled StDev = 48.8985

Figure 43: ANOVA: Accepted and Rejected User FICO Scores



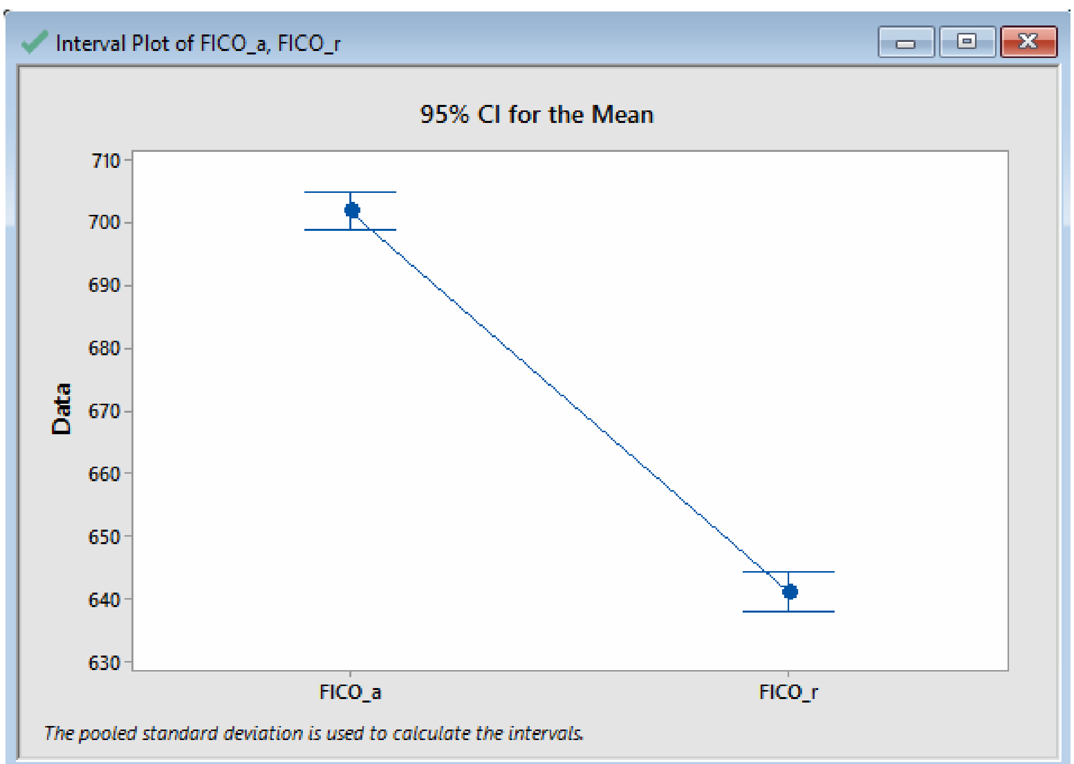


Figure 44: Plots of Means

5.7 Probability Distributions

This section describes the probability distributions used in the simulation module. The statistical software used were Minitab version 17 and Easy Fit Professional version 5.6. The Rand() Function in MS Excel is used to generate random numbers used in sampling. The derived parameters were entered into the *Choose Probability Distribution Function* property of each variable in AnyLogic PLE 7.3.1.

Distribution fitting aids in forecasting approximate frequency of occurrence of the magnitude of the variable in a certain interval. Large data sets can create a few potential issues some of which include that the distribution testing very high power resulting in a small deviation being flagged as statistically significant. This is because large samples increase the power of an analysis to detect a difference. Therefore a goodness-of-fit test becomes sensitive to the slightest, inconsequential departures from a distribution. A good solution is to inspect the graphs and the probability plot in making the decision in selecting the best fitting distribution.

Based on results of the ANOVA illustrated in Figure 44, the data set combines different populations. Distributions were then fitted by separating and then identifying the distribution for the accepted and rejected subpopulations. The choice of the probability distributions of select variables of the accepted 1000 borrowers at a 0.05 significance level along with corresponding parameter are as given in

Table 8: Distribution Parameter. The suitability of the distributions is verified in by generating a random distribution of 1000 values in Minitab and comparing the descriptive

statistics to that of original data extracted from the LC portal. The generated values were found reliable. The final choice of distribution is a factor of compatibility with AnyLogic.

Table 8: Distribution Parameters of Accepted Users

Variables	Distribution	Parameters
Amount	Beta	Shape α1 = 1.9614 Shape α2 = 6.0164 Minimum a = 0.100 Maximum b = 3.500
dti	Beta	Shape α1 = 2.3458 Shape α2 = 2.7369 Minimum a = 0.002 Maximum b = 0.3490

The Amount variable is divided by a factor of 10,000 purely for clarity and manageability in the simulation model. Therefore, a value of *beta(1.9614, 6.0164, 0.100, 3.500)* indicates an actual alpha (shape) value of $19,614 and a minimum of $1,000. The histograms along with fitted curves for the *dti* and *Amount* distribution are displayed in Figure 45and Figure 46.

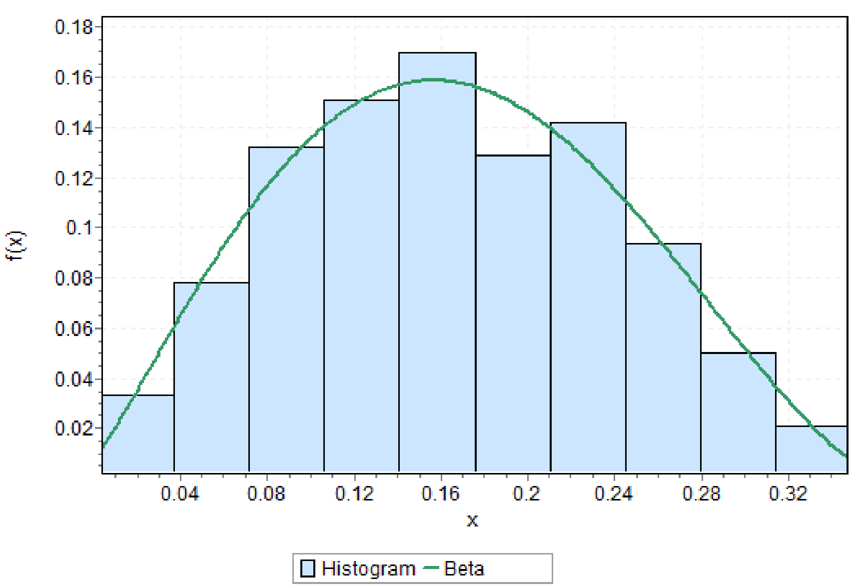


Figure 45: Probability Distribution Function of dti

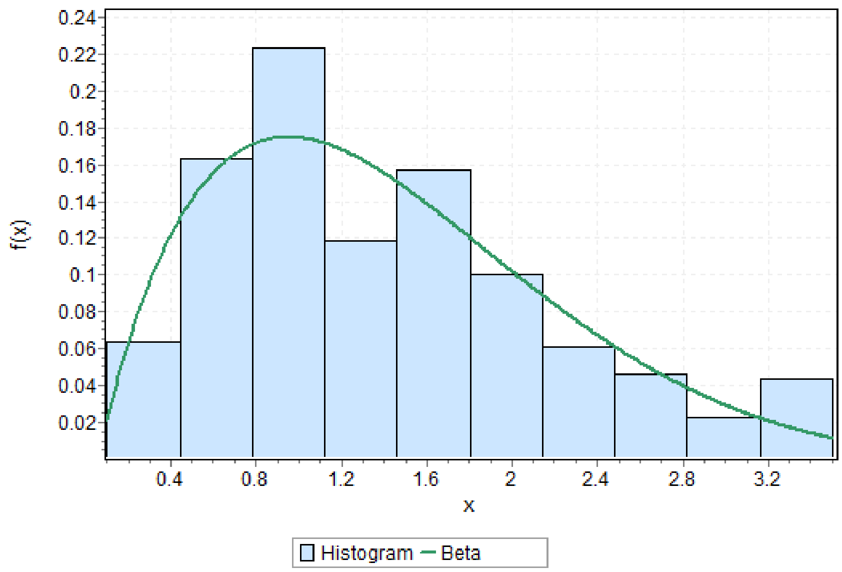


Figure 46: Probability Distribution Function of Amount

5.8 Summary

The case study of Lending Club is presented in this chapter. The competitive landscape, business model and business associated risks are presented in detail. The chapter went on to introduce and analyze the data used in the simulation. The next chapter details the implementation of the proposed framework by calibrating the model using data, compatible with the case study.

CHAPTER 6. IMPLEMENTATION, ANALYSES AND RESULTS

6.1 Formulation of Simulation Model

Overview of business processes of p2p lending presents a starting point for to planning the simulation. Historical data on loan performance introduced in Chapter 5 must be correctly gotten in order to accurately test different scenarios. Mapping of the framework begins with identifying observed objects in the system (borrowers and lenders). Agent Based Simulation, combined with System Dynamics, is an efficient approach to modeling consumer and competing behavior.

Information exchanged between participants can take the form of a broadcast or a one-on-one communication. Lending Club (LC) serves as the intermediate of communication between lenders and borrowers. The availability of funds is communicated to the borrower and the interest rate corresponding to his risk profile. Default behavior of the borrower is also communicated to the lender in order to take decisions.

The system is simulated over a period of eight years to gain insight on the behavior of participants and how their individual or collective actions affect the net income and in turn the profit margin of the system. The output of the overall system is system viability measured in the system by the default rates, net income and profit margin. Outputs of the time-discrete ABM subsystem are fed into the time-continuous SD model (strategic layer).

6.1.1 Supply Chain Mapping and SIPOC

The supply chain mapping is motivated from the activity chain mapping presented in Figure 39 and receives input from the SIPOC.

Supplier	Input	Process	Output	Customer
Lenders	Applications	Screen	Interests	Lenders
Investors	Principal	Review	Repayments	Borrowers
Engineering	Marketing	Approval	Fees	Shareholders
Developers	Internet	Verification	Returns	Community
Stakeholders	Algorithms	Generate Interest	FolioFn	Government
Partner Banks	IT	Post Profile	Notes	
Regulatory Authorities	Servers	Fund	WOM	
Personnel		Repay		
Management				

Figure 47: The SIPOC

The behavior of a supply chain is a function of performance of other participants in the system. The SIPOC provides a high-level understanding of the system. Lending Club is modeled using SCOR Level 2 processes. The activity diagram of Figure 39 provides some insights for mapping the supply chain processes of the business model. LC handles the sourcing of funds (S1) from lenders (D1). The lenders distribute their funds (M2) to borrowers in line with their requests. These loans are then delivered via the online platform to the borrower (D2). Repayments are done by sourcing (SR1) from the borrower in addition to transaction costs and interests and delivered back (DR2) to the original lender.

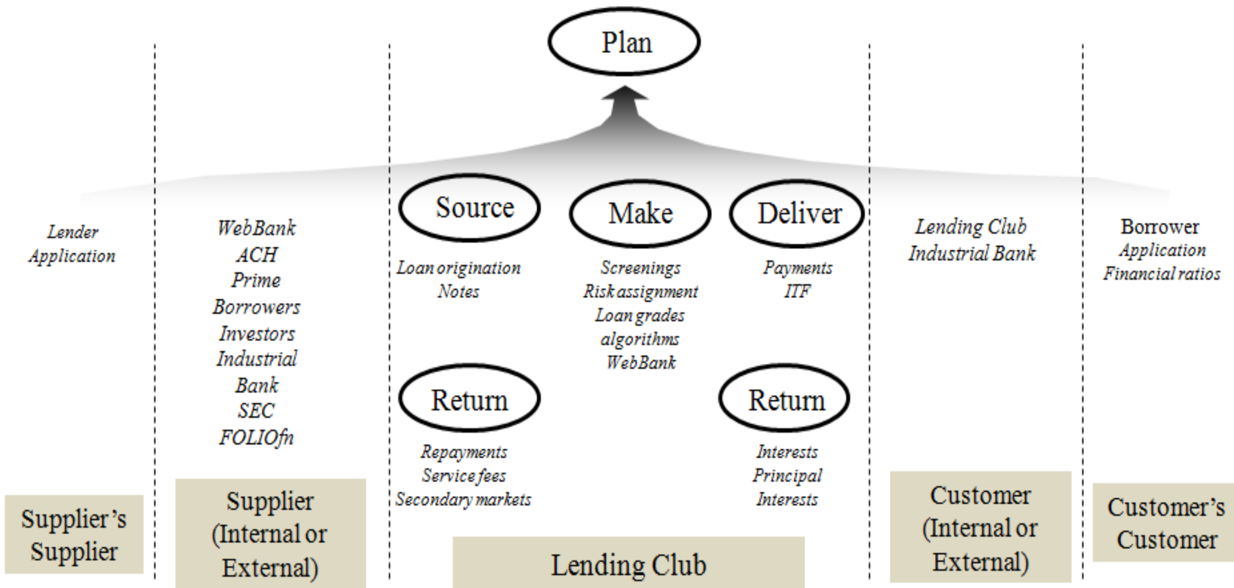


Figure 48: SCOR Strategic Level Loan Completion Process

After specifying the Loan Completion process SCOR Level 1, decomposition mechanics are put in place in order to determine the state of the supply chain Level 2. The "as is" state is documented and adopted in the design of the Level 3 process elements. The SCOR model provides the basic structure used to guide the modeling process which is in turn converted to AnyLogic using the identified performance metrics.

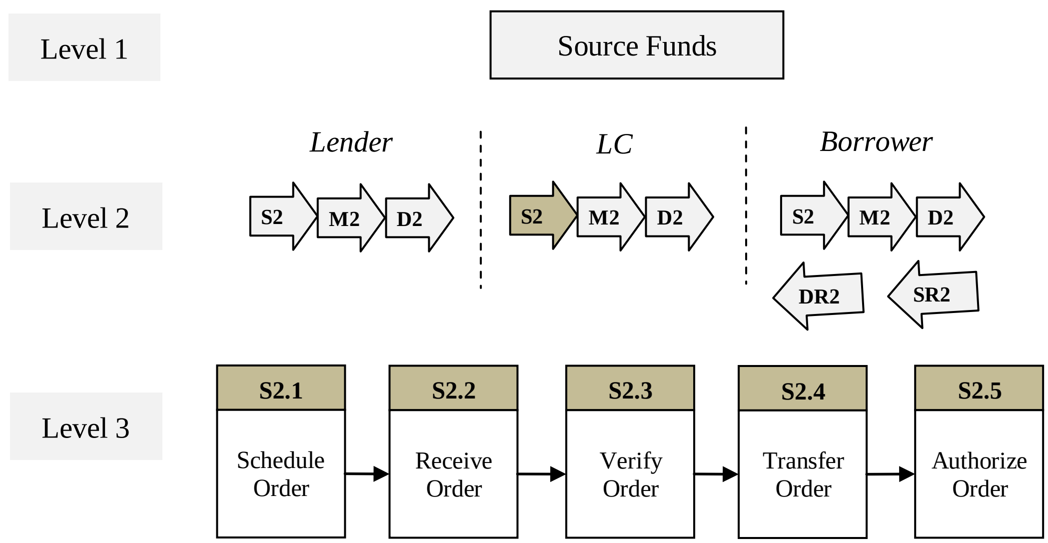


Figure 49: Lending Club SCOR Source Funds Process Mapping

6.1.2 Neural network

The NN is used to map the characteristics of users to different risk decisions and also to copy trust, or its lack of, in the system. The Neuroph framework (www.neuroph.sourceforge.net) is modified for the neural network learning and calculations. The API of the framework makes it easy to integrate with any Java application. Neuroph provides Java class library as well as GUI tool for creating and training neural networks.

To build the NN model representations to explain the data, completed loans i.e. those that were charged off and fully paid are used. It is important to select the right architecture consisting of hidden neurons for the back propagation neural network. The neurons are fully connected from one layer to another (except for the bias neuron in the first 3 layers). The datasets of the accepted and rejected loans are combined. A random sample of 2062 data points from the combined dataset forms the training data used in the learning process. The input is normalized by dividing amount requested (*Amount*) by 3.5, *FICO* by 850 and employment length (*e_emp_length*) by 10. The resulting structure of the network is as given:

Input layer: 4 neurons;

Weights: 75.5855, -137.0480, 16.4224, -99.04098, 159.42823;

Hidden Layer 1: 5 neurons;

Weights: -17.9882, 182.7330, -97.8329, 10.5899, -112.8767, 66.2858;

Hidden Layer 2: 3 neurons;

Weights: 99.8111, -24.8498, 4.1454, -84.0565;

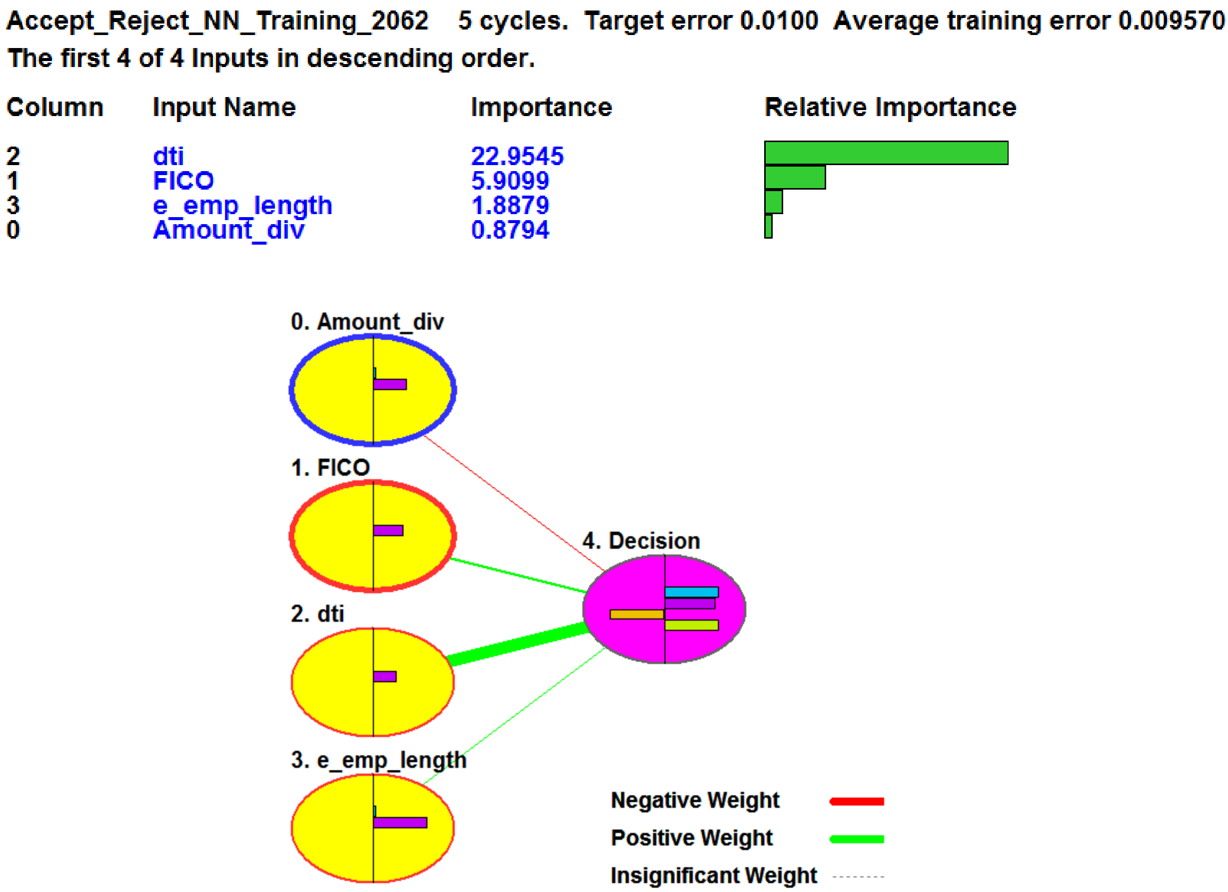
Output Layer: 2 neurons;

Weights: -2.7174, 169.5855;

The extra weight in the input layer and the hidden layers is the bias. The architecture results in two neurons for the output layer using the backpropagation algorithm. The output is 1 0 if "ACCEPTED" and 0 1 if "REJECTED". However, the output layer neurons fire up ANY value between 0 1. A code is written to determine a definitive answer. Therefore, if the output in Output neuron 1 is larger than the output in Output neuron 2 then it the NN thinks it should be ACCEPTED, otherwise it is REJECTED.

Taking that into account a test with the entire dataset is run and the resulting error is **0.1118**. That means that out of the 26493 training values, in 2963 instances the NN is misclassified. To improve the capacity of the NN to represent the information and get better results, the structure of the NN is changed by adding more layers and varying the number of neurons per layer.

Just NN (http://www.justnn.com/) is also used to create the neural network for a sample of the ACCEPTED data. The relative importance of each variable in determining what user is accepted or rejected is as illustrated in the Figure 50.


Accept_Reject_NN_Training_2062 5 cycles. Target error 0.0100 Average training error 0.009570
The first 4 of 4 Inputs in descending order.

Column	Input Name	Importance	Relative Importance
2	dti	22.9545	
1	FICO	5.9099	
3	e_emp_length	1.8879	
0	Amount_div	0.8794	

Figure 50: Neural Network Relative Importance

6.1.3 Agent Based Simulation

The individual behaviors of consumers in the system are modeled in the ABS subsystem. The simulation begins by declaring and initializing all variables. Probabilities are assigned to the different agent variables based on corresponding distributions introduced in the preceding chapter. The loan lifetime is defined by parameter *Term*. The requested *Amount*, *FICO*, *DTI* and *Credit History* are stochastic characteristic of a borrower.

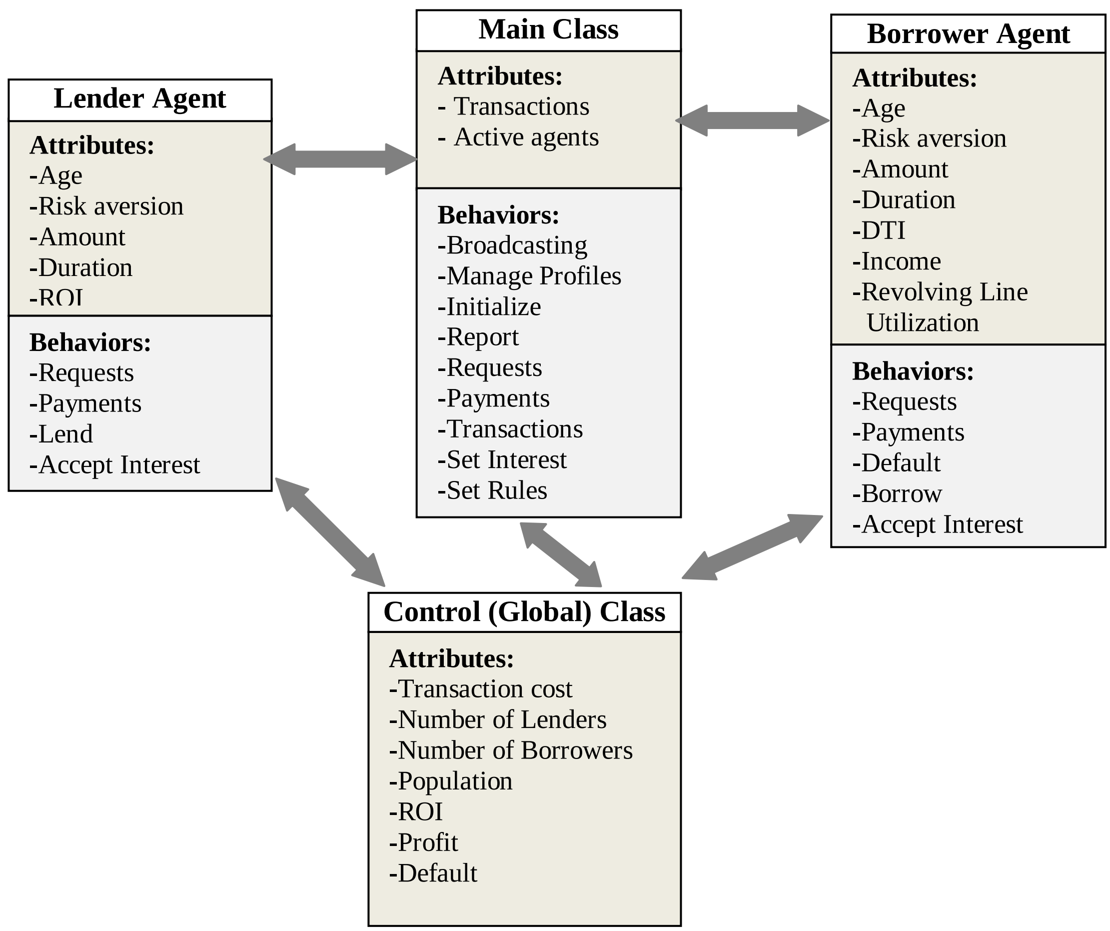


Figure 51: Structure of Agents - classes and their interactions

The users are modeled as agents with individual behaviors. Risk is modeled into agent by utilizing the dti, credit history, fico range, income to generate a corresponding interest rate. Transitions between levels are based on probability distributions functions.

Depending on the user state, transitions are triggered by timeouts or by meeting certain conditions. On executing the program, new borrowers are created and they transition into the

PotentialBorrower state. When the statechart enters the state *PotentialBorrower*, its *FICO*, *DTI* and *Amount* requested are passed to the neural network class which makes a decision on which borrower transitions to the *Screened* state. The time spent in a given state is obtained from the data and follows a uniform distribution reflecting the range associated with its state. For example, a typical Lender takes about 45 days between entry and receiving of first payment. Similarly, the time spent in the *PotentialBorrower* state before screening ranges from 2 to 4 days.

Once the borrower is screened, an interest rate is generated to reflect his risk profile. A draw on the lookup table is used to generate an interest rate that corresponds to the borrower. On receiving the interest rate, the borrower makes a decision to agree or decline the terms of the loan. If he declines, he has an option to follow the *noToAgreement* transition back to the *PotentialBorrower* state where he remains or decide to leave the system. If the borrower agrees to the terms of the loan, he proceeds to the *PostedProfile* state via the *yesToAgreement* transition. The decision to accept interest rate is internal and probabilistic based on the borrower's risk preference and personal goals. A call is made to the *requestServiceB()* function which communicates the borrower profile to all available lenders. If the borrower profile matches a given lender's risk aversion, he accepts and stores the id of the borrower along with its profile information.

Once the lender agrees to fund the borrower, the borrower transitions to the *Funded* state where it remains for a period uniformly distributed to reflect the time it takes to fully fund the request. After which it transitions to the *InRepayment* state where it remains for the term (usually 36 or 60 months). Thirty days after entering the *InRepayment* state, the borrower starts to make payment every 27 to 31 days. This time range reflects the fact that borrowers pay their bills early, on time or late.

There is one transition from *InRepayment* state and this has two branches. One of the branches leads to *FullyPaid* while the other to the *InDefault* state and then to *Exit* where the borrower leaves the system on charge off. The decision at the *TestDefault* branch is made internally and stochastically according to the percentage of borrowers that actually default. The average amount of capital and interests that is repaid, recovered or lost when a borrower defaults is reflected in the system.

LC, which acts as a central dispatcher broadcasts requests for borrower loans to all lenders. For simplicity, we model LC (the dispatcher) is not modeled as having a state but as a function call that responds to requests. LC listens for messages from the borrower and lender side and manages the transaction completion on behalf of the agents. LC inserts a message in the queue and notification is broadcast to borrowers and lenders. *BorrowerAB* and *LenderAB* represent borrower and lender agent classes. The communication instances used in the model is summarized thus:

1. Screening request: a message arrives from the borrower and lender requesting screening
2. Interest rate generation: the LC generates an interest rate and communicates it to the borrower
3. Borrower decision on interest rate: based on the risk profile, the borrower decides to accept or reject the generated interest rate.
4. Lender's decision on interest rate: the lender decides to fund a particular borrower with an associated interest rate based on its risk profile.

5. Payment: payments are communicated to LC and in turn to the lender

6. Default: the borrower leaves the system and the lender and borrower returns are update.

7. Fully paid: a message from the borrower and lender deciding if to go back to the system as potential customers or they can choose to leave the system.

It is assumed that participants are sensitive to ads and word of mouth (WOM). The WOM effect is the way new users are persuaded to purchase a product or adopt a service. Consumers persuade others to adopt a service or buy a good often using word of mouth. Each participant's adoption time will differ, though certain percentage of potential users will adopt the service on a given day. In this system, customer satisfaction measured by behavior to WOM and results from satisfactorily completed loans. Hence, it is expected that as more customers default, the WOM decreases. In LC, a consumer contacts an average of number people in a month or year i.e. a specified contact rate. Agents in the system in turn contact each other and influence potential borrowers to sign up for the service.

Space and request queue management are defined within the *Main* with space and layout requirements configured in the *Environment* object contained in the *Main*. A value of 1000 each was assigned as initial number of borrowers and lenders in the system. The statechart representing borrower and lender behaviors and interactions with the system is given in Figure 52.

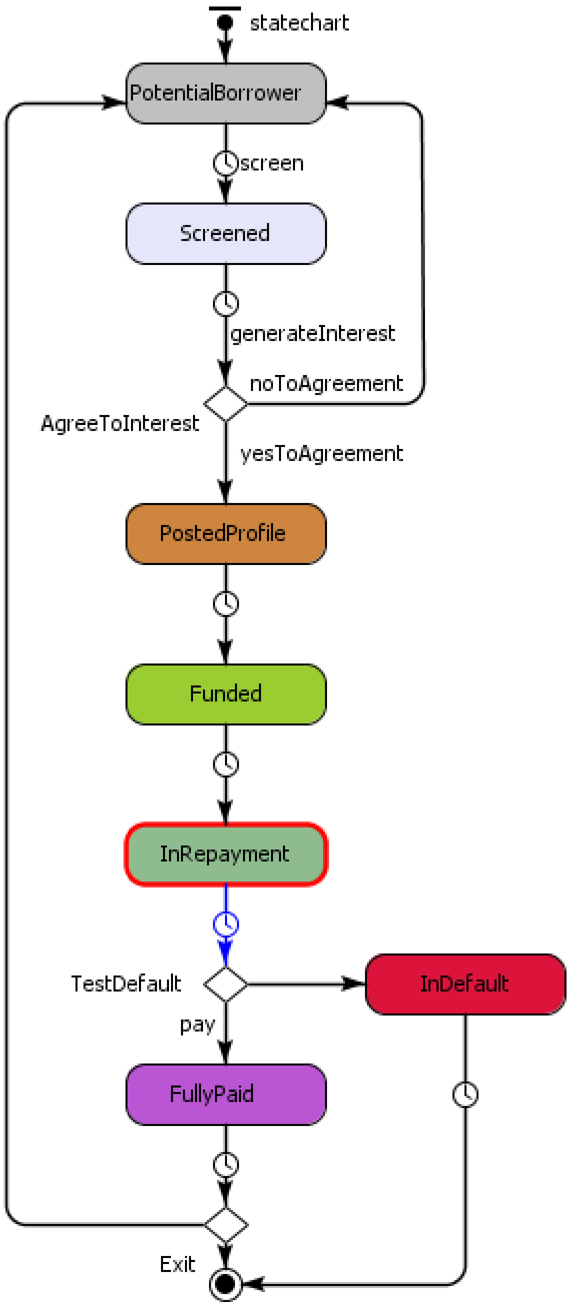


Figure 52: Borrower and Lender Statecharts

An advantage of object oriented ABM is that we can drill into each object – borrower or lender – and view its state and variable values. The change in color according to states gives a visual verification of the performance of the system.

The following are some inputs used in calibrating the agent based model:

- The number of borrowers in the system is initialized to 1000.
- There is a 70% of requesting a loan of 36 months and 30% of requesting 60 months.
- A random borrower can request anywhere from $1000 to $35,000 and based on his profile.
- The contact rate is kept at 1.5% to prevent the number of new agent entering the system from growing too large.

Simulation experiments help to facilitate systematic and quantitative analysis on the effects of factors of interest. Simplifying modeling assumptions adopted for this study include:

1. A given lender is attached to a given borrower.
2. Agents leave the system after they complete paying.
3. Borrowers has an option to return back to the state of screened user.
4. Agents who default must leave the system.
5. Probability distributions are used to generate the agent profiles.
6. Arrival patterns of borrowers and lenders are based on LC user arrival rate.
7. Term of loans is either 36 months or 60 months and the choice follow a probability similar to real data.
8. State transitions are instantaneous and time durations are factored into the timeout triggered property.

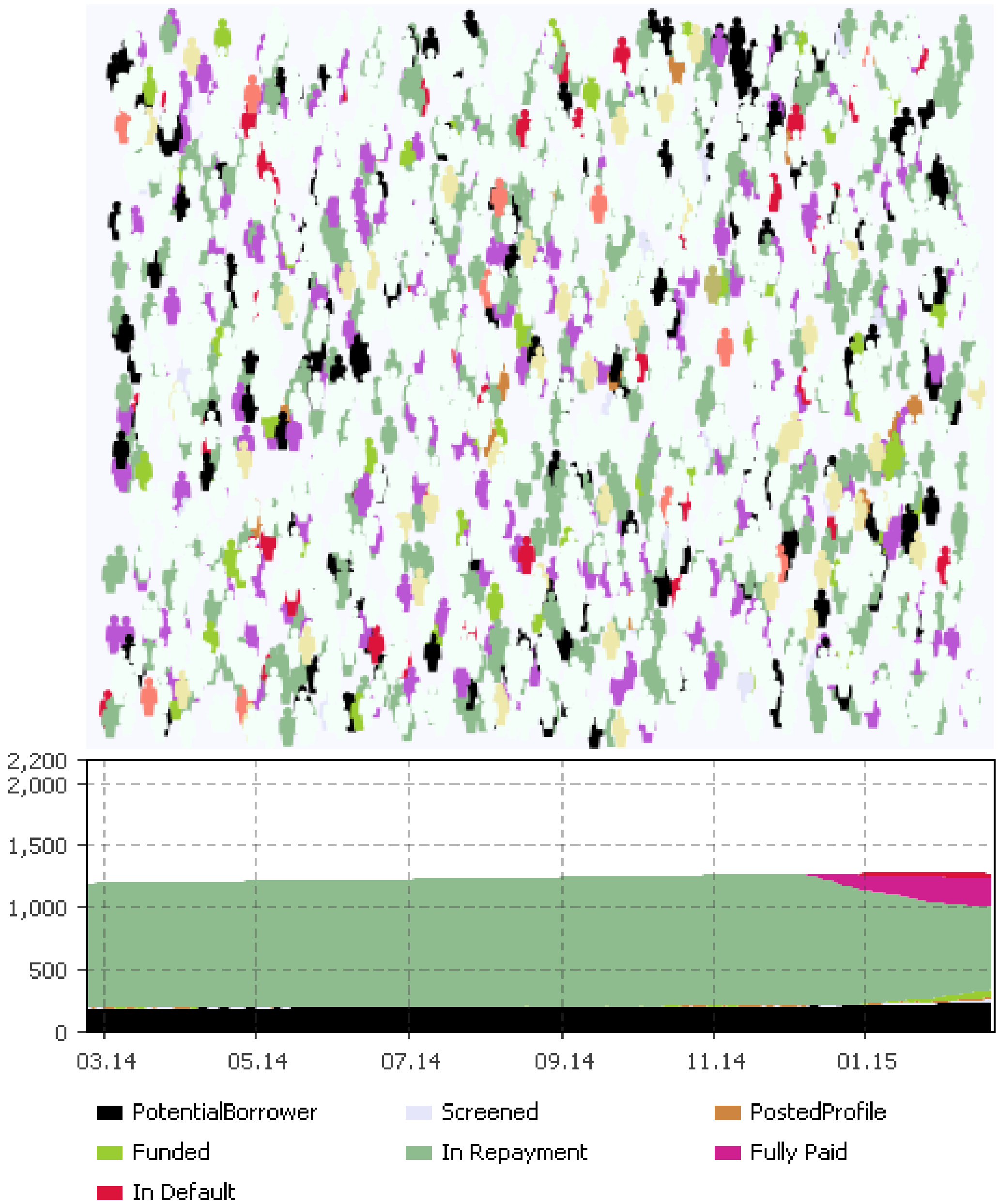


Figure 53: ABMS Interface

6.1.4 System Dynamics

The strategy map illustrated in Chapter 5 as well as the SCOR model serve as a starting point for implementing the SD model and depicting cause and effect linkages in the system. The identified success factors are also mapped to the model. The SD incorporates estimates of the demand, quality, reactions of the customers, costs, and market conditions. The system dynamics phase involves first modeling a causal loop diagram of the peer-to-peer lending environment using identified key system variables.

The causal loop diagram introduced in Chapter 4 forms the backbone of the System Dynamics model. Causal loops are constructed from case study, and literature review to capture interrelationships of critical success factors. In order to incorporate oscillations and delays inherent to real systems, we extend the causal loop to a detailed stock and flow model.

The metrics of interest in the SD model include profitability, customer satisfaction, and responsiveness. In the model, profitability is measured as net income and profit margin. The SD model receives input from the ABM. The output of the system is the projected *AvgNetAnnualizedReturn*, *MarketShare*, *NetIncome* and *ProfitMargin* for a period of the given lending span (eight years in this study). The Net Annualized Return (customer facing metric) is the income from interest less service charges, charge off and including recoveries. *MarketShare* is the amount of the total ecommerce market captured by the simulated company. While *ProfitMargin* (an organization facing metric) is the *NetIncome* less inflation compared to the total income derived from interests.

Based on data gotten from the 2014 Lending Club case study and Forrester Research, the following are some inputs used in calibrating the system dynamics model:

- The initial investment by the C2C company is 500 (with all cash amounts in tens of thousands of dollars)
- US ecommerce sales is $300 Billion.
- The effective tax rate of the organization is 34%

- All transactions accrue a 1% service charge
- The simulation runs from January 1st 2012 for 8 years.

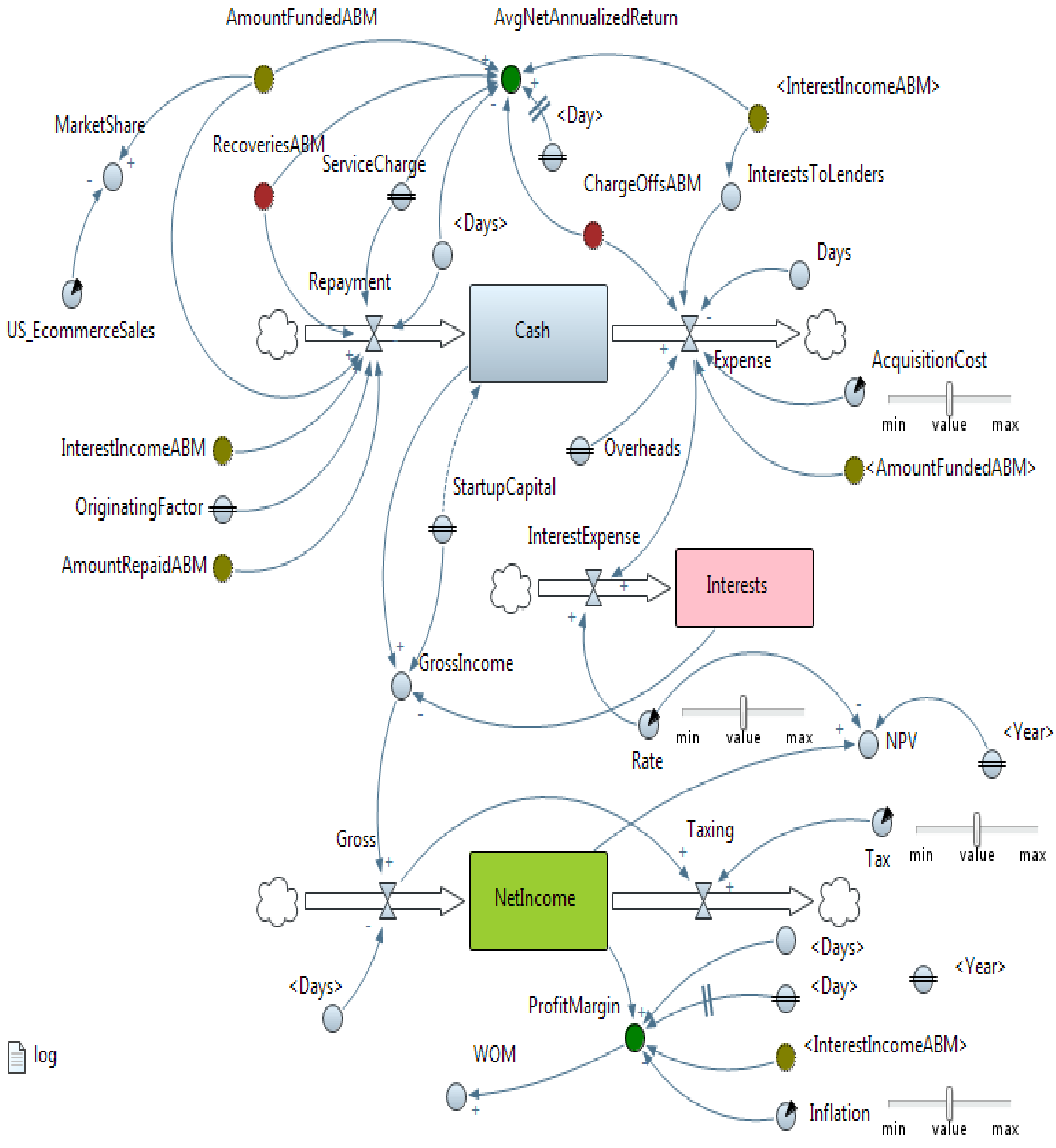


Figure 54: System Dynamics Model

In Figure 54, the points where the ABM is coupled with the SD model are denoted by an *ABM* suffix. For example, The *AmmountFundedABM*, *InterestIncomeABM*, *AmountRepaidABM* are dynamic variables whose values are dependent on an update from the ABM subsystem. The *NetIncome* stock represents an accumulation of the gross income net interest and subtracted by the taxes.

In reality, uncertainty exists in behaviors of users and even the economy. Government regulations are constantly changing and this affects interest rates. When making investment decisions, external factors such as future inflation should be taken into consideration. These model attempts to factor all these behaviors and expectations into its design.

6.2 Results

As introduced in the previous section, the output of the model includes but is not limited to market share and profitability. In this section we illustrate the insights derived from the model. Insights are gotten by examining behavior patterns of the agent base simulation in addition to the systems dynamics subsystem Figure 55.

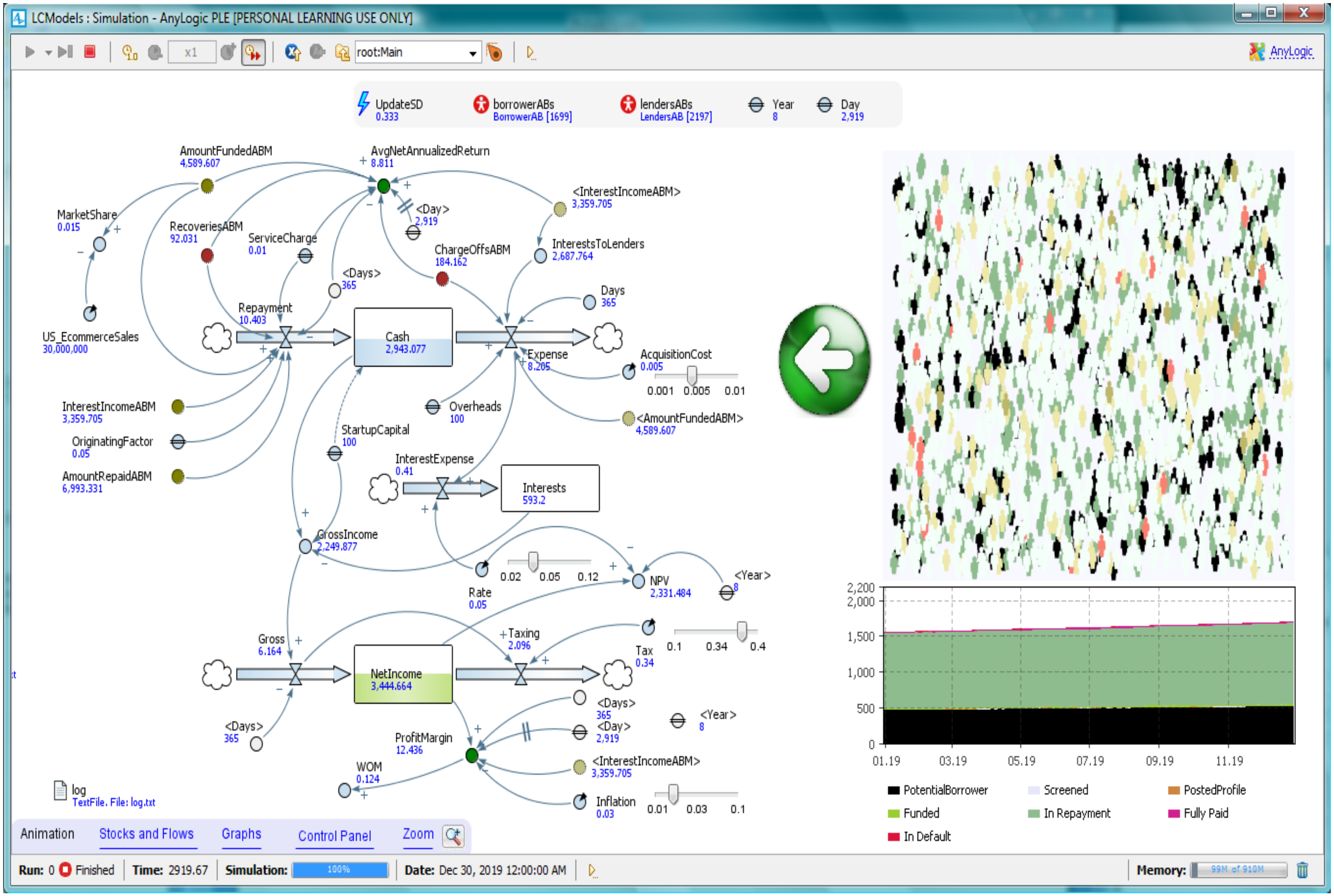


Figure 55: System Interface

Figure 56 shows a zoomed in view of cumulative states of borrowers in the system. Figure 56 (A) illustrates the average proportion of borrowers in different state in the system. Figure 56 (B) provides a visual confirmation that 1000 borrowers initially enter the system and as time (in days on the horizontal axis) progresses, the borrowers start to transition to the *Screened*, *PostedProfile*, *Funded*, *InRepayment* and *FullyPaid* states (Figure 57). Along the way, new users are added to the system by responding to the WOM action of other borrowers and lenders. At the end of the simulation period, a total of about 1700 borrowers and 2100 lenders are in the system. This number can be controlled by increasing the WOM factor. For speed and efficiency, this number is kept low in the present study. As will be noticed, a large portion of the users remain in the *PotentialBorrower* state because most of the borrowers who come into the system do not meet the screening requirements and never progress to the Screened state.

The behavior rules based on observing actual lending club behavior suggest that Net Annualized Return declines exponentially as time progresses. This is in line with the output of the simulation system metric *AvgNetAnnualizedReturn* in Figure 58(B). As time progresses, more borrowers default. Thereby, effectively driving *AvgNetAnnualizedReturn* downwards.

An Increase in *ProfitMargin* results from an increase in the repayments (both principal and interests) and decrease in the charge offs. An increase in *ChargeOff* s has a negative toll on the *NetIncome* and *AvgNetAnnualizedReturn*. This increases the origination fees and creates pressure LC to increase service charges in order to maintain profitability. Moreover, a desire to increase market share further puts pressure on fees.

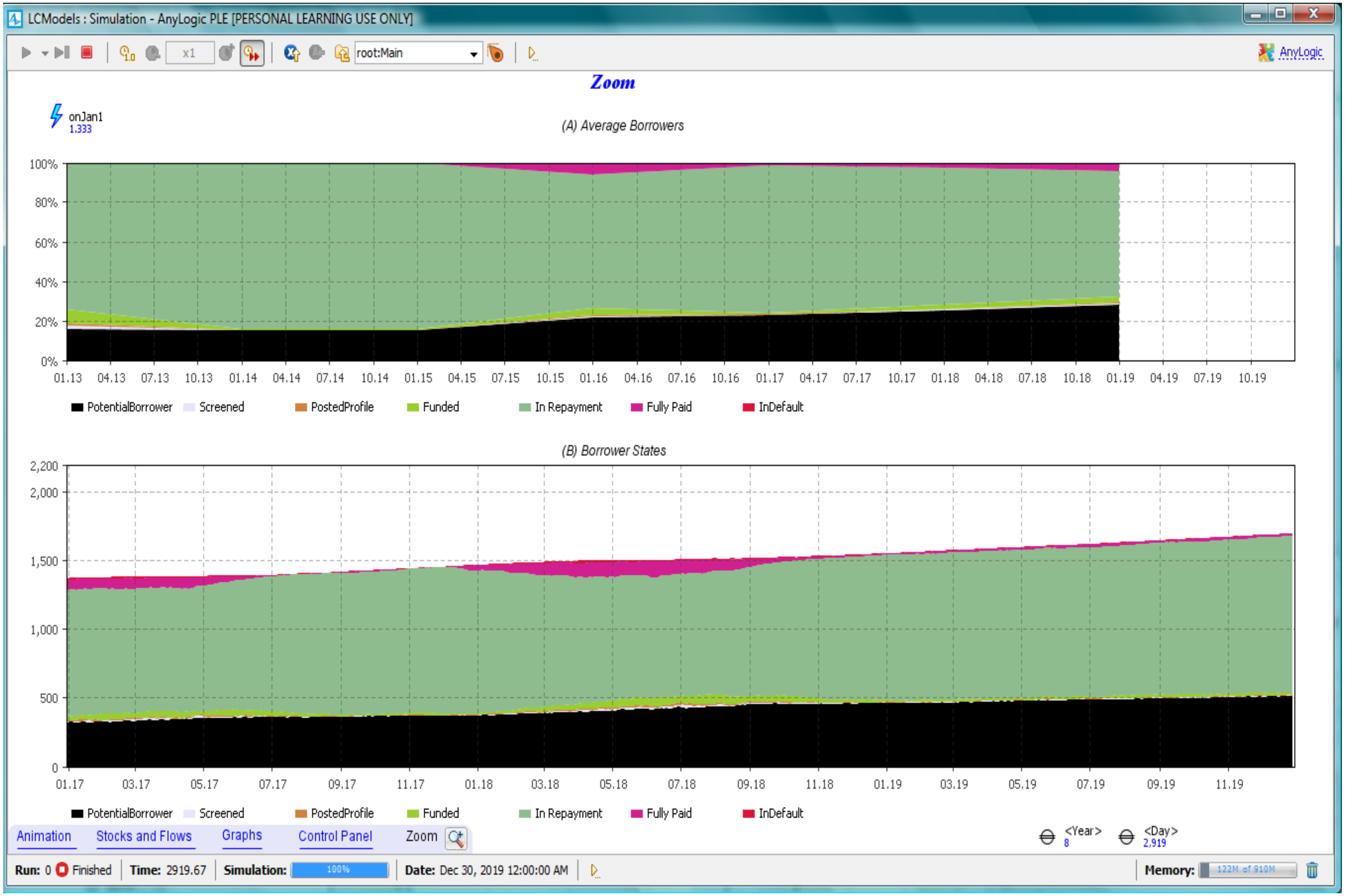


Figure 56: Borrower Profile from ABMS

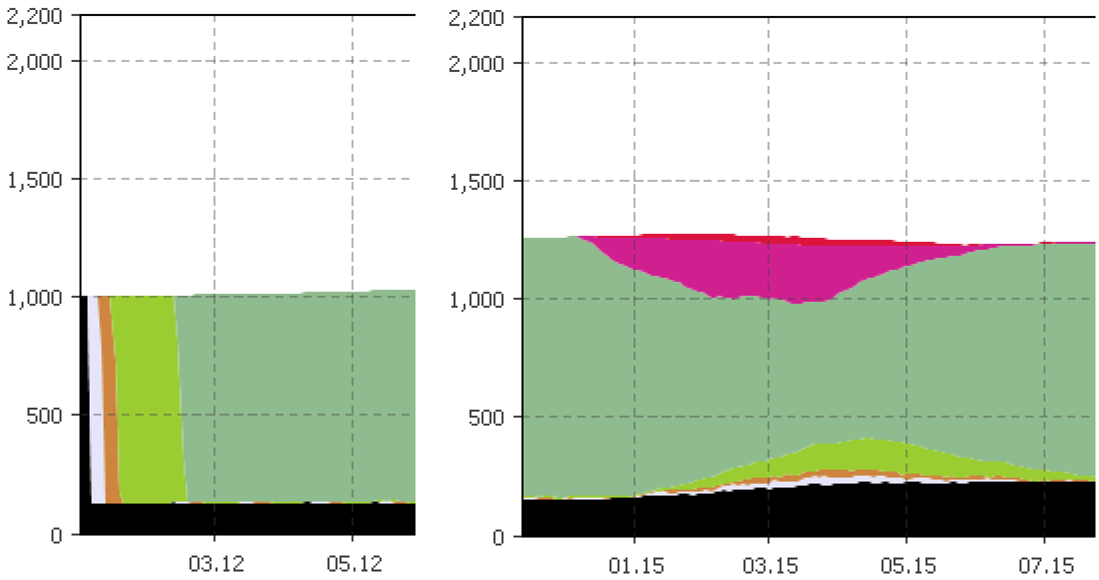


Figure 57: Borrower States in the System

In the early phase of the simulation, the initial capital and cost weigh heavily on the system. In Figure 58(E) we observe exponential growth of *CashStock*. Figure 59 shows the results of the model a different range of dynamics.

The expenses, taxing, repayment flows occur proportional to the net income. The sudden spikes in response in *AmountFundedABMS*, and *MarketShareDS* in Figure 59(B) and Figure 59(F) indicate the full repayment times of the first set of borrowers who requested a Term of 36 months. Most borrowers return to *PotentialBorrower* state where they can request a new amount of money and the process repeats itself. Revenue increases slowly in the first two years due to the fact that the starting number of borrowers is low and because the effect of WOM becomes significant with time. There is a noticeable increase in *AmountFundedABMS* after the first set of borrowers who requested 36 months loan have all repaid their loans.

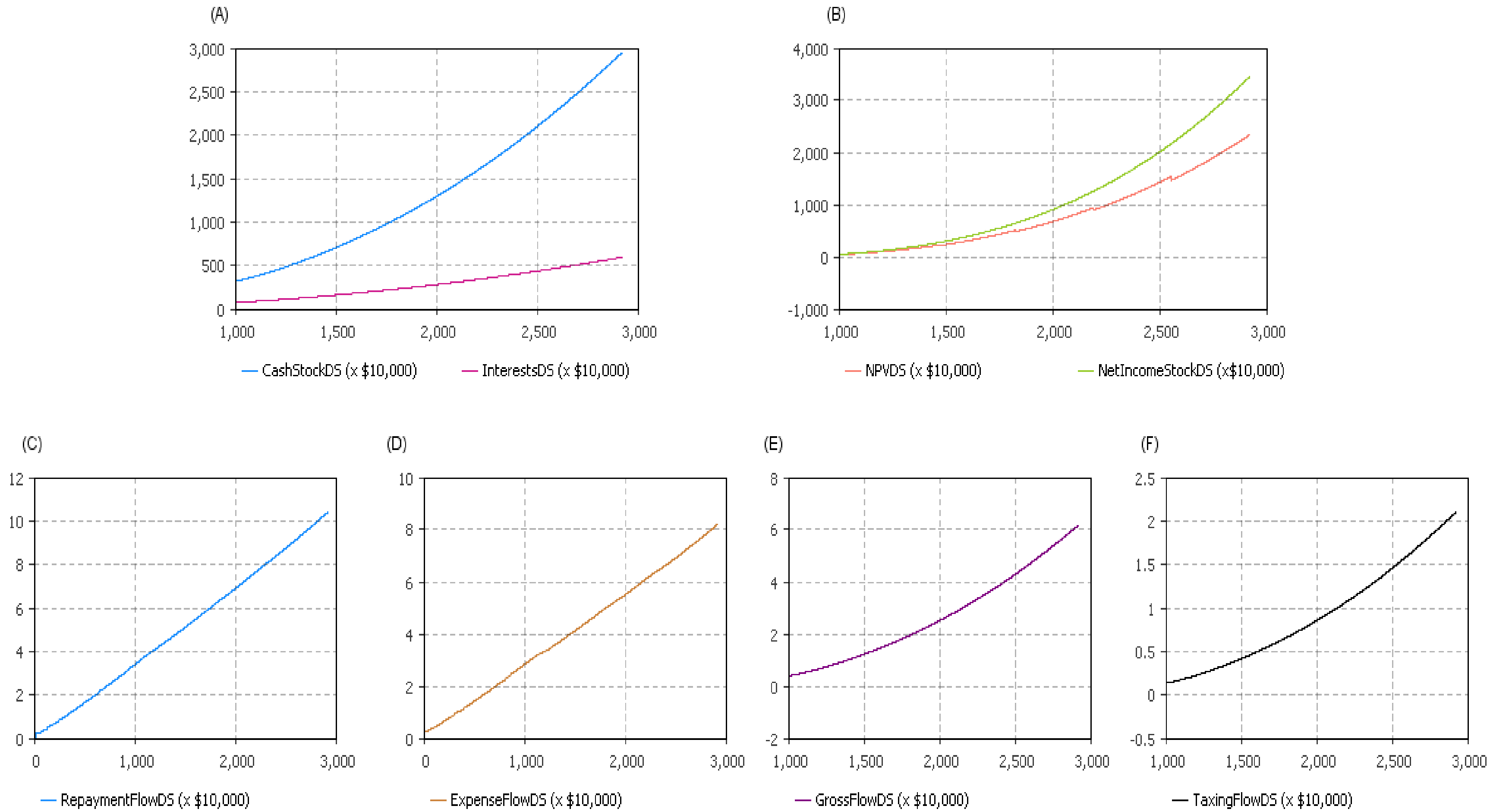


Figure 58: Time Plots of Stock and Flow Behaviors

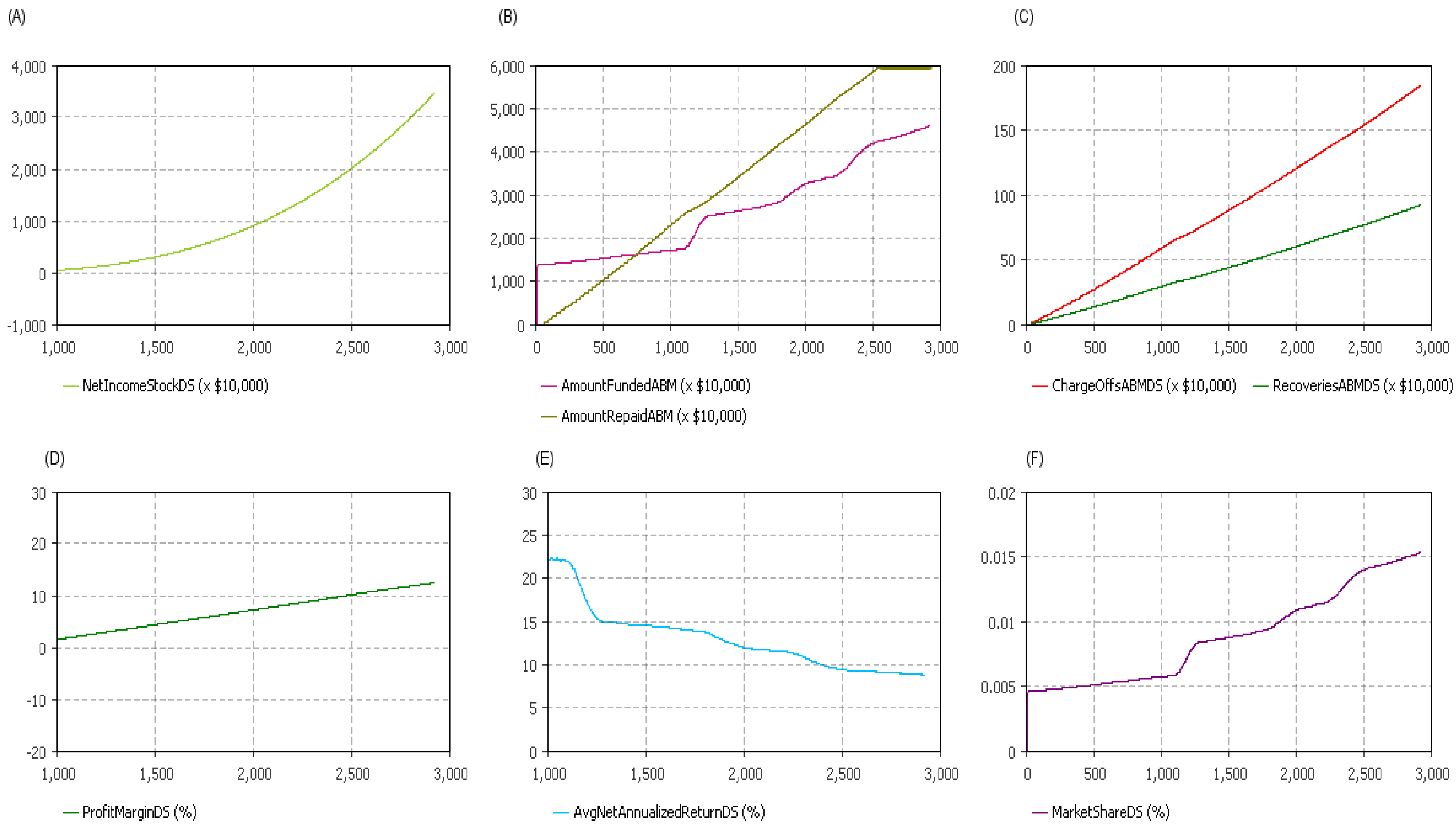


Figure 59: Time Plots of System Metrics

6.3 Policy Development

Decision making is a factor of marketing, quality and price. The effect of policy change is seen in the following stack charts with the result of simulated years form the basis of policy analysis. To perform a sensitivity analysis on the system, a variable takes on multiple values while the other variables are kept constant. This helps to identify what values of a particular variable has a potential of severely affecting the system.

Decision making is a factor of marketing, quality and price. Results from this model indicate the relationship between Acquisition Costs and Profit Margin (Figure 60) as well as Tax and Net Income Figure 61. As the Acquisition cost increases, the Net Income decreases and therefore Profit Margin also decreases. As expected, varying the acquisition cost has minimal effect on the *AvgNetAnnualizedReturn*.

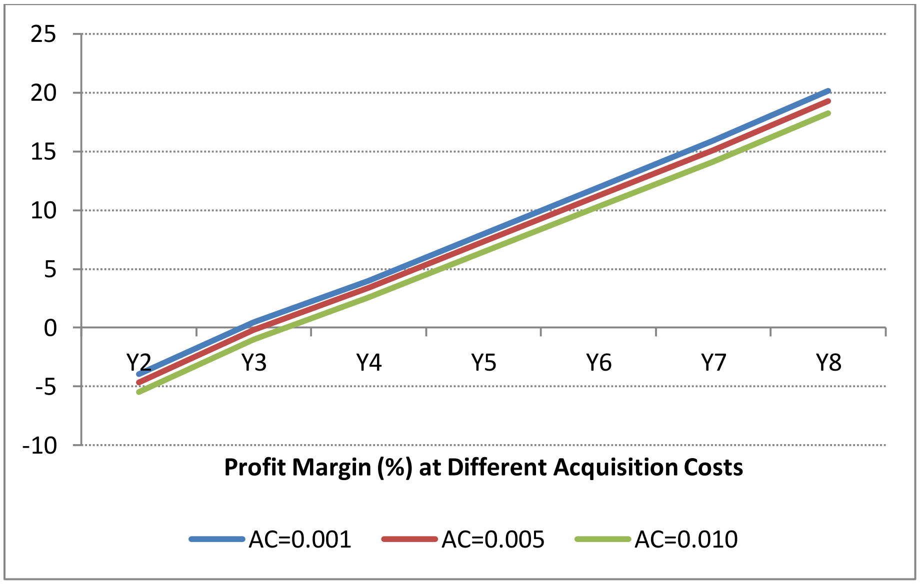


Figure 60: Variation of Profit Margin to Changes in Acquisition Costs

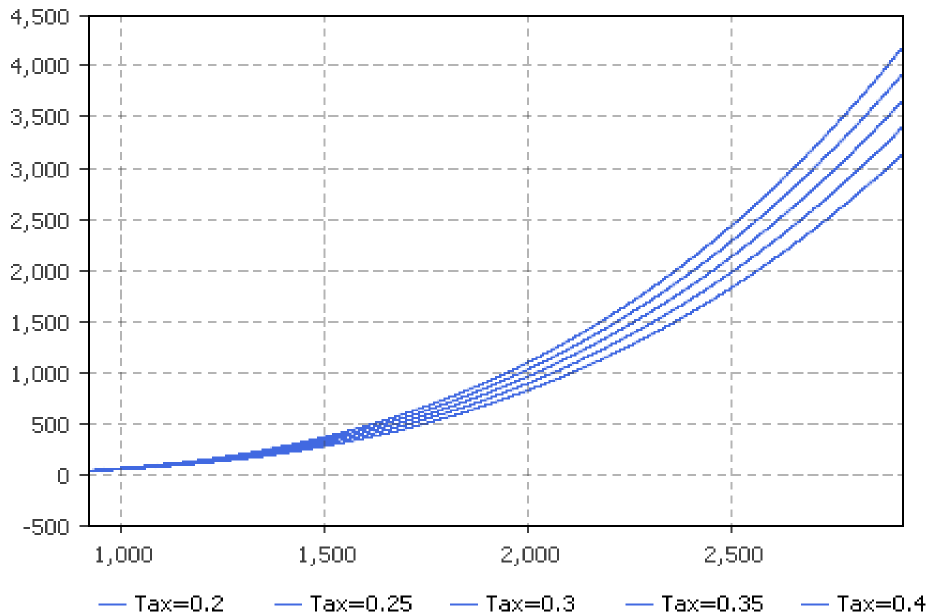


Figure 61: Variation of Net Income to Changes in Taxes

By having a high tax rate pushes the profitability horizon further out into the future. The developed model can be used to develop and test decision rules that shed some light into this problem. On the management front, it is observed that the business model does not become profitable for the company until after the second year due to lower initial capital invested in the organization. This result is determined based on conservative parameter values used to calibrate the system.

6.4 Conclusion

Participant characteristics give way to an aggregate of system behavior. The developed simulation models serve as a tested for managing control actions that incorporate fluctuations and stochasticity. The system dynamics model captures high level abstraction of the system.

Incorporating a multi-model paradigm consisting of agent based simulation allows appropriate choice of techniques that take into consideration different components of the system.

In online consumer-to-consumer lending, risks and uncertainties pervade various aspects of operation. Success of the business model is dependent on the number of lenders and qualified borrowers, capacity of IT infrastructures, employees, facilities and supporting services. The FICO scoring model is used to classify borrowers by riskiness. The model uses a consumer’s historical payments, outstanding debts, amount of credit available, length of credit history, mix of credit and recent new credit applications to make its calculations. The framework offers a structured approach for integrated design that incorporates process and stakeholders and management requirements and lends use to complex systems problems.

CHAPTER 7. CONCLUSIONS AND RECOMMENDATIONS

This chapter provides an overview of this research, a summary of the final results, conclusions and recommendations for future research. The primary outcome of this study is a decision making framework that takes into consideration system behaviors in the consumer-to-consumer ecommerce space. An analysis of the framework based on the selected case study results leads to useful conclusions as presented in this chapter.

7.1 Summary of Research

In CHAPTER 2, the current research applications related to ecommerce hybrid systems is examined. Literature revealed that performance dimensions can be summarized as risk/trust, market share and profitability. Management is ever faced with the dilemma of determining the impact of organization's processes, policies as well as the behavior of participants in the system would generate desired performance levels.

CHAPTER 3 described the approach used to address the research questions. The methodology to develop, and validate the proposed framework is presented. It was deduced that a combination of neural network, supply chain mapping and hybrid simulation presents a practical approach to solving ecommerce business problems.

CHAPTER 4 provided the proposed framework. Industrial engineering, operations engineering and engineering management tools are synthesized and leveraged to present the roadmap for developing a solution to C2C ecommerce complex hybrid systems that takes into account risk and trust related to system participants.

CHAPTER 5 presented the case study of a leading P2P company as well as analyzed associated data. Finally, CHAPTER 6 implemented and validated the developed framework using data from the case study. Simulation proved to be an effective measure for incorporating the behavior of participants in a system and how their actions affect the system on an aggregate level. The resulting simulation incorporates an interface complete with a control panel that enable management test the effects of varying different parameters and user characteristics in the system.

7.2 Conclusions

This study developed an approach to analyzing risk based complex ecommerce business systems. Furthermore, the developed framework is tested systematically on the case study by modularizing the problem into different parts. The resulting model ensures that overlapping of the SD and ADM models occur at defined interfaces with limited redundancy in the system. Results from this study enable managers and stakeholders in the ecommerce space meet desired targets and ensure that desired system performance is brought under control.

A major contribution of the research is in the application of the framework to the peer lending case study. We demonstrate that modeling and simulation of a peer lending case study is an effective way to assess viability of its business model. The developed simulation model takes into consideration difference in customer characteristics and stochasticity in demand patterns. Policy analysis entails recommending the right strategy such as how much is spent on overheads, transaction costs and investment in ads and technology.

The developed framework provides insights to the overall behavior of a consumer-to-consumer ecommerce complex system that seeks to incorporate individual behaviors of users as well as its effect on organizational bottom line. Thereby, providing insights to if a particular business model is profitable and how system performance can be improved. The result is a recommendation for a course of action which complements management’s expertise and intuition. Adopting the right tools to make this judgment can reduce time expended in considering different alternatives.

Selection of a simulation method involved identification of discrete and continuous elements and interactions between the elements. As illustrated in this study, there are benefits of incorporating engineering management tools with hybrid modeling paradigms in the ecommerce space. Incorporating effects of system feedback as well as interaction of variables captures complex behaviors in the system to reveal unintended effects. This presents a clear path to how consumer behavior affects organizational bottom line.

The choice of what users are screened into the system is especially important to the overall success of the system. A neural network is used to develop a model for risk classification using characteristics of the participants in the system. By using the neural network to approve users, the risk of misbehavior is reduced and patterns are easily spotted. The resulting framework can aid in predicting the probabilities of certain behaviors in the system. This assists management in identifying and classifying behaviors, hence mitigating or reducing the risk before it occurs.

7.3 Future Research

This study presents guidelines that provide valuable insights in to the development of hybrid simulations by demonstrating the integrated use of system dynamics and agent based simulation at the right abstraction levels to improve C2C ecommerce system performance.

The current study assumed that a particular borrower request is met solely by one lender. An extension to this will be to explore the case where a borrower's request is met by multiple lenders, and how this affects his individual performance. Further research can also investigate to what extent P2P model can reduce costs in finance systems and if such reduction is worth the associated risk.

The control panel can be improved to externally define characteristics of users coming into the system and to observe how parameter specified affect behavior of the users in the subsystems.

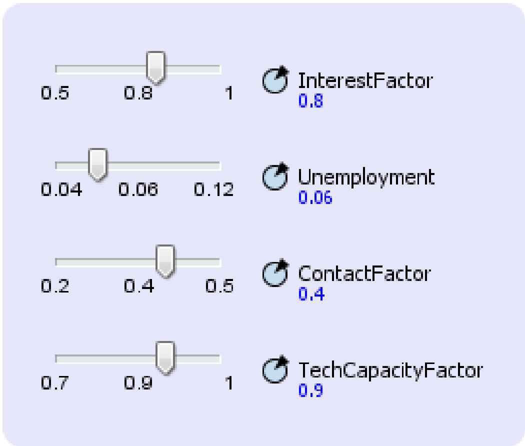


Figure 62: Sample Control Panel Parameters

Neural networks can also be used in other parts of model. For example the lookup table used to assign interest rates to different borrowers can be replaced by another neural network implementation (Figure 63). Validity of the results hinges on correct interpretation of the output of the model. As a result, there is a need to also improve the accuracy of NN prediction algorithm. While dti, FICO, employment were used in the neural network to control for risk in the presented case study, depending on the business model of interest, pertinent variables representing critical success factors can be used to derive a risk management plan.

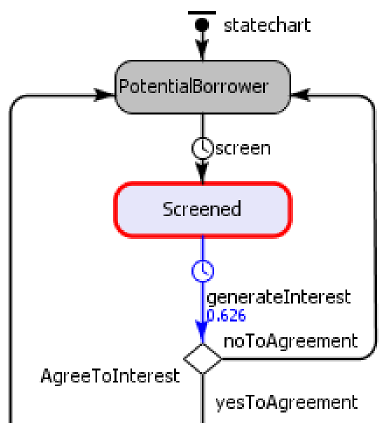


Figure 63: NN Algorithm for State Transitions

It is expected that conceptual modeling approaches will continue to be a beneficial approach for analyzing consumer-to-consumer complex systems. This study lays a foundation for future research to leverage the present study to expand on the guidelines and simulation development in modeling the operations of an organization.

APPENDIX A: MODEL DOCUMENTATION

System Dynamics Variables

AvgNetAnnualizedReturn =

(((InterestIncomeABM

- ServiceCharge*InterestIncomeABM

- ChargeOffsABM + RecoveriesABM)/AmountFundedABM)

/((8 - (Days*8 - Day)/Days))*100)

Expense =

((Overheads + AmountFundedABM * AcquisitionCost

+ InterestsToLenders + ChargeOffsABM)/Days)

GrossIncome =

Cash - InterestExpense - StartupCapital

MarketShare =

(AmountFundedABM/US_EcommerceSales)*100

ProfitMargin =

(((NetIncome *(1-Inflation))/InterestIncomeABM)/((8 - (Days*8 - Day)/Days)))*100

Repayment =

(InterestIncomeABM + AmountFundedABM*(OriginatingFactor+ServiceCharge)

+ AmountRepaidABM*ServiceCharge + RecoveriesABM)/Days

Taxing =

(Gross*Tax/Days)

```
requestServiceB()
	for( LendersAB ld : lendersABs )
		if( ld.borrowerAB == borrower )
			return;
	//add lender request to the queue
	loanRequests.addLast( borrower );
	//and make all lending club check the request queue
	for( LendersAB ld : lendersABs )
		ld.receive( "CHECK REQUEST QUEUE" );

thereAreRequests()
	return ! loanRequests.isEmpty();

getRequest
	//if( ! loanRequests.isEmpty() )
	return loanRequests.removeFirst();
```

Agent Based Simulation

PotentialBorrower

```
shapeBody.setFillColor(black);
get_Main().writeToLog(" Potential " + "Index: "+ getIndex() + " at Time: " +  time());
```

Screened

```
get_Main().writeToLog(" Screened " + "Index: "+ getIndex() + " at Time: " +  time() + "
Ammount: " + Amount);
Repay.restart();
```

yesToAgreement

```
MonthlyPayments = (Amount*(pow((1+InterestRate),(Term/12))))/Term;
MonthlyInterests = (MonthlyPayments*Term - Amount)/Term;
```

Funded

```
shapeBody.setFillColor(yellowGreen);
get_Main().AmountFundedABM+=Amount;
get_Main().writeToLog(" Funded " + "Index: "+ getIndex() + " at Time: " +   time());
```

defaultTransition

```
RepaidAmt=0;
InterestIncome = 0;
get_Main().remove_borrowerABs(this);
Repay.restart();
```

generateInterest

```
InterestRate = customFICOPDF(FICO);
get_Main().requestServiceB(this);
```

CreateNewBorrower

```
randomTrue(BContactRate)?1:0
```

Repay

```
if(statechart.isStateActive(InRepayment))
    {
        get_Main().AmountRepaidABM+=MonthlyPayments;
        RepaidAmt+=MonthlyPayments;
        get_Main().InterestIncomeABM+=MonthlyInterests;
        InterestIncome+=MonthlyInterests;
    }
if(CreateNewBorrower==1)
    {//create new borrowers during repayment at BContactRate
        get_Main().add_borrowerABs();
    }
```

APPENDIX B: NEURAL NETWORK IMPLEMENTATION

Test.java

```
public class test {
	public static void main(String [] args)
	{
		// create training set (logical XOR function)
		DataSet trainingSet =
		DataSet.createFromFile("Accept_Reject_Training_update01.csv", 4, 2, ",");

		// load saved neural network
		NeuralNetwork loadedMlPerceptron =
		NeuralNetwork.createFromFile("myMlPerceptron.nnet");

		int weightCount = 0;

		/*for( int l = 0; l < loadedMlPerceptron.getLayersCount(); l++ )
		{
			for( int n = 0; n < loadedMlPerceptron.getLayers()[l].getNeuronsCount();
			n++ )
			{
				System.out.print(loadedMlPerceptron.getWeights()[weightCount]
				+ " ");
				weightCount++;
			}
			System.out.println();
		}*/

		// test loaded neural network
		//System.out.println("Testing loaded neural network");
		testNeuralNetwork(loadedMlPerceptron, trainingSet);
```

```
}

public static void testNeuralNetwork(NeuralNetwork nnet, DataSet testSet) {
	PrintWriter printer = null;

	try {
		printer = new PrintWriter("testResults.csv", "UTF-8");
	} catch (FileNotFoundException e) {
		// TODO Auto-generated catch block
		e.printStackTrace();
	} catch (UnsupportedEncodingException e) {
		// TODO Auto-generated catch block
		e.printStackTrace();
	}

	//Write headers
	printer.println("Input1, Input2, Input3, Input4, Output1, Output2,
	NeuralNetworkResult, DesiredResult");

	int errorCount = 0;

	for(DataSetRow dataRow : testSet.getRows()) {
		nnet.setInput(dataRow.getInput());
		nnet.calculate();
		double[ ] networkOutput = nnet.getOutput();
		System.out.print("Input: " + Arrays.toString(dataRow.getInput()) );
		System.out.print(" Output: " + Arrays.toString(networkOutput) );
		System.out.println(" Outputln: " +
		Arrays.toString(dataRow.getDesiredOutput()));
```

```
            boolean acceptOutput = networkOutput[0] > networkOutput[1];

        boolean acceptTraining = dataRow.getDesiredOutput()[0] >
        dataRow.getDesiredOutput()[1];

            // Print the given input
            for( int i = 0; i < dataRow.getInput().length; i++ )
            printer.print(dataRow.getInput()[i] + ",");
            // Print the output
            for( int i = 0; i < networkOutput.length; i++ )
            printer.print(networkOutput[i] + ",");

            // Print the output
            printer.print(acceptOutput ? "1," : "0,");
            printer.println(acceptTraining ? "1" : "0");

            if( acceptOutput ^ acceptTraining ) errorCount++;
        }

        printer.close();

        System.out.println("\nError: " + (double)(errorCount) / testSet.size() + " " +
        errorCount + " " + testSet.size());
    }
}
```

Learn.java

```
public class learn {
	public static void main(String [] args)
	{
		// create training set (logical XOR function)
		DataSet trainingSet =
		DataSet.createFromFile("Accept_Reject_2000_Training_update.csv", 4, 2, ",");

		// create multi layer perceptron
		MultiLayerPerceptron myMlPerceptron = new
		MultiLayerPerceptron(TransferFunctionType.SIGMOID, 4, 5, 3, 2);

		System.out.println("Learning started");

		myMlPerceptron.getLearningRule().learn(trainingSet, 0.01, 1000);

		// test perceptron
		System.out.println("Testing trained neural network");

		// save trained neural network
		myMlPerceptron.save("myMlPerceptron.nnet");
	}
}
```

REFERENCES

Afuah, A., & Tucci, C. L. (2000). *Internet Business Models and Strategies: Text and Cases* (1st ed.). McGraw-Hill Higher Education.

Akerlof, G. A. (1970). The Market for “lemons”: Quality Uncertainty and the Market Mechanism. *Quarterly Journal of Economics*, *84*(3), 488–500.

Alshammri, G. (2009). Investigation of Agent or Multi-agent Technologies in E-Commerce Systems. *IJCSNS*, *9*(10), 231.

Alt, R., & Puschmann, T. (2012). The rise of customer-oriented banking - electronic markets are paving the way for change in the financial industry. *Electronic Markets*, *22*(4), 203–215. http://doi.org/http://dx.doi.org/10.1007/s12525-012-0106-2

Alvanchi, A., Lee, S., & AbouRizk, S. (2011). Modeling framework and architecture of hybrid system dynamics and discrete event simulation for construction. *Computer-Aided Civil and Infrastructure Engineering*, *26*(2), 77–91.

Amit, R., & Zott, C. (2001). Value creation in E-business. *Strategic Management Journal*, *22*(6-7), 493–520. http://doi.org/10.1002/smj.187

An, L., & Jeng, J.-J. (2005). On developing system dynamics model for business process simulation. In *Simulation Conference, 2005 Proceedings of the Winter* (p. 10 pp.–). http://doi.org/10.1109/WSC.2005.1574489

Bachmann, A., Becker, A., Buerckner, D., Hilker, M., Kock, F., Lehmann, M., … Funk, B. (2011). Online Peer-to-Peer Lending -- A Literature Review. *Journal of Internet Banking & Commerce*, *16*(2), 1–18.

Bădică, C., Ganzha, M., & Paprzycki, M. (2007). Developing a model agent-based e-commerce system. In *E-Service Intelligence* (pp. 555–578). Springer. Retrieved from http://link.springer.com/content/pdf/10.1007/978-3-540-37017-8_26.pdf

Bodie, Z., Kane, A., & Marcus, A. J. (2011). *Investments*. New York: McGraw-Hill/Irwin.

Boonyathan, P., & Al-Hakim, L. (2007). *Procedure for Modeling and Improving E-SCM Processes*. IGI Global.

Borshchev, A. (2013). *Big book of simulation modeling: multimethod modeling with anylogic 6*. [S.l.]: Anylogic.

Borshchev, A., & Filippov, A. (2004). From system dynamics and discrete event to practical agent based modeling: reasons, techniques, tools. In *Proceedings of the 22nd international conference of the system dynamics society*. Retrieved from http://www.econ.iastate.edu/tesfatsi/systemdyndiscreteeventabmcompared.borshchevfilippov04.pdf

Borshchev, A., Karpov, Y., & Kharitonov, V. (2002). Distributed simulation of hybrid systems with AnyLogic and HLA. *Future Generation Computer Systems*, *18*(6), 829.

Borshchev, A. V., Kolesov, Y. B., & Senichenkov, Y. B. (2000). Java engine for UML based hybrid state machines. In *Proceedings of the 32nd conference on Winter simulation* (pp. 1888–1894). Society for Computer Simulation International. Retrieved from http://dl.acm.org/citation.cfm?id=510653

Brau, J. C., & Woller, G. M. (2004). Microfinance: A comprehensive review of the existing literature. *Journal of Entrepreneurial Finance, JEF*, *9*(1), 1–27.

Bucki, R., & Suchanek, P. (2012). The Method of Logistic Optimization in E-commerce. *J. UCS*, *18*(10), 1238–1258.

Canetta, L., Cheikhrouhou, N., & Glardon, R. (2013). Modelling hybrid demand (e-commerce "+" traditional) evolution: A scenario planning approach. *International Journal of Production Economics*, *143*(1), 95–108. http://doi.org/10.1016/j.ijpe.2010.06.003

Carlsson, C., & Turban, E. (2002). DSS: directions for the next decade. *Decision Support Systems, 33*(2), 105–110. http://doi.org/10.1016/S0167-9236(01)00137-3

Chan, F. T. S., & Chan, H. k. (2005). Simulation modeling for comparative evaluation of supply chain management strategies. *The International Journal of Advanced Manufacturing Technology*, (9). Retrieved from https://login.ezproxy.net.ucf.edu/login?auth=shibb&url=http://search.ebscohost.com/login.aspx?direct=true&db=edsgao&AN=edsgcl.154069249&site=eds-live&scope=site

Chen, Dn, Jeng, B., Lee, W., & Chuang, C. (2008). An agent-based model for consumer-to-business electronic commerce. *EXPERT SYSTEMS WITH APPLICATIONS*, *34*(1), 469–481.

Chen, Dongyu, Lai, F., & Lin, Z. (2014). A trust model for online peer-to-peer lending: a lender's perspective. *Information Technology and Management*, *15*(4), 239–254. http://doi.org/10.1007/s10799-014-0187-z

Chen, L., Danbolt, J., & Holland, J. (2014). Rethinking bank business models: the role of intangibles. *Accounting, Auditing & Accountability Journal*, *27*(3), 563–589. http://doi.org/10.1108/AAAJ-11-2012-1153

Chingning Wang, & Ping Zhang. (2012). The Evolution of Social Commerce: The People, Management, Technology, and Information Dimensions. *Communications of the Association for Information Systems*, *31*, 105–127.

Cope, D. (2008). *Automatic generation of supply chain simulation models from SCOR based ontologies* (Ph.D.). University of Central Florida, United States -- Florida. Retrieved from http://search.proquest.com.ezproxy.net.ucf.edu/docview/89259096/abstract/339D7A60B73446F3PQ/12?accountid=10003

Crook, J. N., Edelman, D. B., & Thomas, L. C. (2007). Recent developments in consumer credit risk assessment. *European Journal of Operational Research*, *183*(3), 1447–1465. http://doi.org/10.1016/j.ejor.2006.09.100

DeLone, W. H., & McLean, E. R. (1992). Information Systems Success: The Quest for the Dependent Variable. *Information Systems Research*, *3*(1), 60–95.

DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. *Journal of Management Information Systems*, *19*(4), 9–30.

Emekter, R., Tu, Y., Jirasakuldech, B., & Lu, M. (2015). Evaluating credit risk and loan performance in online Peer-to-Peer (P2P) lending. *Applied Economics*, *47*(1), 54–70. http://doi.org/10.1080/00036846.2014.962222

Eriksson, H.-E., & Penker, M. (2000). Business modeling with UML. *Business Patterns at Work, John Wiley & Sons, New York, USA*. Retrieved from http://www.utm.mx/~caff/poo2/Business%20Modeling%20with%20UML.pdf

Everett, C. R. (2011). *Information asymmetry in relationship versus transactional debt markets: Evidence from peer-to-peer lending* (Ph.D.). Purdue University, United States -- Indiana. Retrieved from http://search.proquest.com.ezproxy.net.ucf.edu/pqdtft/docview/900575059/abstract/14226EADA06108C41D2/1?accountid=10003

Forrester, J. W. (1961). *Industrial dynamics*. [Cambridge, Mass.] M.I.T. Press, 1961.

García, M. T., Barcelona, M. A., Ruiz, M., García-Borgoñón, L., & Ramos, I. (2014). A Discrete-Event Simulation Metamodel for Obtaining Simulation Models from Business Process Models. In M. J. Escalona, G. Aragón, H. Linger, M. Lang, C. Barry, & C. Schneider (Eds.), *Information System Development* (pp. 307–317). Springer International Publishing. Retrieved from http://link.springer.com.ezproxy.net.ucf.edu/chapter/10.1007/978-3-319-07215-9_25

Ghezzi, A., Mangiaracina, R., & Perego, A. (2012). Shaping the E-Commerce Logistics Strategy: a Decision Framework. *International Journal of Engineering Business Management*, *4*, 1.

Gimenez, C., & Ramalhinho-Lourenco, H. (2004). E-Supply Chain Management: Review, Implications and Directions for Future Research.

Greiner, M. E., & Wang, H. (2010). Building Consumer-to-Consumer Trust in E-Finance Marketplaces: An Empirical Analysis. *International Journal of Electronic Commerce*, *15*(2), 105–136. http://doi.org/10.2753/JEC1086-4415150204

Grieger, M. (2004). An empirical study of business processes across Internet-based electronic marketplaces: A supply-chain-management perspective. *Business Process Management Journal*, *10*(1), 80–100.

Guttman, R. H., Moukas, A. G., & Maes, P. (1998). Agent-mediated electronic commerce: a survey. *The Knowledge Engineering Review*, *13*(02), 147–159.

Haewon Yum, Byungtae Lee, & Myungsin Chae. (2012). From the wisdom of crowds to my own judgment in microfinance through online peer-to-peer lending platforms. *Electronic Commerce Research and Applications*, *11*(5), 469–83. http://doi.org/10.1016/j.elerap.2012.05.003

Hamel, G. (2002). *Leading the revolution: how to thrive in turbulent times by making innovation a way of life*. New York: Plume Book.

Harel, D. (1987). Statecharts: a visual formalism for complex systems. *Science of Computer Programming*, *8*(3), 231–274. http://doi.org/10.1016/0167-6423(87)90035-9

He, B., Shi, Y., Wan, Q., & Zhao, X. (2014). Prediction of Customer Attrition of Commercial Banks based on SVM Model. *Procedia Computer Science*, *31*, 423.

He, M., Jennings, N. R., & Leung, H. (2003). On agent-mediated electronic commerce. *IEEE Transactions on Knowledge and Data Engineering*, *15*(4), 985–1003. http://doi.org/10.1109/TKDE.2003.1209014

Helal, M. (2008). *A hybrid system dynamics-discrete event simulation approach to simulating the manufacturing enterprise* (Ph.D.). University of Central Florida, United States -- Florida. Retrieved from http://search.proquest.com.ezproxy.net.ucf.edu/pqdtft/docview/304353738/abstract/5DB9EBD8191844D2PQ/26?accountid=10003

Helal, M., Rabelo, L., Sepúlveda, J., & Jones, A. (2007). A methodology for integrating and synchronizing the system dynamics and discrete event simulation paradigms. In *Proceedings of the 25th international conference of the system dynamics society* (Vol. 3, pp. 1–24). Retrieved from http://www.systemdynamics.org/conferences/2007/proceed/papers/HELAL482.pdf

Hermann, J. W., Lin, E., & Pundoor, G. (2003). Supply Chain Simulation Modeling Using the Supply Chain Operations Reference Model, 461–469. http://doi.org/10.1115/DETC2003/CIE-48220

Hlupic, V., de Vreede, G., & Orsoni, A. (2006). Modelling and simulation techniques for business process analysis and re-engineering. *International Journal of Simulation*, *7*(4), 1–8.

Hook, G. (2011). Business Process Modeling and simulation. *Proceedings of the 2011 Winter Simulation Conference (WSC)*, 773.

Jacob, M., Suchan, C., & Ferstl, O. K. (2010). Modeling of Business Systems using Hybrid Simulation: A New Approach. In *ECIS*. Retrieved from http://aisel.aisnet.org/cgi/viewcontent.cgi?article=1162&context=ecis2010

Jacobs, B. I., Levy, K. N., & Markowitz, H. M. (2004). Financial Market Simulation. *Journal of Portfolio Management*, *30*, 142–152.

Januszczak, J., & Hook, G. (2011). Simulation standard for business process management. *Proceedings of the Winter Simulation Conference (2011)*, 741.

Johnson, S., Ashta, A., & Assadi, D. (2010). Online or Offline? The Rise of “Peer-to-Peer” Lending in Microfinance. *Journal of Electronic Commerce in Organizations*, *8*(3), 26–37. http://doi.org/10.4018/jeco.2010070103

Joledo, O., Bernard, J., Cisneros, J., & Laval, S. (2013, November). Lending Club - Case Study Analysis. EIN 6182: Engineering Management Final Report.

Joledo, O., Bernard, J., & Rabelo, L. (2014). Business Model Mapping: A Social Lending Case Study and Preliminary Work. *IIE Annual Conference. Proceedings*, 1282–1290.

Kaplan, R. S., & Norton, D. P. (2001). *The strategy-focused organization: how balanced scorecard companies thrive in the new business environment*. Boston, Mass.: Harvard Business School Press.

Kim, D. (2013). Under what conditions will social commerce business models survive? *Electronic Commerce Research and Applications*, *12*(2), 69–77. http://doi.org/10.1016/j.elerap.2012.12.002

Kim, S. M. (2004). *An empirical investigation of the impact of electronic commerce on supply chain management: A study in the healthcare industry* (Ph.D.). The University of

Nebraska - Lincoln, United States -- Nebraska. Retrieved from http://search.proquest.com.ezproxy.net.ucf.edu/pqdtft/docview/305160749/abstract/68018E9ABC6340BBPQ/57?accountid=10003

Kirandeep Chahal, Tillal Eldabi, & Terry Young. (2013). A conceptual framework for hybrid system dynamics and discrete event simulation for healthcare. *Journal of Enterprise Information Management*, *26*(1/2), 50–74. http://doi.org/10.1108/17410391311289541

Kirchmer, M. (2004). E-business process networks - successful value chains through standards. *Journal of Enterprise Information Management*, *17*(1), 20–30.

Krumme, K. A., & Herrero, S. (2009). Lending behavior and community structure in an online peer-to-peer economic network. In *2009 International Conference on Computational Science and Engineering (CSE), 29-31 Aug. 2009* (Vol. vol.4, pp. 613–18). IEEE. http://doi.org/10.1109/CSE.2009.185

Kuhl, F., Weatherly, R., & Dahmann, J. (1999). *Creating computer simulation systems: an introduction to the high level architecture*. Prentice Hall PTR. Retrieved from http://dl.acm.org/citation.cfm?id=318931

Lättilä, L., Hilletofth, P., & Lin, B. (2010). Hybrid simulation models – When, Why, How? *Expert Systems with Applications*, *37*(12), 7969–7975. http://doi.org/10.1016/j.eswa.2010.04.039

Law, A. M. (2009). How to build valid and credible simulation models. *Winter Simulation Conference*, 24.

Lee, J.-S., Zhou, M.-C., & Hsu, P.-L. (2004). A multi-paradigm modeling approach for hybrid dynamic systems. In *2004 IEEE International Symposium on Computer Aided Control Systems Design* (pp. 77–82). http://doi.org/10.1109/CACSD.2004.1393854

Leedy, P. D., & Ormrod, J. E. (2013). *Practical research: planning and design*. Boston: Pearson.

Li, L., Su, Q., & Chen, X. (2011). Ensuring supply chain quality performance through applying the SCOR model. *International Journal of Production Research*, *49*(1), 33–57. http://doi.org/10.1080/00207543.2010.508934

Liang, T.-P., & Huang, J.-S. (2000). A framework for applying intelligent agents to support electronic trading. *Decision Support Systems*, *28*(4), 305–317. http://doi.org/10.1016/S0167-9236(99)00098-6

Liang, T.-P., & Turban, E. (2011). Introduction to the Special Issue Social Commerce: A Research Framework for Social Commerce. *International Journal of Electronic Commerce*, *16*(2), 5–14.

Lin, M. (2009). Peer-to-peer lending: An empirical study. *15th Americas Conference on Information Systems 2009*, *7*, 132 –138.

Lin, M., Prabhala, N. R., & Viswanathan, S. (2013). Judging borrowers by the company they keep: Friendship networks and information asymmetry in online peer-to-peer lending. *Management Science*, *59*(1), 17–35. http://doi.org/10.1287/mnsc.1120.1560

Longo, F., & Mirabelli, G. (2008). An advanced supply chain management tool based on modeling and simulation. *Computers & Industrial Engineering*, *54*(3), 570–588. http://doi.org/10.1016/j.cie.2007.09.008

Lopez-Sanchez, M., Noria, X., Rodríguez, J. A., & Gilbert, N. (2005). Multi-agent based simulation of news digital markets. *International Journal of Computer Science & Applications*, *2*(1), 7–14.

Lorenz, T., & Jost, A. (2006). Towards an orientation framework in multi-paradigm modeling. In *Proceedings of the 24th international conference of the system dynamics society* (pp. 1–18). Retrieved from http://www.systemdynamics.org/conferences/2006/proceed/papers/LOREN178.pdf

Lyons, M. H., Adjali, I., Collings, D., & Jensen, K. O. (2003). Complex Systems Models for Strategic Decision Making. *BT Technology Journal*, *21*(2), 11–27. http://doi.org/10.1023/A:1024419706667

Macal, C M, & North, M. J. (2010). Tutorial on agent-based modelling and simulation. *Journal of Simulation*, *4*(3), 151.

Macal, Charles M. (2010). To agent-based simulation from system dynamics. In *Simulation Conference (WSC), Proceedings of the 2010 Winter* (pp. 371–382). IEEE. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=5679148

Magee, J. R. (2011). Peer-to-Peer Lending in the United States: Surviving After Dodd-Frank. *North Carolina School Banking Institute Journal*, *15*, 139–174.

Mahadevan, B. (2000). Business Models for Internet-Based E-Commerce: AN ANATOMY. *California Management Review*, *42*(4), 55–69.

Majois, C., & Van Damme, S. (2013). Peer to Peer Microfinance: The Case of Zidisha. org. *Louvain School Of Management, France., Available at Https://www. Zidisha. Org/edi Figures/news_docs/Louvain. Pdf, Accessed*, *29*. Retrieved from https://www.zidisha.org/editables/news_docs/Louvain.pdf

Maler, O., Manna, Z., & Pnueli, A. (1992). From timed to hybrid systems. In J. W. de Bakker, C. Huizing, W. P. de Roever, & G. Rozenberg (Eds.), *Real-Time: Theory in Practice* (pp. 447–484). Springer Berlin Heidelberg. Retrieved from http://link.springer.com/chapter/10.1007/BFb0032003

Manchala, D. (2000). E-commerce trust metrics and models. *IEEE INTERNET COMPUTING*, *4*(2), 36–44.

Murphy, J. (2000). Assuring Performance in ecommerce Systems. In *Proc. of the IEE 16th UK Teletraffic Symposium* (p. 29). Retrieved from http://pel.ucd.ie/files/Assuring.pdf

Nilson, L. B. (2010). *Teaching at Its Best: A Research-Based Resource for College Instructors* (3 edition). San Franciso, CA: Jossey-Bass.

North, M. J., & Macal, C. M. (2007). *Managing Business Complexity: Discovering Strategic Solutions with Agent-Based Modeling and Simulation* (1 edition). Oxford ; New York: Oxford University Press.

Ossimitz, G., & Mrotzek, M. (2008). The basics of system dynamics: discrete vs. continuous modelling of time. In *Proceedings of the 26th International Conference of the System Dynamics Society*. Retrieved from http://teoriasistemas.mex.tl/imagesnew/6/6/4/5/2/Simulacion%20discreta%20vs%20Continua.pdf

Pateli, A. G., & Giaglis, G. M. (2004). A research framework for analysing eBusiness models. *European Journal of Information Systems*, *13*(4), 302–314. http://doi.org/10.1057/palgrave.ejis.3000513

Paul, R. J., Hlupic, V., & Giaglis, G. M. (1998). Simulation Modelling Of Business Processes. In *PROCEEDINGS OF THE 3 RD U.K. ACADEMY OF INFORMATION SYSTEMS CONFERENCE, MCGRAWHILL* (pp. 311–320). McGraw-Hill.

Persson, F., Bartoll, C., Ganovic, A., Lidberg, M., Nilsson, M., Wibaeus, J., & Winge, F. (2012). Supply chain dynamics in the SCOR model - A simulation modeling approach. In *Simulation Conference (WSC), Proceedings of the 2012 Winter* (pp. 1–12). http://doi.org/10.1109/WSC.2012.6465030

Persson, Fredrik. (2011). SCOR template-A simulation based dynamic supply chain analysis tool. *International Journal of Production Economics*, *131*(1), 288–294. http://doi.org/10.1016/j.ijpe.2010.09.029

Petrovic, O., Kittl, C., & Teksten, R. D. (2001). *Developing Business Models for Ebusiness* (SSRN Scholarly Paper No. ID 1658505). Rochester, NY: Social Science Research Network. Retrieved from http://papers.ssrn.com/abstract=1658505

Porter, M. E. (1998). *Competitive advantage : creating and sustaining superior performance : with a new introduction / Michael E. Porter*. New York : Free Press, [1998].

Rabelo, L., Eskandari, H., Shaalan, T., & Helal, M. (2007). Value chain analysis using hybrid simulation and AHP. *International Journal of Production Economics*, *105*(2), 536–547. http://doi.org/10.1016/j.ijpe.2006.05.011

Rabelo, L., Eskandari, H., Shalan, T., & Helal, M. (2005). Supporting simulation-based decision making with the use of AHP analysis. In *Proceedings of the 37th conference on Winter simulation* (pp. 2042–2051). Winter Simulation Conference. Retrieved from http://dl.acm.org/citation.cfm?id=1163064

Rabelo, L., Helal, M., Jones, A., & Hyeung-Sik Min. (2005). Enterprise simulation: a hybrid system approach. *International Journal of Computer Integrated Manufacturing*, *18*(6), 498–508. http://doi.org/10.1080/09511920400030138

Rabelo, L., Sarmiento, A. T., Helal, M., & Jones, A. (2015). Supply chain and hybrid simulation in the hierarchical enterprise. *International Journal of Computer Integrated Manufacturing*, *28*(5), 488–500. http://doi.org/10.1080/0951192X.2014.880807

Redmond, U., & Cunningham, P. (2013). A temporal network analysis reveals the unprofitability of arbitrage in The Prosper Marketplace. *Expert Systems with Applications*, *40*(9), 3715–21. http://doi.org/10.1016/j.eswa.2012.12.077

Robinson, S. (2012). Tutorial: Choosing what to model — Conceptual modeling for simulation. In *Simulation Conference (WSC), Proceedings of the 2012 Winter* (pp. 1–12). http://doi.org/10.1109/WSC.2012.6465308

Robledo, L. F., Sepulveda, J., & Archer, S. (2013). Hybrid Simulation Decision Support System for University Management. In *Proceedings of the 2013 Winter Simulation Conference: Simulation: Making Decisions in a Complex World* (pp. 2066–2075). Piscataway, NJ, USA: IEEE Press. Retrieved from http://dl.acm.org/citation.cfm?id=2676128.2676240

Roman, Š., & Kateřina, S. (2012). The Usability of Agent-Based Simulation in Decision Support System of E-Commerce Architecture. *International Journal of Information Engineering and Electronic Business(IJIEEB)*, *4*(1), 10.

Ryan, A., Jackson, H., & Tufano, P. (2010). Lending Club. *Harvard Business School Cases*, 1.

Ryan, J., Reuk, K., & Wang, C. (2007). To fund or not to fund: Determinants of loan fundability in the prosper. com marketplace. *WP, The Standord Graduate School of Business*. Retrieved from http://www.prosper.com/Downloads/Research/Prosper_Regression_Project-Fundability_Study.pdf

Sahlman, W. A., & Kind, E. (2006). Prosper Marketplace, Inc. *Harvard Business School Case, 807-074*. Retrieved from http://www.hbs.edu/faculty/Pages/item.aspx?num=33885

Schmid, H. A., & Rossi, G. (2002). Designing Business Processes in E-commerce applications. In *E-Commerce and Web Technologies* (pp. 353–362). Springer. Retrieved from http://link.springer.com/chapter/10.1007/3-540-45705-4_37

Sengupta, R., & Aubuchon, C. P. (2008). The Microfinance Revolution: An Overview. *Federal Reserve Bank of St. Louis Review, Vol. 90, No. 1*(January/February 2008). Retrieved from http://research.stlouisfed.org/publications/review/article/6256

Sethi, V. (2014). Foundations of E-Commerce - Nanyang Technological University, Singapore. Retrieved November 21, 2015, from https://www.coursera.org/course/ntuecom

Shen, D., Krumme, C., & Lippman, A. (2010). Follow the Profit or the Herd? Exploring Social Effects in Peer-to-Peer Lending. In *2010 IEEE Second International Conference on Social Computing (SocialCom)* (pp. 137–144). http://doi.org/10.1109/SocialCom.2010.28

Siebers, P.-O., & Aickelin, U. (2008). Introduction to Multi-Agent Simulation.

Smeureanu, I., Ruxanda, G., Diosteanu, A., Delcea, C., & Cotfas, L. A. (2012). Intelligent Agents and Risk Based Model for Supply Chain Management. *Technological & Economic Development of Economy*, *18*(3), 452–469. http://doi.org/10.3846/20294913.2012.710178

Speller, T., Rabelo, L., & Jones, A. (2007). Value chain modelling using system dynamics. *International Journal of Manufacturing Technology and Management*, *11*(2), 135–156.

Sterman, J. (2000). *Business dynamics : systems thinking and modeling for a complex world / John D. Sterman*. Boston : Irwin/McGraw-Hill, c2000.

Sulistio, A., Yeo, C. S., & Buyya, R. (2004). A taxonomy of computer-based simulations and its mapping to parallel and distributed systems simulation tools. *Software: Practice and Experience*, *34*(7), 653–673.

Sung, C., & Kim, T. G. (2011). Framework for Simulation of Hybrid Systems: Interoperation of Discrete Event and Continuous Simulators Using HLA/RTI. In *2011 IEEE Workshop on Principles of Advanced and Distributed Simulation (PADS)* (pp. 1–8). http://doi.org/10.1109/PADS.2011.5936768

Sung, T. K. (2006). E-commerce critical success factors: East vs. West. *Technological Forecasting and Social Change*, *73*(9), 1161–1177. http://doi.org/10.1016/j.techfore.2004.09.002

Tako, A. A., & Robinson, S. (2012). The application of discrete event simulation and system dynamics in the logistics and supply chain context. *Decision Support Systems*, *52*(4), 802–815. http://doi.org/10.1016/j.dss.2011.11.015

Thomas, L. C. (2000). A survey of credit and behavioural scoring: forecasting financial risk of lending to consumers. *International Journal of Forecasting*, *16*(2), 149–172.

Timmers, P. (1998). Business Models for Electronic Markets. *Electronic Markets*, *8*(2), 3.

Turner, J. R., & Danks, S. (2014). Case Study Research: A Valuable Learning Tool for Performance Improvement Professionals. *Performance Improvement*, *53*(4), 24–31. http://doi.org/10.1002/pfi.21406

Twomey, P., & Cadman, R. (2002). Agent-Based Modelling of Customer Behaviour in the Telecoms and Media Markets. *Info*, *4*(1), 56–63. http://doi.org/http://www.emeraldinsight.com/journals.htm?issn=1463-6697

Vuksic, V. B., Stemberger, M. I., & Jaklic, J. (2002). Simulation modelling towards e-business models development. *Journal of Simulation*, *2*(2), 25–36.

Vyas, M., & Singh, S. (2011). Risk Management in Banking Sector. *BVIMR Management Edge*, *4*(1), 15–24.

Wang, B., & Moon, Y. B. (2013). Hybrid modeling and simulation for innovation deployment strategies. *Industrial Management & Data Systems*, *113*(1), 136–154. http://doi.org/10.1108/02635571311289719

Wang, H., Huang, J., & Lee, C. (2005). Critical success factors for electronic commerce in Chinese electronic information industry. *Tsinghua Science and Technology*, *10*(S1), 746–752.

Weng, Z. (2007). *A framework for mobile e-commerce based on intelligent agents* (M.Sc.). University of Ottawa (Canada), Canada. Retrieved from http://search.proquest.com.ezproxy.net.ucf.edu/pqdtft/docview/304738548/abstract/ADE25B921A044E6FPQ/1?accountid=10003

Wu, H.-Y. (2012). Constructing a strategy map for banking institutions with key performance indicators of the balanced scorecard. *Evaluation and Program Planning*, *35*(3), 303–320. http://doi.org/10.1016/j.evalprogplan.2011.11.009

Wu, J.-H., & Hisa, T.-L. (2004). Analysis of E-commerce innovation and impact: a hypercube model. *Electronic Commerce Research and Applications*, *3*(4), 389–404. http://doi.org/10.1016/j.elerap.2004.05.002

Zeigler, B. P. (2006). Embedding DEV&DESS in DEVS. In *Proc. DEVS Integrative M&S Symp*. Retrieved from http://acims.asu.edu/wp-content/uploads/2012/02/Embedding-DEVDESS-in-DEVS.pdf

Zhang, T., & Zhang, D. (2007). Agent-based simulation of consumer purchase decision-making and the decoy effect. *Journal of Business Research*, *60*, 912–922. http://doi.org/10.1016/j.jbusres.2007.02.006

Zhong, J., Zhu, W., Wu, Y., & Wang, K. (2012). Agent-based Simulation of Online Trading. *Systems Engineering Procedia*, *5*, 437–444. http://doi.org/10.1016/j.sepro.2012.04.066

Žigić, D., & Hadžić, M. (2012). The Process of Risk Management in Financial Business. *PROCES UPRAVLJANJA RIZIKOM U FINANSIJSKOM POSLOVANJU.*, *9*(2), 33–40.