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DYNAMOD – A Dynamic Agent Based Modelling Framework for Digital Businesses

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Abstract

Digital Businesses have become a major driver for economic growth and have seen an explosion of new startups. At the same time, it also includes mature enterprises that have become global giants in a relatively short period of time. Digital Businesses have unique characteristics that make the running and management of a Digital Business much different from traditional offline businesses. Digital businesses respond to online users who are highly interconnected and networked. This enables a rapid flow of word of mouth, at a pace far greater than ever envisioned when dealing with traditional products and services. The relatively low cost of incremental user addition has led to a variety of innovation in pricing of digital products, including various forms of free and freemium pricing models. This thesis explores the unique characteristics and complexities of Digital Businesses and its implications on the design of Digital Business Models and Revenue Models.

The thesis proposes an Agent Based Modeling Framework that can be used to develop Simulation Models that simulate the complex dynamics of Digital Businesses and the user interactions between users of a digital product. Such Simulation models can be used for a variety of purposes such as simple forecasting, analysing the impact of market disturbances, analysing the impact of changes in pricing models and optimising the pricing for maximum revenue generation or a balance between growth in usage and revenue generation. These models can be developed for a mature enterprise with a large historical record of user growth rate as well as for early stage enterprises without much historical data. Through three case studies, the thesis demonstrates the applicability of the Framework and its potential applications.

Keywords: Business Model, Digital Business, Agent Based Modeling, Simulation, Optimization

Resumo

Negócios Digitais estabeleceram-se como um importante motor para o crescimento económico e têm presenciado uma explosão de novas *startups*. Em simultâneo, permitiram que empresas estabelecidas se tenham tornado em gigantes globais num período de tempo relativamente curto. Negócios Digitais possuem características únicas que tornam a sua execução e gestão muito diferente de um negócio tradicional *offline*. Negócios Digitais lidam com utilizadores *online* que estão altamente interligados e em rede. Isto permite uma rápido fluxo de *word-of-mouth*, a um ritmo muito superior do que alguma vez imaginado em produtos e serviços tradicionais. O custo relativamente baixo de adicionar novos utilizadores levou a uma variedade de inovações na atribuição de preços de produtos digitais, incluindo várias modalidades dos modelos *free* e *freemium*. Esta tese explora as características únicas e as complexidades de Negócios Digitais tal como a suas implicações no desenvolvimento de Modelos de Negócios Digitais e Modelos de Receita.

A tese propõe uma Framework baseada em *Agent Based Modeling* que pode ser utilizada para desenvolver Modelos de Simulação que simulem as complexas dinâmicas presentes nos Negócios Digitais e as interações entre os utilizadores e os produtos digitais. Tais Modelos de Simulação podem ser utilizados para diversos propósitos tais como previsões simples, análises do impacto de distúrbios no mercado, análise de impacto de alterações nos modelos de *pricing* e otimizações de preço entre geração máxima de receita ou um equilíbrio entre crescimento em utilização e geração de receita. Estes modelos podem ser desenvolvidos por empresas estabelecidas com um vasto histórico de taxas de crescimento de utilização tal como por empresas recentes com um histórico reduzido. Através de três casos de estudo, esta tese demonstra a aplicabilidade e potenciais aplicações da Framework.

Termos Chave: Business Model, Digital Business, Agent Based Modeling, Simulation, Optimization

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List of Abbreviations and Acronyms

ABM	-	Agent Based Model
BM	-	Business Model
B2B	-	Business to Business
C2C	-	Consumer to Consumer
B2C	-	Business to Consumer
SaaS	-	Software as a Service

1. Introduction

1.1. Digital Business Models

The growth of the Internet has led to a rapid growth of the Internet Economy in the last decade. Online Businesses have changed the world and opened opportunities for new Business Models that are far more efficient and effective in delivering products and services to consumers. Digital businesses encompass the entire gamut of ventures, from online sale of products and services to social collaboration platforms, and have become a vital engine for the new economy.

Digital businesses have characteristics that are unique and much different from traditional brick and mortar businesses. Digital businesses respond to online users who are highly interconnected and networked. This enables a rapid flow of word of mouth, at a pace far greater than ever envisioned when dealing with traditional products and services (Lunn, 2002). While such a networked global market offers opportunities for quick expansion and global presence, it also allows deficiencies to be magnified leading to quick loss in market share. Thus managing user opinions has been ever more vital than before, and those who learn to harness digital technologies to connect with potential clients surge far ahead of competitors.

The relatively low cost of incremental user addition has led to a variety of innovation in pricing of digital products. Some services are completely free to end users utilising a smart use of targeted advertising, a strategy that enabled Google to grow into a global giant. Other businesses commonly use a freemium business model such that a small percentage of users pay for premium features while a large number of users use the free version. The free users act as marketing agents, spreading word of mouth and thus enabling the model to be sustainable. Businesses often struggle with deciding which features to charge for, and such decisions often can decide whether the business grows sustainably, or collapses with a spiralling revenue deficit due to the increasing cost of free users. Managing the pricing of digital businesses requires new mindsets, and newer tools.

Online markets are extremely volatile, since purely digital businesses can be global in nature thus truly embodying the spirit of businesses without boundaries. Digital Businesses need not register in individual countries and by default have access to a unified global market. This makes agility and alertness of paramount importance, as well as incorporation of systems for early detection of customer dissatisfaction trends and entry of market competitors. By comparison, all traditional methods of market surveys, and analysis of sales data that can warn the management of such trends are extremely slow. Hence new paradigms of automated and continuous customer feedback and new modelling techniques are vital for quick decision making.

Some online companies have been growing at a pace far exceeding what was possible with traditional businesses. Despite this, digital businesses have an extremely high failure rate. This is because of a lack of in-depth understanding on how online businesses work. Business Model (BM) has been an active area of research over the last decade though, and provides us with a structured approach to represent and comprehend the value delivering mechanism of a business. (Walter & Back, 2010) define BM in the following way; "A business model describes ways of creating value for customers and the way business turns market opportunities into profit through sets of actors, activities and collaborations." A Business Model is a set of coordinated strategies that ultimately aim to increase the short-term and long-term profitability of an enterprise. However, current Business Model research has failed to incorporate the key characteristics of a Digital Business, and mostly taken a generic approach. (Baden-Fuller & Morgan, 2010) state that Business Models are not just recipes or scientific models or scale models, but can play all these roles at the same time. Business Models are much more than quantifiable parameters or selectable business options. They also refer to innovations about how value is delivered and revenue is generated. The majority of works on Business Models have focussed on conceptual and exploratory approaches towards Business Models.

Existing Business Model research has been broadly focussed on the organizational and value delivering mechanisms within an organization. It has focussed on how the organization can leverage its internal dynamics, to offer value to its customers and generate revenue. However there has been a lack of research work focussed on the internal dynamics of how customer networks are organized and how customers influence each other. This thesis focuses on the relationships between Business Models and Customers and develops a detailed understanding of how Digital Markets are organised.

This approach involves detailed exploration on how Digital Markets function. In a digital market, potential customers cannot be viewed as isolated online users waiting to be approached with a digital product. Traditional approaches of customer segmentation and targeting is not sufficient to exploit the digital market. This thesis approaches potential customers as a set of interconnected nodes of a network, that interact with each other, have a profound influence on each other through *offline* and *online* "Word of Mouth". Then they make their product adoption decisions based on influences and their willingness to pay.

Businesses are seen as developing their Business Models that aims to provide Value to customers on one hand and generate revenue on the other hand. Both these actions must be balanced and aligned to each other. While *Value Proposition* has been traditionally seen as concerned with the development of the *Product*, in digital products, the marketing must be embedded within the product itself. Thus Marketing Strategy is seen as a part of the Value Proposition itself. The selected Revenue Models are often aligned to the Value Proposition being delivered. For example a Freemium digital product, may have the set of free features carefully selected and kept in mind while designing of the Product itself, so that the free users act as marketing agents by rapidly spreading the word of mouth and getting more paid users in the process.

Contemporary Business Model Research have lacked a focussed approach to Digital Business and have not analysed its applications. Also computational and simulation modelling technologies have made it possible for Business Models to be translated from the conceptual to live working models. Such a model could enable Business Managers have a real market simulation available at their fingertips so that quick decision making about optimising the various elements of the Business Model could be aided. This would be especially helpful for the fast changing world of digital business. However the challenge for such models has been the heterogeneity of business scenarios, and a detailed exploration is required into each specific case before a reliable computational model can be generated. Each digital business is different, but digital businesses have an underlying structure in the way customers are organised, networked and respond to value propositions that are common across various digital business models. By identifying the common structures and exploring the differences, this thesis proposes a generic framework DYNAMOD which can be used to generate simulation models for a variety of different Business Scenarios. This approach provides Managers a toolkit for simulating the impact of different business decisions, simulate various what-if scenarios, and visualise tangible impacts to their Business.

The Digital Market ecosystem is considered as a complex system with a large number of interacting entities. Thus a complex systems modelling approach has been used to model it. Potential users are considered as independent autonomous agents that interact with each other in ways simulating offline and online interactions. Agents develop awareness and varying degrees of influence about a particular product or service. Once the degree of influence crosses a threshold and the product price is below the agent’s willingness to pay, the agent becomes a client.

The application of Agent Based Modeling (ABM) in the area of business and markets is not very common, though literature review reveals that some specific scenarios have been modelled before. The Thesis proposes a generic ABM framework, DYNAMOD, that can be customised and used to model a variety of different Digital Business Scenarios. It can be utilised for achieving a wide variety of modelling objectives such as, making simple growth projections, analysing the impact of changing prices, optimization of prices of different features and tariff plans, optimization of bundling of different features into different pricing tiers. It may also be used for visualising more radical changes such as modifying the advertising expenses, changing the business model. Some of these scenarios have been demonstrated through the application of DYNAMOD to three business cases. Further the model has been used iteratively, using genetic algorithm to demonstrate how optimization of key variables (such as pricing) can be used to generate an optimised solution for the Business Managers.

1.2. Research Questions

Digital Business represent complex networks of interacting online users responding to different value propositions. This thesis aims to model these networks using a complex systems approach to enable Business Model Simulation and Forecasting. Furthermore these simulation models are applied to specific case scenarios where the practical applicability of these simulation models are demonstrated. Thus the following Research Questions are addressed in this thesis:

- **Research Question 1**

  What are the unique characteristics that define a Digital Business? How do these characteristics define the dynamics of the Digital Market?

  Traditional marketing principles alone are not able to explain the complexities of Digital Businesses. A review into the unique nature of online Businesses is vital for developing a deeper understanding of the dynamics and factors involved. Through a literature review, this thesis will explore these unique characteristics and utilise them in the context of development of a modelling framework.

- **Research Question 2**

  How can we accurately predict the evolution of complex digital business models?

  This thesis shall explore the development of simulation models that represent the complex dynamics of Digital Businesses and can be replicated for different Business Scenarios. The following sub-research questions will further explore the different aspects of the simulation of digital business models:

- **Research Question 2.1**

  How can we make forecasts for key business parameters (eg User Growth, Revenue Growth, Rate of Upgrades, etc) based on Existing Business Models?

  This thesis shall explore how simple forecasts can be made through simulation models representing existing business. Simple forecasts can also be made based on historical data, using a variety of forecasting tools thus shall be used for the validation of the Simulation Model. Simple forecasts allow the visualisation of the future based on current business model and market conditions.

- **Research Question 2.2**

  How can we make forecasts based on changing the existing Business or Pricing Models, to visualise the impact of various what-if scenarios?

  The applicability of the simulation models go beyond simply forecasting based on the present business scenario. The purpose of developing such models is to explore the impact of changes in pricing and business models. The thesis will explore several what if business scenarios through different case studies to explore the impact of changing Business Scenarios or Pricing Models.

- **Research Question 2.3**

  How can the configuration of Pricing and Business Models be optimised in an automated way for a particular business objective (eg. Maximising Revenue, or Maximising Growth Rate)?

  The ultimate practical application of this research work is to provide Digital Business Managers with a Toolkit to help optimise the relevant elements of their Business Model. This thesis shall explore various ways of optimisation of prices with the help of a simulation model. This includes application of Genetic Algorithms as an optimisation tool to adjust the various pricing elements to find the most optimal pricing combination.

1.3. Propositions

The basis of this research work is the applicability of Complexity Science to model the complex dynamics of the interactions between online users and the adoption of a particular product or service. This research work has been developed based on the following propositions:

- **Proposition 1**

  Digital Businesses have certain unique characteristics like highly networked users, quick spread of word of mouth, global nature, low incremental usage costs, and innovative and flexible pricing models that make the business dynamics completely different from traditional businesses.

  This proposition is related to Research Question 1. Digital Businesses have unique characteristics due to which its business dynamics are vastly different from Traditional Businesses. Thus starting and managing a Digital Business requires a deep understanding of these business dynamics and requires the use of new approaches, strategies, tools and business models. These Digital Business characteristics are explored through a dynamic simulation modelling framework.

- **Proposition 2**

  Agent Based Modeling can be used to model the interactions between online users and their response to product offerings.

  The study of complex systems represents a new approach to science that investigates how relationships between parts give rise to the collective behavior of a system and how the system interacts and forms relationships with its environment. By modelling the micro level product adoption decisions at the individual level, we try to simulate the macro level business scenario. Agent Based Modeling is an effective way to model systems that contain a large number of interacting "Agents". It is especially effective where rules for interactions between individual agents are well defined and through these interactions, the overall macro phenomena can be observed. This is very similar to an online environment where online users are interacting agents, which respond to product offerings and spread their experience and opinion through word of mouth. Based on literature review, we will explore the modelling of online business environments using Agent Based Modeling.

- **Proposition 3**

  Optimisation of Key Business Model Parameters and Pricing Models can be performed through Simulation Models

  Simulation Models developed in this thesis are simplified representations of the complex dynamics of Digital Businesses. Thus adjustments made in the Business Model Parameters and Pricing Models used in the simulation models can indicate the impact on the overall Business Outcome. Thus the simulation models can be used for optimising these variable and thus serve as a Decision Support System for Managers. The accuracy of the models is directly related to its ability to provide optimisation of these parameters.

1.4. Structure of the Thesis

This thesis has been organised into 11 chapters.

Chapter 1 is the introductory chapter and discusses the overall objectives of the Thesis. It introduces the context of the research and explains why digital businesses are unique and need different strategies as compared to traditional business models. This chapter also introduces the Research Questions and the Propositions used for this Research Work.

Chapter 2 contains the literature review of all aspects of Digital Business. It explores the unique characteristics of Digital Business giving a brief overview of the historical evolution of Digital Businesses. It discusses the unique cost structure of Digital Businesses that have enabled the introduction of Free and Freemium Business Models that have now become a standard for digital products. It also introduces newer marketing strategies such as Viral Marketing, and effective use of the Social Media. Other aspects covered in this chapter include the global markets and increased competition for digital businesses, difficulty in implementing legal protections, and product and marketing integration. Chapter 2 also describes the relevant research area of "Diffusion of Innovations" where the spread of word of mouth is modelled to show how a new product or technology spreads across a set of users. It also talks about existence of Network Effects for many of such digital products.

Chapter 3 details the literature review on Business Models. It discusses the strategic and operational perspectives on BMs that has been the focus of contemporary research. It also lists cases where BM literature have discussed the evolution of BM for specific firms, industry sectors and industry clusters. It further discusses how the unique characteristics of digital businesses relate to the different aspects of Business Models. It discusses the limitations of contemporary BM approaches to address the specific requirements of Digital Businesses and how they can be integrated in a unified framework.

Chapter 4 describes some of the commonly used simulation tools for Business Growth Analysis. It mentions Forecasting techniques as a tool for predicting the future from past time series data. It also discusses the application of System Dynamics, which is based on the identification of the various components and the interrelationships between them which are expressed in terms of mathematical equations. Further it discusses why Agent Based Modeling (ABM) was chosen as a preferred tool for implementing the Digital Business Modeling Framework developed in this thesis. It summarises other research works where

ABM has been used for different business scenarios. It further discusses the NETLOGO, which is the programming interface used in this thesis.

Chapter 5 presents the DYNAMOD framework in its generic form that can be adapted to different Business Scenarios and Objectives to develop ABM models. It discusses the relationship of DYNAMOD to Business Models. It provides a Framework Description where each variable is identified and described. It also explains the logic followed for programming the agents. It discusses the adoption function used by the Agents based on which they make the product adoption decisions. Further it describes a step-by-step methodology for implementing the Framework for each business scenario.

Chapter 6 describes the Methodology used in this research for the development of the model and the selection of the case studies. It further lists the objectives behind selecting the 3 case studies. It also discusses how the 3 cases are validated.

Chapter 7 discusses the application of DYNAMOD to Facebook.com. It discusses the business scenario of Facebook and the modelling objectives. It also discusses the model results and compares the forecast with ARIMA to validate the results. It further discusses two additional simulation scenarios. In one the impact of a privacy issue is modelled, while in the other, the impact of market entry of another competitor is analysed.

Chapter 8 discusses the application of DYNAMOD to CustoJusto.pt which is a Classifieds Ad service in Portugal. It discusses the Business Scenario and Objectives. It then discuses the process for model initialisation process and simulates five scenarios.

Chapter 9 discusses the application of DYNOMOD to Vortal.biz. It is one of the largest e-procurement platform providers in Portugal. This chapter discusses the simulation of users from one tariff plan to another and its impact on revenues. It also optimises the tariff for each plan using genetic algorithms.

Chapter 10 provides a cross case study analysis of the selected cases. It provides a detailed analysis of the similarities and differences between the selected cases with respect to their Business Characteristics and the Modeling Results. This section will help us generate a greater understanding of the capabilities of the DYNAMOD Model. It also provides us with a snapshot of the work developed in the three cases.

Chapter 11 discusses the conclusions of the thesis and proposes a path for future research using the DYNAMOD approach. It briefly describes the motivation behind this thesis explaining the context of this research. It then discusses the contribution of this thesis and the considerations behind the proposed solution. Finally it highlights a roadmap for future research work based on this thesis.

2. Digital Businesses

The historical evolution of Digital Businesses can be traced back to early 2000 when there was an explosive growth of dot-com companies in the United States, and a high degree of investment in the sector. At the time Internet was a very new phenomenon whose potentials were still at its infancy. Digital product differentiation was not as evolved and many companies were crowding around the same business areas especially online retailing. Soaring investor confidence at the time was not matched by the evolved skillsets and business model innovation that was necessary to catapult the fledgling online business space into the fastest growing business area. By 2001 the dot-com bubble had burst and a large proportion of newly set up companies crashed. In the ensuing gloom of the 2001 crash, few had imagined that digital business was preparing itself for resurgence that would revolutionalise the way the world does business.

The mistakes of the era inspired digital companies to realise the importance of Business Model innovation. New companies emerged subsequently that have grown into major global giants. Google, a company slightly more than a decade old has already overtaken Microsoft which was always regarded as a software giant (Barclays, 2013). And for every Google or Amazon, there are thousands of smaller online businesses growing at breakneck speeds and changing the global business landscape.

The Digital Space allowed companies to innovate and differentiate their business offerings in a way that was never previously possible. Some of its natural characteristics such as globalised online markets and low incremental per user costs enable rapid expansion of a successful Digital Business. Digital Businesses are based on effective use of information highways for bidirectional communication between the business and the clients. It makes use of a variety of rich graphical displays which are no longer limited to Desktops and Portable Laptops. Recent advances in mobile technology have expanded the potentials of how technology can be harnessed to provide users with rich content over interactive interfaces on the move.

Thus digital business can provide infinite opportunities for innovation to create new products and services that fulfil different customer needs and often creates new user needs. Digital business has brought in radical changes to existing traditional business sectors such as online travel booking sites to the hotel and airline industry, digital libraries to the publishing industry, music on demand apps like Spotify to the traditional music record industry. The interconnection of users has also given rise to new user needs such as the rise of Social Networks like Facebook, video sharing sites like Youtube, Product Review Sites, amongst others. The web and mobile app interface allows entrepreneurs to start digital businesses and provide innovative services at a fraction of the costs required to set up traditional businesses.

Research has found that companies operating in a primarily online environment are thriving. A recent UK based survey showed that over half of the digital businesses questioned had produced double digit growth over the last 3 years (Barclays, 2013). The average digital business growth rate was 11.4% which was 50 times faster than the rest of the UK economy. The survey also revealed that the average revenue for each online business was 8.9 million pounds in 2012.

Gone are the days when consumers would access the web from a fixed location – they now expect to browse at their convenience, ubiquitously and across a range of different devices. It is vital that online businesses are aware of this trend and make sure they offer the best possible service to anyone accessing their website. A site that has been developed for mobile makes for a more positive customer experience; increasing accessibility and functionality, and boosting customer loyalty among mobile visitors (Funk, 2011). (Barclays, 2013) revealed that only 11% of online businesses have a mobile app or mobile-ready website. Online businesses are thriving in comparison to the rest of the economy and mobile is the next big challenge they must address.

Mobile applications and websites offer more opportunities for online businesses to create services personalised to each customer. Location-based services are one popular way of doing this. Accessible on mobile devices through the mobile network or GPS, they use information on the geographical position of a customer's mobile device. This allows businesses to share relevant promotions, deals and rewards based on location. Research found that of those businesses that do have mobile apps or websites, almost half (48%) of them stated that location-based services was one of the main functions (Boons & Lüdeke-Freund, 2012). Examples of new innovative business models include Taxi Aggregators (like Uber) that allow any car user to work as a part time Taxi Service Provider through just the use of a mobile app.

For the success of Digital Entreprises, not only is the product innovation important, but an equally vital aspect is the Business Model Innovation. The unique characteristics of Digital Businesses provide for unique challenges and opportunities. Understanding these unique characteristics are the key for developing optimised Business Models and Pricing Strategy. In this section, we discuss some of the key characteristics that form the defining features of digital businesses and make them unique.

2.1. Free and Freemium Models due to low cost per user

Digital businesses have a unique feature. While costs of infrastructure and servicing of clients has increases over time for traditional businesses, these costs have been falling rapidly in the case of digital businesses. The key infrastructure costs – Storage, Processing and Bandwidth, have continued to follow Moore's Law and have steadily plummeted (Anderson, 2009). As companies have embraced economies of scale, the servicing cost per client have been tending to zero (Teece, 2010). This has led to experimentation with new business model forms that reflect these low incremental per-user costs. Very low per-user costs have led to the growth of Free and Freemium business models, where the end user receives tangible products or services without a cost. While Free services are mostly supported by advertising, in case of Freemium, a small percentage of people paying for premium services, or generating revenue through indirect sources (Teece, 2010).

Freemium acts as a substitute for traditional advertising. It encourages quick adoption of a product which can then be monetized in various forms such as sale of a premium version of the product or advertising to the existing users of a free product (Pujol & Enterprises, 2010). The key advantages of offering a free version of a product are as follows:

1. Increases adoption and subsequent word of mouth.
2. Enables Demonstration of a scaled down version of a product that could increase purchase of premium version.
3. Increases the product value for paid clients, by enlarging the user base, if the product exhibits a Network Externality.
4. Indirect Monetization though the use of advertising revenue or client usage statistics.

However, even the introduction of a Freemium model can be risky, where achieving the critical number of free users switching to become paid users, and a critical expansion rate, can make the business grow virally or its inability can collapse the business under the costs of its free users (Bekkelund, 2010).

2.2. Viral Marketing

Viral Marketing refers to the fast and infectious spread of a product adoption across the market. It involves strategies for rapid uptake of electronic peer to peer referrals (De Bruyn & Lilien, 2008). It also involves an effective utilization of word of mouth or established networks of clients, through an excellent value proposition that is low cost or free. In digital business, automated viral marketing strategies are sometimes used to induce viral marketing with little intervention from the users, or sometimes even without the knowledge of users. A commonly cited example is Hotmail, which became very popular due to automatically adding its web-link at the end of each email sent by a Hotmail user (Montgomery, 2001).

However excessive viral marketing might create a perception of the product as spam and lead to negative opinions about the product in the minds of potential adopters (Kalyanam, McIntyre, & Masonis, 2007). Hence, although it is an effective tool, viral marketing must be carefully exploited.

Research work on viral marketing has been approached from two different disciplines, computer scientists, and marketing. Originally introduced to computer science by Domingos and Richardson (Domingos & Richardson, 2001), the problem was formalized by Kempe, Kleinberg, and Tardos (Kempe, Kleinberg, & Tardos, 2003) who described the problem as selecting the correct individuals to seed with a product in an arbitrary network given a fixed marketing budget. They showed that their formalization of this problem is in fact NP (Non-Deterministic Polynomial), but presented some heuristic solutions to the problem, with some provable approximation. However, their best approximation algorithm requires global knowledge of the network; in other words, in order to be implemented the marketing manager would need to know every node in the network and how it is connected to every other node; unfortunately, this is an unrealistic requirement in many real-world cases. Leskovec, Adamic, and Huberman (Leskovec, Adamic, & Huberman, 2007), on the other hand, take a descriptive approach to viral marketing. Similarly within marketing research, Goldenberg, Libai and Muller (Goldenberg, Libai, & Muller, 2010) use a cellular automata model to describe adoption processes and characterize which individuals have the greatest effect on adoption. Goldenberg and others have also examined the role of hubs (individuals with a high number of friends) in the adoption process.

2.3. Globalization and Intense Competition

Another feature of digital business is intense competition. Since entry barriers to markets tend to be low and national boundaries are not significant hurdles, the entry of new competitors takes place at a phenomenal speed (McGrath, 2010). In traditional businesses, a large number of competitors would have meant a highly fragmented market share. A unique feature of digital business is that often a dominant player assumes an extremely large proportion of the market share. This is because of the low cost structure (often zero or near zero) of the digital business, where pricing cannot be used as a differentiating parameter. The network effects associated with well connected users mean that a well designed product, usually the first mover, would virally expand due to positive customer feedback (Gallagher & West, 2009). Marginal deficiencies in the product or services offered can lead to customer dissatisfactions that can propagate through the network of the potential user base, with a considerable effect on future product adoption. This is especially true since forums and product reviews are easily accessible to customers today. Traditional means of advertising to increase consumer awareness has been largely replaced by consumer recommendations, publicity through forums and user communities (Dwyer, 2007). Thus, companies could see a rapid market penetration as well as rapid market decline if a better competitor emerges.

An example of this phenomenon can be observed in the case of social networks. When they first emerged, the concept became very popular with young people as a form of quick networking. But the immense network effects meant that only one dominant player could survive the competition. By 2006, Hi5, Orkut, as well as Facebook were dominant players. Eventually users in individual countries started switching to the social network used by a majority of their friends. Finally Facebook gained market dominance and this led to the ultimate extinction of Orkut and Hi5.

2.4. Difficulty in implementing Legal Protections

It has become extremely difficult to enforce copyright protection in digital businesses. Rampant piracy of digital products is a fine example. New business models that target at alternative sources of revenue need to be adopted (Teece, 2010). The music industry has evolved, and new models of song sales such as iTunes are being used. The software industry has been addressing this challenge by providing Software as a Service, pay as you go, and other pricing models, reducing the initial cost of purchase (Grewal et al., 2010). Subscription based services also provide support and additional benefits, thus discouraging users to go for pirated softwares.

Similarly difficulty in checking software piracy have led many software companies to switch to a Software as a Service (SaaS) model. They deliver services over web platforms where access to services can easily be controlled and monitored. Often customers also find it more economical to pay in smaller bundles of usage rather than pay upfront.

Another challenge faced by Digital Businesses is the difficulty in obtaining patents for their product design. Patents and Trademarks are commonly ignored by smaller competitors emerging from other parts of the world. Thus a digital company can capitalise on its innovations by being the first to launch and scale up and thus creating a brand name for itself. It can then leverage economies of scale to fight off smaller competitors.

2.5. *Product and Marketing Integration*

Digital markets often do not provide room for drawing board development of business strategies that can be slowly tested in the market and tweaked as time goes on. For effective marketing in the digital world, marketing strategies should not be separate from product, but rather marketing should be built into the product itself (Grewal et al., 2010). Market opportunities must be quickly exploited, before a competitor catches up. This integrated approach to the digital business strategy, which incorporates product development, marketing and pricing forms the underlying principle of a digital business model.

An example of integration of marketing within the product itself is the integration of incentives to invite friends to enhance the usage of a product . This has been successfully implemented in games such as Farmville as well as all major social networks like Linkedin, Facebook. In other cases, the web or mobile application integrates like and share button to spread awareness over Facebook. In some games invitation to friends can unlock advanced levels or features and substitute monetary purchase.

(Jiang, 2010) suggests that market adoption of a digital product is largely influenced by three main factors: *Network Externalities*, where free adopters increase future adopter valuation of a product; *Demonstration Effects,* where software adoption significantly increases if users can try the software before purchase; and finally *Word of Mouth Effect,* in which free adopters help to accelerate the diffusion of a new product.

It is these effects that make the marketing of digital products a challenging task that online companies are still struggling to cope with. Not only are traditional rules of market economics insufficient, but market responses change so rapidly that reaction time needs to be much less than in traditional business areas. Often a wrong strategy can lead to irreparable consequences to the reputation, which can spell negative image throughout the marketplace, which few companies can recover from.

2.6. *Diffusion of Innovations*

Diffusion of Innovations has been an active research area and reflects adoption decisions made by individual consumers. It is very relevant to Digital Businesses because the spread of word of mouth over online networks is a critical determining factor for the success or failure of a Digital Business, and Diffusion of Innovations research literature provide for tools and techniques that can be used to model production adoption across an online marketplace. Adoption decisions are made in a complex, adaptive system and result from the interactions among an individual's personal characteristics, perceived characteristics of the innovation, and social influence (Schramm, Trainor, Shanker, & Hu, 2010). There are two broad classical approaches to modeling diffusion: econometric and explanatory. Econometric approaches, such as the Bass model, “describe and forecast the diffusion of an innovation in a social system” (Bass, 1969). Econometric approaches forecast growth within a product category by modeling the timing of first-purchases of the innovation by consumers and are more applicable when market growth rate and market size are of primary interest. Explanatory approaches, as first proposed by (Gatignon, 1985) establish that the diffusion of a product in a defined market is equivalent to the aggregation of individual consumer adoption decisions. Some recent attempts have been made to complement these classic approaches with Agent Based Models (Delre, Jager, Bijmolt, & Janssen, 2007; Diao, Zhu, & Gao, 2011; Stonedahl, Rand, & Wilensky, 2008).

2.6.1. Word of Mouth

Literature has assumed word of mouth (WOM) to be the influence of neighbors. This is a relevant assumption for offline word of mouth since such communication is mostly limited by geographical location. (Keller, 2006) estimates that 90% of WOM conversations for traditional goods and services takes place offline.

When dealing with digital products, the scenario changes. (Keller Fay, 2006) states that even for traditional products, just 15% of consumers account for one third of WOM conversations in America, and those “Conversation Catalysts” rely heavily on the Internet as a resource for the information they pass along to their family and friends. Although no specific research exists, for online digital products, it is expected that the share of online word of mouth is considerably larger.

Word of mouth communication is more effective when the transmitter and recipient of information share a relationship based on homophily (tendency to associate with similar persons), trust and credibility. (Brown, Broderick, & Lee, 2007) conducted research on online word of mouth and report that online homophily is almost entirely independent of interpersonal factors, such as an evaluation of individual age and socio- economic class, traditionally associated with homophily. The idea of individual-to-individual social ties is less important in an online environment than in an offline one. Individuals tend to use websites as proxies for individuals. Thus, tie strength was developed between an information seeker and an information source as offline theory suggests, but the information “source” is a Web site, not an individual.

(Tran, 2012) deduces that indirect influence from the larger population can have a greater effect than direct personal contacts on an individual, thus indicating a strong Global influence, rather than just the neighborhood influence. Thus, a Global Influence tends to come into play when a large proportion of the population holds a positive influence over a particular brand.

(Goldenberg, Libai, Moldovan, & Muller, 2007) predict that the net effect of advertising at early stages when the product is still not stable could enable a larger creation of negative influence, which could possibly reduce the subsequent market uptake of a product. Thus at an early stage digital products can be negatively impacted by a high degree of advertisement and subsequent adoption, especially when the product is still at a rudimentary state.

(Feng & Papatla, 2011) states that the incentive to spread word of mouth reduces, as a product is already well known. They go further to deduce that elevated awareness is created by a high advertising budget, reduces the word of mouth propagation. They also state that highly satisfied or highly dissatisfied customers are likely to engage in more word of mouth than other customers.

(Goldenberg et al., 2007) state that for a traditional product, negative word of mouth spreads up to 2 levels of agent chains but a positive word of mouth can go on spreading much further. While the extent may vary, there is general agreement in the literature that a dissatisfied customer influences others more than a satisfied one (Herr & Kardes, 1991). This consensus is built both on evidence that dissatisfied customers communicate with others more than satisfied ones and that recipients of this communication place more weight on negative information.

2.6.2. Network Effects

Network effects exist when consumers derive utility from a product based on the number of other users (Goldenberg et al., 2010). These effects are especially relevant for several online businesses, especially since various online products and services exhibit some form of network effects, such as social networking sites and online marketplaces. Social Networking sites like Facebook, Linkedin are common examples of the same.

(Goldenberg et al., 2010) predict a *chilling effect of network externalities.* They propose that a product with a network externality has a slower initial adoption compared to a product that does not have any network externalities. The higher growth rate due to the network effects occurs only after the product has crossed a certain adoption critical threshold.

Double Sided network effects refer to scenarios where the focus of the business is to bring buyers and sellers into contact. Popular examples are sites like Ebay and Amazon. The unique characteristic of this business model is that network effects are extensively at play. Buyers are seeking a platform where there are many vendors to choose from and vendors are seeking a platform where there is a large target customer base. Such a network effect can grow exponentially. However, the first mover in this business can have an advantage as there are high switching costs for existing clients who may already have an established business network.

2.7. Pricing of Information Goods/Services

The information industries have always raised challenging business model issues because information is often difficult to price, and consumers have many ways to obtain certain types of products without paying. Figuring out how to earn revenues (i.e. capture value) from the provision of information to users/customers is a key (but not the only) element of business model design in the information sector (Teece, 2010). Pricing of Digital Products is another important area of research, especially the impact of various dynamic pricing strategies and the immensely successful Freemium-based business models.

Pricing of digital products often involves splitting the product into different sub-categories and re-bundling them. The unit of charge for digital products must change. Smaller units of charge, focusing on pay per use or per month subscription charges have met with success in the digital world (Docters, Tilstone, Bednarczyk, & Gieskes, 2011).

Internet based businesses often have a challenge to price products at different optimal levels globally. The same product may have the possibility to be priced higher or lower in different countries, due to varying willingness to pay, and different competition scenarios. However, implementing such price variations is often difficult in the Internet world, and may require differentiated services for different parts of the world. (Docters et al., 2011; Liu, Cheng, Tang, & Eryarsoy, 2011).

A challenge facing digital products is piracy. This is especially threatening in the case of music and books. Offering Enterprise licenses with unlimited copies is a limited solution to tackling piracy at the Enterprise level (Liu et al., 2011). The Freemium model has been successful at tackling piracy by providing a lower valued but commonly used components of a product for free, and charging higher for premium components. For a successful Freemium model to work, it is vital for devising efficient digital bundle strategies, where the free component acts as a bait for the user (Docters et al., 2011). New Business models like Spotify have evolved where music on demand is free for PC but on subscription for mobile users, thus de-incentivising piracy.

There exists a variety of pricing models that are suited for different types of Digital Businesses. Many apps are based on a one time transaction fee, whereas SaaS services are usually based on a recurring subscription. Other services like Amazon Cloud hosting charge based on the usage. Other models experimented with include Donations which have been successfully used by Wikipedia.

2.8. *Types of Digital Businesses*

(Croll & Yoskovitz, 2013) have identified six main types of Digital Businesses. The performance of each of these types of Digital Businesses are usually measured using different Performance Metrics as detailed in Table 2.1.

Table 2.1 Key Performance Metrics for six types of digital businesses.
Source (Croll & Yoskovitz, 2013)

Digital Business Type	**Examples**	**Key Performance Metrics**	**Description of Metrics**
E-Commerce	Amazon, Expedia, Wal-Mart	Conversion rate	Number of visitors who buy something.
		Purchases per year	Number of purchases made by each customer year.
		Average shopping cart size	Amount of money spent on a purchase.
		Abandonment	Percentage of people who begin to make a purchase, and then don't.
		Cost of customer acquisition	The money spent to get someone to buy something.
		Revenue per customer	The lifetime value of each customer.
		Top keywords driving traffic to the site	Those terms that people are looking for, and associate with you—a clue to adjacent products or markets.
		Top search terms	Terms those lead to revenue, or don't have any results.
		Effectiveness of recommendation engines	How likely a visitor is to add a recommended product to the shopping cart.
		Virality	Word of mouth, and sharing per visitor.
		Mailing list effectiveness	Click-through rates/ability to make buyers return & buy
SaaS – Software as a Service	Gmail Basecamp Mendley	Attention	How effectively the business attracts visitors.
		Enrollment	How many visitors become free or trial users.
		Stickiness	How much the customers use the product.
		Conversion	How many of the users become paying customers, and how many of those switch to a higher-paying tier.
		Revenue per customer	The money a customer brings in within a time period.
		Customer acquisition cost	The costs to get a paying user.
		Virality	How likely customers are to invite others and spread the word, and how long it takes them to do so.
		Upselling	What makes customers increase their spending, and how often that happens.
		Uptime and reliability	The complaints, escalations, or outages in a company
		Churn	The users and customers leave in a given time period.
		Lifetime value	How much customers are worth from cradle to grave.
Free Mobile App	Angrybird Torque	Downloads	Number of users downloaded the application, as well as related metrics such as app store placement, and ratings.
		Customer acquisition cost	The costs of getting a user and getting a paying customer.
		Launch rate	The percentage of users who download the app, actually launch it, and create an account.

		Percent of active users/players	The percentage of users who've launched the application and use it on a daily and monthly basis.
		Percentage of users who pay	How many of your users ever pay for anything.
		Time to first purchase	The time between user activation and making a purchase.
		Monthly average revenue per user (ARPU)	It is based on purchases and watched ads including application-specific information.
		Ratings click-through	The percentage of users who put a rating or a review.
		Virality	On average, how many other users a user invites.
		Churn	How many customers have uninstalled the application, or haven't launched it in a certain time period.
		Customer lifetime value	How much a user is worth from cradle to grave.
Media Site	CNN CNET	Audience and churn	How many people visit the site and how loyal they are.
		Ad inventory	The number of impressions that can be monetized.
		Ad rates	Sometimes measured in cost per engagement.
		Click-through rates	How many of the impressions actually turn into money.
		Content/advertising balance	The balance of ad inventory rates and content that maximizes overall performance.
User Generated Content	Wikipedia Facebook Youtube	Number of engaged visitors	How often people come back / how long they stick around.
		Content creation	The percentage of visitors who interact with content .
		Engagement funnel changes	How well the site moves people to more engaged levels of content over time.
		Value of created content	The benefit of content, from donations to media clicks.
		Content sharing and virality	How content gets shared, and how this drives growth.
		Notification effectiveness	The percentage of users who, when told something by push, email, or another means, act on it.
Two-Sided Marketplace	Ebay Custojusto.pt Vortal.biz	Buyer and seller growth	The rate at which you're adding new buyers and sellers, as measured by return visitors.
		Inventory growth	The rate at which sellers are adding inventory such as new listings as well as completeness of those listings.
		Search effectiveness	What buyers are searching for, and whether it matches the inventory you're building.
		Conversion funnels	The conversion rates for items sold, and any segmentation that reveals what helps sell items.
		Ratings and signs of fraud	The ratings for buyers and sellers, signs of fraud, and tone of the comments.
		Pricing metrics	If you have a bidding method in place (as eBay does), then you care whether sellers are setting prices too high or leaving money on the table.

The above table demonstrates the different performance metrics that can be monitored for different types of Digital Businesses. The selection of the main metrics to be monitored depends on the business, its revenue model and in what stage of growth it is currently in. A business in its early stages will focus more on virality, new user addition and user retention. A more established business seeking to monetise will choose to focus more on parameters like average revenue per client and conversion rate to paying customer. Selection of parameters is an important and critical step for effective monitoring of a Digital Business.

The first type of Digital Business is the E-commerce. This is the most common type of Business model where a visitor buys a product or a service. Most common examples include

Amazon.com, Expedia, and Wal-Mart. Most E-commerce companies make money in a straightforward way by charging for the products bought which are then delivered directly or electronically. These are not considered as a purely digital business because these are constrained by physical factors, such as the supply of product and the delivery chains.

The second type of Digital Business is Software as a Service (SaaS). Such a business provides software on a on demand basis, usually delivered through the website itself. Popular examples include Gmail, Salesforce, Basecamp, etc. Most SaaS providers generate revenue from a monthly subscription while others based on usage. Often a tiered service is provided and finding the best mix of tiers and prices is a constant challenge.

The third type of business is the Free Mobile App which try to monetise in other ways. This is a steadily growing market segment with Android and i-Phone usage growing at a rapid pace. Common ways to monetize include providing downloadable content (eg Maps, Vehicles), providing greater customization, saving time, elimination of countdown timers, Upselling to a paid version and in-game ads.

The fourth type of business is a Media Site, that engages the user into clicking several pages and watching several videos. Thus they are able to monetise targeted advertising revenue more intensively and often have a free business model.

The fifth type of business is that of user generated content. Common examples include Wikipedia, Facebook and Youtube. They must keep evolving the strategy for engagement to make users spend more time on the site. In cases such as Wikipedia, the percentage of creators vs lurkers must be maintained above a threshold to ensure good content creation. They often use ad supported or donation based pricing model.

The sixth type of business is a Two-sided marketplace which are different from an e-commerce site, since the sellers are independent of the site owners. They have a double sided network effect. Common examples include online marketplaces, real estate, ebay, and dating sites. The two case studies in this thesis, Vortal.biz and Custojusto.pt are examples for this type of Business.

2.9. Summary

This section has identified some of the unique characteristics of Digital Business that are vital to account for while designing a Business Model for a Digital Business. Some of these characteristics such as Word of Mouth and Viral Marketing are relevant for traditional businesses also, but the scale, speed and complexity of these approaches when applied to Digital Businesses make them unique. When these characteristics are well understood and integrated into Digital Business Model, these can help overcome the challenges faced by Digital Businesses and harness the true potentials of Digital Technologies.

Contemporary Business Model Research, as detailed in Section 3, has largely ignored the specific requirements of Digital Businesses. Digital Business Characteristics, as discussed in this section, helps us frame the generic rules of Digital Business that must be kept in mind while designing a successful Business Model. It also provides us with a theoretical framework that shall aid us to develop the DYNAMOD simulation model in Section 5.

The Literature Review revealed that there is a lack of research that integrates all the unique characteristics of Digital Businesses under one unified research work. Academic models related to certain aspects of digital business were found and have been explained in this section. What was found lacking was a unified framework that identifies and integrates all the various aspects of Digital Business. Such an attempt has been made in this thesis by integrating the various characteristics into a modelling framework that can be used to create case specific simulation models.

3. Business Models

3.1. State of play regarding Business Models

Academic interest in defining a formal and comprehensive definition for "Business Model" (BM) started to develop during the era of Internet boom, at the turn of the last millennium (Magretta, 2002). The concept of BM started gaining importance because it was felt that a systematic and comprehensive method of modelling the various elements of a Business could provide a generic roadmap for business designers. However, various definitions of the concept have been proposed, and the role of BM in designing a business has been debated (Palo & Tähtinen, 2011). Most of the last decade has been spent on defining the scope and role of BMs and competing definitions have been proposed. Most of these definitions have built upon ideas from strategic management, value chains, research based theory, strategic networks, and cooperative strategies (Stewart & Zhao, 2000)(Morris, Schindehutte, & Allen, 2005)(Mason & Mouzas, 2012). However, Business Model research has not specifically focussed on Digital Businesses and hence none of the Business Model Frameworks discussed in this chapter incorporates the unique characteristics of Businesses that are built primarily based on online platforms. This thesis will develop a modelling framework in Section 5 that shall focus on certain aspects of Business Model and apply them to a Digital Business context. Note that despite the similarity in terminology, BM and Business Process Modelling are not the same thing. A business process is a collection of related, structured activities or tasks that produce a specific service or product. Business Process Modelling is the logical representation of a Business Process such as a well defined workflow. Several tools for modelling such business processes already exist in addition to modelling languages such as BPMN (Dijkman, Dumas, & Ouyang, 2008).

(Lambert & Davidson, 2013) performed a detailed analysis of BM research papers and concluded that while most research seek to describe BMs, there is no empirical research that aims to predict a firm's success based on models that they adopt. While empirical studies have been performed linking BM features to the firm's overall success (Brettel, Strese, & Flatten, 2012), predictive models for a firm based on capturing its BM, has never been conceptualised. The possibility of developing such predictive computational models is feasible, as demonstrated by the application of Agent Based Models in Marketing and Business.

Reviewing the research on BMs reveals that there is yet no unanimous definition. (Lambert & Davidson, 2013) performed a comprehensive analysis of BM application literature from 1996 to 2010 and found 69 relevant papers. They categorised these into three prominent research themes: a) BM as a basis for enterprise classification. b) BMs and Enterprise performance c) BM innovation.

(Zott, Amit, & Massa, 2011) performed another exhaustive review of the research on BMs in various contexts. They concluded that literature that exists on BMs addresses the following three phenomena: a) E-Business and the use of Information Technology, b) Strategic issues such as Value creation, Competitive advantage, and Firm performance, c) Innovation and Technology Management. We build upon the exhaustive research review conducted through the selected papers, highlighting the need for Computational Modelling based applications in this area.

Although Business Modelling definitions have been changing, there is a consensus that BMs refer to the comprehensive, all encompassing aspects of a firm that give it the ability to stay competitive. In fact, it can be seen as a framework that describes all the features that fundamentally are responsible for the success or failure of a business. The extent to which a well detailed Business Model coupled with adequate information about the business environment conditions can theoretically predict the success or failure of a Business Venture remains to be explored.

The simplest proposed definition of a BM is simply the economic model of the company. Relevant decision variables include revenue sources, pricing methodologies, cost structures, margins, and expected volumes (Morris et al., 2005)**.** One of the earliest definitions of BM was proposed by (Stewart & Zhao, 2000), who defined it as "a statement of how a firm will make money and sustain its profit stream over time." Major decision variables that were identified included production or service delivery methods, administrative processes, resource flows, knowledge management, and logistical streams.

Other early definitions were based on the strategic elements such as those that define the market position, and growth opportunities. Most early works were based on revenue streams for web based companies (Mahadevan, 2000). Other contributions enlarged the scope to product offerings, value creation processes, and organizational architecture.

There is almost unanimous agreement that the creation of value forms the central pillar of a business model, because the creation of value provides a justification for the business organization. Different authors have proposed other complementary components that comprise the Business Model. (Shafer, Smith, & Linder, 2005) identified four types of BM components: Strategic Choices, Creating Value, Capturing Value, and The Value Network. Figure 3.1 shows the elements of Shafer's BM Components.

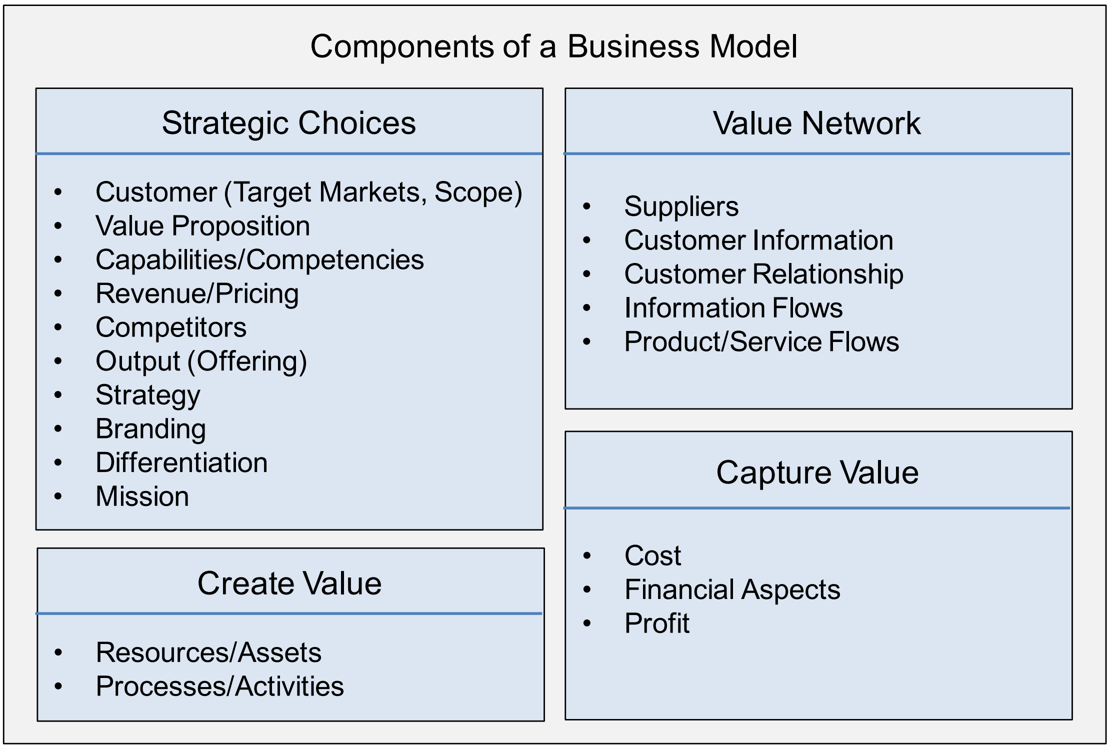


Figure 3.1 Elements of Shafer's Business Model Components (Shafer et al., 2005)

(Shafer et al., 2005) argue that while a BM facilitates the testing and analysis of a firm's strategic choices, it is not in itself a strategy. Creating Value and Capturing Value are two vital activities that firms must perform to remain viable. Value is created by organizing the resources and internal processes in a way that differentiates a firm from competition. In this process firms develop core competencies and positional advantages. While creating value, firms capture value by organizing resources, monetizing their advantages, and having the right pricing strategies. The processes of creating and capturing value occur across a value network that involves key stakeholders. Thus it is vital to efficiently organize the flow of information and ensure coordination amongst themselves.

Subsequently, another comprehensive definition of BM was provided by (A Osterwalder, 2005) who identified nine building blocks of a business model: Value Proposition, Client Segments, Distribution Channels, Client Relationships, Revenue Flows, Partner Networks, Key activities, Key resources, Cost structure. (Figure 3.2)

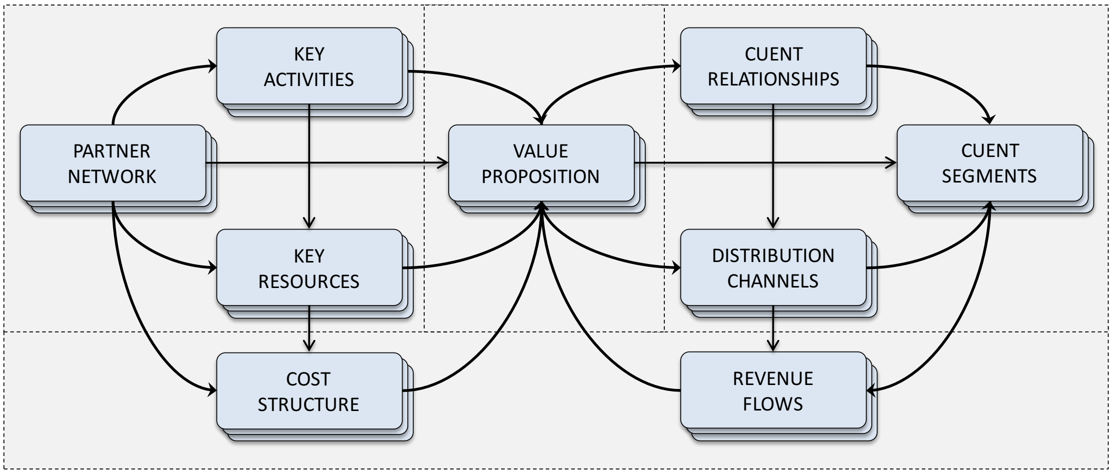


Figure 3.2 Osterwalder's nine BM Building Blocks. Source (A Osterwalder, 2005)

Merging the results of (A Osterwalder, 2005) and (Doganova & Eyquem-Renault, 2009), (Boons & Lüdeke-Freund, 2012) proposed the following elements of a generic BM concept:

1. Value proposition: what value is embedded in the product/ service offered by the firm;
2. Supply chain: how are upstream relationships with suppliers structured and managed;
3. Customer interface: how are downstream relationships with customers structured and managed;

A financial model based on costs and benefits from the above three can be developed detailing their distribution across BM stakeholders (Mason & Mouzas, 2012; Morris et al., 2005; Stewart & Zhao, 2000). For already established companies it is possible to accurately identify each of these elements, but for a new company, it may be more difficult to ascertain all the elements. However, a detailed proposal that considers the above elements can be used to determine the configuration that could enable a company to be profitable.

(Feng & Papatla, 2011; Muniesa, Millo, & Callon, 2007) state that a BM is a "market device", an intermediary between different innovation actors such as companies, research institutions, financiers. According to them, BMs serve as reference points towards circulating a comprehensive "narrative" to describe their ventures amongst this network of actors.

(Doganova & Eyquem-Renault, 2009), (Callon et al., 2007) state that a BM is a "market device", an intermediary between different innovation actors such as companies, research institutions, financiers. According to them, BMs serve as reference points towards circulating a comprehensive "narrative" to describe their ventures amongst this network of actors.

(Wirtz, 2010) defined BM by identifying three streams. The first stream consisted of technology, since adoption of information technologies forms a vital tool to access markets. Web based interfaces are immensely important, whether or not the value proposition includes a digital product. The second stream describes the organizational features, and emphasizes that a BM can also be a strategic tool aimed at improving the value chain. This stream emphasises organizational efficiency as a means of representing, planning and structuring the business (Linder, 2000). The third stream is based on strategy, and focuses on market competition. Creating and delivering customer value lies at the heart of strategy planning for any BM (Boons & Lüdeke-Freund, 2012). The BM can also be a source of competitive advantage. (Chesbrough, 2010) provides a discussion on the barriers to BM Innovation citing some examples where BM innovation has been successfully used.

(Mason & Mouzas, 2012) explores the flexibility offered by different business through the way organisations select and integrate three inter-related elements to devise flexible business models, i.e. network influence, transactional relationships, and corporate ownership. Affected by situated practices in each business network and the market position or business size, companies select and integrate various configurations of these elements to respond to the constantly evolving demands of end-customers.

(Sabatier, Craig-Kennard, & Mangematin, 2012) provides an interesting discussion on the triggers that can cause disruptive BM changes in the Pharmaceutical industry. Based on analyzing the changes that biotechnologies and bioinformatics have brought to the drug industry, they identify and characterize three triggers of change that can create disruptive business models. They suggest that, in mature industries experiencing strong discontinuities and high technological uncertainty, entrants' business models initially tend to fit into the industry's established dominant logic and its value chains remain unchanged. But as new technologies evolve and uncertainty decreases, disruptive business models emerge, challenging dominant industry logics and reshaping established value chains.

(Palo & Tähtinen, 2011) identify the generic elements of a business model in the field of technology-based services and uses those elements to build a networked business model. A networked business model reflects a situation when it is impossible for a single company to govern all the relevant resources and activities needed in developing, producing, and marketing technology-based services. (Vives & Svejenova, 2011) propose an integrative framework on BMs that combines and connects concepts pertinent to the literatures of strategy, entrepreneurship, and organization.

There has also been some more specific industry based approaches to Business Models such as the Music Industry. Through changes in the recorded music market since the 1870s, (Mason & Spring, 2011) explore how business models emerged, took on multiple sites and evolved through their practice over time. They look at how interlinking business models become spread out across the business network as different network actors play their part. (Demil & Lecocq, 2010) illustrate their framework with the case of the English football club

Arsenal FC over the last decade. They view business model evolution as a fine tuning process involving voluntary and emergent changes in and between permanently linked core components, and find that firm sustainability depends on anticipating and reacting to sequences of voluntary and emerging change, giving the label 'dynamic consistency' to this firm capability to build and sustain its performance while changing its business model.

(Baden-Fuller & Morgan, 2010) point out that BMs act as various forms of model: to provide means to describe and classify businesses; to operate as sites for scientific investigation; and to act as recipes for creative managers. They argue that studying business models as models is rewarding in that it enables us to see how they embody multiple and mediating roles.

Using Catalonia as a context, (Casadesus-Masanell & Ricart, 2010) derive recommendations by presenting and analyzing examples of companies, referred to as "new generation companies," that have innovated in their business models. The case studies illustrate the contributions of the business model notion to the competitiveness debate. (Doganova & Eyquem-Renault, 2009) explore the role of BMs in the innovation process using a case study of a startup, Koala.

(Mäkinen & Seppänen, 2007) propose a taxonomical criteria to classify current Business Model conceptualisations. The results of the paper revealed that the current business model concepts comply poorly with the taxonomical criteria. The assessment of taxonomical compliance in this paper exposed major opportunities for enhancements in the existing conceptualizations of business model.

(Morris et al., 2005) have sought to provide direction in addressing some of the more vexing questions surrounding models. The model represents a strategic framework for conceptualizing a value-based venture. Their framework allows the user to design, describe, categorize, critique, and analyze a business model for any type of company. It provides a useful backdrop for strategically adapting fundamental elements of a business. By specifying the elements that constitute a model, the framework enhances the ability to assess model attributes. A model that ignores one or more of the specified components will suffer in terms of its comprehensiveness, while inconsistency can manifest itself both in terms of the fit among decision areas within a given component as well as the fit between components.

While academic definitions have been proposed for BMs, industry has also been proposing and adopting a BM approach. IBM has published a component BM and is filing patents for the same (shown in Table 3.1) (Chesbrough, 2010).

Table 3.1 IBM Business Component Model. Source (Chesbrough, 2010).

<table>
<tr><th></th><th>Business Administration</th><th>New Business Development</th><th>Relationship Management</th><th>Servicing and Sales</th><th>Product Fulfillment</th><th>Financial Control and Accounting</th></tr>
<tr><td>re</td><td>Business Planning</td><td>Sector Planning</td><td>Account Planning</td><td>Sales Planning</td><td>Fulfillment Planning</td><td>Portfolio Planning</td></tr>
<tr><td rowspan="2">Control</td><td>Business Unit Tracking</td><td>Sector Management</td><td>Relationship Management</td><td rowspan="2">Sales Management</td><td rowspan="2">Fulfillment Planning</td><td rowspan="2">Compliance Reconciliation</td></tr>
<tr><td>Staff Appraisal</td><td>Product Management</td><td>Credit Assessment</td></tr>
<tr><td rowspan="3">Execute</td><td>Staff Administration</td><td>Product Delivery</td><td rowspan="3">Credit Administration</td><td>Sales</td><td>Product Fulfillment</td><td>Customer Accounts</td></tr>
<tr><td rowspan="2">Product Administration</td><td rowspan="2">Marketing Campaigns</td><td>Customer Dialogue</td><td rowspan="2">Document Management</td><td rowspan="2">General Ledger</td></tr>
<tr><td>Contact Routing</td></tr>
</table>

The Component BM is a logical representation or map of business components with business areas along the rows and operational levels along the columns. IBM claims that this approach facilitates the transformation to internal and external specialization. It makes it possible to have a consolidated view of the various departments (Business Components) that exist within an organization and describes the mutually exclusive set of activities they must perform. Further, it describes the resources, the people, knowledge, and assets that support those activities. The governance model describes how each component is managed as a separate entity. Similar to a stand alone business, each business component provides and receives business services to and from the other business components.

3.2. Relationship between Business Models and Digital Business

Business Model Research identifies the relationships between the different aspects of the value delivering mechanism of an Enterprise. It is a broad area of research that is applicable to all industry segments. However Digital Businesses have certain unique characteristics that necessitate a different approach to their analysis.

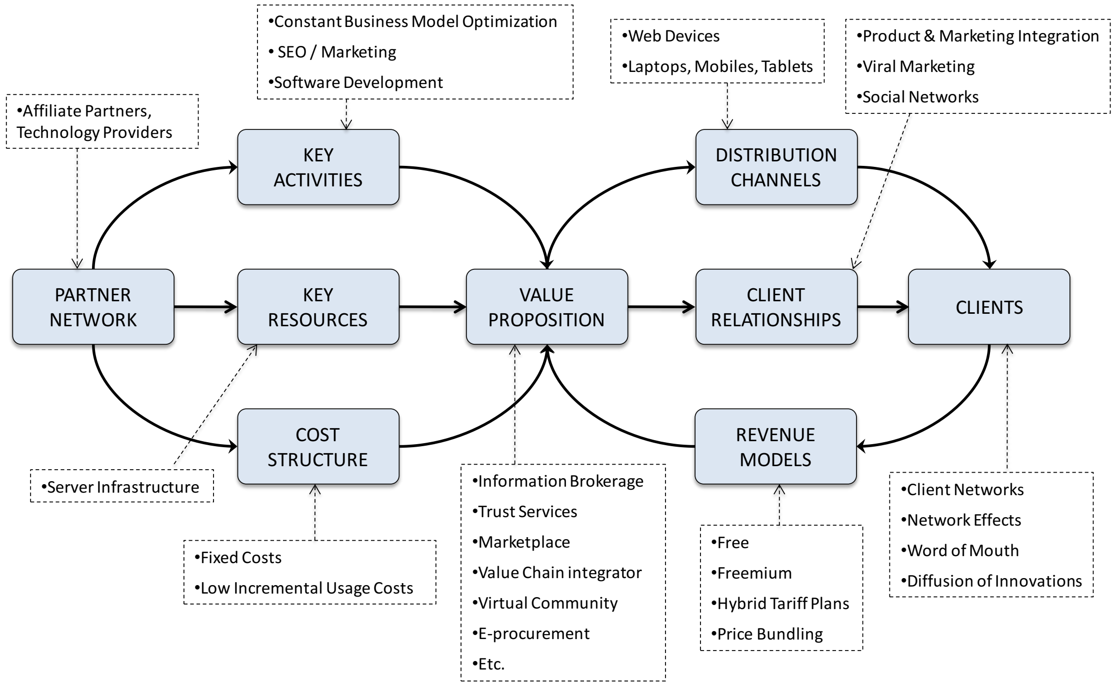


Figure 3.3 Application of Digital Business Elements to Osterwalder's Business Model Canvas

In Figure 3.3, we place some of the key characteristics of Digital Businesses and map them to the Business Model Elements on Osterwalder's Business Model Canvas (Alexander Osterwalder, 2004). While traditional Business Model approaches view Clients as a set of segmented static entities, Digital Businesses must be approached differently. Clients are networked entities, who share opinion and feedback through a variety of Word of Mouth. They exhibit network effects and the clients themselves act as marketing agents for companies. Company to Client Relationships are largely replaced by relationships where Social Networks play a wide role. Marketing Channels are replaced by strategies of scale where the marketing is integrated within the product itself. Viral Marketing is another example of the same. A variety of Revenue Models are explored, including Free and Freemium. More innovative strategies of pricing are explored than those traditionally envisaged.

The other BM blocks tend to be more static as they are more or less similar for all digital business and hence their configuration is not as relevant. The distribution channels for all purely digital business is a digital device such as a laptop, tablet or mobile. The resource requirements are purely server and data infrastructure. Almost all digital companies have extremely low incremental usage costs and hence try to have economies of scale. The key activities primarily include constant BM optimisation to adapt to changing conditions, and continuous software development, and engagement in Search Engine Optimisation (SEO) and other online marketing activities.

(Croll & Yoskovitz, 2013) have identified some of the key Business Model elements of a Digital Business (See Figure 3.4). Acquisition channel describes how the customers are reached for the first time. This include strategies that can enhance the word of mouth such as introducing an artificial virality to the product. Eg. Dropbox was made popular by rewarding users who recommended it to other users. Paid advertising is one of the most expensive method of customer aquision. Other techniques include Search Engine Management, using the social media, affiliate marketing, public relations or placing the product in an App Market.

Selling tactics are used to convince the visitor to start using the product. These range from using Discounts and incentives, giving free trials to providing freemium service. Other innovative tactics have been used such as asking the client to pay for privacy and personal space like in the case of Slideshare, where slides uploaded by free users are publically available.

The Revenue Models include one time subscription, recurring subscription, consumption charges and donations. Others monetize indirectly through advertising clicks or resale of user data (eg Twitter's firehose license).

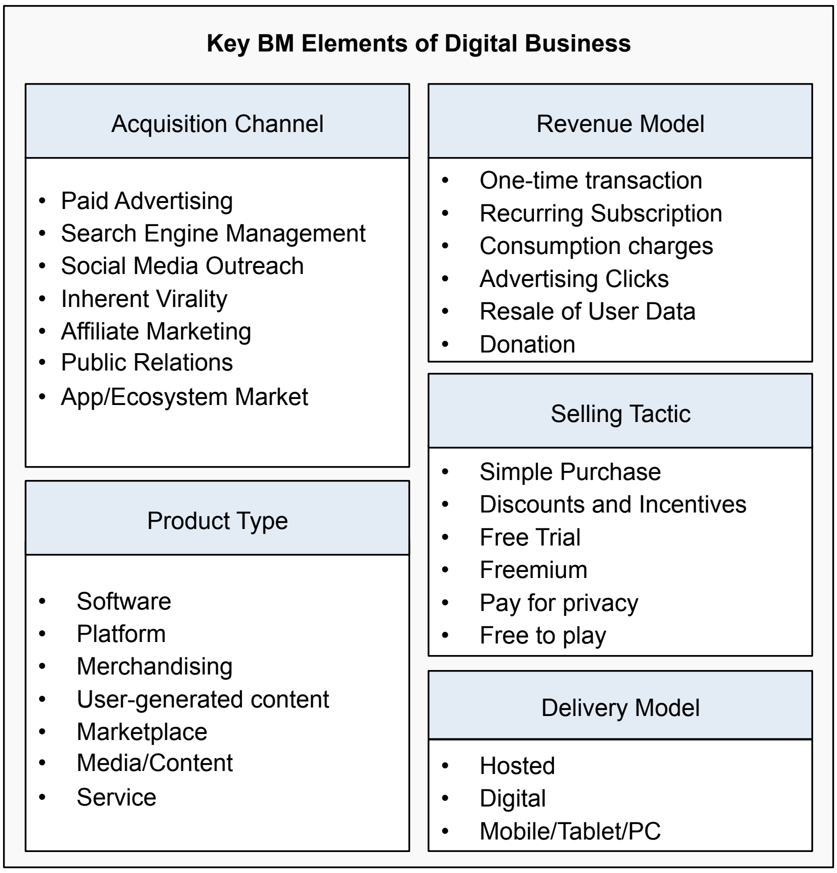


Figure 3.4 Key BM Elements of a Digital Business. Source (Croll & Yoskovitz, 2013)

3.3. *Relevance of Business Models to this Thesis*

Research on the Business Model has focussed on a broad picture of how firms create and deliver value. There has been limited research work on Business Models that acknowledges the unique characteristics of Digital Business. (A Osterwalder, 2005) have coined the term e-business models and propose a framework that can help existing traditional businesses choose an online business model to complement their Business. The framework is aimed at existing businesses considering an e-business model rather than those designing Internet-only organisations where the e-business model is also the business model. No comprehensive work on Business Model was found that incorporated the unique characteristics of Digital Businesses and provided tools and frameworks for purely online businesses that must survive in a completely different market reality and business dynamics.

This thesis is aimed at providing a framework for optimising the configuration of digital businesses and thus a literature review of Business Models is vital to an enhanced understanding of State of the Art in this area. This thesis also attempts to develop a framework for a simulation model that can be used to simulate the market adoption of a digital product. The Framework has been discussed in Section 5.

3.4. *Summary*

Business Model Research has primarily focussed on the following four issues. Firstly, some try to identify the strategic and operational aspects of organising a business. Secondly, some identify the network elements of a business entity. Thirdly, some describe the Business Model Evolution of a specific firm. Fourthly, some also explore the Business Model Evolution for a specific industry sector or industrial cluster

The literature review suggests that despite not having a universally accepted definition for BMs, there is a clear understanding that a BM can include any aspect of the Business that affects its ability to deliver value and create demand for its product or service. Thus, there is a strong correlation between BM and the performance potential of a company. The term "Business Model" is broad and covers several features of a Business Organization. The evaluation of an organization's BM is at two levels; one ensuring that each aspect of the model is designed and executed efficiently; the other ensuring that the business components are well integrated and complementary.

The boundaries of BM definition are becoming less fuzzy, and BM analysis has now been quite extensively used to conceptualise and evaluate a firm's business proposition. Most analysis has been in a descriptive, conceptual form, and the current state of the art lacks attempts at quantification and modelling of BMs so that computational models can be developed for specific forecast and simulation.

However, as BM definitions become more comprehensive, their ability to make specific performance predictions increase. The application of complexity science models have the potential to convert partial sets of business rules and data into predictive scenario-based models that could be used for business forecasting, performing predictive "what if" experiments.

In this thesis, Business Model Research works have been approached with the objective of identifying how they can be developed further in the context of Digital Business. Traditional BM literature provides us with a broad based identification of different elements of a business value chain. Some of its elements such as a the organization, networking and interactions of users amongst themselves has not been given enough relevance. Other areas such as cost structures are less relevant in the Digital Business context since they usually have minimal incremental usage costs. Hence this thesis looks at Business Models with a more narrow perspective of that of a purely Digital Business.

4. Tools for Business Growth Modeling and Analysis

4.1. Forecasting

Forecasting is the most simple form of analysing past time series data to predict the future (Rossi & Sekhposyan, 2011). It is based on the presumption that Business Data is cyclic in nature and the past can be a good indicator of the future. It does not require any understanding of the systemic complexities of the Business. For application to digital business, forecasting may only be appropriate for very large and static enterprises due to the dynamic nature of the Business.

Forecasting is a good approach when details about the underlying dynamics of the system are not well understood and predictions are based purely on the past. Hence other approaches such as simulation models, that model the business environment can make much more accurate forecasts and respond to various what-if scenarios that simple forecasting cannot.

The traditional foresting techniques are as following: regression, multiple regression, exponential smoothing and Iterative reweighted least-squares technique. The traditional forecasting techniques have been modified so that they are able to automatically correct the parameters of forecasting model under changing environmental conditions. Some of the techniques which are the modified version of these traditional techniques are adaptive load forecasting, stochastic time series and support vector machine based techniques (Singh, Ibraheem, Khatoon, Muazzam, & Chaturvedi, 2012).

Regression is one of the most widely used statistical techniques and it is often easy to be implemented. The regression methods are usually employed to model the relationship of data. This method assumes that the data can be divided in a standard trend and a trend linearly dependent on some factors influencing the data. The mathematical model can be written as:

$$L(t) = Ln(t) + \sum a_i x_i(t) + e(t)$$

Where, Ln(t) is the normal or standard observation at time t, a_i is the estimated slowly varying coefficients, $x_i(t)$ are the independent influencing factors such as external effects, e(t) is a white noise component, n is the number of observations.

Multiple Regressions is another popular method and often used to forecast the variables affected by a number of external factors. Multiple Regression analysis for forecasting uses the technique of least-square estimation (Mbamalu & El-Hawary, 1993).

Exponential smoothing is one of the approaches used for forecasting where future data points are modeled based on previous data, then used to predict the future. Example, in

Moghram and Rahman's exponential smoothing model, the electricity load at time t, y(t), is modelled using a fitting function and is expressed in the form (Moghram & Rahman, 1989)

$$y(t) = \beta(t)T\, f(t) + e(t)$$

Where, f(t) is the Fitting function vector of the process, β (t) is the Coefficient of vector, e(t) is the White noise and T is the Transpose operator. The Winter's method is one of existing exponential smoothing methods having capacity to analyze seasonal time series directly. It is based on three smoothing constants for stationary, trend and seasonality.

Autoregressive Moving-Average (ARMA) Model represents the current value of the time series y(t) linearly in terms of its values at previous periods [y(t-1), y(t-2),..] & in terms of previous values of a white noise [a(t), a(t-1),…]. For an ARMA of order (p,q), the model is written as: (Singh et al., 2012)

$$y(t) = \varphi 1 y(t-1) + \ldots + \varphi p y(t-p) + a(t) - \varphi 1 a(t-1) - \ldots - \varphi q(t-q).$$

A recursive scheme is used to identify the parameters, or using a maximum-likelihood approach.

Autoregressive Integrated Moving-Average (ARIMA) Model: If the process is dynamic/non-stationary, then transformation of the series to the stationary form has to be done first. This transformation can be done by the differencing process. By introducing the ▼ operator, the series ▼ X(t) = (1-B)X(t). For a series that needs to be differenced d times and has orders p and q for the AR and MA components, i.e. ARIMA (p; d; q), the model is written as (Singh et al., 2012)

$$\Phi(B) \blacktriangledown d\, X(t) = \theta(B) * a(t)$$

Monte Carlo Simulations are a broad class of computational algorithms that rely on repeated random sampling to obtain numerical results; typically one runs simulations many times over in order to obtain the distribution of an unknown probabilistic entity. They are often used in physical and mathematical problems and are most useful when it is difficult or impossible to obtain a closed-form expression, or infeasible to apply a deterministic algorithm. Monte Carlo methods are mainly used in three distinct problem classes: optimization, numerical integration and generation of draws from a probability distribution(Singh et al., 2012).

In physics-related problems, Monte Carlo methods are quite useful for simulating systems with many coupled degrees of freedom, such as fluids, disordered materials, strongly coupled solids, and cellular structures (see cellular Potts model). Other examples include modeling phenomena with significant uncertainty in inputs such as the calculation of risk in business and, in math, evaluation of multidimensional definite integrals with complicated boundary conditions. In application to space and oil exploration problems, Monte Carlo–based predictions of failure, cost overruns and schedule overruns are routinely better than human intuition or alternative "soft" method.

4.2. System Dynamics

The basis of the System Dynamics is the recognition that the structure of any system—the many circular, interlocking, and sometimes time-delayed relationships among its components—is often just as important in determining its behavior as the individual components themselves (Dutta, Lee, & Yasai-Ardekani, 2014). System dynamics uses a combination of first-order linear and non-linear difference equations to relate qualitative and quantitative factors within and across time periods and is based on the principles developed by Forrester to study managerial and dynamic decisions using control principles (Nazareth & Choi, 2014). It is based on the identification of the various components and the interrelationships between them which are expressed in terms of mathematical equations. System Dynamics are based on the identification of cause-effect relationships, and help us understand how relatively simple systems display a high degree of non-linearity.

A causal loop diagram (CLD) is a formal tool used to graphically illustrate causal relationships among variables of a system (Stermann, 2000). The CLD can be used to identify feedback loops that exist within the system under consideration. A feedback loop has causal relationships among system components such that when one component is changed, the perturbation traverses along the loop resulting in a change to the originating component. When a change in the originating component causes a change in other components that strengthens the original process, the feedback loop is termed a positive or a self-reinforcing loop. If the response of other components along the loop counteracts the original change, a negative or balancing loop is deemed to exist. When a system has multiple interacting feedback loops, then it is expected to exhibit complex dynamic behaviour.

System Dynamics has been used previously to model technology adoption, such as (Fisher, Norvell, Sonka, & Nelson, 2000) in the case of agro business industry. Other diverse areas that they have been applied to include urban wastewater collection (Rehan, Knight, Unger, & Haas, 2014) and information security management (Nazareth & Choi, 2014). However System Dynamics require the rules of the behavior to be written at a higher level, such as how the whole population of consumers will respond to a marketing activity rather than how a particular individual will respond.

4.3. Genetic Algorithms

Genetic Algorithms is a search heuristic that is based on the process of Natural Selection. It finds an optimal solution by introducing random mutations to the last best solutions and testing its performance through a fitness function. This process is continued unless the optimal solution is found. This approach is especially effective when there exists a large number of possible solution sets. (Oreski & Oreski, 2014)

By simulating natural evolutionary process, the algorithm offers the capability of converging towards the global extreme of a complex error surface. It is a global search technique that simulates the natural evolution process and constitutes a stochastic optimization algorithm. Since the GA simultaneously evaluates many points in the search space and need not assume the search space is differentiable or unimodal, it is capable of asymptotically converging towards the global optimal solution, and thus can improve the fitting accuracy of the model.

The general scheme of the Genetic Algorithm process is briefly described here. The integer or real valued variables to be determined in the genetic algorithm are represented as a D-dimensional vector P for which a fitness f(p) is assigned. The initial population of k parent vectors P_i, i = 1, k, is generated from a randomly generated range in each dimension. Each parent vector then generates an offspring by merging (crossover) or modifying (mutation) individuals in the current population. Consequently, 2k new individuals are obtained. Of these, k individuals are selected randomly, with higher probability of choosing those with the best fitness values, to become the new parents for the next generation. This process is repeated until *f* is not improved or the maximum number of generations is reached. (Singh et al., 2012)

In the context of this Thesis, Genetic algorithms have been used to simultaneously optimise the pricing of several plans and features so that revenue maximization can be achieved.

4.4. Agent Based Modeling

Agent Based Model is built on proven, very successful techniques such as discrete event simulation and object oriented programming (North & Macal, 2007). Discrete-event simulation provides a mechanism for coordinating the interactions of individual components or "agents" within a simulation. Object-oriented programming provides well-tested frameworks for organizing agents based on their behaviours. Simulation enables converting detailed process experience into knowledge about complete systems. ABM enables agents who represent actors, or objects, or processes in a system to behave based on the rules of interaction with the modelled system as defined based on detailed process experience.

Advances in computer technology and modelling techniques make simulation of millions of such agents possible, which can be analysed to make analytical conclusions.

A key challenge for its application in the area of Business and Management is the identification of quantifiable variables. Representing Business Models as computable variables is a challenge as BMs use natural language as well as graphics that enable visualisation and human cognition. However computational models must be able to perform simulation and manipulation of data.

Business Market Simulations fall under the category of complex non-linear systems for which simple, intuitive, analytical solutions are not readily available. Possible candidate methodologies for the evaluation of such complex systems include Neural networks, Bayesian networks, and Agent Based Models. Neural Networks as well as Bayesian networks are both based on developing predictive models that require a huge number of data sets to train coefficients. However, in business applications, especially for new businesses, obtaining a large number of data sets is rare (North, Macal, & Aubin, 2010).

Literature review demonstrates that the most promising and widely adopted tool for making business and market simulation models has been Agent Based Modelling (ABM) [(Rand & Rust, 2011), (Schramm et al., 2010)**]**. ABMs will need to incorporate complex sets of variables that establish relationships between BM Components on the one hand and their relationships with Market and Environmental factors on the other. ABMs allow increasing complexity to be appropriately modelled without making the model overly complex or needing exponentially high training data-sets, unlike many other competing tools (North & Macal, 2007).

The literature review reveals that applications of Agent Based Modelling have been made to model specific areas of Business. (Cao & Chen, 2012) apply ABM to the prediction of financial distress. They use four simulation agents: enterprise, product, bank and macro environment to examine the causes of financial distress in enterprises' different life cycle stages.

ABMs have previously been used to model a variety of situations related to Business and Marketing, some of which are discussed below:

a) **Product Adoption.** (Kim, Lee, Cho, & Kim, 2011) used simulation agents to model a customer's car purchase decision based on information provided by mass media, subjective attributes of the car, and social influence. (Diao et al., 2011) developed a simulation that creates a consumer durable market where dynamic price fluctuations are explored with respect to demand and supply variations. (Schramm et al., 2010) use ABM to define consumer and brand agents and study product diffusion at micro and macro levels. (Delre et al., 2007) used ABM to study the effect of different promotional strategies on the diffusion of a new product.

b) **Consumer Behaviour.** (Vanhaverbeke & Macharis, 2011) modelled consumer mobility in an artificially generated world imitating the spatial configuration of a city. It provided insights about consumer store preferences and ideal store locations. (Zhang & Zhang, 2007) simulated the decoy effect which is the shift in consumer preference between two products when a third is introduced. (Eppstein, Grover, Marshall, & Rizzo, 2011) simulated the spatial and social effects, and media influences on consumers to simulate adoption of hybrid electric vehicles.

c) **Market Share.** (Kuhn, Courtney, Morris, & Tatara, 2010) simulated Frontier Airline's market share through an ABM that models internal policies, competitors, and environmental factors such as fuel costs, federal regulation, and credit availability.

d) **Demand Forecasting.** (Ikeda, Kubo, & Kobayashi, 2004) forecast the Business Performance by applying game theory to ABM. They develop a Decision Tree Monte Carlo Business Valuations.

e) **Merchandise Management.** (Park & Park, 2003) developed an ABM for the management of merchandise. It aims to help retailers automate stocking decisions based on customer preference simulation. Other tools used are Data Envelopment Analysis, Genetic Algorithm, Linear Regression, and Rule Induction Algorithm.

f) **Multiscale consumer market model:** ABM was applied to a large model representing consumers, retailers and suppliers. This model was successfully applied by Procter & Gamble, directly influencing managerial decisions (North et al., 2010). (Tay & Lusch, 2005) provide a discussion on ABM applicability of Hunt's General Theory of competition, in which competition is disequilibrium provoking, and both innovation and organizational learning are endogenous. (Chen, Jeng, Lee, & Chuang, 2008) implements a multi-agent framework to integrate online buyers to collectively make purchase decisions.

As discussed, ABMs have been applied to a wide range of Business and Marketing applications, including making simulations for financial analysis, consumer preference, pricing and product adoption, market share, supply chain, demand forecasting, business valuation and merchandise management. All of these are highly important components of a BM. Critical actors, such as Clients, Potential Clients, Competitors, as well as Suppliers and Distributors have been modelled as Agents in the various published research works. The interactions between these actors in the real world, such as word of mouth and network effects is often modelled in an Agent Based Application.

(North & Macal, 2007) state that Agent Based Modelling and Simulation (ABMS) is based on the notion that the whole of several systems or organizations is greater than the sum of its constituent parts. Hence, agent based systems must be understood as collections of interacting systems. A BM provides a component based approach, where several components are vital for the success of the firm. Even a networked BM can be simulated with the use of agents.

(North et al., 2010) demonstrate that Agent Based Modelling has already been used for modelling the dynamics of the entire supply chain used by Proctor & Gamble. The model included consumers, retailers and manufacturers. The behaviour of each of these stakeholders is captured by the model and the simulation is being used by decision makers to take critical decisions.

BMs are used by organisations for abstraction of their organization. As we move towards efficient ways to capture business information to create BMs that capture more information about the firm's capabilities, the potentials for forecasting the business success increase. (Kuhn et al., 2010) demonstrated the possibilities of predicting market share based on certain BM attributes of Frontier Airlines.

Thinkvine is the first company to offer ABM based solutions for helping companies make their marketing plans (Thinkvine, 2012). Based on customer agents, and modelling advertising and word of mouth influences, Thinkvine offers customers services to help make key decisions related to selecting appropriate sales channels, making market segmentations, and developing pricing models.

(Bellman et al., 2013) addresses the issue of capturing Internet behaviour to deliver relevant advertisements. ABM approaches can also be used for modeling user response to different sources of advertising. It can also be used response modelling to identify the most critical target groups, complementing traditional approaches for the same (Lee, Shin, Hwang, Cho, & MacLachlan, 2010).

4.5. Why ABM is a better modelling tool?

ABM is the most appropriate tool that enables modelling at the micro level of the individual users and enables its global impacts to be seen. Thus this modelling tool is most appropriate to modeling consumer adoption scenarios where individual consumer preferences and behaviours are easy to measure and their global impact needs to be evaluated.

System Dynamics is another modelling approach which on the other hand tries to identify causal relationships and define mathematical models that can predict future scenarios. Such approaches benefit from having a simplistic relations that explain the broader macro scenario.

However digital businesses are rapidly changing dynamic environments where small micro level trends in user preferences often lead to rapid changes in market share. Our aim is to develop a tool that aids Businesses to capture these micro level variations in consumer behaviour on a periodic basis to aid, warn, visualise the future market potentials at the same time providing for a testbed for various what-if scenarios. Hence with the computational powers existing today, ABMs provide a more realistic representation of the real Business Environment.

Forecasting tools such as Monte-Carlo simulations are good predictors for future scenarios, but require a large historical data for making future predictions. However in the world of online business, the statement “Past shows the Future” does not usually hold true. Businesses have grown rapidly and often declines as rapidly, belying all expectations. The only real indicators for precise Business Forecasts is the current customer opinions, satisfaction level, willingness to pay, and word of mouth propagation that determine future outcome. A good sample of customer opinions could provide much more reliable indicators for the future than huge amounts of historical records. ABM approaches don’t just try to make forecasts but recreate the entire market scenario that can not only provide us with future trends but also provide for changing the existing Business Model conditions to visualise the impact. Thus ABM also can be used as an optimisation tool.

Since ABM models represent the actual Business Environment, they are the most generic models that can be customised to varying modelling objectives. In comparison, most other modelling techniques are more specific in nature. Since we aim to develop a generic framework applicable to all types of digital businesses, ABMs provide us the ideal approach for the same.

4.6. Netlogo

NetLogo is an agent-based programming language and integrated modeling environment. It was selected for implementing the ABM framework presented in this thesis, due to its customisability and graphical features to easily present the simulation results.

NetLogo was designed, in the spirit of the Logo programming language, to be "low threshold and no ceiling". It teaches programming concepts using agents in the form of turtles, patches, "links" and the observer. NetLogo was designed for multiple audiences in mind, in particular: teaching children in the education community, and for domain experts without needing to program the graphical interface unlike many other softwares. Netlogo has become popular amongst the scientific community and many scientific articles have been published using NetLogo (Alden, Timmis, & Coles, 2014).

The NetLogo environment enables exploration of emergent phenomena. It comes with an extensive models library including models in a variety of domains, such as economics, biology,physics, chemistry, psychology, system dynamics. NetLogo allows exploration by modifying switches, sliders, choosers, inputs, and other interface elements. Beyond exploration, NetLogo allows authoring of new models and modification of existing models.

NetLogo is freely available from the NetLogo website, https://ccl.northwestern.edu/netlogo/. It is in also in use in a wide variety of educational contexts from elementary school to universities.

NetLogo was designed and authored by Uri Wilensky, director of Northwestern University's Center for Connected Learning and Computer-Based Modeling.

4.7. Summary

The literature demonstrates that ABMs have been applied to create models that can simulate a variety of different Business Scenarios with varying objectives. This provides a compelling evidence that ABMs can be a suitable tool to model customer adoption and Business Model simulation for Digital Businesses.

Previous research has focussed on developing strategies for Validation Techniques for ABMs (Garcia, Rummel, & Hauser, 2007; Midgley, Marks, & Kunchamwar, 2007; Rand & Rust, 2011), and ABMs are now well recognised as a scientific and robust approach to simulation.

Literature studies show that there is a definite need for a ABM based framework development which would allow future research to build upon earlier research studies. Thus arbitrary selection of modelling variables and modelling strategies will begin to shift towards development of customisable frameworks for a specific type of Business Models. We attempt to do the same for Digital Businesses in this thesis.

5. The DYNAMOD Framework

The DYNAMOD Framework has been developed based on the academic literature collected and based on inputs from various industry leaders. Its purpose is to provide researchers and companies engaged in online businesses with a generic framework that can be used for developing Computational Modeling Systems that can represent their Business Models and their Business Environment, in order to perform advanced simulations for predicting business growth dynamics. DYNAMOD is based on Agent Based Modeling, which enables dynamic representation of the online marketplace. Every online user that could be a potential customer for a product or service is represented as an Agent in DYNAMOD (See Figure 5.1). These agents interact with each other and share information about new products and services. At the same time, they are influenced by external sources such as Advertising. The model captures these influences, and simulates their impacts in order to predict future business scenarios.

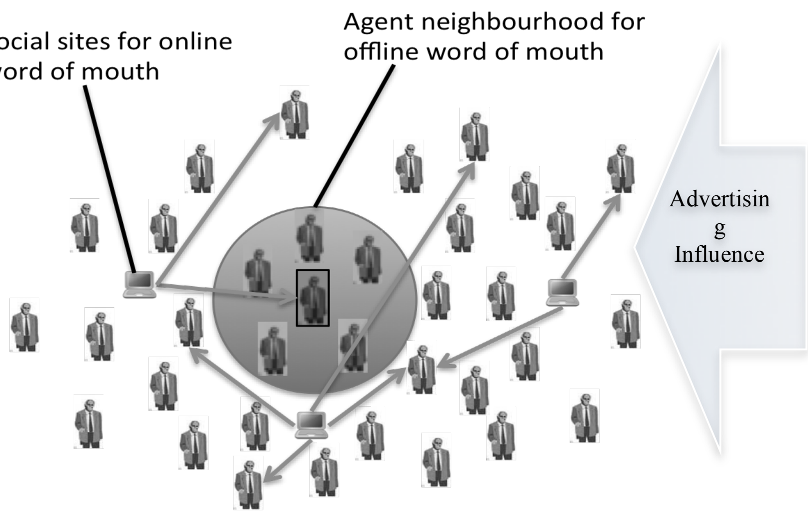


Figure 5.1 Conceptual Representation of The DYNAMOD Framework

5.1. Relationship of the DYNAMOD Framework to Business Models

The DYNAMOD Framework develops a set of approaches and standard reference models to build an Agent Based Simulation Model that incorporates Client Networks, Client Behaviour and Client Response to Value Propositions, Client Relationships, Revenue Models and Distribution Channels. Figure 5.2 demonstrates the scope of the DYNAMOD Framework with respect to Osterwalder's Business Model Canvas. This figure shows that not all aspects of the traditionally accepted domains within Business Model are explored in this Framework. The focus shall be on the five elements from the customer's perspective. However a key feature will be a deeper exploration into client networks and how clients comprise of interacting, communicating entities, often replacing the marketing functions of the firm itself.

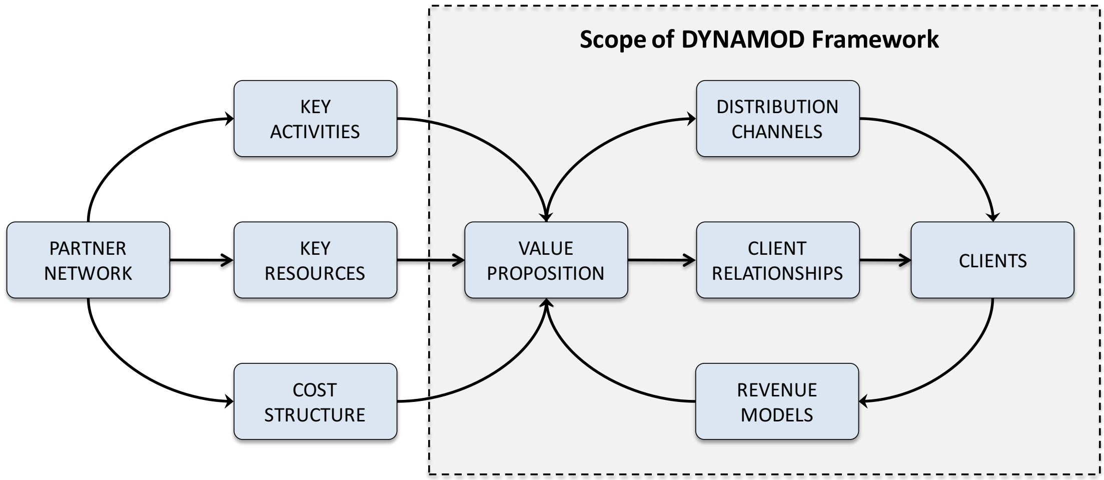


Figure 5.2 Scope of DYNAMOD Framework within Osterwalder's Business Model Canvas

The DYNAMOD Framework will be able to develop models capable of simulating and answering key questions such as what are the optimal Distribution Channels to be used for the delivery of the service (Desktop, Mobile, Tablet), which clients to target, what value proposition to offer and what revenue models to adopt. The framework shall focus on quantifying the business model elements such that they can be converted into optimization problems and can be used for developing computational models.

The left side of Osterwalder's Model that includes Partner Networks, Key Activities, Key Resources and the Cost Structure which also very important for digital businesses, are unique to each business. Contemporary literature on Business Models have already covered the theoretical aspects of these elements. It was not possible to include them in a generic Agent Based Modeling Framework and hence they have been left out of the scope of this thesis.

5.2. DYNAMOD Component Architecture

The model is customizable and extendible to implement a diverse set of Business Model components, suitable for a variety of Business Scenarios. Figure 5.3 shows a conceptual relationship of the various components the DYNAMOD Framework. The model core consists of many interacting agents that represent a market. The model includes standard variables and logics for implementing influence and satisfaction scores for each agent. This core component handles the simulation and interaction, and defines what constants are needed to initialize the key features of the model.

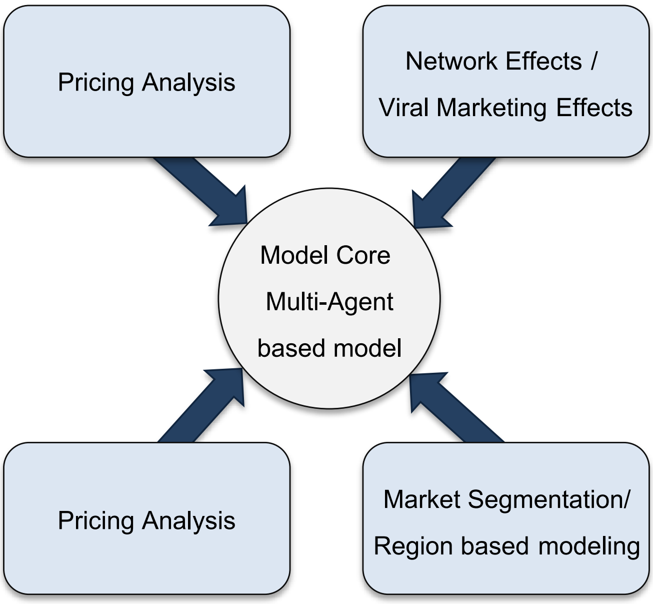


Figure 5.3 DYNAMOD Component Architecture

Other features are added to the model in the form of modules, as and when necessary, for different case scenarios. In the current scope of the model, four additional modules have been envisaged, but additional components can always be added for modeling other scenarios.

Competitor Analysis involves introduction of competitors who can have competing influences on consumers, and then monitoring the switching behavior of consumers. **Pricing Analysis** involves introduction of various charging units, and their impacts on consumer adoption. It also involves the introduction of Freemium Business Models into the model, and simulates the adoption of Free and Paid components of the Businesses. This module is not needed in case of Free Business Models. Businesses that have an inherent **Network Effect** or are based on **Viral Marketing** need to add additional logics that change the rate of product adoption. The **Market Based Segmentation** or **Region Based Modeling** changes the dispersion of agents in the model space, to represent different clusters of agents. This can represent different classes of customers with varying purchasing powers, or can represent customers on different continents.

5.3. Framework Description

At the core of the Framework are the User Agents who are autonomous entities representing a potential client in a networked digital market. The User Agent contains all the variables that define the characteristics of a potential user, who gets influenced by his neighbours, advertising and the brand value and then takes an informed adoption decision. The list of all core variables used in the DYNAMOD FRAMEWORK are listed in Figure 5.4. The individual characteristics of each Agent is derived from the global distribution of User Characteristics as discovered through a randomized Sample Survey. The key distributions such as average and standard deviation values of Willingness to Pay (WTP), Satisfaction score, Influence to Word of mouth, brand value and advertising are stored within the System Characteristics Class.

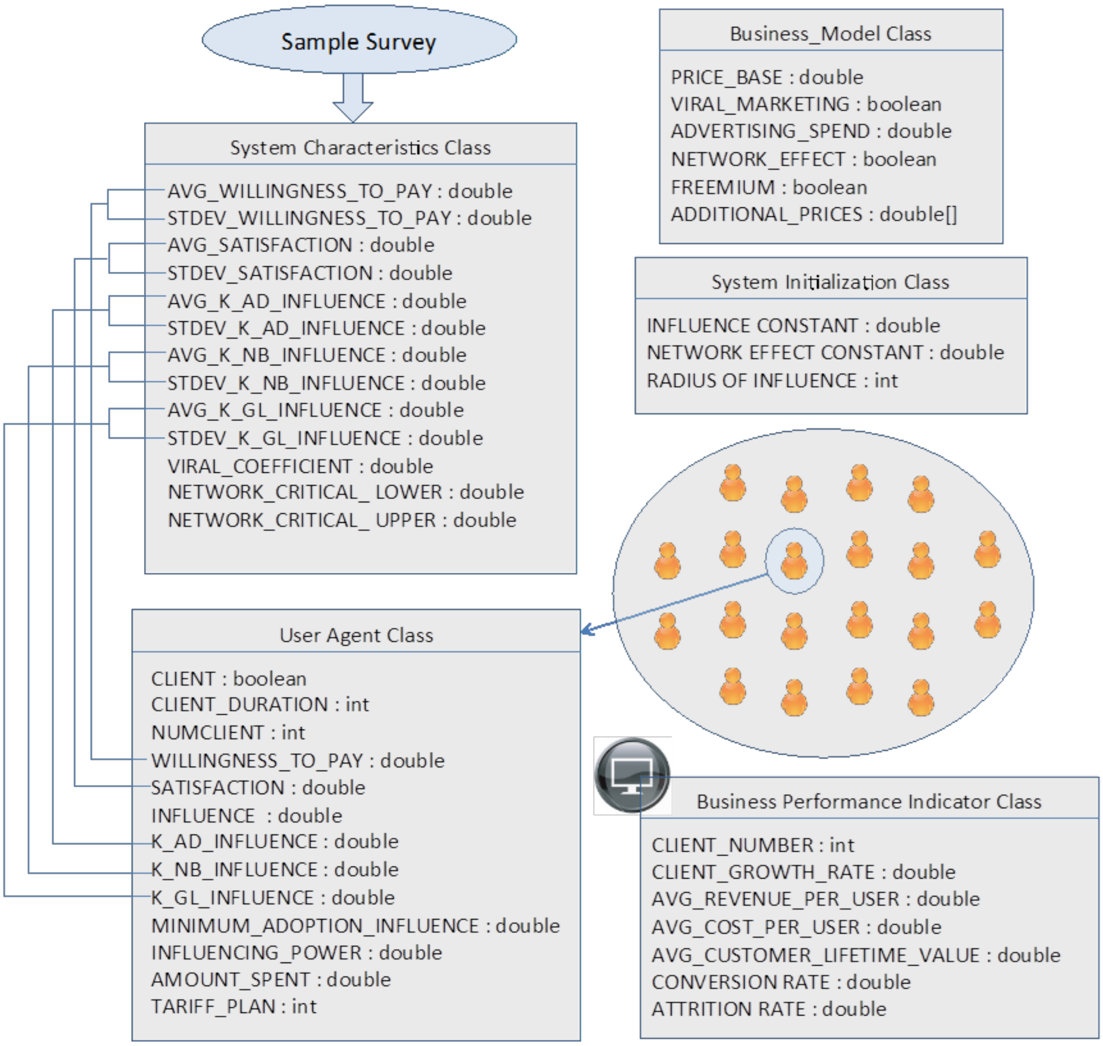


Figure 5.4 Dynamod Framework Variables

The Business Model Class contains the variables that define characteristics of the Business Value Proposition, such as pricing for various features and tiers, and the marketing strategy adopted. It also lists the intrinsic characteristics of the product such as Network Effects or not. This class also contains the variables that the company must adjust to optimise the Business Model.

The System Initialization class consists of constants that must be initialised during the model initialization phase. This requires the parameters to be adjusted using an iterative method to make sure that the model forecast fits the historical record as closely as possible. For business cases which do not have a past historical record, such as startups or businesses with a recent radical change in the business model, this step may be omitted. In this case the model will accurately predict the trend and can be equally applicable for optimisation of results but may not forecast as accurately.

The Business Performance Indicator Class is the window to the model and consists of all key performance indicators that the model is designed for. These indicators also serve as key characteristics that must be optimised, such as revenue maximisation.

Figure 5.5 illustrates the steps that an Agent goes through as it performs the steps of the Agent Based Modeling environment. During the initialization phase, it is assigned the user characteristics from the system characteristics class. Each agent is assigned the properties that reflect the distribution of the characteristics derived from a randomized Sample Survey that is previously conducted. The agents are assigned the willingness to pay, and the coefficients that determine their susceptibility to respond to the various sources of influence such as Word of Mouth, Brand Value and Advertising Influence. Then depending on the starting stage of the simulation model, the agents are assigned whether they are clients or not. If they are clients they are assigned a satisfaction score which must be greater than 0.25 (which is the threshold to be a client). If it is not a client, it is assigned a satisfaction score below 0.25 which is based on the sample survey from respondents who are not yet clients.

After the initialisation phase, the model runs are executed, with each step representing a definite time period. The agents change their influence based on other factors and then when their influence crosses the threshold of 0.25, they become a client. For more complex simulations, they may switch from one plan to another based on their requirements and willingness to pay. The following sections describe the involved variables in a much greater detail.

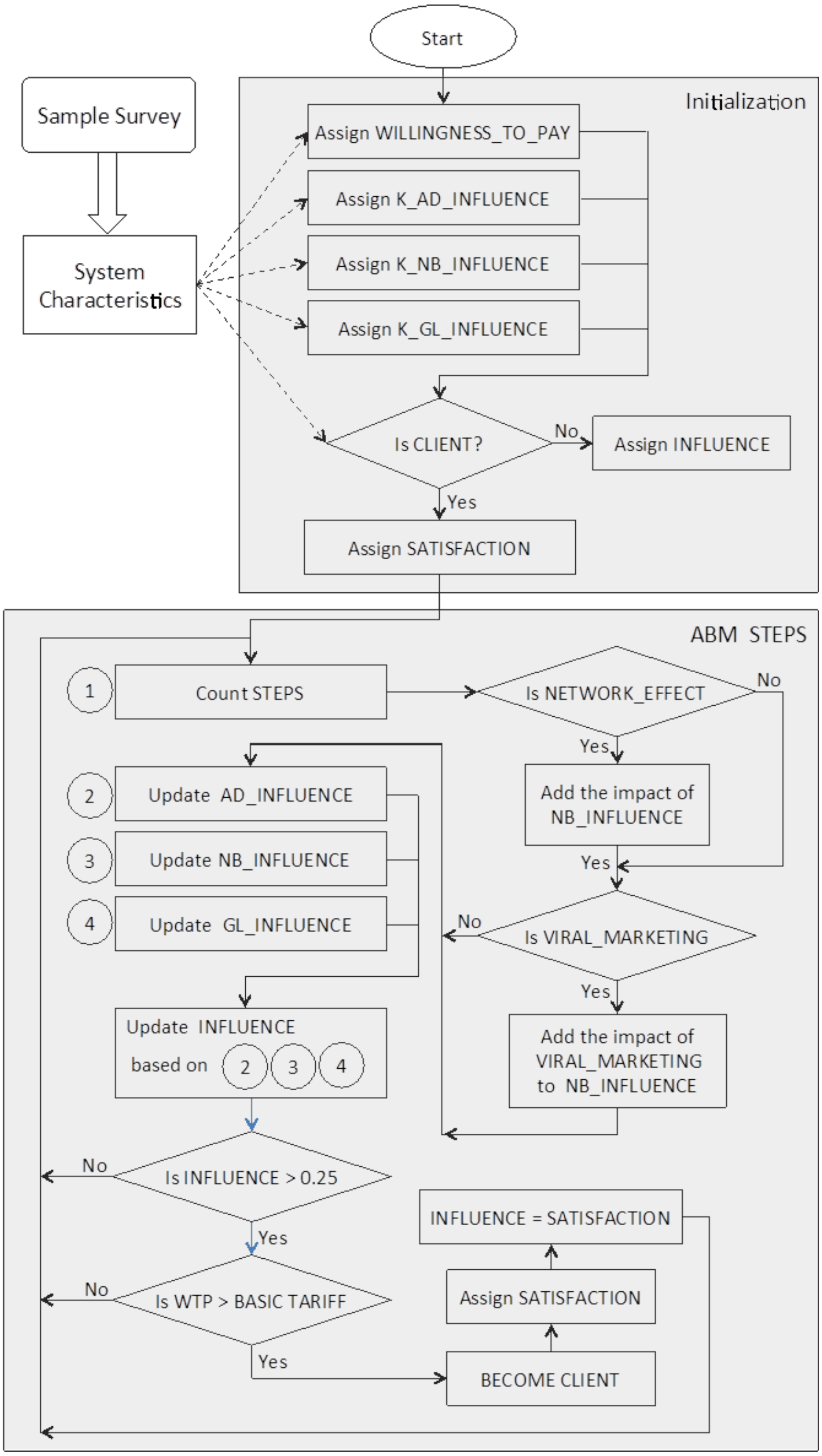


Figure 5.5 Flowchart detailing Agent Modeling Steps

5.4. DYNAMOD User Agents

Each User Agent represents a potential customer. User Agents interact with each other, hold opinions about a product, even discuss and share it with other agents with whom they are networked. They respond to marketing campaigns and peer reviews, and then decide to adopt a product or not. After adopting a product, these agents evaluate the product and are satisfied with their purchase to varying degrees. Their satisfaction level becomes the source of positive or negative influence to their peers.

Adoption of a product is also related to the willingness to pay for a particular product. If the product is free, as in case of a freemium pricing model, the willingness to pay is not a barrier to adoption, and the adoption is therefore usually much quicker.

Table 5.1 enumerates the variables that control the behavior of User Agents.
These variables include information regarding the simulation history of each user agent such as when it became a client, how long it has been a client and how many times before it had been a client but stopped due to reduced satisfaction.

The Default Values for Influence Constants were chosen after experimentation with various model configurations. However, they must be tweaked for each case scenario based on sample surveys from users. The Default MINIMUM-ADOPTION-THRESHOLD of 0.25 and MINIMUM-SATISFACTION-THRESHOLD of 0.1 are reference values for when a user will begin to adopt a product and when the user will give up using it in the absence of a competitor. These are provided as reference scores for users to keep in mind while providing satisfaction scores, during the sample surveys.

Other variables, also obtained from sample surveys, include the propensity of the user to get influenced from its Neighbours, Advertisings and Brand influences, and Willingness to Pay. If the product has multiple tariff plans, then each set of tariff plans will have their own willingness to pay.

Table 5.1 User Agent Variables

	Variable Name	Description	Value Range
1	CLIENT?	Is the agent a client or not?	YES/NO
2	CLIENT_ DURATION	How long has the agent been a client?	0 to infinity (months)
3	NUMCLIENT	No. of times been client before	0 to infinity (months)
4	SATISFACTION	Only if agent is a client, degree of satisfaction	0 to 1
5	INFLUENCE	A factor relevant for degree of influence for an agent that is not and has never been a client. If agent is a client then INFLUENCE = SATISFACTION	-1 to +1
6	K_AD_INFLUENCE	Influence factor from advertisements and promotions. Based on Sample Surveys.	0 to 1
7	K_NB_INFLUENCE	Influence factor from immediate neighbors. Based on Sample Surveys.	0 to 1
8	K_GL_INFLUENCE	Influence factor from global adoption/Brand Value. Based on Sample Surveys.	0 to 1
9	WILLINGNESS_TO_PAY	Maximum price that a user is willing to pay.	0 to 1
10	MINIMUM_ADOPTION_THRESHOLD	Minimum INFLUENCE level that can convince an agent to adopt a product. DEFAULT=0.25	0.25
11	MINIMUM_SATISFACTION_THRESHOLD	Minimum SATISFACTION level below which the user will cease to be a client. DEFAULT=0.1	0.1
13	INFLUENCING _POWER	Importance of influence of the agent over other agents. DEFAULT=1	1 to 10
14	AMOUNT_SPENT	Total Amount Spent till date	0 to infinity
15	TARIFF_PLAN	Tariff Plan	1,2,3,4..

5.5. *Adoption function*

Diffusion of Innovation literature has used two major forms of adoption functions. In the Bass like model, adoption occurs through individual innovation or through peer imitation. In the threshold model, each user adopts only when a certain threshold of its neighbors have adopted (Stonedahl & Rand, 2010). We shall use a hybrid adoption function that we detail below:

The Influence score of i^{th} Agent A_i on a scale of 0 to 1. For an agent to adopt a particular product,

$$A_i^{\text{Influence}} \geq 0.25 \text{ (Adoption Threshold)}$$

This adoption threshold has been specifically defined for the DYNAMOD model, and while asking users for satisfaction/influence scores in the sample survey, this value has been kept in mind while developing the scoring scale.

Also, if the online service is not free then for adoption, the price offered must be lower than his willingness to pay. The adoption influence is updated on each iteration by averaging it with a new computed value of the $A_i^{\text{Influence}}$

$$A_i^{Influence} = \frac{Old\ A_i^{Influence} + A_i^{Influence-Coefficient} \times New\ A_i^{Influence}}{1 + A_i^{Influence-Coefficient}}$$

The New $A_i^{\text{Influence}}$ is computed through a combination of 3 components.

$$\begin{aligned} New\ A_i^{Influence} &= \textit{Influence of Neighbours in Radius R} \\ &\quad + \textit{Global Brand Influence from All Agents} \\ &\quad + \textit{Advertising Influence} \end{aligned}$$

Where (Adapted from adoption function used by (Tran, 2012)):

$$\textit{Influence of Neighbours in Radius R} = Avg\ (\textstyle\sum_R A_i^{Influence})\ .\textit{K-NB-INFLUENCE}$$

$$\textit{Global Brand Influence from All Agents} = Avg\ (\textstyle\sum A_i^{\text{Influence}}).\text{K-GL-INFLUENCE}$$

$$\textit{Advertising Influence} = \text{Spend}^{\text{Ad}}.\ \text{K-AD-INFLUENCE}$$

Each Agent responds differently to the three different sources of influence, Word of Mouth, Global Brand Influence and Advertising Influence which is multiplied by the three respective coefficients K-NB-INFLUENCE, K-GL-INFLUENCE and K-AD-INFLUENCE are the respective constants that determine the relative weights of the three types of influences modelled these are assigned based on the sample surveys conducted and is based on the relative importance respondents give to the various sources of influence.

Once an Agent becomes a Client, then onwards, the key parameter will be the Satisfaction and not Influence. The satisfaction level will not be influenced by neighbours or advertisements but rather be a function of the product's utility. In this model we have used the satisfaction scores that have been collected from sample surveys. Hence:

If A_i = Client, $A_i^{Influence} = A_i^{Satisfaction}$ and A_i continues to remain a client unless $A_i^{Satisfaction} <$ 0.25. In this current model, once the user stops being a client, he doesn't become a client a second time. However this is specific to the context of the business being modeled.

5.6. *Sources of Influence*

There are several means through which an Agent can be influenced regarding a product. These various sources can affect his degree of influence, and hence the chances of adopting of a particular product.

5.6.1. Word of Mouth

Offline Word of Mouth - This consists of user agents interacting with their own circle of friends and acquaintances. Offline Word of Mouth is primarily concentrated in the geographical vicinity of the agent. The model seeks to simulate real life word of mouth, by simulating the influence of agents in the immediate vicinity of a particular agent (Feng & Papatla, 2011).

Online Word of Mouth - In addition to User Agents, there exist Linking Agents which represent Social Websites, Blogs, User Forums, Review Sites (Brown et al., 2007). These provide means for the large scale dissemination of opinions and experiences among users.

The net effect of online and offline Word of mouth influence is denoted by the variable $A_i^{Influence}$ and is computed by the average of $A_i^{Influence}$ for all agents within the radius R if the agent is still not a client. Otherwise $A_i^{Influence} = A_i^{Satisfaction}$

5.6.2. Global Influence

(Tran, 2012) deduces that indirect influence from the larger population can have a greater effect than direct personal contacts on an individual, thus indicating a considerable Global influence, in addition to the neighborhood influence. We have incorporated a factor for Global influence in our model and it is denoted computed by the average of all $A_i^{Influence}$ of all the agents in the simulation. This score does not have a profound impact in the early stages but once a product becomes popular it affects future adopters.

5.6.3. Advertising Influence

Advertising targets the potential users of a product, but it is generally dispersed across various target segments (Feng & Papatla, 2011). In our model we have assumed advertising to have a general effect in increasing influence among those who have never been clients. The variable K-AD-INFLUENCE determines the individual response of an agent to a particular advertising campaign. Advertising campaigns tend to have an associated cost, which usually is much higher than steps that promote the spread of word of mouth.

5.6.4. Viral Marketing influence

Viral Marketing refers to incorporating strategies within the product itself that cause the users to knowingly or unknowingly influence prospective customers in a rapid way. (Kalyanam et al., 2007) mention through the experiences of Plaxo Inc. that despite the huge benefits of Viral Marketing, careful strategizing is necessary. One of the main risks is the Ebola Syndrome, where the online user may be bombarded with too many messages or may perceive the product to be an invasion of his privacy. We have incorporated a variable VIRAL_COEFFICIENT in the model which denotes the number of other users that become influenced by each existing client per month. Determination of this coefficient can be through data from the case study or through sample surveys.

5.7. Revenue Models

Digital Businesses are devising innovative strategies for revenue optimization while at the same time ensuring an optimal client base expansion rate (Hayes & Finnegan, 2005). As discussed above, Free and Freemium are two revenue strategies that have enabled the viral adoption of a product. Usually Free services are Advertisement Supported (Indirect Revenue Source) and require an immense number of users to be commercially viable. On the other hand, Freemium services, try to charge a small percentage of subscribers (Direct Revenue Source). Major means of direct revenue include:

a) One time purchase: This is typically used for softwares where it is difficult to monitor usage after purchase. For high priced products, other revenue streams can provide a long-term revenue stream for the business and a lower initial cost for the client.
b) Charging a Periodic Subscription Fee: This can significantly reduce initial purchase cost. Typical examples include sites selling library access to journals and magazines.
c) Charging for Value added purchases: This can be used to augment revenues in addition to another direct or indirect revenue based service, and can also be used as a primary revenue source in freemium business models.
d) Transaction Fee: This is typically used by platforms that facilitate some kind of transaction between buyers and sellers.

Business Model innovation often includes innovations in revenue streams and companies often use hybrid revenue streams. DYNAMOD is designed to be customizable and incorporate various revenue streams and perform simulations such that cash flow trends can be predicted and visualized.

5.8. Network Effect

Network Effect refers to the characteristic of a particular product or service to provide a greater utility as the number of clients grows (Gallagher & West, 2009)(Li, Liu, & Bandyopadhyay, 2010). Network Effects are primarily of two types:

1. Single Sided Network Effects

All kinds of collaborative sites that depend mostly on user generated content exhibit this effect. Typical examples are social networking sites like Facebook, video sharing sites like Youtube, Travel sites like TripAdvisor, and online gaming sites.

2. Double or Multiple Sided Network Effects

This includes products that have two or more types of clients each one benefitting the other. Typical examples include e-marketing sites such as e-bay, e-procurement sites.

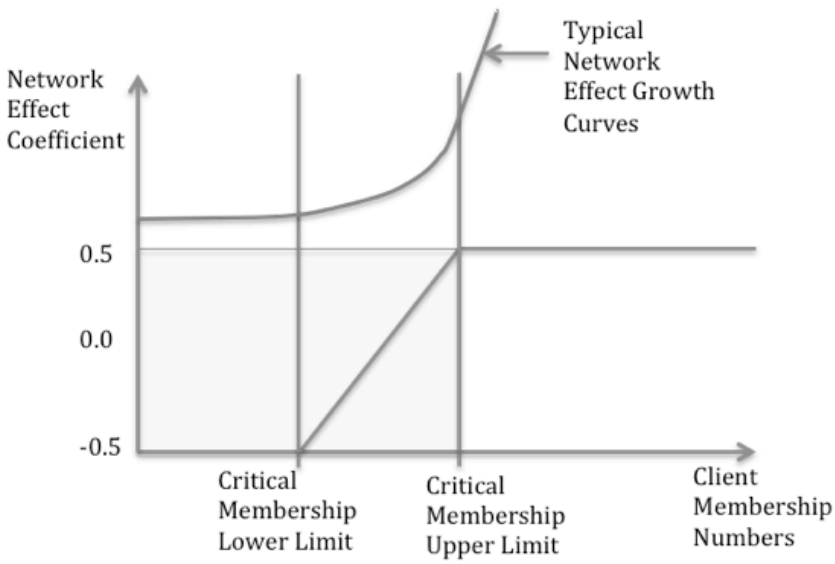


Figure 5.6 Network Effect Coefficient

In order to model the network effects, we have introduced a network effect coefficient (N-COF) in our model (See Figure 5.6). When the percentage of users who are clients within the neighborhood of an agent is below the critical membership lower limit, the value of the network coefficient is -0.5. This causes a slowdown in the adoption requirement, owing to a chilling effect of network externalities (Goldenberg et al., 2010). Within the critical membership range, the coefficient moves from -0.5 to +0.5, and we begin to see a higher growth rate. The network coefficient (N-COF) is multiplied by a network effect constant (N-CONST Range 0 to 1) and added to the influence factor for deciding value of adoption thresholds. Network effects tend to cause a hockey stick growth pattern to be more skewed.

In the case of double sided network effect, N-COF is dependent on the percentage of clients from the other agent type.

5.9. Competitor Analysis

The DYNAMOD framework can also be utilized to make competitor analysis if sufficient details on the product offering of a competitor can be provided. The model can be programmed where agents can make choices between two or more product offerings. Such an analysis would require well-designed surveys of the perceived satisfaction scores of each product. Such an analysis can be very useful in scenarios in which a competitor has a competitive advantage due to a superior product feature, and upgrading one's own product would require finite time and resources. Competitive DYNAMOD simulations could provide us with approximations of market share advantage that a competitor could have within this finite time, and its implications on the business due to the network effects involved.

5.10. List of Variables

In this section we define the variables and parameters that are critical to define the Multi-Agent Based Modeling system. This section defines the generic elements that can be customized for individual business cases.

5.10.1. Business Model Definition

The variables in Table 5.2 determine the components of the Business Model. These variables can be adjusted to change the nature of the product or service being offered. Included are variables for the pricing of the goods or services, investments in advertising and development, and the nature of the business. These variables determine which logics will be implemented within the model, and are therefore key factors governing the functioning of the model.

Table 5.2 Variables for defining Business Model

	Variable Name	Description	Value Range
1	PRICE_BASE	Unit Price. In case of pricing with multiple tiers/features, multiple variables are used.	0 to infinity
2	VIRAL_MARKETING	Is Viral Marketing incorporated?	YES/NO
3	ADVERTISING_SPEND	Expenses in Sales and Marketing with respect to total expenses	0 to 100%
4	NETWORK_EFFECT	Is Network Effect incorporated?	YES/NO
5	FREEMIUM	Is freemium adopted?	YES/NO

5.10.2. System Characteristics (Based on Sample Surveys)

System Characteristics are key variables that define the variables and thresholds of the agents in the system (See Table 5.3). Most of these variables are determined through conducting representative sample surveys of clients to understand their behavior. They include factors such as how satisfied users are with a product, what their expectations are, how much they are willing to pay, how influenced they are by advertising campaigns and by word of mouth. In case the product exhibits viral marketing or has an inherent network effect, these variable details can also be collected by sample surveys. The Satisfaction is on a scale of 0 to 1 where 0.25 is the threshold above which a user adopts a product, as long as his willingness to pay is above the price.

INFLUENCE CONSTANT and NETWORK EFFECT CONSTANT are the two main variables that are used for model initialization. The default values indicated are only typical values and values within a range of these typical values must be tested to obtain the best value that provides the best model fit with observed data during the initialization phase.

Table 5.3 Variables defining System Characteristics

	Variable Name	Description	Value Range
1	AVG_WILLINGNESS _TO_PAY	Average willingness to pay	0 to 1
2	STDEV_WILLINGNESS _TO_PAY	Standard deviation willingness to pay	0 to 1
3	AVG_SATISFACTION	Average Satisfaction	0 to 1
4	STDEV_SATISFACTION	Standard Deviation Satisfaction	0 to 1
5	AVG_K_AD_INFLUENCE	Average Influence factor from advertisements and promotions	0 to 1
6	STDEV_K_AD_INFLUENCE	Standard Deviation Influence factor from advertisements and promotions	0 to 1
7	AVG_K_NB_INFLUENCE	Average Influence factor from immediate neighbors.	0 to 1
8	STDEV_K_NB_INFLUENCE	Standard Deviation factor from immediate neighbors.	0 to 1
9	AVG_K_GL_INFLUENCE	Average Influence factor from Global Adoption/Brand Value	0 to 1
10	STDEV_K_GL_INFLUENCE	Standard Deviation Influence factor from Global Adoption/Brand Value	0 to 1
11	VIRAL_COEFFICIENT	New users influenced per month by each existing client	0-infinity
12	NETWORK_CRITICAL _ LOWER	Network Effect Critical Membership Lower Limit DEFAULT=10%	0-100%
13	NETWORK_CRITICAL _ UPPER	Network Effect Critical Membership Upper Limit DEFAULT=20%	0-100%

5.10.3. System Initialization Variables

There variables are initialised during the Initialisation and Validation Phase as described in Table 5.4. These parameters are adjusted so that the model run during the initialization phase is as close as possible to the historical data.

Table 5.4 System Initialization Variables

	Variable Name	Description	Value Range
1	INFLUENCE_ CONSTANT	Key initialization factor that determines the rate at which influence is updated DEFAULT=0.04	0-1
2	NETWORK_ EFFECT_ CONSTANT	A constant that is multiplied by the network effect coefficient to determine influence. DEFAULT= 0.01	0-1
3	RADIUS_OF_ INFLUENCE	The Radius in terms of number of pixels within which other agents can influence a particular agent. DEFAULT=4	1 to 10

5.10.4. Monitored Business Performance Indicators

Table 5.5 lists out key performance indicators that must be monitored for different business scenarios. DYNAMOD enables simulated results for each of these business indicators that can help managers monitor the key performance metrics and thereby obtain optimal values for Business Model Parameters.

Certain Business Parameters have a very important role, depending on the nature of the Business Model. For example, if the product is based on Viral Growth, then monitoring Viral rate becomes very important. For a Freemium model, the conversion rate is very important.

Table 5.5 Variables indicating Business Performance Indicators

	Variable Name	Description	Value Range
1	CLIENT_NUMBER	Total no. of clients	0 to infinity
2	CLIENT_GROWTH_RATE	No. of clients added last month	0 to infinity
3	AVG_REVENUE_PER_USER	Average Revenue generated per user per month	0 to infinity
4	AVG_COST_PER_USER	Average cost per user per month	0 to infinity
5	AVG_CUSTOMER_LIFETIME_VALUE	Average lifetime value per user (Profits – Losses)	0 to infinity
6	CONVERSION RATE	No. of free users turning to paid users per month	0 to infinity
7	ATTRITION RATE	No. of clients left last month	0 to infinity

5.11. *Application Methodology of DYNAMOD Framework*

The DYNAMOD Model is a general purpose Agent Based Modeling Framework that can be customized to various specific Business Scenarios. Application must follow a structured approach to model a Business Scenario. Here we list the steps to be followed to generate a ABM Simulation Model (Figure 5.7).

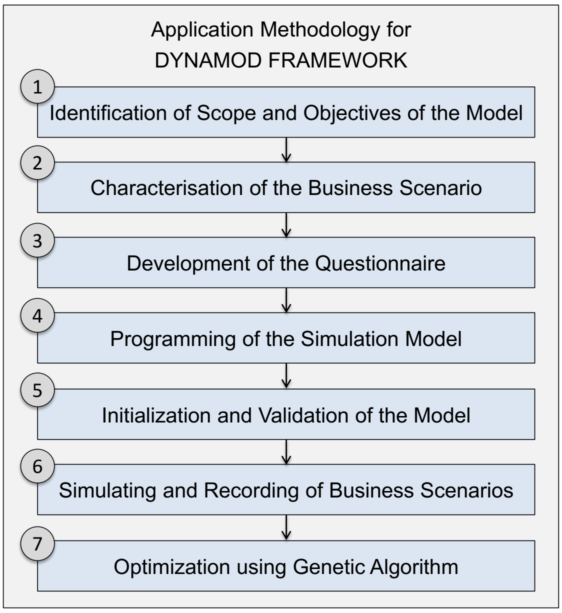


Figure 5.7 Steps for the Implementation of the DYNAMOD Framework

The DYNAMOD Model is a general purpose Agent Based Modeling Framework that can be customized to various specific Business Scenarios. Application must follow a structured approach to model a Business Scenario. Here we list the steps to be followed to generate a ABM Simulation Model.

5.11.1. Identification of Scope and Objectives of the Model

The business scenario must be completely analysed to identify which Business Model elements are most critical for the success or failure of the business. This is critical to identify which "Monitored Business Performance Indicators" are vital for the specific scenario. Also at an early stage, the Business Managers must decide the simulation constraints and what are the key variables that the simulation must be based upon. For example, the company might be having a clear idea about using a Freemium based tariff plan, but may require the simulation to advise what pricing to fix for the paid tier. At this stage all possible business alternatives must be clearly identified and corresponding variables must be listed.

5.11.2. Characterisation of the Business Scenario

The business scenario must be well understood so that appropriate Business Model variables are selected. At this stage, the key business characteristics must be identified which include the following:

a) The total potential market size

b) Whether the Business is at an Early, Intermediate or Mature Stage

c) Whether there exhibits a Network effect or not? If yes, then the quantum of network effect must be measured through the questionnaire.

d) Whether any form of Viral Marketing is used?

e) Which kind of pricing models are used and intended to be experimented with? Eg. Freemium, Subscription plan based, Feature Based, Usage Based, etc.

f) What kind of Marketing Strategy is used? What are the advertising expenditures?

g) How competitive is the scenario? How many main competitors exist and how the feature sets compare with respect to competition?

5.11.3. Development of the Questionnaire

The questionnaire must be developed based on the inputs required for the model. It may be sent to a set of existing users or include a wider set of potential users. The opinions of respondents are quantified and then the average and standard deviation is computed. This distribution is applied to all the clients in the simulation model.

Default Elements of the Questionaire

- User Profile
  a. Demographics
  b. Current Tariff Plan
- Sources of Influence
  a. How the user first heard about the current product
  b. Rating of the comparative importance placed to the various sources of influence. Eg Word of Mouth, Advertising, Brand Value
  c. How many clients have started using the product based on his recommendation
  d. Does he post actively on blogs/forums
- Satisfaction / Awareness (in case is not a client yet)
  a. Degree of Satisfaction with different aspects of the product
  b. If it involves other entities, eg range of products on a shopping site, variety of buyers/sellers on a procurement platform, then satisfaction with the other entities.

- Willingness to Pay – Users can be directly asked about their maximum willingness to pay for a particular product, or a set of products and services. Respondents have a tendency to report a lower value and hence there is generally a bias. It is can countered in the following ways:
  a. Assigning a higher weight to a larger willingness to pay.
  b. Provide a set of WTP options and ignore the responses of the lowest option.

Additional Elements of the Questionaire

- Network Effects – Devise questions that gauge the degree of network effect. Eg. How many of your friends must shift to the Social Network Platform before you start using it?
- Viral Marketing – Questions such as were you introduced to the product based on an automated message from a friend's profile or his automated posting on social media.

One needs to be creative while designing the questionnaire, so that the key objectives of the question are captured.

5.11.4. Programming of the Simulation Model

Based on the questionnaire results, the agents are initialised to reflect the reality. DYNAMOD proposes a standard set of rules about the behavior of agents based on academic research. These include how the agents interact, how the various sources of influence are computed and how they respond to different scenarios, as previously detailed in this section. However, these rules need to be customized to different scenarios and behavioural coefficients need to be customized as and when required. A variety of modelling languages can be used such as NETLOGO, ANYLOGIC, MASON, and SWARM amongst others.

5.11.5. Initialization and Validation of the Model

The model must be initialised and validated based on historical time series data. This is important for making accurate forecasts for a future time period. The historical data is initialised to compute the ideal values of the following key constants:

1. RADIUS OF INFLUENCE
2. INFLUENCE CONSTANT
3. NETWORK EFFECT CONSTANT

The initialization of the above constants enable the forecasted time series to closely follow the reality. The process of initialisation is based on dividing the available and relevant time series data into two parts, the earlier part as the initialization set while the later part as the validation set. The above constants are adjusted so that the simulation followed the initialization curve as closely as possible. Once the constants are fixed, the model is allowed to run and the results compared with the validation set. This enables the validation of the accuracy of the model forecasts. Model results are computed as the average of 30 or more model runs.

There may be scenarios where historical record may not be available, such as in the case of startups or in the case there has been a change in the product or business model and the past data is not relevant. DYNAMOD can be an indispensible tool in such scenarios where other forecasting methods are ineffective. However, the forecast of specific numbers, such as no. of clients, revenue may not be very accurate since initialisation is not possible. Still, the trends and impact of business decisions can be very accurately simulated in such scenarios. Also relative data such as percentage of users in different tariff plans can be accurately predicted without the requirement of an initialization set.

5.11.6. Simulating and Recording of various Business Scenarios

A initialised and validated model is ready for a Business Manager to play with and visualise the impact of various business decisions that he may take. It is like a flight simulator that can be used to test various possibilities. Interesting patterns and insights may emerge from these simulations.

5.11.7. Optimization using Genetic Algorithm

When a large number of possible business scenarios exist, such as the possibility of assigning a range of prices to different tariff plans, then the usage of a genetic algorithms is possible to quickly reach a optimised solution. These can be quickly and effortlessly implemented within the DYNAMOD model. It is important that all possibilities are defined and a fitness function be defines. A fitness function may be the maximisation of revenue, or maximisation of growth rate or a set of different business objectives.

6. Research Methodology

The development of this thesis has followed methodologies for the various phases of the thesis.

6.1. Collection of Literature Review

The theoretical basis for this research work is based on 3 complementary Research Areas as shown in Figure 6.1. Thus a literature review of all these 3 complementary areas were performed to identify the characteristics of the proposed framework.

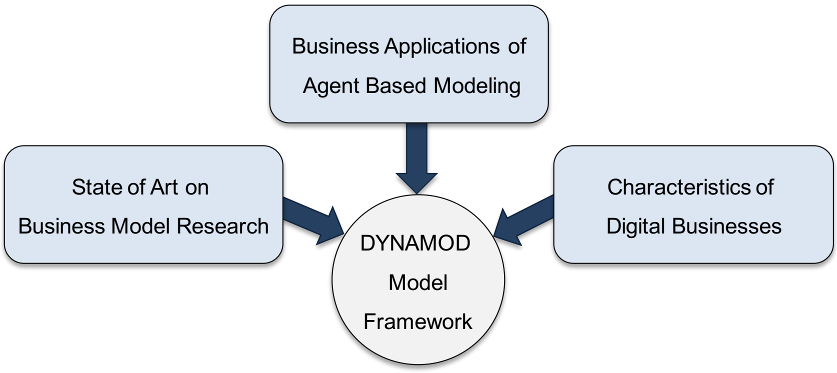


Figure 6.1 Research Areas that lead to the development of DYNAMOD Framework

The State of Art in Business Model Research provides us with an overview of the different elements of a firm that have been explored in academic works, that together help create value by an organization. Business model Research explores the theoretical relationships between the various elements of a business value proposition. It provides us with the base to build the DYNAMOD Framework. Not all the elements of a Business Model are explored within this Framework, but only those that deal with direct interaction with the clients.

A study of the unique characteristics of a Digital business provides us the unique ways in which online users interact and share feedback about a digital product. It also provides us with the unique attributes of a Digital Firm that must be modelled to develop the DYNAMOD Framework. When the two areas, Digital business and Business models are merged, a more focussed approach to Business Model is explored.

Finally the implementation of simulation models requires the selection of an appropriate modelling tool that can model the Digital business Scenario which can be represented as a Complex System. Agent Based Models are an appropriate tool for this purpose. The thesis explores other previous applications of Agent Based Modeling in Business and Marketing to provide us with key insights explored by other researchers.

6.2. *Development of the DYNAMOD Framework*

A complex systems approach was used to develop a framework that is applicable to a large variety of Digital Business scenarios. This framework is aimed to make a simplified representation of how online users are interconnected, respond to value propositions, and spread influence over each other. The DYNAMOD Framework was designed for the core module to include the definition for a generic set of entities, relationships and procedures applicable to all digital businesses while recognising the fact that each business case is unique and the entities must be adapted to reflect the specific business cases. It further defines additional components that may be invoked as the modelling scenario may require.

The implementation of this framework has been based on a modelling technique known as Agent Based Modeling. ABMs build on proven, very successful techniques such as discrete event simulation and object oriented programming (North & Macal, 2007). Discrete-event simulation provides a mechanism for coordinating the interactions of individual components or "agents" within a simulation. Object-oriented programming provides well-tested frameworks for organizing agents based on their behaviours. Simulation enables converting detailed process experience into knowledge about complete systems. ABM enables agents who represent actors, or objects, or processes in a system to behave based on the rules of interaction with the modelled system as defined based on detailed process experience. Advances in computer technology and modelling techniques make simulation of millions of such agents possible, which can be analysed to make analytical conclusions.

6.3. *Selection of the Case Studies*

The DYNAMOD Framework provides us with a customisable generic framework that can be adopted to a variety of online Business Cases with varying business objectives. Three case studies have been chosen to demonstrate the range of applicability of the DYNAMOD Modeling Framework.(Figure 6.1)

Table 6.1 Selection of Business Case Studies

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Type of Business</td></tr>
<tr><td>Business to Business (B2B)</td><td>Consumer to Consumer (C2C)</td></tr>
<tr><td rowspan="2">Market Condition</td><td>Competitive</td><td>Vortal.biz : Mature Stage</td><td>Custojusto.pt : Intermediate Stage</td></tr>
<tr><td>Monopolistic</td><td></td><td>Facebook.com : Mature Stage</td></tr>
</table>

The selection of the companies have been done to ensure that we have a variety of Business Cases based on two dimensions: Market Conditions and Type of Business.

A. Market Condition: Digital Businesses have the tendency to either grow very rapidly or fail miserably. This is especially true for pure digital services which don't have a physical counterpart (eg. Delivery of physical goods or services). This is even more so in the case of digital businesses with network effects. Thus, the dominant player often emerges with almost complete dominance of the market leading to a Monopolistic scenario (eg. Facebook, Google). In contrast a non-monopolised digital space is still evolving with competing partners. The companies can be further categorised as:

- **Early Stage** companies are relatively new entrants, often trying to introduce a new or innovative idea. Their Business Model is still at an experimental stage. There is a very high failure rate at this stage. They have little historical business data, hence application of DYNAMOD model is difficult to Validate. Hence no such case has been included in this thesis. However DYNAMOD model is very much applicable to such scenarios especially since no other forecasting model can work without historical data.
- **Intermediate Stage** companies have reached the second stage after having established a viable Business Model. They provide a reasonable level of historical data for DYNAMOD validation. CustoJusto.pt is a well established online classifieds platform in Portugal in this stage that has been selected as a case study for this thesis.
- **Mature Stage** companies have a well established dominance over their target markets. They have a mature Business Model that has passed the test of time and achieved success. They usually provide a large amount of historical data for validation. Facebook.com and Vortal.biz are two such examples that have been selected as case studies for this thesis.

B. Type of Business: There exists two types of clients: Business Clients and End Users. Business Clients usually are not that cost sensitive but look for long term stable business relationships while end users are more cost sensitive and switch between competitors more easily. Digital businesses are classified into three main categories:

- **Business to Business (B2B):** These types of businesses are either providing services to another company or helping companies provide business to other companies. We have selected Vortal.biz as an example of this type for building a case scenario.
- **Business to Consumer (B2C):** These types of businesses are either targeting end users or providing a platform for companies to offer services to end users. Although we have not selected a business case from this type, DYNAMOD model is equally applicable to this scenario.

- **Consumer to Consumer (C2C):** These types of businesses allow end users to interact with each other or trade with each other, essentially providing a platform for end users to interact. Two such examples CustoJusto.pt and Facebook.com have been selected for this thesis.

6.3.1. Main Objectives of Selected Case Study

The three selected case studies have the following main objectives. A comparison is also given in Table 6.2.

1. **Facebook.com**
   - To demonstrate the simple forecasting capabilities of the DYNAMOD model to forecast future growth scenario.
   - Forecast the impact of introduction of a competitor.
   - Forecast the impact of change in user sentiments due to privacy concerns.
2. **CustoJusto.pt**
   - Making simple forecasts about future growth trends.
   - Analysing sensitivity to changes in pricing and simulating its impact on revenue.
   - Assessing impact on business growth due to change in Advertising Expenditure
   - Impact of change in the Business Model.
3. **Vortal.biz**
   - Modeling of complex tariff plans and optional features
   - Forecast of user upgrades to different tariff plans.
   - Impact of user upgrades due to change in pricing of different plans.
   - Optimization of pricing of different tariff plans using genetic algorithms.

Table 6.2 Modeling objectives for different case studies

Modeling Objectives		**Facebook.com**	**Custojusto.pt**	**Vortal.biz**
Simple Forecast		✓	✓	✓
Competitor Analysis		✓		
Simulating change in business scenario		✓	✓	
Price Sensitivity Simulation	Pricing of Features		✓	
	Tariff Plans		✓	✓
Simulating impact of change in advertising spend			✓	
Optimization using Genetic Algorithm				✓
Probability Distribution of Model Prediction				✓

6.4.

6.5. *Validation of Case Studies*

The simulation models are used for a variety of case scenarios other than making simple forecasts. However the validation of other scenarios is not practical since the altered business scenario is difficult to be replicated in real. Hence, the validation of the case studies is done by comparing the model forecasts based on considering older time series data (initialization data set) and making the forecasts for a later period (validation data set), whose values are already known. Then the same initialisation data set is used for making forecast using ARIMA forecasting models. The accuracy of the DYNAMOD forecasts is then compared with the ARIMA forecasts. This process of validation is followed for the first two cases: Facebook.com and Custojusto.pt.

However for Vortal.biz case, only the last two years of data was relevant, since a new platform was launched at that time, and the user experience was dramatically changed. Hence comparison based on previous data was not accurate. No other forecasting tool can make a future forecast just based on current year's data and this is a unique advantage of using DYNAMOD tool. Hence for validation of the model, the forecast for 2014 is made based on 2013 data, and compared to the forecast for 2014 based on 2012 data. Thus the consistency of the two predictions is used as validation of the degree of confidence in the simulation model.

6.6. *Data Collection*

Data for all the 3 cases were collected based on online questionnaires sent to randomly selected users representing a cross section of customers across different tariff plans and subscribing to different features. The historical record was obtained directly from the companies considered in case of Custojusto.pt and Vortal.biz and from publically declared user base in case of Facebook.com.

7. Case Study 1 - Facebook

7.1. Business Scenario and Objectives

7.1.1. Business Scenario

Facebook is an extremely popular social networking site that enables users to share messages and posts. It exhibits a strong Network Effect, because the more friends a user has on Facebook, the more useful Facebook can be in communicating with them. Also, users as well as organizations can make group or community pages for social interactions, and social marketing. Facebook is primarily a free service that is supported by advertising (Manyika, 2011). The advertising revenue is directly proportional to the number of active users. In addition to a social networking platform, Facebook also allows developers to develop games and applications within Facebook. Numerous applications and games are developed by third party developers over Facebook. Users need virtual currency to play these games and use the applications, and can purchase these currencies with Facebook Money. Facebook charges 30% from all these transactions[1].

The bulk of Facebook's revenue still comes from advertising despite the revenues from Facebook Money and adds bought by application providers. Facebook's revenues were $1.97 billion in 2010 and rose to $3.71 billion in 2011. This was due to a 69% growth of advertising revenue. The number of ads delivered grew by 42% and there was an 18% growth in their average price. Facebook's advertising revenue was $3.15 billion and $557 million from Facebook Payments. While the share of revenue from advertising was 99% in 2010, it fell to 83% in 2011.[2]

In 2011, 19% of Facebook's total revenue was from Zyngya (a company that develops Facebook games like Farmville), while 12% of the Total Revenue was derived from Facebook Payments and ads by Zyngya, the remaining 7% coming from Facebook advertisements on Zyngya's application pages. Thus, around 70% of Facebook Payments was received from Zyngya alone. The numerous applications and games have different Business Models. Some provide free services, while others charge direct or indirect payments from users. Hence, to model accurately, the success or failure of each Business Venture, we will need to create separate DYNAMOD models for each application. The dominance of a single company demonstrates that extremely rapid word of mouth among Facebook clients and the inherent network effect make it very difficult for the second in line to compete against a

[1] http://www.web-strategist.com/blog/2012/05/19/Facebook-a-brilliant-business-model/

[2] Facebook Quarterly Submissions to US Securities and Exchange Commissions, http://www.sec.gov/Archives/edgar/data/1326801/000119312512325997/d371464d10q.htm

dominant player. While Zyngya has 270 million monthly active users, the second in line, Microsoft apps, has only 70 million monthly active users.[2] Statistics for Facebook were obtained from their public declaration (Table 7.1).

Table 7.1 Facebook Statistics (Source: Stock Market Declaration by Facebook.[3]

Quarter ends	Monthly Active Users (million)	Advertising Revenue (million $)	Payments and other Revenue (million $)	Average Monthly Advertising Revenue Per User ($)	Expenses (million $)	Average Monthly Cost per user ($)	Average Monthly Profit before taxes per user ($)
Jun 30 2009	242						
Sep 30 2009	305						
Dec 31 2009	360						
Mar 31 2010	431						
Jun 30 2010	482	424	8	0.29			
Sep 30 2010	550	450	17	0.27			
Dec 31 2010	608	655	76	0.36			
Mar 31 2011	680	637	94	0.31	343	0.17	0.14
Jun 30 2011	739	776	119	0.35	488	0.22	0.13
Sep 30 2011	800	798	156	0.33	540	0.23	0.10
Dec 31 2011	845	943	188	0.37	584	0.23	0.14
Mar 31 2012	901	872	186	0.32	677	0.25	0.07
Jun 30 2012	955	992	192	0.35	1,927	0.67	-0.32
Sep 30 2012	1007	1,086	176	0.36	885	0.29	0.07
Dec 31 2012	1056	1,329	256	0.41	1062	0.33	0.08

While DYNAMOD makes it possible to model each of the Business Applications separately, such a modeling would require very detailed data for each third-party Facebook Application. As a result, we leave modeling of the adoption of Facebook Applications and revenue from Facebook Payments out of the scope of this paper. For illustrative purposes, we model revenue from advertising sources only.

In addition to user pages, Facebook allows organizations and companies to set up Facebook pages, which can be "liked" by users. These pages are used by organizations to announce

[3] http://www.sec.gov/Archives/edgar/data/1326801/000119312512325997/d371464d10q.htm

news and promotions to their fans and followers. Facebook has not yet devised a way to monetize Fan pages. However, Businesses are increasingly interested in having a large fan base in Facebook. Facebook could move to alternative monetization strategies that could capture additional revenue.

7.1.2. Identification of Scope and Objectives of the Model

The DYNAMOD Based model seeks to simulate the market growth for Facebook. The scope of the model would involve simulation of Market Expansion and Revenue Generation predictions based on Facebook's Advertising Revenue. Since the Advertising revenue is directly proportional to the number of active monthly users, we have used it as the primary indicator in our model.

We have periodic growth numbers of actual active clients from June 2009 to September 2012. We have used data from June 2009 until June 2011 to initialize the Agent Based Model. Records from September 2011 to September 2012 are used as validation data. The predictions from the DYNAMOD model for this period are compared with the actual historical data from this same period to gauge the accuracy of the prediction model. Beyond this period of September 2012, we make business forecasts for Facebook based on different scenarios. DYNAMOD is a flexible framework that can be used in a variety of scenarios. Through this case study we demonstrate some of its capabilities for predicting and simulating highly mature business scenarios.

7.2. Model Development

7.2.1. Identification of Business Model Components and associated variables

7.2.1.1 Business Model Definition

Facebook is a Social Networking site that incorporates a strong network effect. Being a free service, there are no financial barriers to adoption. PRODUCT-QUALITY variable determines what kind of investment the company has made in quality and features, compared to the maximum possible. We provide a high value of 0.9 for the same, since the past two years data shows that R&D investment has been 27% of the total expenses which is extremely high for an established product (Table 7.2). This variable is just a scale based on the company's internal assessment of product innovation investment, which can be tweaked during simulation to see the response of increased product quality and features on customer adoption. In the current case, a value of 0.8 indicates that there is not much scope left for increasing R&D Expenses.

Table 7.2 Business Model Variables for Facebook

	Variable Name	Description	Value
1	PRICE-LEVEL	Unit Price	0 (Free)
2	R&D-INVESTMENT	Investment in R&D with respect to total expenses	27%
3	VIRAL-MARKETING	Is Viral Marketing incorporated?	NO
4	ADVERTISING-EXPENSES	Expenses in Sales and Marketing with respect to total expenses	21%
5	NETWORK-EFFECT	Is Network Effect incorporated?	YES
6	FREEMIUM	Is freemium adopted?	NO
7	COST-PER-USER	Monthly cost per User	$0.29 per client/month*
8	REVENUE-PER-USER	Monthly Revenue per User	$0.34 per client/month*

***Based on 2011 and 2012 Data Source** Facebook IPO Declaration

Similarly, the past 2 years data reveal that money spent on Sales and Marketing was 21% of total expenditure. This shows a considerable expenditure on Sales and is quite close to the maximum possible for a company of this nature.

7.2.1.2 Identification of Agents and Agent Parameters

Facebook is a single sided network and consists of users interacting with each other. Consequently, a single type of agent is used in this model. We have customized the default template for User Agent to Simulate a Facebook Agent. Since no costs are associated with a Facebook user, associated variables were removed from the default template.

7.2.1.3 Identification of Relationships and Agent Behavior

A sample survey was conducted amongst Facebook users to identify general opinions about Facebook among users and non-users. Questionnaires were posted over the social media and most of the respondents were of mixed professional backgrounds, including a mix of students and working professionals. A total of 112 people participated in the survey out of which 102 were Facebook users. The respondents were a mixture and a representative sample. The results from the survey are shown in Table 7.3.

Table 7.3 Results of the Sample Survey for Facebook

Parameter	Mean	Standard Deviation	Methodology
Satisfaction (For the 102 clients)	0.684	0.082	Satisfaction evaluated based on Usability, Looks, Features
Influence (For the 10 non-clients)	0.110	0.060	Influence evaluated based on Familiarity, Perceived Utility
Influence from advertisements and promotions	0.213	0.127	Evaluators were asked to evaluate all four of these parameters at the same time so they could also relatively assess the influence from each of these sources.
Influence from friends/aquaintances	0.410	0.160	
Brand/Global Influence	0.110	0.010	
Influence from Online Recommendations	0.121	0.098	

Evaluators were asked to keep in mind that their adoption threshold for using Facebook should be 0.25 and abandonment threshold, (ie. a satisfaction score below which they would stop using Facebook) would be 0.1. This means that if a user thinks that the product is just bearable, and is not really satisfied with it, but still using it, he should give a score of 0.1 or 0.2. If he is as happy with the product as his expectations were when he first started using it, then he should give a score above 0.25. A user should give negative scores only if he is too dissatisfied with the product and actively advises his friends not to use the product.

7.2.2. Model Initialization through Data Obtained through Sample Surveys

7.2.2.1 Demographic Analysis

The first step is to estimate the number of potential users of Facebook. There are 2255 million global Internet users according to the 2012 International Database of the US Census Bureau. At the time of this writing Facebook is officially banned and blocked in seven countries, namely, China, Vietnam, Iran, Uzbekistan, Tajikistan, Pakistan and Bangladesh. Discounting for the online population in these countries, the total number of online users is 1661 million users. However in some other regions Facebook faces severe competition from regional competitors. This is in addition to increased global competition from Google Plus.

Table 7.4 Facebook penetration in countries with other prominent competitors

Country	Major Competitor	Online Users (million)	Facebook Users as a percentage of Online Users
South Korea	Cyworld	40.8	22.83%
Japan	Mixi	101.3	16.04%
Brazil	Orkut	88.9	82.85%
India	Orkut	119.7	67.26%
Russia	vKontakte	69.8	12.36%

While it is clear that Brazil and India have been steadily adopting Facebook in recent months, data suggests that Russian, Japanese and South Korean markets are very strongly tied to regional competitors (Table 7.4). Due to the strong network effect exhibited by social network sites, it is difficult for Facebook to replace well established regional competitors. One possibility would be for Facebook to purchase these regional companies. We also estimate that a small percentage of online users are using simple mobile devices who find it difficult to navigate a complex site like Facebook or some users who are completely disinterested in using social networks. Discounting for the above we have estimated a potential customer base of 1400 million users for Facebook. However this potential user base can increase in case of increase in number of online users, or lifting of Facebook sanctions in some countries. Such complexities could be added into the model, however, for the sake of maintaining simplicity have not been included.

The possibility of the rise of Google Plus affecting the user base of Facebook has been discussed in section 8.

7.2.2.2 Model Initialization

Computing an agent base of 1400 million agents requires immense computing power. However it is technically feasible to use Agent Compression techniques to run the model with a limited number of Agents (Wendel & Dibble, 2007). We approximated 1 agent for every 1 million users. Hence the simulation was initialized to 1400 agents. The simulation is initialized based on a randomized sample of influence rate surveyed from a randomly collected sample of users and non-users. Since we do not have the growth data for Facebook prior to June 2009, we let the model run until the number of users reached a level similar to that recorded for active users in June 2009, i.e., 242 million users. The model initialization variables have been explained in Table 7.5.

Table 7.5 Model Initialization Constants

	Initialization Constants	Description
1	INFLUENCE-CONSTANT	This is a factor that is multiplied by the sum total of influences to derive the new influence factor for an agent
2	NETWORK-EFFECT-CONSTANT	This is a factor that is multiplied by the network effect coefficient before it is finally added to other influence factors.
3	NETWORK-EFFECT-UPPER-LIMIT	This is a critical percentage of users who are clients within a region, above which the network effect remains a constant and its value does not increase. DEFAULT = 30%
4	NETWORK-EFFECT-LOWER-LIMIT	This is a critical percentage of users who are clients within a region, above which the chilling effects due to the network effect starts to decline. DEFAULT = 10%

We take the data for the first 24 months as the initialization data, and initialize the average agent satisfaction levels based on sampled data. Model initialization is vital to ensuring that the model is appropriately configured. It allows us to test the accuracy of our model. We have data for a period of 39 months. We will use the first 24 months of data to initialize the model and then use the remaining months to test the effectiveness of the model.

Initial runs of the model revealed that a reasonable range of Network Effect Constant was between 0.0002 and 0.002, while for Influence Constant it was between 0.005 and 0.020. A total of 172 model runs were performed by varying these two constants, and monthly changes in the number of clients were noted. This was done using the Behavior Space feature in NETLOGO. The monthly client counts of each model run were recorded, and June 2009 was identified as the period when the model reached a state closest to 242 million clients. Model predictions for number of active users of Facebook was recorded for each trimester for each model run. Square of the prediction error for each trimester was computed and then added for each model run by comparing the predicted value with the actual data. The run which had the least sum of squared errors was selected.

The best fitting of the data was obtained where influence-constant = 0.0104 and network-effect-constant = 0.0009. Once these values were obtained, 10 model runs were executed to find the closest fitting model run, which was used for analysis.

7.2.3. Programing

The model was developed using NETLOGO, which is an intuitive and user friendly software designed for the development of Agent Based Models. The world was represented with a square plane where agents represent online users that are randomly distributed.

The model has assumed 6% of the users as highly connected, who make movements in random directions, thereby thus changing their neighborhoods. The remaining users are in fixed positions and thus have a static neighborhood. The model snapshot can be shown in Figure 7.1.

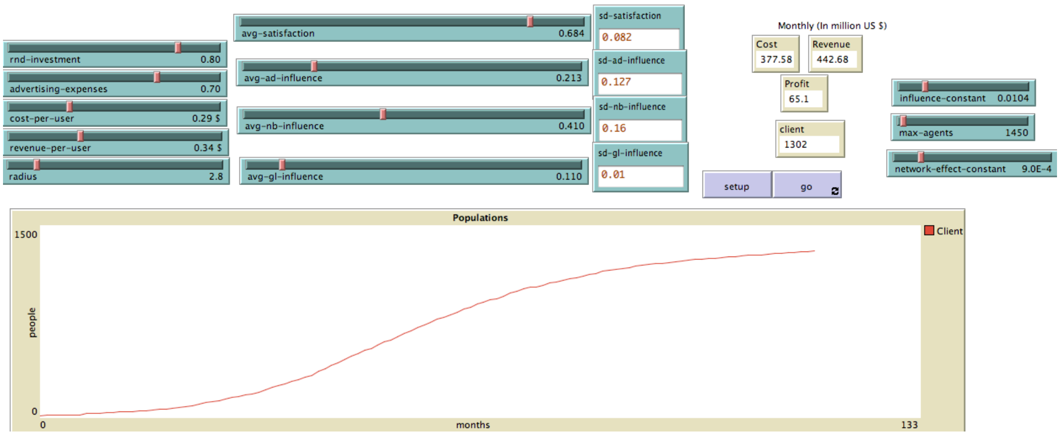


Figure 7.1 DYNAMOD Simulation of Facebook using NETLOGO

7.3. *Model Results*

The Model was initialized based on active monthly users historical data from June 2009 untill June 2011. After initialization, the model was used for making forecasts of future user adoption until June 2015. The actual data after June 2011 are used only to verify the predictions of the model (Figure 7.2).

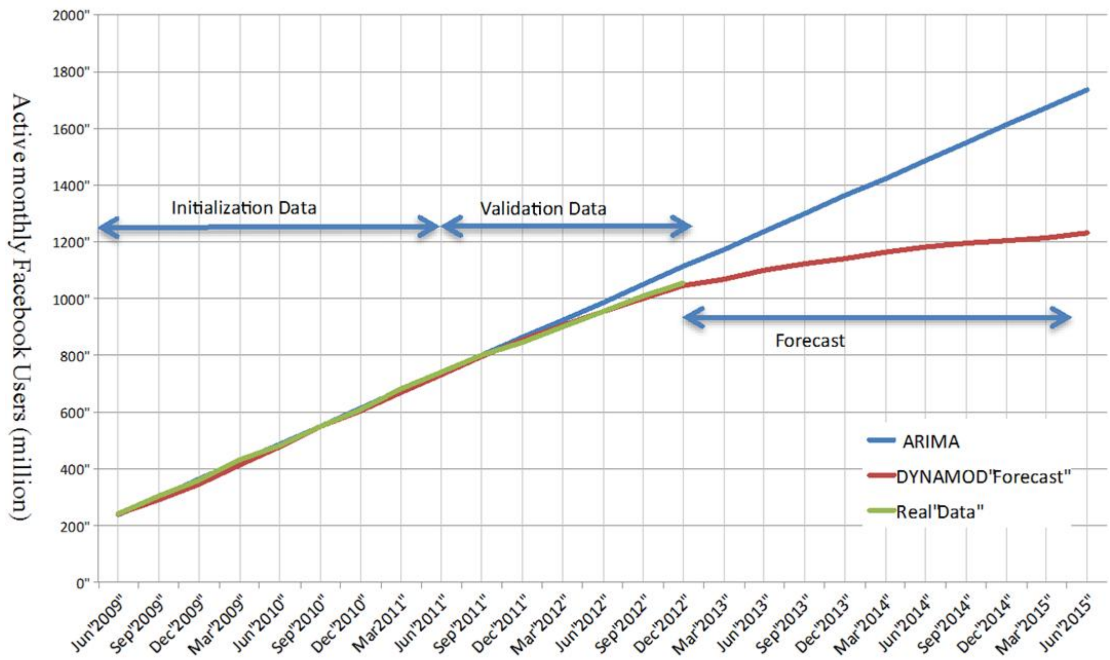


Figure 7.2 DYNAMOD Forecasts for Facebook

To test the accuracy of forecast by the DYNAMOD model, we also used another forecasting tool-ARIMA (Figure 7.3).

Total number of customers at any time Ct according to the Dynamod model= $\sum A_{\mathrm{i}}^{\mathrm{client=1}}$

Number of customers according to data at any month t =$C^{A}{}_{t}$

Number of customers at any month t according to the ARIMA Forecast = R_t

The Root Mean Square Error for the initialization data was

$$\frac{\sqrt{\sum_{Jun\ 09}^{Jun\ 11}(Ct - C^{A}\mathrm{t})^2}}{\text{Count} - \text{Records(Jun 09} - \text{Jun 11)}} = 3.18$$

The actual growth of Facebook active users slows down over the validation period. Hence the regression line moves away from the actual growth line. However the DYNAMOD model is able to predict the slowdown and closely follows the actual growth line.

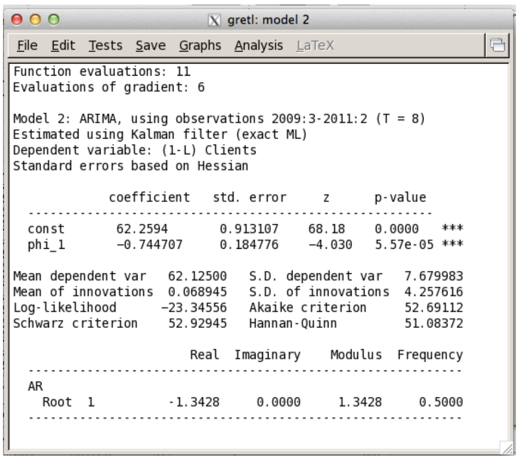
For the Validation Period between Sep 2011 and Dec 2012, RMS Error during Validation phase for DYNAMOD prediction was:

$$\frac{\sqrt{\sum_{Sep\ 11}^{Sep\ 13}(Ct - C^{A}\mathrm{t})^2}}{\text{Count} - \text{Records (Sep 11} - \text{Dec 12)}} = 3.91$$

For the same Validation phase, the ARIMA Error was:

$$\frac{\sqrt{\sum_{Sep\ 11}^{Sep\ 13}(Rt - C^{A}\mathrm{t})^2}}{\text{Count} - \text{Records (Sep 11} - \text{Dec 12)}} = 19.08$$

This validates that the DYNAMOD model forecast is closer to real data than the Regression Model. This demonstrates that DYNAMOD can be leveraged for business growth simulations, in this case, a very mature business which has already reached a majority of global users. While the main aim of the Model is not to be used as a pure forecasting tool, a good forecast ensures that the model is efficiently configured and ready for making further analysis.



```
gretl: model 2
File Edit Tests Save Graphs Analysis LaTeX
Function evaluations: 11
Evaluations of gradient: 6

Model 2: ARIMA, using observations 2009:3-2011:2 (T = 8)
Estimated using Kalman filter (exact ML)
Dependent variable: (1-L) Clients
Standard errors based on Hessian

             coefficient   std. error     z      p-value
  -------------------------------------------------------
  const       62.2594       0.913107    68.18    0.0000   ***
  phi_1       -0.744707     0.184776    -4.030   5.57e-05 ***

Mean dependent var   62.12500   S.D. dependent var   7.679983
Mean of innovations  0.068945   S.D. of innovations  4.257616
Log-likelihood      -23.34556   Akaike criterion     52.69112
Schwarz criterion    52.92945   Hannan-Quinn         51.08372

                        Real  Imaginary    Modulus  Frequency
  -----------------------------------------------------------
  AR
    Root  1          -1.3428     0.0000     1.3428     0.5000
  -----------------------------------------------------------
```

Figure 7.3 ARIMA Forecast Results using GRETL

7.3.1. Additional Scenarios

The DYNAMOD Framework provides us with a generic framework that can be customized and applied to a variety of Business Cases and Scenarios. Our intention in this paper is to demonstrate its applicability to different Business Scenarios. To demonstrate this, we incorporate two potential growth barriers to Facebook and examine future scenarios in our model. The first is related to the perception of privacy issues among the users. The second is related to the growth of Google Plus as a major global competitor to Facebook.

The impact of both these effects will be added into the model from Jan 2013, to see its impact on the growth numbers.

7.3.2. Privacy Issues in Facebook

There have been increasing concerns among Facebook Users related to privacy of their information. Instances such as the claim by Instagram (Owned by Facebook) that it has the rights to sell pictures uploaded on their servers have fuelled such concerns. Other fears include the possibility of misuse of user related data. For example, 4.7 million users have "liked" a Facebook Page related to a health condition or treatment, which could be used by an insurer against their clients.[4] Several others have discussed their vacation plans publically, providing information that could be used by potential burglars. Whether these privacy issues are real or not, they could have a negative impact on Facebook user adoption.

We have studied a scenario in which a sudden announcement or news item causes a large number of users to develop a fear of using Facebook. We have found that people having a fear of privacy violation, reduce their satisfaction or influence level by 0.6 based on the

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[4] http://www.nbcnews.com/technology/technolog/consumer-reports-facebook-privacy-problems-are-rise-749990

sample survey. This high factor means that such users will not only stop using Facebook but will also influence their friends and acquaintances against it.

To incorporate these fears, let us assume two scenarios:

1. Where 5% of the users have these fsears.
2. Where 10% of the users have these fears.

The model simulates conditions for not only the abandonment of Facebook by users having these fears, but the negative influence that these users would have on other users who have these fears. Figure 7.4 shows the drop in growth rate, should a sudden news item result in a sizable percentage of users dropping their confidence in Facebook. The simulation shows that the sudden announcement will immediately have a negative impact, but if Facebook maintains its high level of usability and value, the growth will continue to grow, albeit slower.

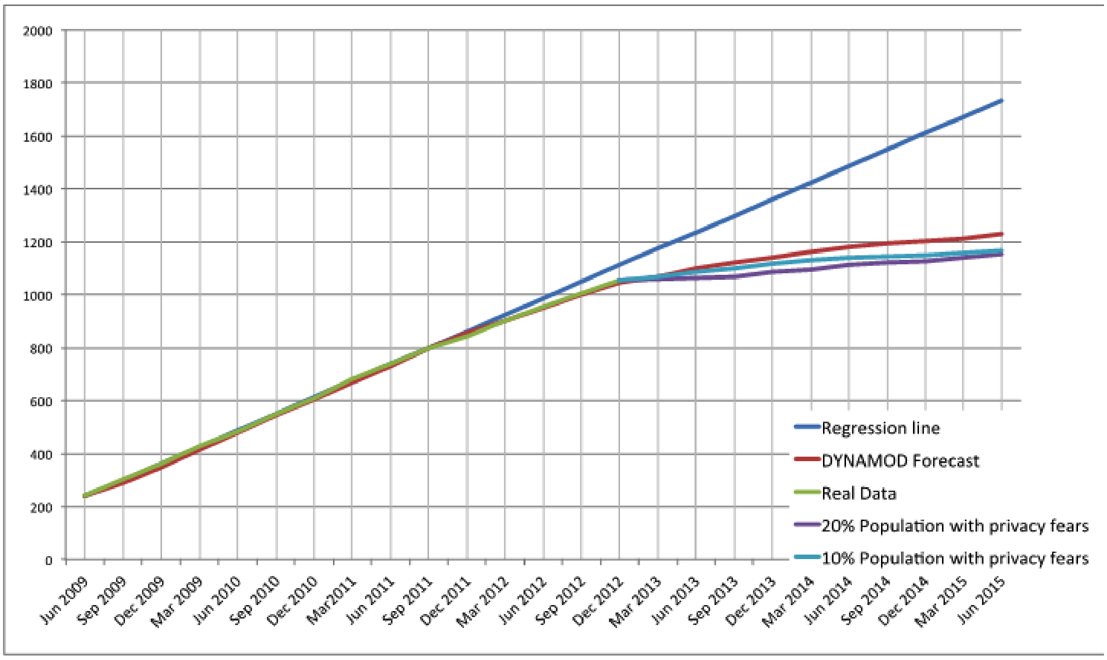


Figure 7.4 DYNAMOD projections for populations with privacy fears

7.3.3. Increased popularity of Google Plus

Google Plus is a rival social networking application launched by Google in June 2011. Due to the high popularity of Google, and the large scale integration of Google Plus with existing Google products, it has quickly gained a user base of 100 million active monthly users. Due to the network effect and free to use nature of Social Networks, it has been observed that users usually tend to use more than one social network at the same time, and may switch only if a significant percentage of their friends have moved to the new Social Network. Hence, Facebook has not yet suffered a notable impact due to the launch of Google Plus. However in case Google Plus gains market share, beyond a point users could begin to abandon Facebook.

It is very difficult to determine the threshold percentage of friends shifting to Google Plus that would cause a user to abandon Facebook. We asked our respondents, what percentage of your friends would have to move to another social network, to induce you to stop using Facebook completely?” The Options given were 50%, 60%, 70%, 80% and 90%. Most respondents answered 80%, and so it was selected as the threshold.

DYNAMOD has been designed to incorporate competitor analysis. In this case we will need to incorporate certain basic rules into the simulation. First, we replicate all variables for Google Plus as we did for Facebook. Second, if 80% of the local neighborhood of an agent begins to use Google Plus, then the user will abandon the use of Facebook. In this simulation Google Plus is assigned a slightly higher initial influence mean value of 0.13 compared to 0.11 of Facebook. This means that users have slightly more positive experience with Google Plus.

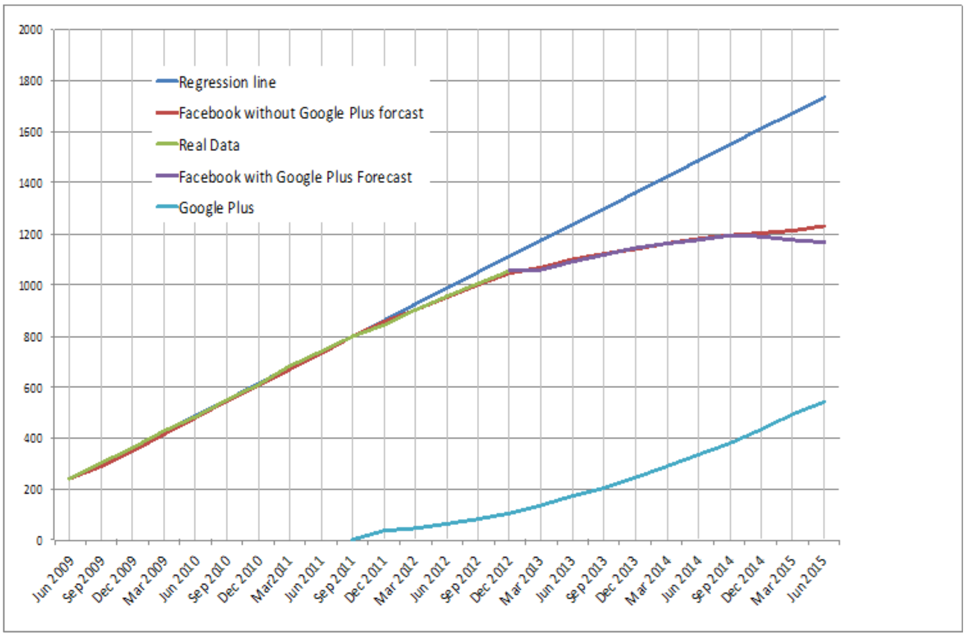


Figure 7.5 Introduction of Google Plus with a slightly better user experience

As can be seen from Figure 7.5, to make even a slight impact to Facebook’s growth, Google Plus would have to reach at least the 400 million monthly active user mark. Facebook would still maintain its huge lead, and the strong network effects would influence users not to abandon Facebook, except in some small pockets, or countries where Google Plus might gain complete dominance. In most other Google Plus markets they will co-exist with Facebook.

7.3.4. Comparison with latest growth data

The developed model was initialised based on data upto June 2011, and thus initial the forecasting was done till December 2012, which was the data which was available at the time this model was developed. As seen in Figure 7.6, the growth projections matched extremely well with real data until December 2012. We have added the latest data available at the time of writing the thesis, as represented by the violet line in the graph. The purpose was to see, till how far in the future, the forecasting based on Agent Based Modeling remains accurate.

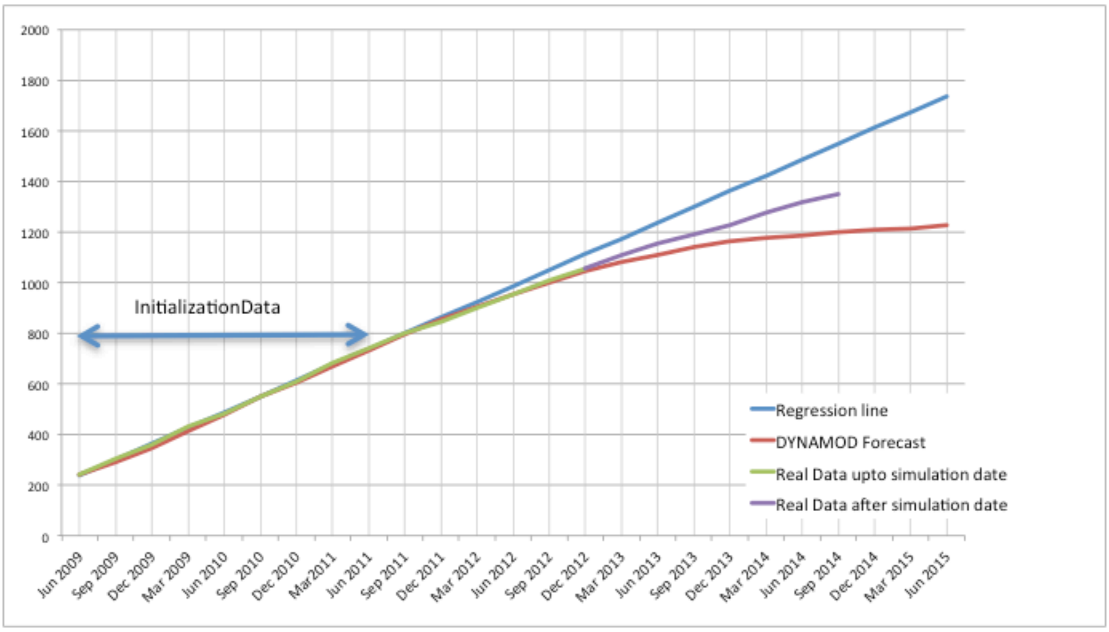


Figure 7.6 Comparison with latest growth data

It was observed that forecasting accuracy remained within reasonable levels of tolerance till June 2013, after which the predicted client acquisition started growing much faster than the predicted growth rate. This demonstrated the ability of DYNAMOD to have a prediction accuracy of upto two years. DYNAMOD was able to predict a decreasing growth rate as Facebook.com reaches closer to its potential target market. The higher than predicted growth rate might be due to factors such as increased internet penetration, improved facebook features, or growth of additional apps that engaged users more than before.

However a two year accuracy is also reasonable, since any deployment of DYNAMOD as a commercial tool, must be accompanied with a periodic revision of User Behaviour through new Sample Surveys, and reanalysis of the potential market size.

7.4. *Case Study Discussion*

The Facebook case study demonstrated the applicability of DYNAMOD in predicting the overall growth trends of a large global social network by simulating the spread of work of mouth and network effects. Facebook is an example of a purely digital business that does not have any physical or human interaction with the clients. Its value is generated for the user based on user generated content, and thus it is vital for Facebook to encourage a high level of user engagement in the form of posting pictures, comments, opinions, and inviting more friends to join the network.

It was demonstrated that the DYNAMOD model could forecast the growth evolution much more precisely than any other forecasting tool. Since Facebook has a free pricing model, price sensitivity was not evaluated. However two alternate business scenarios were selected to demonstrate the flexibility of the DYNAMOD model to forecast the impact of changes in external business environment.

A Facebook user shares a lot of personal information including pictures, and personal information that is intended only for the friends in his online network. Thus any fear of a breach of privacy could potentially have a huge impact on Facebook. . In 2012, Instagram which stores the facebook pictures had claimed the right use user content and pictures. The impact led to a sizable percentage of Facebook users generating fear about their personal data and stopping to use Facebook. In the first case, we analyse the impact of such a rumour or fear on the overall growth projections of Facebook.The simulations revealed that even a 5% population having such fears can potentially lead to a significant reduction in the growth of Facebook.

The second scenario explored the impact of a competitor like Google Plus, and how its growth would potentially affect the usage of Facebook.com. This model showed that due to the network effect in play, a large number of users would continue to use the competitor platform simultaneously till a critical mass of their friends do not move to the new platform. That is why the model showed minimal impact to Facebook in the long run despite the introduction of Google Plus, even if its features are better in some respects.

8. Case Study 2 - CustoJusto.pt

8.1. Business Scenario and Objectives

CustoJusto.pt is the Portuguese subsidiary of Schibsted Classified Media (SCM), which provides services in the area of online classifieds in Switzerland, Spain, Frence, Belgium, Italy and Austria. It also owns sites in Malaysia, Argentina, Mexico, Brazil and Columbia. However the focus of our study was just the Portuguese operations. The website was launched in December 2008. It is an online classifieds company that is very broad in terms of its target market. Every type of product – old or new could be advertised on the site, including but not limited to Real Estate, Rentals, Cars, Tools, etc.

It has a freemium Business Model that allows users to post and view unlimited number of Ads for free. Interestingly, the users are charged for Editing an Ad. Although there were some opinions that it would not be used due to users choosing to post new free Ads instead, the charge was kept presuming that some would like to pay for the convenience of easily making minor edits to a posted ad. In addition, the users are charged for 3 premium visibility services, which increase the prominence of the posted Ads. The rates for the charges are as follows:

1. Editing an Ad (PS1): 2 Euros per modification made to the advertisement.
2. Bumping the Ad (PS2): 6 Euros; Puts the ad on top of the list once every week for 8 weeks.
3. Urgent Tag (PS3): 3 Euros; An orange "Urgent" Tag is displayed on top of the Ad making it look more prominent.
4. The Gallery (PS4): 10 Euros per week; A prominent view on the right side of the page, providing greater visibility to the advertisements.

CustoJusto.pt faced an unhealthy competition from its rival Olx.pt due to the latter launching an advertising blitzkrieg, with the intention of killing off Custojusto.pt in a market highly dependent on network effects and where only one can emerge as the winner. To guard its market share Custojusto.pt was spending 80% of its expenses on advertising, making the cost structure unsustainable. At the same time it was not sure if its pricing was optimal or not, and what would be the growth structure. We proposed the development and modeling of its Business Case using the Agent Based Modeling Framework with the intention of studying the following objectives.

- **Objective 1** – What would be the growth in terms of number of users in the next 2 years with the existing Business Scenario.

- **Objective 2** – Is charging for "Editing an Ad" viable and if so what should be the optimal value?
- **Objective 3** – How do customers choose between the three offered Premium Services? How does change in Pricing of one impact the others?
- **Objective 4** – What would be the impact in user growth if the advertising costs were to be halved?

Also the management was considering whether instead of being merely a classifieds posting site, Custojusto.pt could expand and become an e-marketplace and a financial intermediary. This would enable buyers and sellers to conduct financial transactions without physical contact using postal systems. This could greatly increase the geographical range of buyer-seller interactions leading to more usage and more traffic. But the biggest benefit would be the possibility to charge on a percentage of the value transacted. However there were skeptics also in the company, and anxiety about the risks of being a financial intermediary especially regarding frauds committed by a buyer or a seller.

- **Objective 5** – When the business model is changed to that of a financial intermediary, what is this critical percentage of users experiencing fraud that would lead to a progressive decline in number of users?

8.2. Model Development

8.2.1. Estimating Model Size

In May 2013, which was the last month for which records were obtained, Custojusto.pt had an average of 154,623 daily unique visitors and 4,750 daily unique sellers. In the same month, the number of estimated unique monthly visitors were 927,741.

Detailed interviews were conducted with the Business Managers to understand the nature of the Business. Portugal has 5.95 million users[5] while the average household size in Portugal is 2.6[6]. In our assessment, buying and selling of household items, is typically generally done by one member for each household. Hence the typical market size for such a free classified service would typically be 5.95 million/ 2.6 = 2,288 million users. Using Agent Compression techniques to run the model with a smaller number of Agents (Wendel & Dibble, 2007), we approximate 1 agent for every 1 thousand users. Hence the simulation was initialized to 2,288 agents. Mature markets like Portugal have a relatively steady population and a saturated

[5] http://www.internetworldstats.com
[6] http://www.pordata.pt

internet penetration and hence the total market size can assumed to be constant for the test period.

8.2.2. Conducting Sample Survey

To initialize the agents, we conducted an online sample survey in June 2013 to obtain a random sample of user opinion towards the website and their response to different sources of advertising. The questionnaire was sent to 2000 random users of Custojusto.pt and we received a response from 157 users. The questions pertained to the following

1. Measuring Client Satisfaction
2. Which premium services interest the clients.
3. What is the average frequency of posting of new ads.
4. What is the maximum willingness to pay for each service.
5. How the clients were introduced to Custojusto.pt
6. How many clients have started using Custojusto.pt based on their recommendations.
7. How likely are the various sources of advertising, campaigning, online and offline WOM to influence their product adoption decision

For this case study we have conducted a one-time sampled questionaire. However client satisfaction and behavior change with time, and we are in the process of building an automated platform which will automate the process of conducting periodic sample surveys and feed back the results to the simulation model, so that the model can adapt to changes in the market. The results of the questionnaire are in Table 8.1 and Table 8.2.

8.2.3. Modeling the Agents

We will define 2288 agents, and denote them as A_0 to A_{2288}. These agents will be randomly distributed over a two dimensional space. Each agent A_i will have a set of variables that will define its characteristics.

For example, each agent has a variable *influence* which denotes how aware is he of a particular product. Once this *influence* crosses a threshold and the product price is less than customer willingness to pay (in this case 0), the agent becomes a client. Once he is a client then it is the *satisfaction* score that becomes relevant. This satisfaction score for an Agent A_i is denoted as $A_i^{\text{Satisfaction}}$

Based on our Sample Survey, on a scale of 0 to 1, we have initialized :

$$\bar{A}_i^{\text{Satisfaction}} = 0.663$$

$$\sigma A_i^{\text{Satisfaction}} = 0.211$$

Hence each agent which is a user will initially be assigned a satisfaction score such that the overall consumer population follows this mean and standard deviation.

Similarly other variables, that denote degree of influence to various sources are also initialized as follows:

Table 8.1 Survey Results for various sources of Influence

Influence-x (Source of Influence)	$\bar{A}_i^{\text{Influence-X}}$ **(Mean Influence)**	$\sigma A_i^{\text{Influence-X}}$ **(Std. Deviation)**
Influence-TV	0.596	0.286
Influence-Online-Ads	0.551	0.286
Influence-Brand	0.367	0.113
Influence-OnlineWOM (Blogs, Forums)	0.469	0.318
Influence-OfflineWOM (Friends, Relatives, Colleagues	0.693	0.252

Subsequently, we modeled the information related to the 4 premium revenue sources mentioned in Section 2, which we shall denote as PS1, PS2, PS3, PS4. In our questionnaire we asked the respondents whether they are using a particular service or not, if they are interested if it fits their willingness to pay and their maximum willingness to pay for that service.

Table 8.2 Results of Sample Surveys regarding Premium Services

	PS1- Editing an Ad	**PS2- Bumping an Ad**	**PS3- Urgent Tag**	**PS4- The Gallery**
$pA_i^{\text{PSx- user}}$: Probability of being a user	0.064	0.019	0.026	0.013
$pA_i^{\text{PSx-interested}}$: Probability of being interested, if matches willingness to pay	0.108	0.429	0.378	0.327
Current Price	€2	€6	€3	€10
$\bar{A}_i^{\text{PSx-WTP}}$: Mean value of willingness to pay (€)	0.664	2.186	1.331	2.379
$\sigma A_i^{\text{PSx-WTP}}$: Standard Deviation of willingness to pay (€)	1.639	2.860	2.034	2.975

The Agents are initialized with the sampled data and mimic user decision making to become an active user of Custojusto.pt and whether to use its premium services. Figure 8.1 shows a flowchart of this decision making process by an agent. An agent gets influenced from various sources of influences with the Influence Rates being based on Sample Surveys. The

Willingness to Pay (WTP) is also based on the results of the Sample Surveys. After becoming a client, the Agent takes decisions regarding the use of the four Premium Services (PS). Figure 8.1 shows the logic followed by a user Agent in the simulation model.

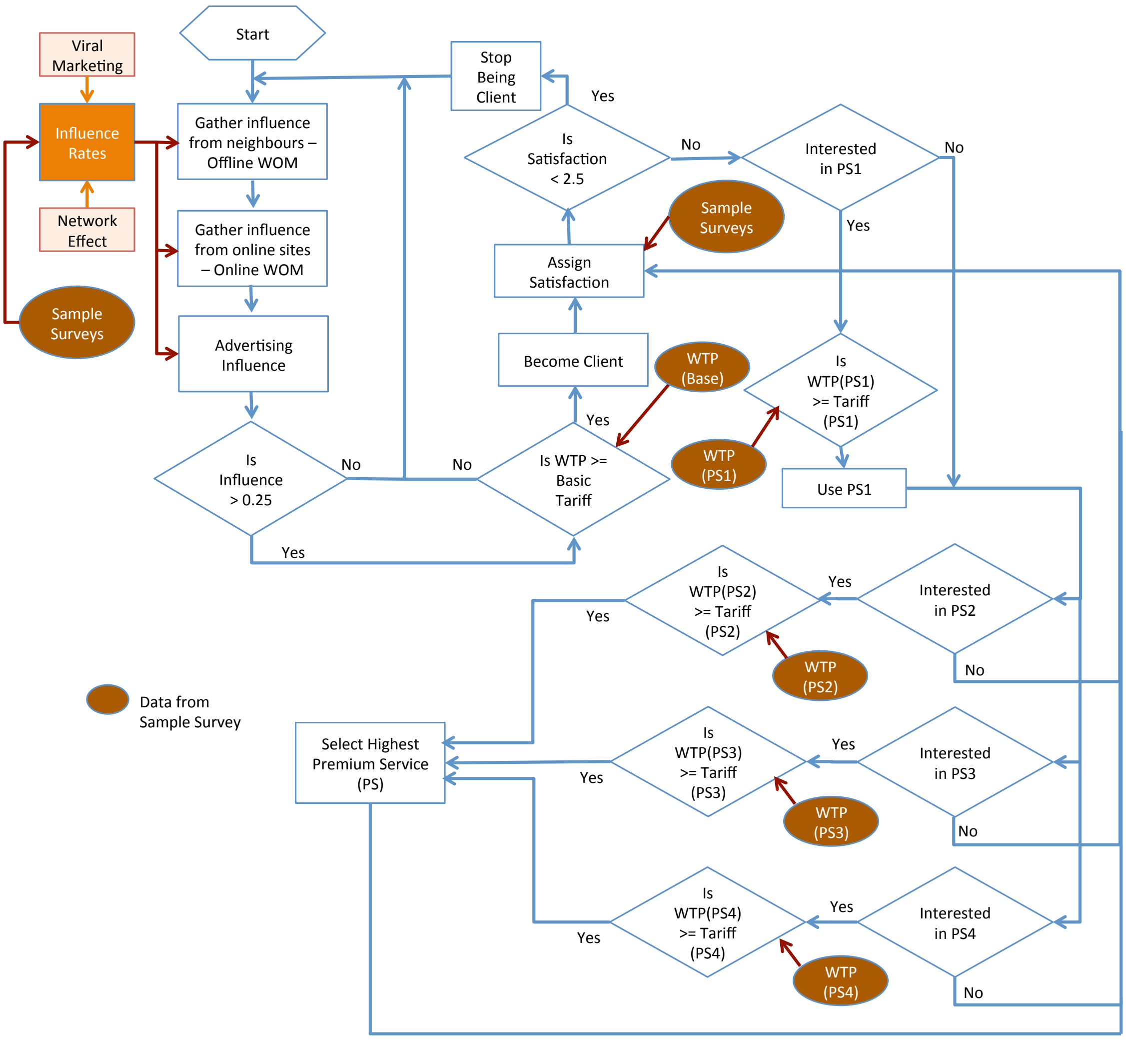


Figure 8.1 Flowchart of a user Agent in Custo Justo DYNAMOD Model

8.2.4. Defining Model Run Parameters

The model has a very high offline Word of Mouth factor as was apparent from our sample surveys. It also benefits from a high network effect coefficient since having a large number of Sellers attract a large number of Buyers and vice versa. Hence we enable the network effect in the model. We obtained data for the number of users accessing the site every month to estimate the monthly users to the site for 53 months from Jan 2009 to May 2013. We divided the data into two sets: From Jan 2009 to July 2011 as the initialization set and from August 2011 to May 2013 as the validation set.

The first set of data is used to initialize the model. In this phase, the data is used to adjust the key model coefficients: namely *Influence_Coefficient* which determines the rate of change of influence of non-customers in a population and the *Radius_of_Influence* which determines the area around an Agent within which other Agents get influenced through offline Word of Mouth. These Coefficients are determined to ensure that the model prediction is closest to the model initialization data. Subsequently, the model is allowed to run till July 2015. The data from August 2011 till May 2013 is used to validate the results of the Model.

Since ABM models are stochastic in nature, it is important to run the model several times. Following the guidelines mentioned by (Rand & Rust, 2011), for each set of results, the model was run 30 times using NETLOGO BehaviourSpace feature and the model results were averaged.

8.3. Model Results

8.3.1. Scenario 1 – Simple Forecasting

The real data as well as the model prediction is plotted in Figure 8.2. This helps us not only make the validation of the model but also enables us to make a 2 year forecast as defined in our first objective, "What would be the growth in terms of number of users in the next 2 years with the existing Business Scenario?"

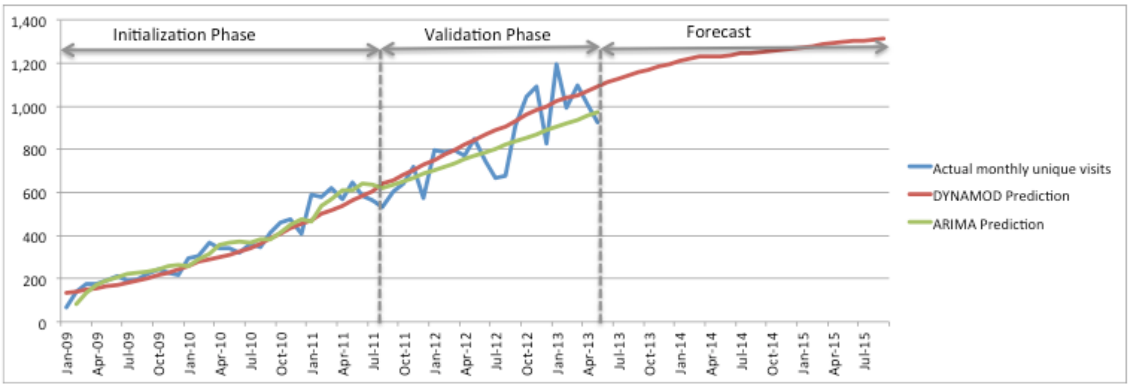


Figure 8.2 DYNAMOD Model Run Results

The data is highly seasonal. This is because it was not possible to obtain the actual number of users registered, because only sellers need to register on the site while buyers need not register on the site. Hence we have used unique monthly visitors to the site to estimate the value of actual number of customers. However all customers may not log in to the site every month. Hence the actual data is very seasonal since buying and selling behavior increases in the holiday season. Because of this cyclic nature, we will compute the mean error, so that the positive and negative errors cancel out.

Total number of customers at any time Ct = $\sum A_i^{\text{client}=1}$

Number of customers according to data at any month t $=C^{A}_{t}$

We have divided the real historical data into 2 parts, data initialization and data validation. The former is used to train the model where the key coefficients are initialized, the latter is used to validate the prediction accuracy of the model.

Mean Absolute Percentage Error during Initialization phase =

$$\frac{\sum_{Jan\ 09}^{Jul\ 11}\left(\frac{|Ct - C^{A}\mathrm{t}\,|}{C^{A}\mathrm{t}}\right)\%}{\text{Count} - \text{Months (Jan 09 } - \text{ Jul 11)}} = 10\%$$

Mean Absolute Percentage Error during Validation phase =

$$\frac{\sum_{Aug\ 11}^{May\ 13}\left(\frac{|Ct - C^{A}\mathrm{t}\,|}{C^{A}\mathrm{t}}\right)\%}{\text{Count} - \text{Months (Aug 11 } - \text{ May 13)}} = 11\%$$

While the main aim of the Model is not to be used as a pure forecasting tool, a good forecast ensures that the model is efficiently configured and ready for making further analysis. To validate the forecasting efficiency of the current model we compare it with ARIMA Simple Exponential Smoothing forecasting. Figure 8.2 shows the plot of ARIMA with simple exponential smoothing along with DYNAMOD forecast and the real historical values and Table 8.3 details the result of both. As the model error is same the ARIMA simple Exponential Smoothing predictions, the Agent Based Model can be considered as well initialized.

Table 8.3 Historical user data with predictions

	Actual monthly unique visits (Thousands)	**DYNAMOD Prediction**	**ARIMA Prediction**	**DYNAMOD % Error**	**ARIMA % Error**
Jan-09	66	134			
Feb-09	142	139	82	2	42
Mar-09	178	148	133	17	25
Apr-09	175	156	171	11	2
May-09	192	163	189	15	1
Jun-09	210	169	207	19	1
Jul-09	193	179	225	7	16
Aug-09	199	190	228	5	15
Sep-09	221	203	232	8	5
Oct-09	242	215	244	11	1
Nov-09	230	229	259	0	13
Dec-09	217	242	263	11	21
Jan-10	296	260	260	12	12
Feb-10	306	279	292	9	5

Mar-10	368	288	315	22	14
Apr-10	341	300	355	12	4
May-10	344	312	365	9	6
Jun-10	323	325	372	1	15
Jul-10	361	341	367	6	2
Aug-10	348	365	381	5	9
Sep-10	415	388	383	7	8
Oct-10	462	407	414	12	10
Nov-10	474	433	451	9	5
Dec-10	409	455	478	11	17
Jan-11	591	469	464	21	22
Feb-11	579	500	536	14	7
Mar-11	623	517	571	17	8
Apr-11	571	540	610	6	7
May-11	646	562	610	13	6
Jun-11	585	585	642	0	10
Jul-11	564	608	634	8	12
Aug-11	534	640	620	20	16
Sep-11	604	658	637	9	5
Oct-11	639	683	653	7	2
Nov-11	718	705	670	2	7
Dec-11	575	731	687	27	19
Jan-12	796	752	704	5	12
Feb-12	787	777	721	1	8
Mar-12	798	798	737	0	8
Apr-12	769	822	754	7	2
May-12	847	843	771	0	9
Jun-12	747	867	788	16	6
Jul-12	670	888	804	33	20
Aug-12	678	905	821	33	21
Sep-12	909	933	838	3	8
Oct-12	1,045	961	855	8	18
Nov-12	1,094	982	871	10	20
Dec-12	826	1,001	888	21	7
Jan-13	1,195	1,024	905	14	24
Feb-13	995	1,039	922	4	7
Mar-13	1,096	1,052	938	4	14
Apr-13	1,007	1,070	955	6	5
May-13	928	1,093	972	18	5
Mean Error				11%	11%

8.3.2. Scenario 2 - Analysing Price Sensitivities

Editing an Ad

"Editing an Ad" is a premium service that is charged at €2 per edit. However it is not a popular service because instead of editing old ads, users can always post new ads for free. Once the model is configured it is possible to change the value of this service to view the customer adoption rate.

Calculating Maximum Profitability

We shall program the model to modify "Editing the ad" cost and note the number of users of the service after a 6 month period. We shall conduct the model run for 6 sets of values: €0.50, €1.0, €1.5, €2.0, €2.5, and €3.0. As indicated by our survey we will use an average per client ad-post rate of once in 2.3 months.

Table 8.4 Price Sensitivity Simulation for Editing an Ad

Price of feature	€0.5	€1.0	€1.5	€2.0	€2.5	€3.0
No. of Users	165,981	156,864	95,672	75,961	33,238	13,431
Revenue	€36,082	€68,201	€62,394	€66,053	€28,902	€11,679

This answers our second objective, "Is charging for "Editing an Ad" viable and if so what should be the optimal value?"

As can be seen from Table 8.4, Revenue Maximization can be made by changing the price of "Editing an Ad" from €2 to €1. Thus charging for editing an ad is viable.

This insight can also be sought from direct mathematical analysis of the current data. However, that would only provide us with a snapshot of the current price sensitivity. By incorporating the results into a dynamic model, we can visualize the long term impacts of a change in the pricing.

8.3.3. Scenario 3 - Selection between enhanced Ad Visibility Premium Services

Custojusto.pt provides users options for 3 advanced ad-visibility services, namely Bumping the Ad(PS2), Urgent Tag(PS3), and The Gallery(PS4). We assume that a client would normally select only 1 of the three offered services. Based on the sample survey, the percentage of clients currently using the 3 services are 1.9%, 2.6% and 1.3% and those interested in using the 3 services are 42.9%, 37.8% and 32.7% respectively if the services match their Price Limits. These distributions are used to set the interested flag for each Agent for each service: ($A_i^{\text{interested-PSx}}$)

Similarly a maximum willingness to pay is assigned to each agent for each service: ($A_i^{\text{WTP-PSx}}$)

If ($A_i^{\text{interested-PSx}}$)=TRUE, and ($A_i^{\text{WTP-PSx}}$)≥Price-RSx, then, ($A_i^{\text{subscribed-PSx}}$)=TRUE

Also, if ($A_i^{\text{subscribed-PSx}}$)=TRUE for more than one case, where *x* can be 2, 3, or 4, then we assume that the client will choose the more expensive plan (since we presume that it offers him greater utility and it fits his budget).

Table 8.5 Simulation effect of reduction in cost of PS2

Case	**Cost of PS2**	**Cost of PS3**	**Cost of PS4**	**6 months after start of Forecast Phase (Nov 2013)**		
				%Clients using PS2	**%Clients using PS3**	**%Clients using PS4**
1	€6	€3	€10	2.2%	3.2%	2.7%
2	€4	€3	€10	3.8%	3.1%	2.7%
3	€2	€3	€10	16.4%	2.9%	2.3%
4	€0	€3	€10	43.1%	2.8%	2.1%

This answers our third objective, “How do customers choose between the three offered Premium Services? How does change in Pricing of one impact the others?”

While a variety of possible effects can be simulated by modifying the cost of the Premium Services, in Table 8.5 we have shown the result of modification of cost of PS2- Bumping the Ad. We have tried to explore the impact in percentage of users if the cost of PS2 is progressively decreased till €0.0. According to the simulation, there is a huge jump in number of users using PS2 when price is reduced from €4.0 to €2.0. Contrary to common sense expectations, the increase in clients using PS2 does not come at the cost of other premium services. As the percentage of clients using PS2 goes up from 2.2% to 43.1%, the percentage of clients using PS3 and PS4 does not go down that drastically as one would expect.

8.3.4. Scenario 4 - Modifying Advertising Costs

The high Value of $\bar{A}_i^{\text{Influence-TV}} = 5.96$ and $\bar{A}_i^{\text{Influence-online-ads}} = 5.51$ shows that users are highly influenced by online ads. Hence it will be interesting to see the impact of change in Advertising Budget which is currently 80% of the total costs. Suppose we reduce this expenditure share to 40% of total expenses, thus bringing down overall company expenses.

$$\text{Cost}^{\text{Ad}} = 0.4 \text{ from } 0.8$$

We make the change from on running the model from June 2013, and observe the value of number of users 6 months later, in Dec 2013. According to the model,

$$\text{Count } \sum_{Dec\ 13} \text{Ai where } (\text{Cost}^{\text{Ad}} = 0.8) = 1{,}194$$

$$\text{Count } \sum_{Dec\ 13} \text{Ai where } (\text{Cost}^{\text{Ad}} = 0.4) = 1{,}189$$

Surprisingly, the difference in number of users 6 months after the 50% reduction in advertising expenses is not much according to the model. While, its true that Advertising plays a major role, Word Of Mouth, especially offline word of mouth has a far greater influence, $\bar{A}_{\text{i}}^{\text{ OfflineWOM-Friends}} = 6.93$. Also the model has already reached 50% market penetration, hence the critical mass has already been achieved, and the site can sustain itself due to strong Network Effects and an effective Word of Mouth influence. According to the model predictions, it could be wise to spend lesser on Advertising and use those resources in the development of new services. This answers our fourth objective: "What would be the impact in user growth if the advertising costs were to be halved?"

8.3.5. Scenario 5 – Radical Change in Business Model

Here we discuss our fifth objective: "When the business model is changed to that of a financial intermediary, what is this critical percentage of users experiencing fraud that would lead to a progressive decline in number of users?"

The Agent Based Simulation Model works well when the model parameters are well defined. However Business Model change can be more drastic than adjustment in pricing and costs. Often it may incorporate a radically new business offering. DYNAMOD is still useful and relevant in such scenarios, since it helps us conceptualize such a change. For example, consider the scenario where Custojusto.pt does not offer just a classifieds service but also takes on the role of an intermediary for financial transactions. It can encourage sellers to post an item, thus increasing the geographical range of the transaction, by ensuring that the buyers pay online first. Not only can it drastically increase site usage, but can also allow Custojusto.pt to start charging on each transaction. However such a move must incorporate Buyer Protection policies, to make sure that buyer confidence in Custojusto.pt does not reduce.

If the buyer received a perfect item but wrongly claimed not to receive or receive a defective product and claim chargeback from the seller, the seller would be upset and lose satisfaction. Similarly if the seller commits a fraud, the buyer would be upset. When a user experiences a fraud, his satisfaction level goes down and he may not only quit using the site, but also influence other users. However, as long as the percentage of users experiencing fraud is below a critical percentage, the positive experience of others would make the site continue to grow. However the moment this critical percentage is reached, the negative word of mouth would cause bad publicity. Consequently the drop off rate would further increaseand eventually get higher than the rate of acquiring new users leading to an uncontrollable decline.

The DYNAMOD model can be used to compute the potential risks of loss in confidence in the site due to fradulent buyers and sellers. Let us assume that when a buyer or sellers encounters a fraud business partner, his satisfaction level goes down by 0.2 points. Such a scenario can be incorporated through simply incorporating the following variables:

$$A_i^{\text{fraud-seller}} = \text{TRUE}$$

This variable if flagged means that the agent is fraud and may indulge in selling a fraud product. We can make simulations by changing the percentage of fraud users in the system.

$$A_i^{\text{fraud-buyer}} = \text{TRUE}$$

This variable is flagged if the buyer is generally used to making false claims even when the posted product is Authentic.

We have assumed that an online transaction will occur by an agent once every We shall run this model by changing both the above Fraud Percentage as 1%, 2%, 5%, 10%. (Table 8.6)

Table 8.6 Simulation results with different fraud percentages

	Fraud Percentage			
No. of Clients in	1%	2%	5%	10%
6 months	1,204	1,201	1,097	1,014
12 months	1,265	1,256	1,020	907
18 months	1,333	1,315	937	811
24 months	1,397	1,374	856	712

If the fraud percentage is low, then the increased business due to buyers and sellers engaging over a larger geographical distance provides real benefits. However if tendency of clients to engage in fraud increases, the reputation and customer satisfaction levels go down thus leading to clients abandoning the site. According to simulation results presented in Table 8.6, as long as percentage of users indulging in fraud is up to 2%, customer growth rate will not be significantly affected.

8.4. Case Study Discussion

CustoJusto.pt is a classifieds ad provider that is an example of a double sided platform with a freemium business model. This case study demonstrates the ability of DYNAMOD to model such business scenarios where not only is a linear growth prediction is modelled but also the sensitivity to pricing and its revenue impact is explored. The historical monthly unique site visits is not linear unlike the case of Facebook.com. This is because sale and purchase of second hand products has some cyclic and random variations about a mean line. The first simulation model made a growth prediction based on the Initialization Data set until July 2011. The predictions until April 2013 were found to be as accurate as the ARIMA forecasting for the same period. Thus the model was found to be reasonably accurate in terms of making future growth forecasts.

Since a freemium pricing model is used, pricing does not have an impact on the growth of user visits. However the platform charges for certain premium features such as Editing an Ad and enhanced visibility of advertisements. It tests the impact of a change in the price of Editing an Ad on its usage and uses the model to find out the optimim pricing for Editing an Ad. Further the model, simulates the usage relationships between three competing visibility enhancement features on offer, and explores how the change in the price of one affects the usage of the others. The simulation showed that the reduction of the price of one feature leads to increased usage of the same without drastically affecting the usage of the other competing features but beyond this point it starts to cannibalise other features as more and more people will start shifting to this.

The model also explores the impact if the current business model is replaced with an alternate one where shipping of the product is managed and the platform also acts as a financial intermediary. The model successfully computes the risk of a negative impact of fraud committed by users of the platform. Such insights can provide Business Managers with useful data before they take decisions affecting the business model.

9. Case Study 3 - Vortal.biz

9.1. Modeling Scenario and Objectives

9.1.1. Modeling Scenario

Vortal.biz is the largest procurement platform provider in Portugal and has a market penetration close to 90% of its assessed potential market. Such a high penetration was possible due to the use of a freemium pricing model and the ability to attract a high percentage of large buyers. Vortal´s platform is an example of a double sided platform that tries to attract large volume buyers on one side and sell monthly subscription plans to various vendors on the other side. The buyers include both public and private entities. Contracts with buyers are often negotiated on a case to case basis with large discounts being offered to bulk buyers to make the platform more attractive for sellers. Sellers are offered the choice of choosing between a range of tariff plans. This paper only focuses on creation of an Agent Based Simulation Model for the sellers. This is firstly because contracts with buyers are more arbitrary in nature and hence difficult to model and secondly, in a short time period of one or two years, the number of buyers do not significantly change due to a saturated market penetration by Vortal.biz. Hence the business may be modeled as a single sided platform despite being a double sided platform in reality.

9.1.2. Tariff Plans

The Sellers are offered a freemium tariff plan with the Universal plan as a basic free plan. Smart Plans offer 4 advanced features while Best Plans offer 4 more advanced features. Universal, Smart-Gov and Best-Gov plans offer clients access to opportunities only from the Public entities while Smart-Eco and Best-Eco also offer opportunities for the Private as well as public entities (Table 9.1). The Sellers are charged a Monthly Tariff based on the company size according to which four Tiers of Tariff are offered. However since the largest number of clients are in Tier 1, we will consider only Tier 1 in this simulation. Similar simulation models can be prepared for other Tiers.

Table 9.1 Tariff Plans - Pricing and Features

	Universal (U)	**Smart-Gov (SG)**	**Smart-Eco (SE)**	**Best-Gov (BG)**	**Best-Eco (BE)**
Market	Public	Public	Private + Public	Public	Private + Public
Monthly Tariff	0	120	170	170	250
Premium Features					
1. Opening, Attaching and Signing Multiple Files		✓	✓	✓	✓
2. Export of Proposals and Import of Prices		✓	✓	✓	✓
3. Display of Recommendations in Supplier's Finder		✓	✓	✓	✓
4. Display of Company's Certificates in Supplier's finder		✓	✓	✓	✓
5. Display of Company Logo in Supplier's Finder				✓	✓
6. Display of Profile and News in Supplier's Finder				✓	✓
7. Display of Catalogues of Products and Services				✓	✓
8. Access to Business Statistics				✓	✓

9.1.3. Model Objectives

The model seeks to simulate the customer response to different plans and offerings in order to develop an agent based simulation model that can simulate the impact of changes in pricing of the various Tariff Plans. Also, the company was interested in viewing the attractiveness of offering users the option of using one of the premium features without upgrading to the higher tariff plan. Such a scenario was also modeled in this simulation. To summarise, the specific objectives of the model are as follows:

1. Simulate the upgrade of customers to newer tariff plans.
2. Simulate the subscription of a single feature instead of upgrading to a newer tariff plan.

The Vortal Model is based on the customization of the DYNAMOD Simulation model that has been applied to a variety of online business case studies before.

9.2. *Model Development*

9.2.1. Formalization of the Simulation Model

Client Upgrades

The model tries to simulate the upgrade of users to higher tariff plan based on their willingness to pay. The upgrade choice for users is based on the assumption that a user will only choose to upgrade one level up at a time, and a user on a plan with access to public as well as private opportunities will not like to move to a plan that restricts opportunities for him to only the public opportunities. Hence, the Universal users may upgrade to Smart-Gov or Smart-Eco, Smart-Gov users may choose to move to Smart-Eco to expand their markets or may choose to move to Best-Gov plan if they would like to continue access to the same public opportunities but with enhanced features. Similarly users may upgrade from Smart-Eco as well as Best-Gov to Best-Eco. (See Figure 9.1)

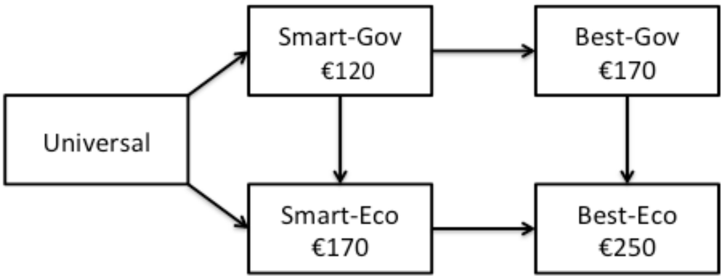


Figure 9.1 Client Upgrade Options

To determine if a user is willing to upgrade to a higher plan or not, we need to identify the user willingness to pay for the higher plan. This was determined through sample online surveys where each user was asked about his interest and willingness to pay for the tariff plan options that he is most likely to upgrade to.

For each User Agent A_i,

The current plan, A_i [plan] = 0, 1, 2, 3, 4, 5 corresponding to Universal, Smart-gov, Smart-eco, Best-gov, Best-eco.

Willingness to Pay for an agent A_i currently on Plan n for Plan m = A_i [WTP – n – m]

Current Price for Plan n = Price-n

An agent with A_i on universal plan will upgrade to Smart-Gov if it is willing to pay more than the current price.

If (A_i [WTP-0-1] >= Price-n) , A_i [Plan] = [0 to 1]

In case an agent is eligible to upgrade to more than one higher plan, he will upgrade to the plan that he sees a higher value, ie, his willingness to pay is higher.

For any optimized pricing model, the company is interested in maximizing the Total Monthly Revenues.

Total monthly revenue= R = nSG * Price-1 + nSE * Price-2 + nBG * Price-3 + nBE * Price-4

Where nSG, nSE, nBG and nBE are the number of Agents currently on plan Smart Gov, Smart Eco, Best Gov and Best Eco respectively.

Optional Features

Vortal was interested in using this model to simulate the impact of additional revenue generation models. One of the possibilities included the introduction of users to chose one optional premium feature from a higher plan without needing to upgrade to a higher plan. The features are listed as follows:

$$\{f1, f2, f3, f4\} \in SG, SE$$

$$\{f5, f6, f7, f8\} \in BG, BE$$

A user at plan U does not have access to any of the features. He may chose to subscribe to f1 or f2 or f3 or f4 but not to more than one of them at the same time. Similarly one of f5, f6, f7 or f8 is available to a user of SG or SE Tariff plan. Features must be priced in a way such that they do not cannibalise the upgrades to a higher tariff plan. The set of possible monthly prices for the eight features are:

{f1, f2, f3, f4} can have the following prices {€40, €60, €80, €100}

{f5, f6, f7, f8} can have the following prices {€30, €40, €50, €60}

An agent with A_i on universal plan will upgrade to f1 if it is willing to pay more than the current price of f1. If this is true the flag f1 for the agent A_i is set to 1.

If (A_i [WTP-0-f1] >= Price-f1) , A_i [f1] = [0 to 1]

The users willingness to pay for different features were again collected through the sample survey. User's willingness to pay for each of the features were evaluated and a distribution of the same was used for programming the agents in the simulation model. If an agent's willingness to pay is higher for more than one feature, and he is not ready to make the switch to a higher tariff plan, then the feature for which his willingness to pay is the highest shall be adopted to. If he has the same willingness to pay for more than one feature, then the order of utility for features according to the overall utility of various features based on the sample survey (Figure 9.2).

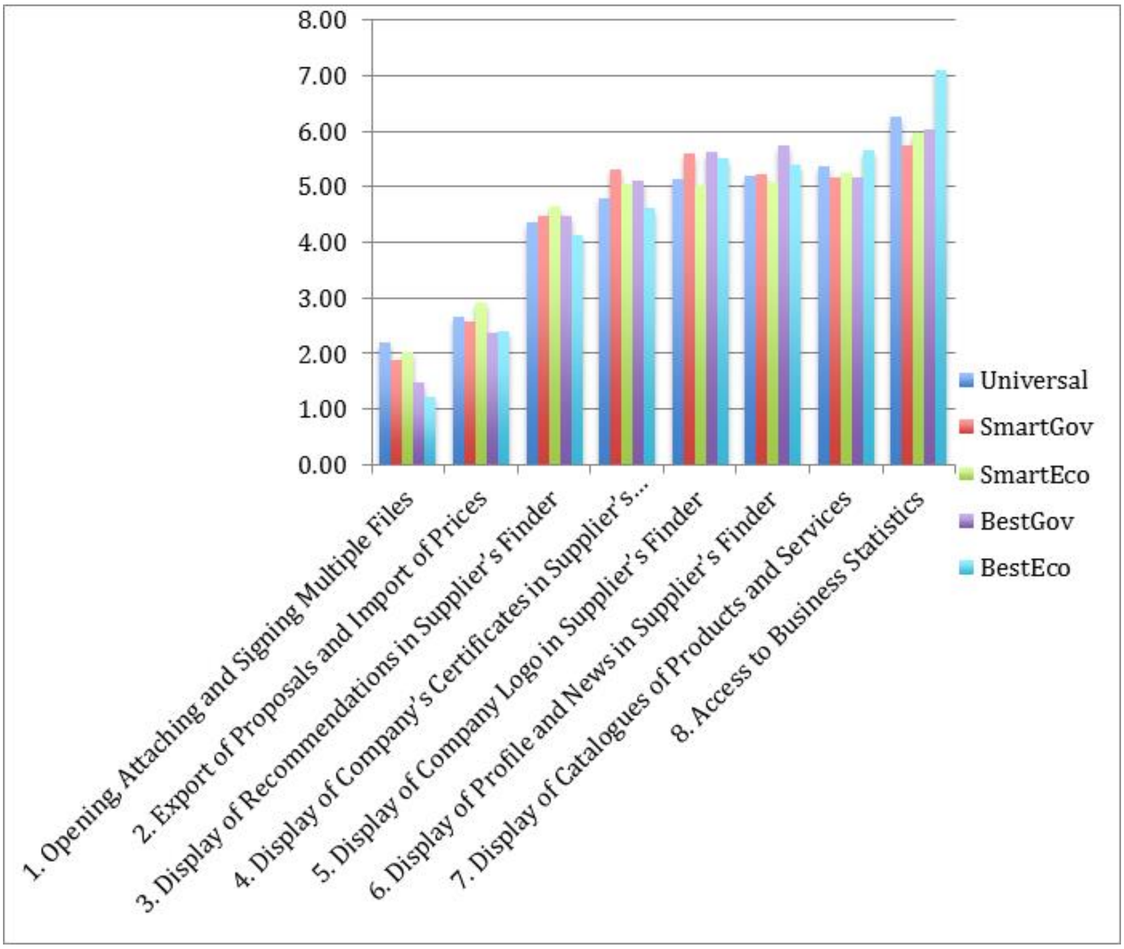


Figure 9.2 Utility of different features based on user responses

9.2.2. Upgrade Preferences from the data collected for the Vortal Model

An Agent Based Model mimics the real life consumer opinions and preferences and uses these to simulate the larger business scenario. To gauge user opinions, preferences and willingness to pay for various tariff plans, we conducted an online questionnaire to gauge the user satisfaction, influence from various sources of advertising and willingness to pay for upgrade to a higher plan. The total number of respondents were 365 (U – 290, SG- 37, SE - 19, BG- 15, BE-4). The distribution of respondents according to the maximum willingness to pay for an upgrade is shown in Table 9.2

Similarly, the willingness to pay for each of the 8 features was obtained from the respondents and arranged according to the current tariff plan that they are currently on. These were fed into the Simulation Model for the purpose of simulating user adoption of feature based pricing.

Table 9.2 Willingness to pay for upgrades based on Sample Survey

Upgrade	**Max. Willingness to Pay**						
U to SG	€120	€100	€80	€60	€40	<€40	NI
	11.47%	3.23%	2.51%	3.94%	5.38%	52.69%	20.79%
U to SE	€170	€150	€130	€110	€90	<€90	NI
	6.13%	0%	1.78%	2.14%	2.85%	51.96%	35.15%
SG to BG	€170	€150	€130	€110	€90	<€90	NI
	21.16%	2.63%	10.53%	10.53%	13.16%	39.47%	2.52%
SG to SE	€170	€150	€130	€110	€90	<€90	NI
	5.56%	2.78%	8.33%	2.78%	25%	38.89%	16.67%
SE to BE	€250	€230	€210	€190	€170	<€170	NI
	10%	0%	0%	5%	10%	50%	25%
BG to BE	€250	€230	€210	€190	€170	<€170	NI
	14.14%	0%	0%	0%	7.14%	57.14%	21.57%

9.3. Model Results

9.3.1. Model Validation

To validate the model we obtained the actual number of users for each price plan in the end of 2012 and 2013 from Vortal (Table 9.3). We initialized the model to have different agent types based on the number of users on different tariff plans in 2012. The user willingness to pay were attributed to the agents based on the survey results.

Table 9.3 Historical record of subscriptions to various tariff plans

	U	**SG**	**SE**	**BG**	**BE**	**Total**
2012	8227 91.686%	431 4.803%	218 2.429%	46 0.512%	51 0.568%	8973
2013	7888 84.753%	679 7.295%	458 4.921%	167 1.794%	115 1.235%	9307

The model is allowed to run till it reaches the closest to the real value of number of SG users in 2013. Hence the real value of SG in 2013 is your to determine the average number of steps that constitute a one year period for the simulation model. The model was run 1000 times to monitor the stochastic variability of the results (See Figure 9.4, Figure 9.5, Figure 9.6, Figure

9.7). This enable us to visualize a probability distribution of the forecasts. The average number of steps the ABM took to just cross the number 679 of SG users in 2013 was 60. Hence 60 steps represented a time scale of one year and the model was run 1000 times for 60 steps and other parameters were measured. Hence, we shall use the forecasts for agents on other tariff plans to validate the accuracy of forecasts of the model for 2013.

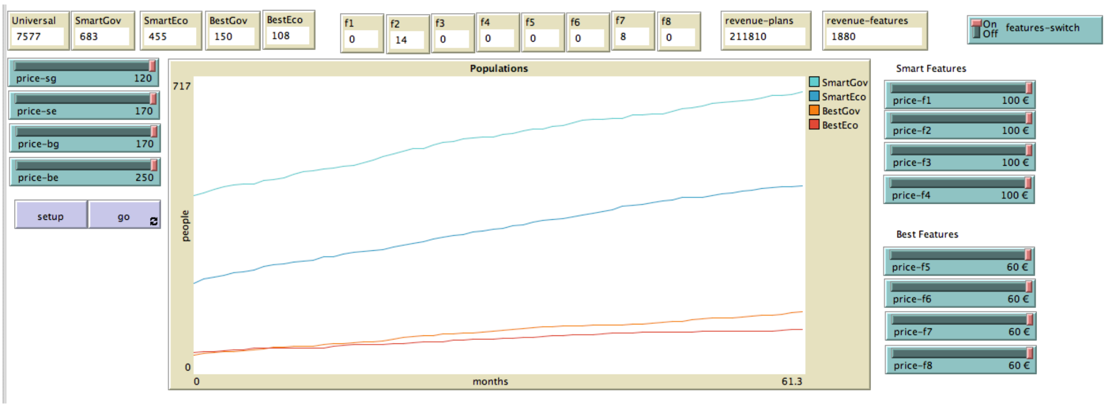
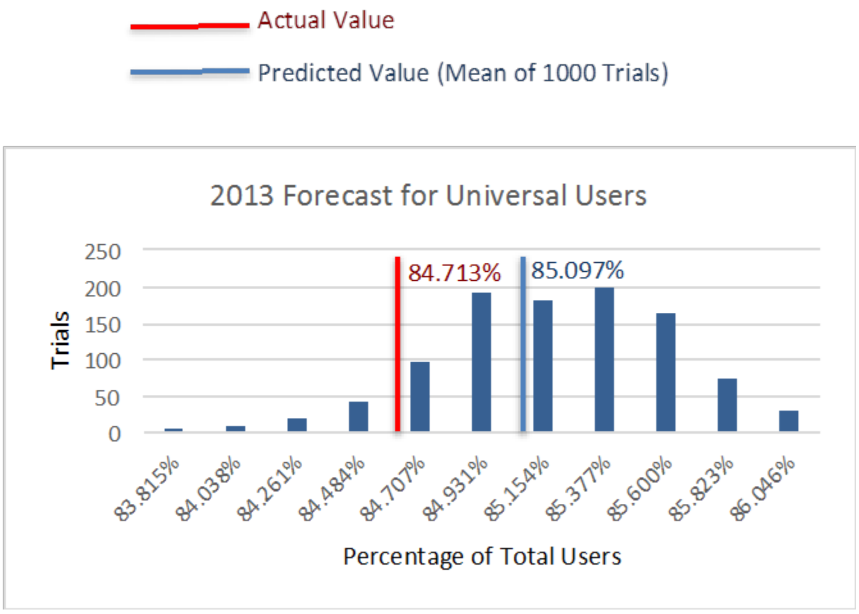


Figure 9.3 Netlogo Screenshot for Vortal Model

The price of the optional features were set at the maximum possible value, ie, €100 and €60 for the first four and last four features respectively. The simulation results showed that in one year, an average of 11.48 users and 8.96 users subscribed the f2 and f7 features respectively. There were no subscribers for any of the other features. Thus this price point was set too high. We shall discuss further how an optimization of prices can be achieved using genetic algorithms.

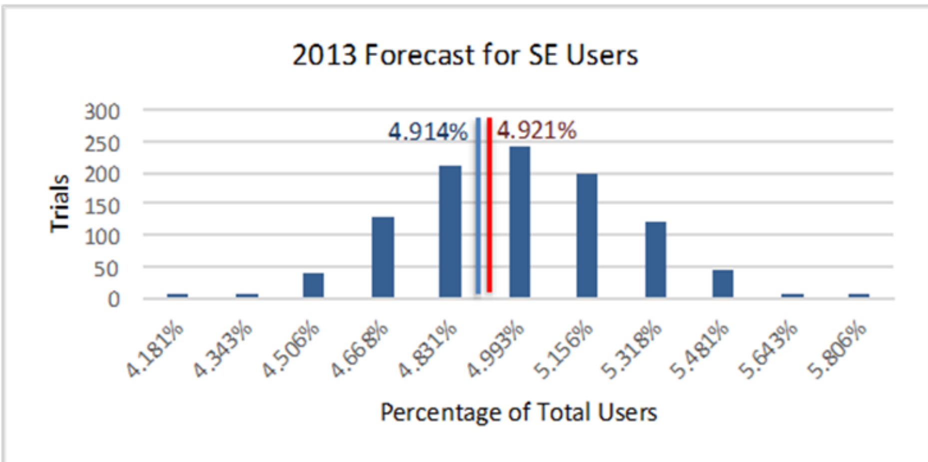
The model represents a highly saturated market condition, where there is a high market penetration. Already all major vendors in Portugal are using the Vortal Platform. The model forecasts a strong shift from the free users of Vortal towards becoming paying customers as well as customers upgrading from the "Smart" Plans to the "Best" Plans. It further closely forecasts the percentage of users in various plans with an error of less than 1% in all the cases. However this error is negative across all the paid plans thus showing a small bias where the model predicts a lower willingness to pay than in reality. This bias may be corrected in future research work by implementing other means of gauging willingness to pay other than direct questionaires, for example, Vickery Auction . The prediction capabilities of this model cannot be compared with any other existing forecasting tool, because no forecasting tool enables future prediction when only one set of data for the current period exists. The DYNAMOD model is not just a forecasting tool, but rather a toolkit that enables us to capture the underlying business scenario in the form of user satisfaction and willingness to pay end enables us to make future forecasts based on a variety of what-if scenarios.

Distribution of Model Forecasts for 1000 trial runs for the year 2013 based on 2012 data. The distribution of the model predictions are compared with the actual figures for 2013 which are represented by the red vertical line.



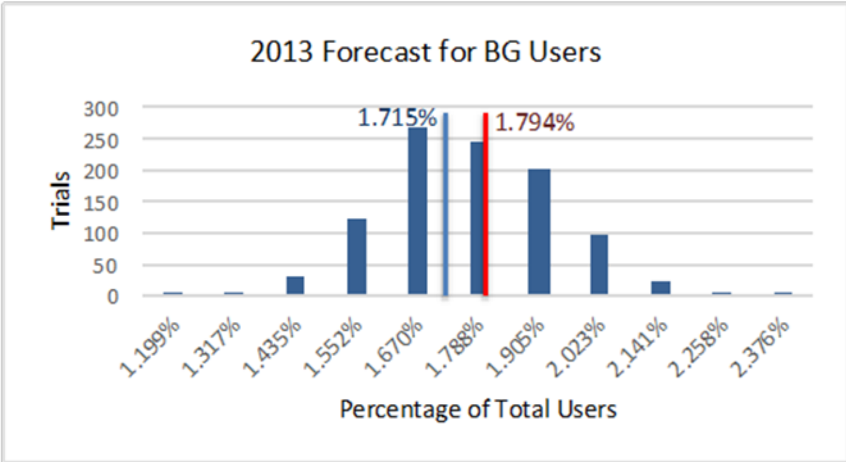
Mean	85.097%
Variance	1.65516E-05
St Dev	0.004068369
Error	+0.384 (+0.45%)

Figure 9.4 Forecast for 2013 for Universal Users based on 2012 Data



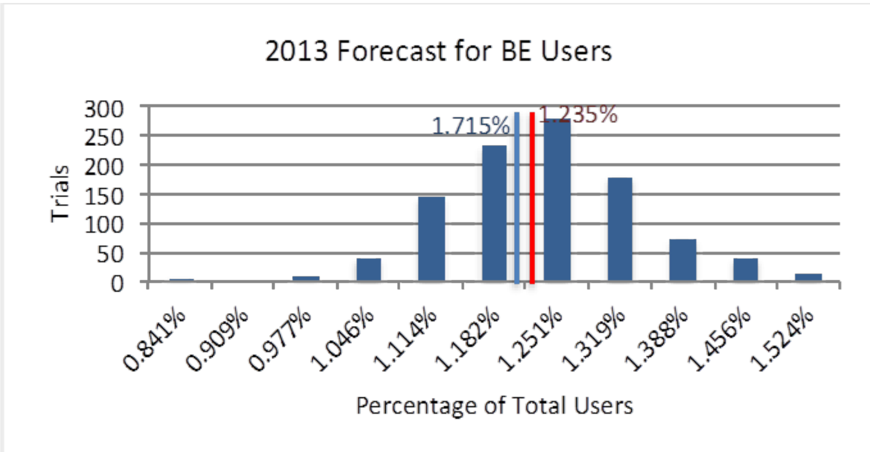
Mean	4.914%
Variance	6.16021E-06
St Dev	0.002481976
Error	-0.007 (-0.14%)

Figure 9.5 Forecast for 2013 for SE Users based on 2012 Data



Mean	1.715%
Variance	2.61007E-06
St Dev	0.001615571
Error	-0.079 (-4.40%)

Figure 9.6 Forecast for 2013 for BG Users based on 2012 Data



Mean	1.205%
Variance	9.72953E-07
St Dev	0.000986384
Error	-0.03 (-2.43%)

Figure 9.7 Forecast for 2013 for BE Users based on 2012 Data

9.3.2. Model Forecast for 2014

We shall make forecasts for 2014 based on data from 2013 (See Figure 9.8 - Figure 9.15). The projections show a continued trend of users migrating from Universal users to higher plans and the same is presented in Figure 9.8. To compare these forecasts with a 2 year forecast we also make a forecast for 2014 based on the 2012 data. Both these forecasts have been presented next to each other. The comparison of the two predictions demonstrate a close prediction and consistent results. The shift in users from free to paid plans in 2014 forecast based on 2013 data is slightly more than that based on 2012 data consistently across all paid plans. However the difference is less than -1% across all paid plans. This is consistent with the slight negative bias while measuring willingness to pay through direct questionaires as discussed previously. When forecast are made over a two year period, the bias tends to be more prominent than over a one year period.

- **Comparison of distribution of Model Forecasts for 1000 trial runs for the year 2014 based on 2013 data and 2012 data.**

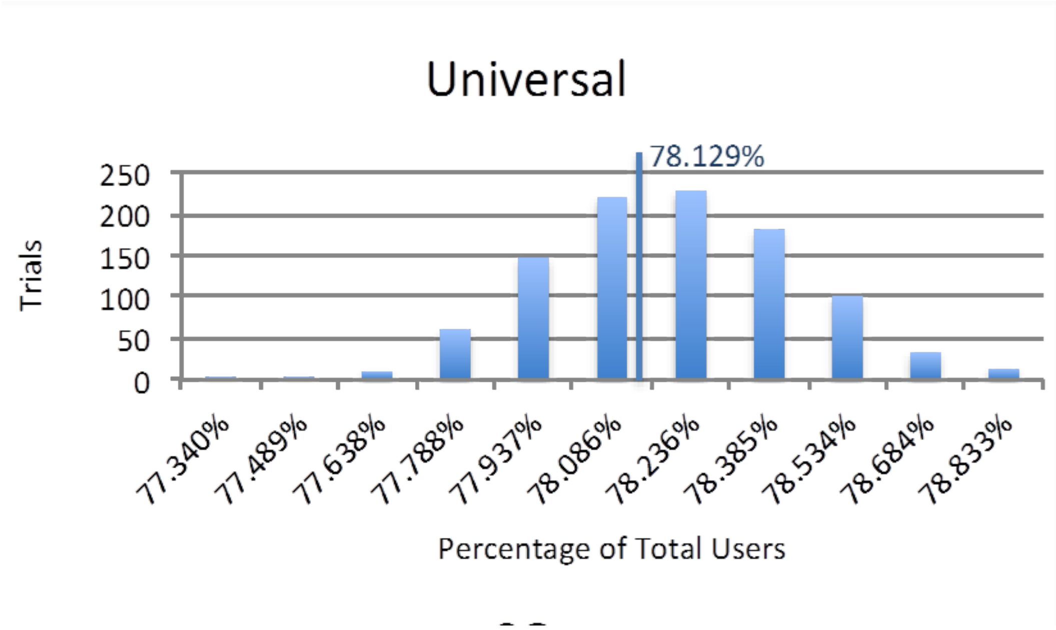


Figure 9.8 Universal Forecast for 2014 based on 2013 Data

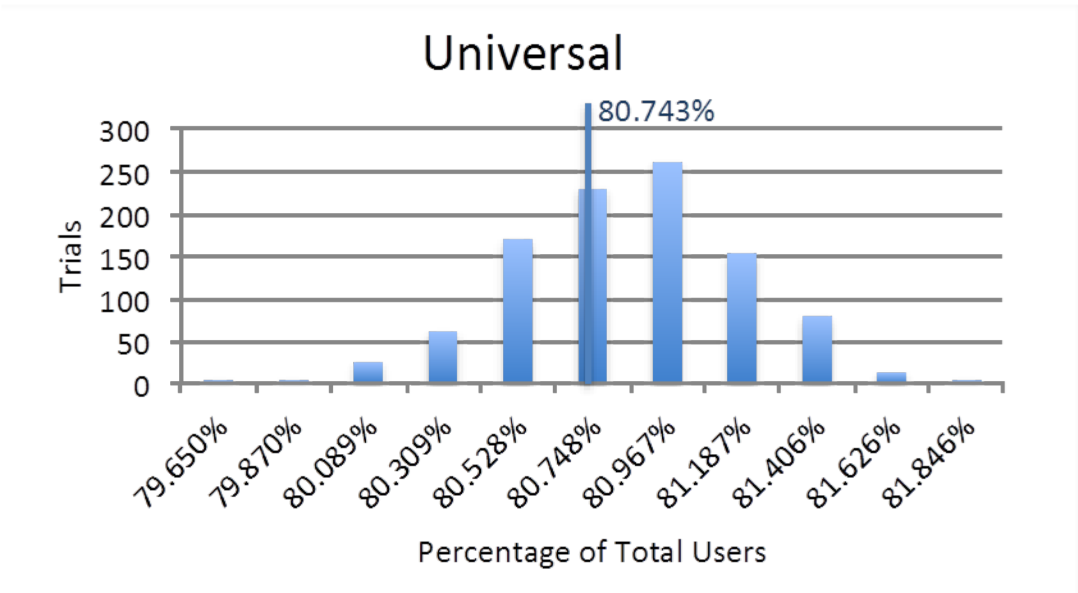


Figure 9.9 Universal Forecast for 2014 based on 2012 Data

• **Comparison of distribution of Model Forecasts for 1000 trial runs for the year 2014 based on 2013 data and 2012 data.**

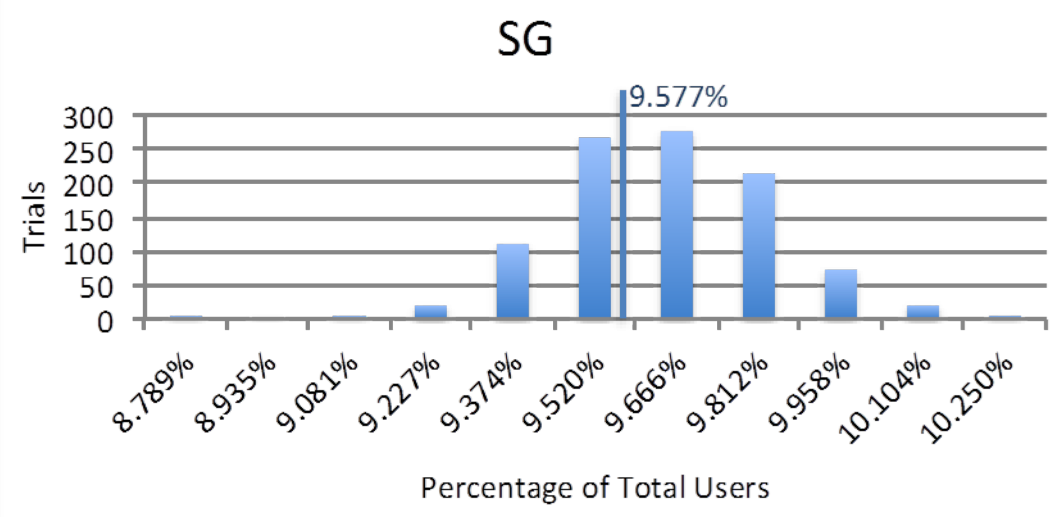


Figure 9.10 SG Forecast for 2014 based on 2013 Data

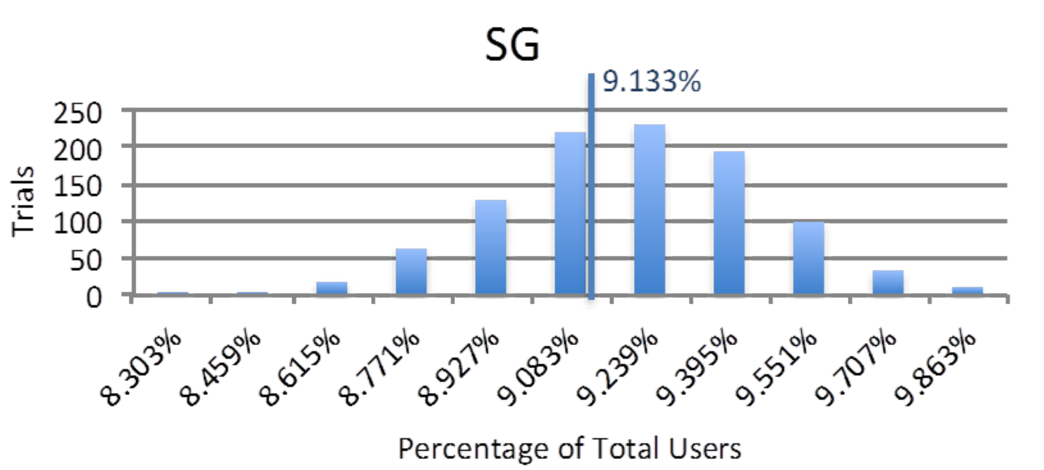


Figure 9.11 SG Forecast for 2014 based on 2012 Data

- **Comparison of distribution of Model Forecasts for 1000 trial runs for the year 2014 based on 2013 data and 2012 data.**

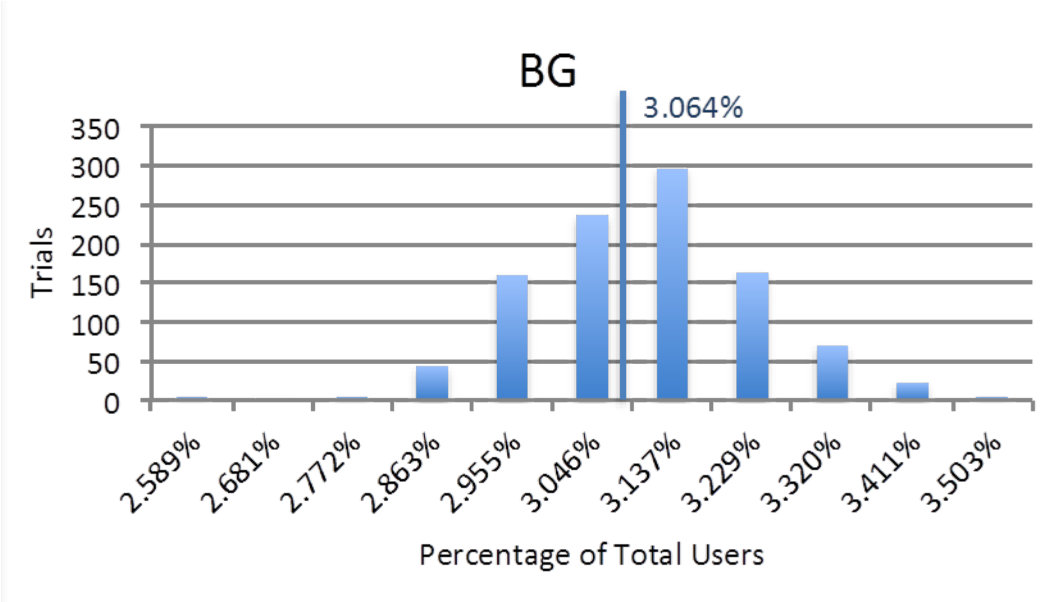


Figure 9.12 BG Forecast for 2014 based on 2013 Data

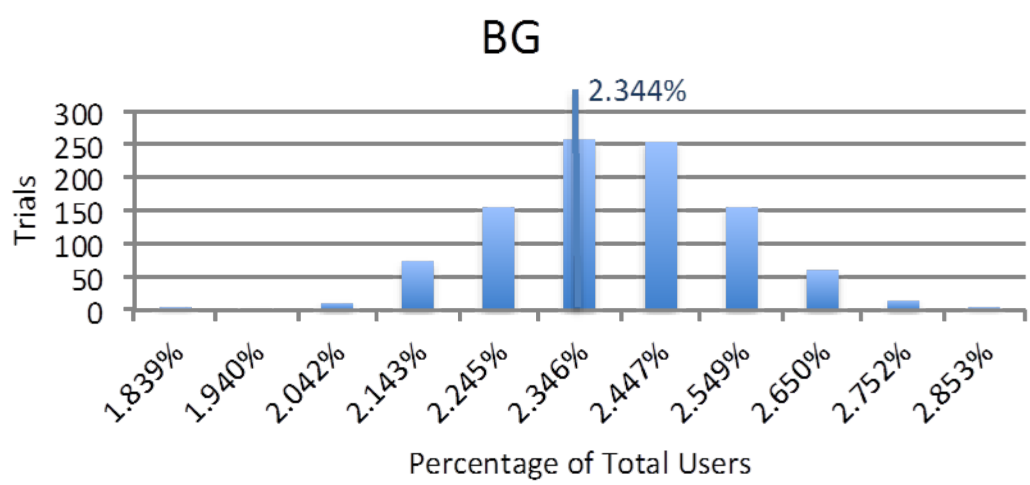


Figure 9.13 BG Forecast for 2014 based on 2012 Data

- **Comparison of distribution of Model Forecasts for 1000 trial runs for the year 2014 based on 2013 data and 2012 data.**

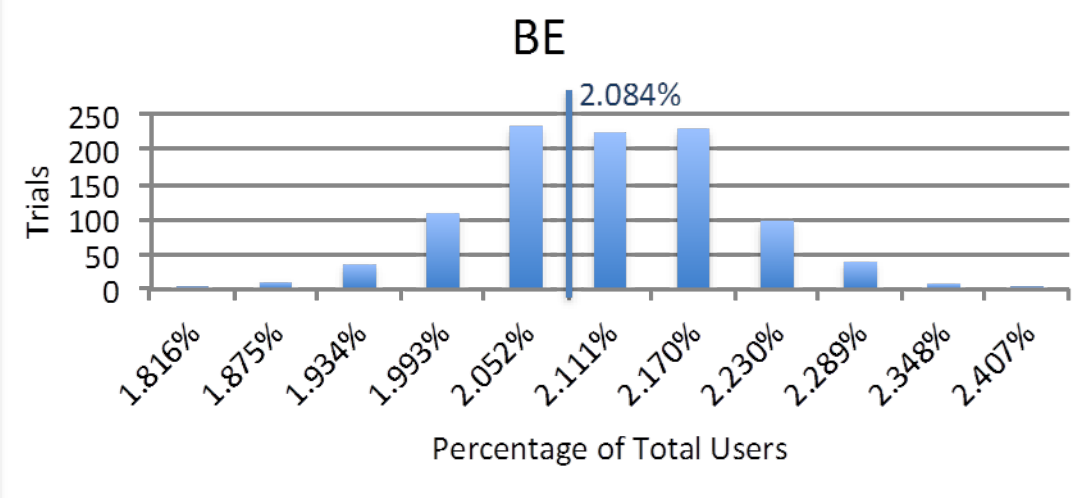


Figure 9.14 BE Forecast for 2014 based on 2013 Data

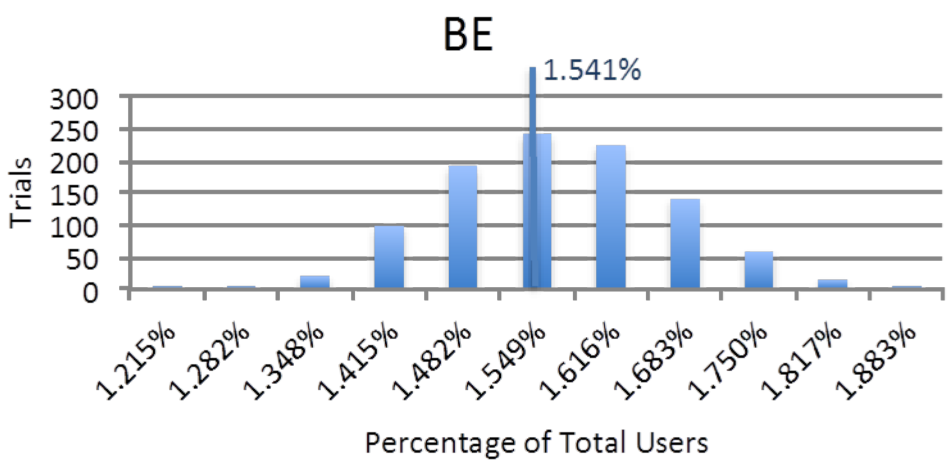


Figure 9.15 BE Forecast for 2014 based on 2012 Data

9.3.3. Optimization of Prices using Genetic Algorithm

The DYNAMOD tool is not simply a forecasting tool but a simulation model that can provide projections for a variety of business scenarios. In this case we may use it to study the revenue generated by varying the prices of the various tariff plans. The pricing of tariff plans is complex since pricing of one often affects the demand for other plans and features. We shall demonstrate how a powerful tool, known as genetic algorithms can be utilized with the model to obtain the optimized pricing. Genetic algorithms allow us to solve a complex optimization problem such as this where the objective is to maximize the fitness function. In this case the fitness function is to maximize the sum of revenue from plans and revenue from additional features. The optimized set of prices is shown in Figure 9.16. Figure 9.17 shows the configuration selected for the Genetic Algorithm.

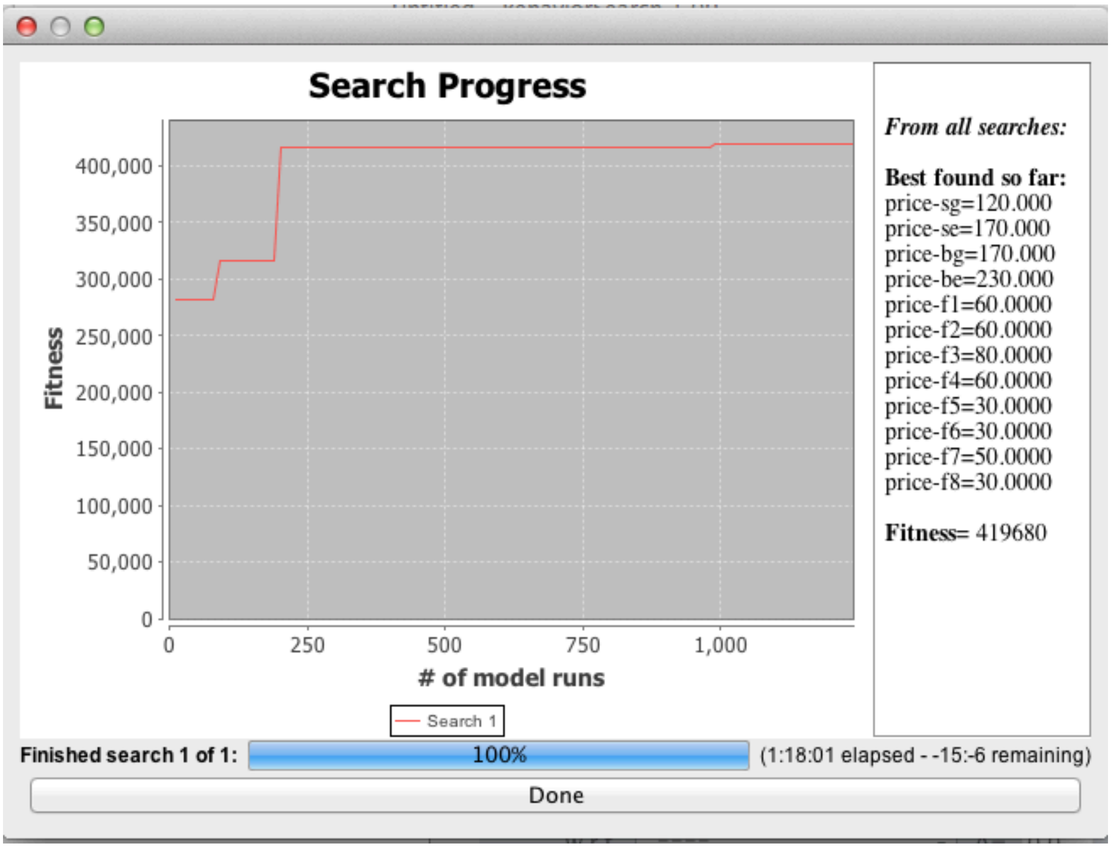


Figure 9.16 Applying Genetic Algorithm using Behaviour Search

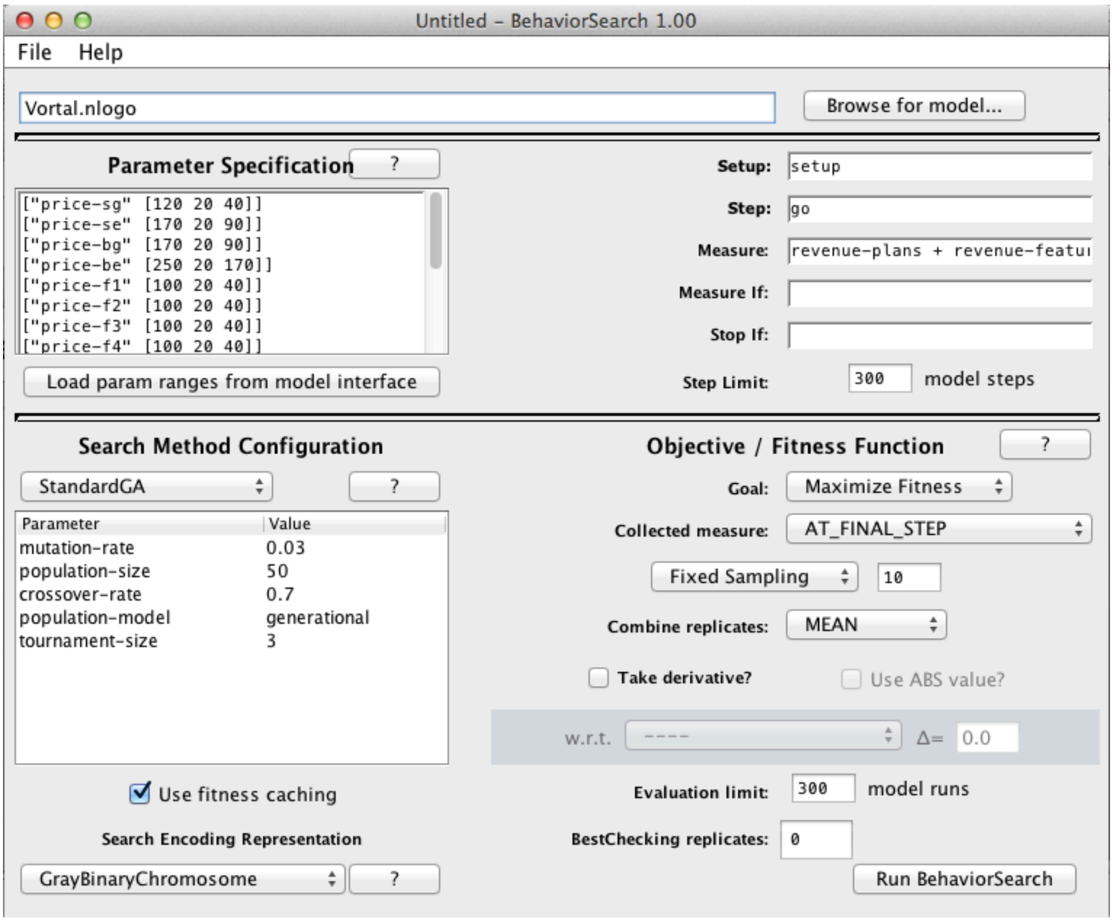
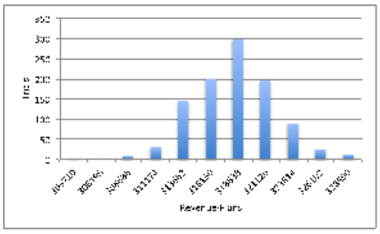
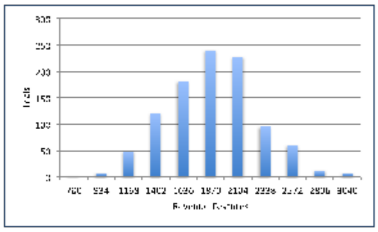
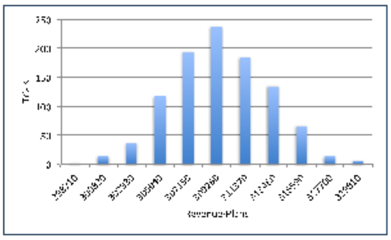
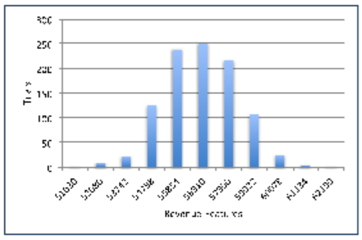


Figure 9.17 Genetic Algorithm Search Parameters

Table 9.4 shows a comparison of the projections of revenue based on two scenarios. Scenario 1 involves maintaining the existing pricing for all plans and selecting the maximum price for all the 8 features. Scenario 2 involves using the optimized prices for plans and features based on the solution provided by the genetic algorithm. The optimized solution provides us with a mean revenue of €364771.79 as compared to €318879.28 in the first scenario. This is despite the fact that there is a small decrease in revenue from plans alone, but the increase in revenue from features compensates for it.

Table 9.4 Revenue projections for current and optimized scenarios

	Scenario	**Monthly Revenue-Plans:**	**Monthly Revenue-Features:**
1.	Plans – Existing Price Features – Max Price	 Mean €317109.96 Variance 12752654.45 St Dev 3571.085893	 Mean €1769.32 Variance 147110.6482 St Dev 383.5500596
		Total Revenue: €318,879.28	
2.	Plans - Optimal Price Features – Optimal Price	 Mean 308466.74 Variance 12469633.61 St Dev 3531.236838	 Mean 56305.05 Variance 2158127.725 St Dev 1469.056747
		Total Revenue: €364,771.79	

9.4. *Case Study Discussion*

Vortal.biz is one of the largest B2B procurement platforms in Portugal. It is an example of a two sided marketplace based on connecting large buyers with sellers. The platform uses a freemium model where additional features are offered to clients in the form of monthly tariff plans. Since negotiations with Buyers are made on an individual basis, based on the volume of purchase, we have not modelled the Buyers in this simulation. The purpose of this simulation was to model the change of Tariff Plans by users, and the implications on the change of prices of the Tariff Plans on the change of plans. Also the implications of offering the users to select just one feature from a higher tariff plan instead of upgrading to the higher plan was explored.

Vortal.biz had completely modified their platform and features three years ago, and hence the data before that was not relevant for this modelling. Hence we had only two years of relevant data (2012 and 2013) for performing the simulation and modelling. This case demonstrated the ability of DYNAMOD to even simulate the business scenario where very little historical data is available.

To validate the simulation, forecasts were made for 2013 based on 2012 and the forecasts were found to be very close to the actual data in 2013. Subsequently, Genetic Algorithms were used to optimise the pricing of the Tariff plans and additional features to maximise the revenue. In this case study, the simulation model were run 1000 times, and instead of averaging the results, a distribution of the results have been presented. This provides us with a distribution of future potentials rather than a specific value.

10. Cross Case Study Analysis

This thesis demonstrated the applicability of the DYNAMOD modelling framework to three different Business Scenarios. These Case Studies demonstrated the applicability of DYNAMOD as a generic modelling framework that can be applied to specific modelling scenarios to develop Agent Based Models that can be used to simulate, visualise and optimise different elements of the Business Model. The DYNAMOD framework is especially suited for purely digital businesses, which do not have an associated physical infrastructure like delivery mechanisms. Such businesses are not affected by other factors such as physical infrastructure and hence much more dynamic in nature. Hence the word of mouth and network effects have a more profound influence on such businesses rather than those which are offline and have merely an online presence. The three case studies selected fulfil these criterion.

In this section we shall perform a detailed analysis of the similarities and differences between the selected cases with respect to their Business Characteristics and the Modeling Results. This section will help us generate a greater understanding of the different aspects of online businesses with respect to the selected cases.

10.1. Business Characteristics

10.1.1. Purely Digital Businesses

All the three selected case studies are examples of purely digital businesses. This means that a user needs only a computing device (Desktop, Laptop, Mobile, Tablet) and an internet connection to have access to the digital product. There is no need for a physical interface such as a delivery mechanism, nor is there a need for human interaction for the normal use of the platform.

Facebook.com is the world's largest Social Network with 1350 million monthly unique users in September 2014. Launched just a decade ago, before which the concept of a Social Network did not exist, it eliminated all competitors to emerge as the winner. Social networks are purely digital in nature and the value is generated as users contribute with more content, and sharing more details about their lives, opinions, pictures, and events with other friends on the network. Thus there is no direct interaction between the Facebook staff and the users of Facebook, except when inaapropriate content is to be reviewed by the Facebook staff. Neither is there any physical delivery involved.

Custojusto.pt is similarly a purely digital service provider that allows users to post advertisements regarding the sale of a second hand product or a service. Currently Custojusto.pt does not act as an intermediary and merely provides a platform for users to share information. They have no direct interaction with customers expect for a process of review of submitted classified to ensure conformance of posted content to the site's rules.

Vortal.biz is also a digital service that allows B2B procurement. All of its major services do not involve human interaction or physical infrastructure. Buyers use the platform to float tenders and invite sellers to quote their price for those tenders. The entire process takes place on their online platform.

10.1.2. Network Effects

The three selected cases are all examples of products with a strong network effect. This implies that as more users become clients, the greater is the utility for other users. Thus such kinds of businesses are difficult to grow initially, but become monopolistic with time, as seen in the case of Facebook. Thus generating a critical mass is the key to reaching a sustainable growth rate.

In the case of Facebook, the more the number of users, the more useful will it get for existing users. This is because, the greater is the probability for the existing friends to also be a user on Facebook. This further incentivises growth in users within a region, society, educational and professional group. Also a greater number of Facebook users would mean a greater probability that new people that existing users meet are already on Facebook and can be easily connected with.

In the case of Custojusto.pt and Vortal.biz, the network effect is two sided instead of one sided as in the case of Facebook. Both of them have buyers and sellers that are connected using the platform. An increase in number of buyers leads to greater opportunities for the sellers, and an increase in the number of sellers leads to greater choice for the buyers. Although Custojusto.pt and Vortal.biz are operating in C2C and B2B business domains, the two sided network effect exhibited by both of them are similar in nature.

10.1.3. Pricing Structures

While Facebook.com is using a free pricing structure, Custojusto.pt and Vortal.biz both have a freemium pricing structure. Facebook.com allows for all users to freely access all the features of the social networking platform. Its revenue model is based on advertising and through third party apps on Facebook.com, like games like Zyngya. The free model allows Facebook.com to scale up at a rapid pace.

In contrast both Custojusto.pt and Vortal.biz use a freemium model where the basic features are offered free to the majority of the users. It is only a small percentage of users that pay for enhanced features and hence generate the revenue for the companies. The key difference between the two is, that while Custojusto.pt charges for additional visibility of the posted advertisements on a one time basis, Vortal.biz offers a monthly tariff plan based on the features offered. Vortal.biz bundles the additional features into different pricing plans.

Being a C2C business, Custojusto charges a very small amount to have a large consumer base. In contrast, Vortal.biz, being a B2B service, has much lesser clients and subsequently has a higher pricing.

10.2. Simulation Results

10.2.1. Simple Forecasting and Validation

The general procedure for initialising and validating a DYNAMOD simulation model involves the division of historical evolution of data showing the number of clients, into two parts: The initialization dataset and the validation dataset. The initialization constants in the model are adjusted till the model results fit as close to the initialization data set. This gives us the confidence that the initialisation constants have been properly calibrated and the model accurately describes the business scenario. Then the model is used to simulate data for the validation phase. The comparison of the simulated and actual data from the Validation Phase provides us with a degree of confidence about the accuracy of the model forecast and its ability to predict the impact of changes in the Business Scenario. This approach has been followed in both, the Facebook.com and the Custojusto.com cases.

In the case of Facebook.com, the user must log into the system to use the platform. Hence the metrics used for the measurement was monthly unique users, as defined by the number of unique users who logged in at least once in a month into the Facebook platform. However in the case of Custojusto.pt, only the sellers must log in to post a classifieds ad. However since a large majority of users are buyers, who do not log into the site, the metrics used was monthly average unique visitors to the site. In both these cases, the DYNAMOD prediction was recorded for the validation phase, and average error was computed when compared with the real data.

To compare the accuracy of the DYNAMOD predictions, another forecasting technique, ARIMA, was used to forecast for the validation phase based on the data from the initialization phase. In the case of Facebook.com, the error in ARIMA forecast was much larger than the error due to the DYNAMOD forecast. However in the case of Custojusto.pt, the error due to

ARIMA as well as DYNAMOD were the same. Thus in both the cases it was validated that DYNAMOD was properly initialised and provides a reasonably good forecast.

The data for Facebook.com during the initialization phase was linear, and any forecasting tool would predict a linear growth. This is because all forecasting tools are based on the principle that past is the basis of the future. However Facebook.com was already reaching saturation, and growth beyond a point would get increasingly difficult. While no forecasting tool, can gain this insight from purely past data, the DYNAMOD simulation model captured this, and hence its forecasts for the future showed a declining growth rate, and not a linear growth. When compared with the latest data, the declining growth rate is confirmed, thus demonstrating the potential of DYNAMOD to assimilate and predict the business growth much more accurately than any other forecasting tool.

In the case of Vortal.biz, a particularly difficult scenario existed and hence a different validation procedure was adopted. A new platform with new features was introduced around three years ago, and hence previous historical data was not applicable. Hence only data for two years was available, 2012 and 2013. No forecasting tool is capable of forecasting based on only two points of data. For any reliable forecast using only 2 data sets, the tool must comprehend the market dynamics. Thus DYNAMOD demonstrated its versatility in this scenario. To validate, DYNAMOD was used to predict the percentages of users using different tariff plans in 2013 based on data from 2012. The 2013 predicted and actual data were found to be very close, thus validating the accuracy of the DYNAMOD Model.

10.2.2. Simulating Change in Business Scenario

The main advantage of using DYNAMOD Models is to not just have the ability to forecast the future, but to simulate the impact of a changed Business Scenario and perform what if analysis. For each of the three selected business cases, the capabilities of DYNAMOD have been demonstrated by simulating the changes in the Business Scenario. These changes include both, changes in Business Model internally, as well as the changes in business environment externally. After making these changes the ABM model was allowed to run to monitor the impact of changes in client numbers, client tariff plan selection, or revenue generated.

In the case of Facebook.com, two alternate business scenarios were explored. The first one involved the impact of a perceived privacy violation amongst the users. In 2012, Instagram which stores the facebook pictures had claimed the right use user content and pictures. The impact led to a sizable percentage of Facebook users generating fear about their personal data and stopping to use Facebook. Although Facebook subsequently reassured users, the simulation scenario studied the long term impact of such a fear where 5% of users have these fears and where 10% of the users have these fears, and made projections for the drop in client base.

The second scenario involved the impact of a competitor like Google Plus, entering the market and providing a better user experience. The simulation results showed that even in that case, the impact of network effect would ensure that the growth rate of Facebook remains unaffected despite some users simultaneously using Google Plus also. This has proven to be quite an accurate picture more than 2 years after this simulation was conducted. Google Plus has about a fifth of the client usage as Facebook, and Facebook's growth rate has been even higher than as predicted in this simulation (Borisson, 2014).

The case of Custojusto.pt also simulates the impact of certain Business Model changes. The impact of reducing the advertising expenditure from 80% of the total costs to 40% of the total costs is explored. The simulation showed that due to the strong network effect and the already high market penetration by Custojusto.pt, the reduction in advertising will have a minimal impact on future growth and usage. Thus there is the potential of reducing advertising expenditure to make the company more sustainable.

A second scenario was simulated where the company changes its role from a classifieds ad platform to a trading platform where it also acts as a financial intermediary. The associated risks of fraud by buyers or sellers were analysed, and it was found that as long as the number of users committing fraud was less than 2%, a change in the Business Model could be sustainable.

In the case of Vortal.biz, an additional scenario was explored, where users were allowed to select one feature of a higher tariff plan, rather than upgrading to a higher tariff plan. The simulation showed that there would be very few people upgrading at the prices that was being considered by the company. The objective of the simulation was to suggest an optimal pricing for these features in such a way that revenue from tariff plan upgrades was not compromised.

The above examples demonstrate the versatility of DYNAMOD to simulate new business scenarios, often even after the simulation model has been created and initialised. It demonstrates the capabilities of DYNAMOD to act as a Decision Support Tool for Managers of Digital Businesses.

10.2.3. Price Sensitivity

One of the most common applications of DYNAMOD is the simulation of impact in changing the pricing structure and predict its impact on client usage, client behaviour, plan upgrades and revenue. This allows the managers to play around with the prices of various plans and features and see what pricing structure offers the maximum potential for revenue generation and growth, depending on the current objectives of the company.

In the case of Facebook.com, the revenue model is free. Hence price sensitivity was not applicable. This has been implemented in both the other cases. In the case of Custojusto.pt, the price sensitivity was demonstrated by changing the price of one of the offered features , “Editing an Ad”, and visualising its impact on the total revenue after 6 months. The simulation revealed that reducing the price by half from €2 to €1 resulted in revenue maximization. An alternative pricing sensitivity that was explore in this model was the impact of change in price of one of the three competing visibility features offered to the client. The simulation showed that as the price of “Bumping the Ad” was lowered, it led to increased usage without cannibalising the usage of other Visibility Enhancement Features.

In the case of Vortal.gov, only the optimised prices using genetic algorithms were simulated and the increase in revenue using the optimised prices were obtained.

10.2.4. Optimization using Genetic Algorithms

The DYNAMOD Models provide us with the ability to modify the pricing of different features and plans and visualise its outcome. In case a Digital Business contains a large number of features, tariff plans then it is often difficult to optimise the pricing of all the different elements. Often the elements are related to each other, and making the price of one feature very cheap can cannibalise the usage of another more expensive feature. Sometimes reducing the price may lead to increased usage and hence a higher revenue.

For complex optimisation scenarios, Genetic Algorithms can be used to automate the process of optimization of pricing of the different elements. The optimization can be performed with different objectives in mind. These objectives define the fitness function of the Genetic Algorithm. For example, a company in a mature state might want to optimise the revenue, but a company looking for high growth might optimise for maximum growth while also ensuring that the revenue is not negative.

We have demonstrated the use of Genetic Algorithms in the case of Vortal.biz for the simultaneous optimization of the pricing of 4 paid tariff plans and 8 optional features. The fitness function was maximising the revenue. The optimization indicated that the current pricing of the Tariff Plans are close to optimal, but the proposed price of the optional features are too high and must be reduced.

10.2.5. Probability Distribution

Agent Based Simulation Models are non deterministic and the output of each model run is always slightly different. Based on best practices (Rand & Rust, 2011), for the case of Facebook.com and Custojusto.com, 30 model runs were considered and the average values were used. This helped provide us with an average value based on which the graph for future evolution was plotted.

However in some scenarios, especially when predictions for a finite time in future need to be made, the probability distribution of the model results is interesting and relevant, as it not only provides a prediction, but also a range of probabilities around the prediction. This has been used in the case of Vortal.biz, and the probability distribution of the outputs have been shown.

11. Conclusions

11.1. The problem and the motivation

The rapid growth of the Internet has led to a completely new business area, the area of Digital Entrepreneurship. Everyday, thousands of young entrepreneurs across the world are launching their own digital business, merging creative ideas with innovative business models. Most governments are also realising that after the economic crisis, the digital business has the potential to create new jobs and growth at an exponential pace. And through this process, innovative ideas are reshaping the world, bringing increased efficiency to traditional business processes, and creating new interactive lifestyles. Digital Businesses have the potential to go global and grow at a pace never imaginable for traditional businesses. They are not constrained with physical limiting factors, and infrastructural and human resource limitations. They have a low initial investment and extremely low incremental investment which make them well suited to achieve economies of scale. For each large enterprise, there emerge thousands of thriving small companies providing a better solution globally.

However digital businesses also suffer from a high failure rate because the rules of operation in the Digital Space are completely different from that of other traditional businesses. Traditional Management philosophies, practised since ages, are now found obsolete in this digital age. This is especially true for purely digital enterprises that require no physical or human interactions with clients and are conducted purely through digital devices such as mobiles, tablets and computers. The extremely rapid rate of spread of word of mouth means a positive opinion about a product can spread rapidly increasing customer adoption while at the same time negative opinions could destroy its reputation. This combined with the fact that companies are competing globally, a new competitor could emerge suddenly from another part of the world and take over the market share.

Digital tools allow Entrepreneurs to innovate and differentiate their business offerings in a way that was never possible. Not only are a variety of interactions and interfaces possible, but technology also allows the integration of different services to devise completely new product offerings. Thus digital businesses can provide infinite opportunities for innovation to create new products and services that fulfil different customer needs and often create new user needs.

The low cost of entry usually means that competing with price alone could prove difficult. Most services are thus being offered using a freemium model, where the basic versions of a digital product is usually offered free of cost and pricing models are intelligently designed to charge for additional features. The free users also perform the role of traditional marketers by spreading the positive word of mouth and popularising the product. Other techniques such as viral marketing are employed to automate or encourage this process of Word of Mouth for increased product adoption. However if a critical percentage of free users do not convert to paying clients, revenue generation will not be enough. Businesses often struggle with deciding which features to charge for, and such decisions often can decide whether the business grows sustainably, or collapses with a spiralling revenue deficit due to the increasing cost of free users. Managing the pricing of digital businesses requires new mindsets, and newer tools.

Business Models strategies are often difficult to fathom, and most successful companies often end up pivoting more than once before they come up with a sustainable business model. In this era of intense competition, a digital business must be agile, and adapt its product offering and pricing model very rapidly to continue to grow. Literature review revealed that while Business Model has become an area of increased academic interest, not much research has been done on Digital Business Models which specifically incorporate the unique characteristics of Digital Businesses. Also current approach to Business Models has been mostly descriptive without specific tools for modelling and optimising the different elements of Business Models. Business managers need well defined tools to aid quick decision making and optimising the key elements of pricing and business models to help them create scalable and efficient Digital Businesses.

11.2. Contribution of this Thesis

The thesis aims to explore and elaborate of the unique characteristics of Digital Businesses that make their management significantly different from other traditional areas of Business. It further seeks to explore how these characteristics define the dynamics of a Digital Market. Further this thesis explores ways to accurately predict the evolution of complex digital Business Models such that forecasts of key business parameters such as user growth, revenue growth and client behaviour can be possible. This thesis also explores the ability to make forecasts based on changing the existing business or pricing models to visualise the impact of various what-if scenarios. Finally, the thesis tries to seek ways for automating the optimisation of complex pricing models for different business objectives such as maximising revenue or maximising growth.

A literature review illustrating the unique characteristics of Digital Businesses is provided which starts with a historical evolution of Digital Businesses. Other characteristics identified were the unique low cost structure, innovative pricing models such as free and freemium, and unique marketing strategies such as Viral Marketing and the effective use of Social Media. Other aspects of digital businesses such as the difficulties in implementing legal protections and globalised markets have also been explored. The thesis has also explored different ways of classifying digital businesses. Other relevant areas such as Diffusion of Innovation and Word of Mouth have also been discussed since they provide effective approaches to model a Digital Business.

A literature review of Business models is provided that discusses the strategic and operational perspectives on BMs that has been the focus of academic research. Academic literature show that BM research identify the different value creating elements within a firm's value creation processes as well as discuss BM evolution for specific firms and industry segments. However no literature targeting Digital Businesses was found that addresses the unique characteristics of Digital Businesses. It was identified that only the client side elements of BM which include the Pricing Models, Value Proposition, Client Segments and the Distribution Channels are explored in this Thesis.

Finally, a simulation framework, DYNAMOD, is proposed in this Thesis that can be customised to different Business Scenarios and can be used to simulate a variety of different business cases and modelling objectives. The modelling methodology identified to be most appropriate for this purpose was Agent Based Modeling. Thus a generic modelling framework was proposed which listed all the generic variables of such a simulation model and detailed the relationships, flowcharts and logics for developing the simulation model.

To explore other applications of Agent Based Modeling in Business and Marketing, a literature review has been presented detailing all such applications such as product adoption, consumer behaviour, market share, demand forecasting, merchandise management and multiscale consumer market models. The literature review revealed that for all such applications, variable selection has been arbitrary. A structured framework like DYNAMOD would greatly help in the quick creation of well defined simulation models for different Digital Business Scenarios.

11.3. The considerations to develop the proposed solution

The adoption of digital products and services by interconnected online users can be seen as an example of complex interacting systems. In such systems, defining the underlying individual interactions and behaviour patterns can lead to greater insights about the large scale behaviour of the system as a whole. Thus a digital business ecosystem can be represented by interconnected autonomous entities representing a potential client in a networked digital market. The User Agent contains all the variables that define the characteristics of a potential user, who gets influenced by his neighbours, advertising and the brand value and then takes an informed adoption decision.

The DYNAMOD Framework is intended to develop models capable of simulating evaluating key business model parameters such as the optimal Distribution Channels to be used for the delivery of the service (Desktop, Mobile, Tablet), which clients to target, what value proposition to offer and what revenue models to adopt. The framework focuses on quantifying the business model elements such that they can be converted into optimization problems and can be used for developing computational models.

Finally, the applicability of the DYNAMOD Modelling Framework is demonstrated through three different business scenarios: Facebook.com, Custojusto.pt and Vortal.biz. All the three selected case studies are examples of purely digital businesses. This means that a user needs only a computing device (Desktop, Laptop, Mobile, Tablet) and an internet connection to have access to the digital product. There is no need for a physical interface such as a delivery mechanism, nor is there a need for human interaction for the normal use of the platform. The selected case studies were a mixture of different characteristics. While Facebook.com is a user content driven social network, the other two cases are examples of double sided networks. While Vortal.biz is a B2B business, the others are C2C businesses.

Through the selected case studies, it was demonstrated that the DYNAMOD framework can be used in a variety of different Business Scenarios and with different modelling objectives. On one hand it can make very accurate forecasts, while at the same time it can model minor as well as major changes in the Business Scenario and Business Models and forecast its implications. One of the most useful applications is the ability to change the pricing model of one or more elements and forecast the revenue and growth implications of such a change. In one of the cases, Vortal.biz, the probability distribution of the forecasts have been analysed and presented and genetic algorithms have been used to automate the process of reaching an optimised solution with the objective of maximising overall revenues.

11.4. Limitations

This thesis proposes a new framework for modelling Online Markets for Digital Businesses. However it has only focussed on the aspects of Business Model that relate to the interactions between the Business and the customers through networked online markets. The research has not focussed on other aspects of Business Models that relate to the choice of Business Partners, Key Activities, and Infrastructure Choices.

The model proposed in this thesis is generic in nature and must be customised to specific Digital Business scenario that is intended to be modelled. This research work has not gone into details of specific modifications the the framework that must be made to incorporate different types of Digital Businesses other than the case studies already explored in this thesis. This is a limitation that can be explored in future work.

Also the framework has been designed for implementing segmentation and multi region based simulation, this has not been explored in the case studies discussed in this thesis. This would involve complexities in terms of modelling the appropriate interactions between different regions and market segments.

Another practical limitations was that the models developed were based on one time questionaires. Ideally questionaires at different periods of time would help have a greater understanding of the evolution of customer satisfaction and influences with time.

11.5. Areas for Further Development and Research

This Thesis has proposed a new approach to Business Models in the context of a highly relevant but somewhat neglected area of Digital Businesses. Future research on Business Models more focussed on Digital Businesses and identifying the relevant performance metrics for different types of Digital Businesses shall be very relevant.

The DYNAMOD Framework proposed is generic and hence does not identify the detailed variables relevant for different Business Scenarios. It contains the major elements that define the flow of word of mouth and defines the structure for simulating its spread across online networks. However future work can focus on creating more specific frameworks for specific types of Digital Businesses like Two sided networks, free mobile apps, etc.

The business cases covered in this thesis used only one sample survey which provided a snapshot view of customer behaviour. This snapshot was used as a template for user preferences across a large period of time. The accuracy of the forecasts and predictions would be much higher if periodic sample surveys were taken and introduced into the model. This can be achieved through the integration of automated questionnaires with the modelling system. Longitudinal studies that evaluate the effectiveness of the DYNAMOD Framework while new user survey data is fed periodically, will be extremely effective in validating and improving the tool.

The selected cases have focussed on Revenue Models and Pricing as the key variables. Other elements of the business models can also be explored in future case studies and relevant simulation models can be developed. These could include scenarios such as selection of the ideal delivery channels (eg. Mobile App vs Tablet App vs Web Application) or the selection of the right advertising and customer acquisition channels (such as Paid Advertising vs Search Engine Management vs Social Media outreach).

This thesis has attempted to provide Digital Businesses with a scientific methodology to model, simulate and optimise some of the key elements of their Business Models. However, the creation of a successful business is more of an art, and the modelling tool can only provide an assistance in optimising the key variables, and alerting about potential slowdowns in growth. However analytical and experiential review is needed to make major pivots in specific stages of the business. Though, no modelling tool can replace the need for such analysis, but DYNAMOD provides a very useful tool to provide greater insights for such analysis and can prove to be a very useful Decision Support System.

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13. Appendix

13.1. Netlogo Code – Case Study 1 Facebook.com

```
globals [


  slider-check-1    ;; Temporary variables for slider values, so that if sliders
  slider-check-2    ;;   are changed on the fly, the model will notice and
  slider-check-3    ;;   change people's tendencies appropriately.
  slider-check-4
  slider-check-5
  slider-check-6
  slider-check-7
  slider-check-8

  network-effect-lower
  network-effect-higher

  minimum-influence
  minimum-satisfaction
  initial-clients
]

turtles-own [
  client?           ;; If true, the person is a client.
  client-length     ;; How long the person has been a client
  numclient         ;; Number of times been client before
  k-ad-influence    ;; The influence factor level to advertising (0-1)
  k-nb-influence    ;; The influence factor level to neighbours (0-1)
  k-gl-influence    ;; The influence factor level to global (0-1)
  influence         ;; The neighbour influence factor level
  satisfaction      ;; Satisfaction level once the agent is a client
  ad-influence
  nb-influence
  gl-influence
  network-effect-coefficient
  movement?
  var-network-effect
]

;;;
;;; SETUP PROCEDURES
;;;

to setup
  clear-all
  setup-globals
  setup-people
  reset-ticks
end

to setup-globals
  set slider-check-1 avg-satisfaction
  set slider-check-2 sd-satisfaction
  set slider-check-3 avg-ad-influence
```

```
  set slider-check-4 sd-ad-influence
  set slider-check-5 avg-nb-influence
  set slider-check-6 sd-nb-influence
  set slider-check-7 avg-gl-influence
  set slider-check-8 sd-gl-influence
  set avg-ad-influence 0.213
  set sd-ad-influence 0.127
  set avg-nb-influence 0.41
  set sd-nb-influence 0.16
  set avg-gl-influence 0.11
  set sd-gl-influence 0.01
  set minimum-influence 0.25
  set minimum-satisfaction 0.1
  set initial-clients 0;242
  set influence-constant 0.0104
  set network-effect-constant 0.0009
  set network-effect-lower 0.03
  set network-effect-higher 0.1
end

to setup-people
  crt max-agents
    [ setxy random-xcor random-ycor
      set shape "person"
      set client? (who < initial-clients)
      set movement? (who < (0.06 * max-agents))
      set client-length 0
      ifelse client? [
        assign-satisfaction
        set influence satisfaction
        set numclient 1
        ]
       [
         set satisfaction 0
         set numclient 0
         set influence random-normal 0.11 0.06
         check-client
       ]
      set ad-influence 0
      set nb-influence 0
      set gl-influence 0

      assign-k-ad-influence
      assign-k-nb-influence
      assign-k-gl-influence

      assign-color ]
end

;; Different people are displayed in 3 different colors depending on health
;; green is not infected
;; blue is infected but doesn't know it
;; red is infected and knows it

to assign-color  ;; turtle procedure
  ifelse not client?
    [ set color white ]
    [ set color red ]
end
```

```
;; The following four procedures assign core turtle variables.  They use
;; the helper procedure RANDOM-NEAR so that the turtle variables have an
;; approximately "normal" distribution around the average values set by
;; the sliders.


to assign-satisfaction
  set satisfaction random-normal avg-satisfaction sd-satisfaction
  if (satisfaction > 1) [set satisfaction 1]
  if (satisfaction < -1) [set satisfaction -1]
end

to assign-k-ad-influence  ;; turtle procedure
  set k-ad-influence random-normal avg-ad-influence sd-ad-influence
    if (k-ad-influence > 1) [set k-ad-influence 1]
  if (k-ad-influence < 0) [set k-ad-influence 0]
end

to assign-k-nb-influence  ;; turtle procedure
  set k-nb-influence random-normal avg-nb-influence sd-nb-influence
      if (k-nb-influence > 1) [set k-nb-influence 1]
  if (k-nb-influence < 0) [set k-nb-influence 0]
end

to assign-k-gl-influence  ;; turtle procedure
  set k-gl-influence random-normal avg-gl-influence sd-gl-influence
      if (k-gl-influence > 1) [set k-gl-influence 1]
  if (k-gl-influence < 0) [set k-gl-influence 0]
end


;;;
;;; GO PROCEDURES
;;;

to go
check-sliders
ask turtles
    [

      reporter
      assign-influence
      ifelse client?
       [ set client-length (client-length + 1)
        check-unclient

       ]
      [ check-client ]

      move
    ]

tick
end

;; Each tick a check is made to see if sliders have been changed.
;; If one has been, the corresponding turtle variable is adjusted

to reporter
 let clients count turtles with [ client? ]
```

```
end

to check-sliders


  if (slider-check-1 != avg-satisfaction)
    [ ask turtles [ if client? [
        assign-satisfaction
        set influence satisfaction ]]
      set slider-check-1 avg-satisfaction ]

  if (slider-check-2 != sd-satisfaction  )
   [ ask turtles [ if client? [
        assign-satisfaction
        set influence satisfaction ]]
      set slider-check-2 sd-satisfaction ]

  if (slider-check-3 != avg-ad-influence )
    [ ask turtles [ assign-k-ad-influence ]
      set slider-check-3 avg-ad-influence ]

  if (slider-check-4 != sd-ad-influence )
    [ ask turtles [ assign-k-ad-influence ]
      set slider-check-4 sd-ad-influence ]

  if (slider-check-5 != avg-nb-influence )
    [ ask turtles [ assign-k-nb-influence ]
      set slider-check-5 avg-nb-influence ]

  if (slider-check-6 != sd-nb-influence )
    [ ask turtles [ assign-k-nb-influence ]
      set slider-check-6 sd-nb-influence ]

  if (slider-check-7 != avg-gl-influence )
    [ ask turtles [ assign-k-gl-influence ]
      set slider-check-7 avg-gl-influence ]


  if (slider-check-8 != sd-gl-influence )
    [ ask turtles [ assign-k-gl-influence]
      set slider-check-8 sd-gl-influence ]

end

;; People move about at random.

to move  ;; turtle procedure
  rt random-float 360
  if (movement?) [fd 1]
end

to assign-influence
  ifelse (count other turtles in-radius radius != 0) and (not client?)
 [ set nb-influence ((k-nb-influence) * (mean [influence] of other turtles in-radius radius))


   set gl-influence ((k-gl-influence) * (mean [influence] of turtles))

   set ad-influence (k-ad-influence * advertising-expenses)
```

```
   let fraction ((count other turtles with [client?] in-radius radius)/(count other turtles in-radius radius))
   ifelse (fraction < network-effect-lower) [set network-effect-coefficient -0.5]
   [ifelse (fraction > network-effect-higher) [set network-effect-coefficient 0.5][set network-effect-coefficient (((fraction - network-effect-lower)/(network-effect-higher - network-effect-lower)) - 0.5)]]

   set var-network-effect (network-effect-constant * network-effect-coefficient)

   set influence (influence + (influence-constant * (nb-influence + gl-influence + ad-influence)) + var-network-effect)

   if (influence < -1) [set influence -1]
   if (influence > 1) [set influence 1]
   ]
 [set influence satisfaction
   ]

end

to check-unclient
  if ( satisfaction < minimum-satisfaction )
   [
     set client? false
     set color white
   ]
end

to check-client


    if (influence >= minimum-influence)
     [
       set client? true
       set color red
       assign-satisfaction
       set numclient (numclient + 1)
     ]


end



;;;
;;; MONITOR PROCEDURES
;;;

to-report client
  ifelse any? turtles
    [ report (count turtles with [client?]) ]
    [ report 0 ]
end
```

13.2. Netlogo Code – Case Study 2 CustoJusto.pt

```
globals [

 revenue-final
 clients
  network-effect-lower
  network-effect-higher

  minimum-influence
  minimum-satisfaction
  initial-clients
  avg-satisfaction
  sd-satisfaction
  avg-ad-influence
  sd-ad-influence
  avg-nb-influence
  sd-nb-influence
  avg-gl-influence
  sd-gl-influence
  max-agents
  advertising-expenses
  revenue

  ps1-interested-prob
  ps2-interested-prob
  ps3-interested-prob
  ps4-interested-prob

  ps1-max-wtp-mean
  ps2-max-wtp-mean
  ps3-max-wtp-mean
  ps4-max-wtp-mean

  ps1-max-wtp-sd
  ps2-max-wtp-sd
  ps3-max-wtp-sd
  ps4-max-wtp-sd

  ps1-cost
  ps2-cost
  ps3-cost
  ps4-cost

]

turtles-own [
  client?          ;; If true, the person is a client.
  client-length    ;; How long the person has been a client
  numclient        ;; Number of times been client before
  k-ad-influence   ;; The influence factor level to advertising (0-1)
  k-nb-influence   ;; The influence factor level to neighbours (0-1)
  k-gl-influence   ;; The influence factor level to global (0-1)
  influence        ;; The neighbour influence factor level
  satisfaction     ;; Satisfaction level once the agent is a client
  ad-influence
  nb-influence
  gl-influence
```

```
  network-effect-coefficient
  movement?
  var-network-effect

  ps1-interested?
  ps1-user?
  ps1-max-wtp

  ps2-interested?
  ps2-user?
  ps2-max-wtp

  ps3-interested?
  ps3-user?
  ps3-max-wtp


  ps4-interested?
  ps4-user?
  ps4-max-wtp



]

;;;
;;; SETUP PROCEDURES
;;;

to setup
  clear-all
  setup-globals
  setup-people
  reset-ticks
end

to setup-globals

  set avg-satisfaction 0.663
  set sd-satisfaction 0.211
  set avg-ad-influence 0.551
  set sd-ad-influence 0.286
  set avg-nb-influence 0.693
  set sd-nb-influence 0.252
  set avg-gl-influence 0.367
  set sd-gl-influence 0.113

  set minimum-influence 0.25
  set minimum-satisfaction 0.1
  set initial-clients 66
  set influence-constant 0.0104
  set network-effect-constant 0.0009
  set network-effect-lower 0.03
  set network-effect-higher 0.1

  set max-agents 2280
  set radius 4
  set advertising-expenses 0.9

  set ps1-interested-prob 0.108
```

```
  set ps2-interested-prob 0.429
  set ps3-interested-prob 0.378
  set ps4-interested-prob 0.327

  set ps1-max-wtp-mean 0.664
  set ps2-max-wtp-mean 2.186
  set ps3-max-wtp-mean 1.331
  set ps4-max-wtp-mean 2.379

  set ps1-max-wtp-sd 1.639
  set ps2-max-wtp-sd 2.860
  set ps3-max-wtp-sd 2.034
  set ps4-max-wtp-sd 2.975

  set ps1-cost 2   ;original
  set ps2-cost 3   ;original 6
  set ps3-cost 2   ;original 3
  set ps4-cost 5   ;original 10



  set revenue 0
  set revenue-final 0




end


to setup-people
  crt max-agents
    [ setxy random-xcor random-ycor
      set shape "person"
      set client? (who < initial-clients)
      set movement? (who < (1 * max-agents))
      set client-length 0



      ifelse client? [
        assign-satisfaction
        set influence satisfaction
        set numclient 1
        ]
       [
         set satisfaction 0
         set numclient 0
         set influence 0.1
         check-client
       ]


      set ad-influence 0
      set nb-influence 0
      set gl-influence 0

      assign-k-ad-influence
      assign-k-nb-influence
      assign-k-gl-influence
```

```
    assign-color ]

  ask n-of (ps1-interested-prob * max-agents) turtles
  [
    set ps1-interested? true
    set ps1-max-wtp random-normal ps1-max-wtp-mean ps1-max-wtp-sd
  ]

      ask n-of (ps2-interested-prob * max-agents) turtles
  [
    set ps2-interested? true
    set ps2-max-wtp random-normal ps2-max-wtp-mean ps2-max-wtp-sd
  ]


      ask n-of (ps3-interested-prob * max-agents) turtles
  [
    set ps3-interested? true
    set ps3-max-wtp random-normal ps3-max-wtp-mean ps3-max-wtp-sd
  ]

      ask n-of (ps4-interested-prob * max-agents) turtles
  [
    set ps4-interested? true
    set ps4-max-wtp random-normal ps4-max-wtp-mean ps4-max-wtp-sd
  ]

end

to assign-color
  ifelse not client?
    [ set color white ]
    [ set color red ]
end


to assign-satisfaction
  set satisfaction random-normal avg-satisfaction sd-satisfaction
  if (satisfaction > 1) [set satisfaction 1]
  if (satisfaction < -1) [set satisfaction -1]
end

to assign-k-ad-influence  ;; turtle procedure
  set k-ad-influence random-normal avg-ad-influence sd-ad-influence
    if (k-ad-influence > 1) [set k-ad-influence 1]
  if (k-ad-influence < 0) [set k-ad-influence 0]
end

to assign-k-nb-influence  ;; turtle procedure
  set k-nb-influence random-normal avg-nb-influence sd-nb-influence
      if (k-nb-influence > 1) [set k-nb-influence 1]
  if (k-nb-influence < 0) [set k-nb-influence 0]
end

to assign-k-gl-influence  ;; turtle procedure
  set k-gl-influence random-normal avg-gl-influence sd-gl-influence
      if (k-gl-influence > 1) [set k-gl-influence 1]
  if (k-gl-influence < 0) [set k-gl-influence 0]
end
```

```
to go

if (clients > 1500) [stop]
reporter
set revenue 0
ask turtles
    [
      assign-influence
      ifelse client?
       [ set client-length (client-length + 1)
        check-unclient
       ]
      [ check-client ]

      move
    ]

assign-services

set revenue-final revenue

tick
end

to assign-services
  ask turtles with [(ps1-interested? = true) and (client? = true)]
  [
    ifelse (ps1-max-wtp >= ps1-cost) [set ps1-user? true ][set ps1-user? false]
  ]

  ask turtles with [(ps2-interested? = true) and (client? = true)]
  [
   ifelse (ps2-max-wtp >= ps2-cost) [set ps2-user? true ][set ps2-user? false]
  ]

  ask turtles with [(ps3-interested? = true) and (client? = true)]
  [
   ifelse (ps3-max-wtp >= ps3-cost) [set ps3-user? true ][set ps3-user? false]
  ]

  ask turtles with [(ps4-interested? = true) and (client? = true)]
  [
   ifelse (ps4-max-wtp >= ps4-cost) [set ps4-user? true ][set ps4-user? false]
  ]


  ask turtles with [(client? = true)]
  [
     ifelse (ps4-user? = true)
     [set ps2-user? false
      set ps3-user? false
     ]
     [
        if (ps2-user? = true)
        [set ps3-user? false
        ]

     ]
```

```
    if (ps1-user? = true) [set revenue (revenue + ps1-cost)]

    if (ps2-user? = true) [set revenue (revenue + ps2-cost)]

    if (ps3-user? = true) [set revenue (revenue + ps3-cost)]

    if (ps4-user? = true) [set revenue (revenue + (ps4-cost * 4))]
   ]

end


to reporter
 set clients count turtles with [ client? ]

end



;; People move about at random.

to move  ;; turtle procedure
  rt random-float 360
  if (movement?) [fd 1]
end

to assign-influence
  ifelse (count other turtles in-radius radius != 0) and (not client?)
 [ set nb-influence ((k-nb-influence) * (mean [influence] of other turtles in-radius radius))


   set gl-influence ((k-gl-influence) * (mean [influence] of turtles))

   set ad-influence (k-ad-influence * advertising-expenses)

   let fraction ((count other turtles with [client?] in-radius radius)/(count other turtles in-radius radius))
   ifelse (fraction < network-effect-lower) [set network-effect-coefficient -0.5]
   [ifelse (fraction > network-effect-higher) [set network-effect-coefficient 0.5][set network-effect-
coefficient (((fraction - network-effect-lower)/(network-effect-higher - network-effect-lower)) - 0.5)]]

   set var-network-effect (network-effect-constant * network-effect-coefficient)

   set influence (influence + (influence-constant * (nb-influence + gl-influence + ad-influence)) + var-
network-effect)

   if (influence < -1) [set influence -1]
   if (influence > 1) [set influence 1]
   ]
 [set influence satisfaction
   ]

end

to check-unclient
  if ( satisfaction < minimum-satisfaction )
   [
    set client? false
    set color white
```

```
  ]
end

to check-client


    if (influence >= minimum-influence)
     [
       set client? true
       set color red
       assign-satisfaction
       set numclient (numclient + 1)
     ]
end

;;;
;;; MONITOR PROCEDURES
;;;

to-report client
  ifelse any? turtles
    [ report (count turtles with [client?]) ]
    [ report 0 ]
end
```

13.3. Netlogo Code – Case Study 3 Vortal.biz

```
globals [
  upgrade-percent ; percent of clients who check for upgrade with each tick

  std-price-sg
  std-price-se
  std-price-bg
  std-price-be

  initial-clients
  initial-universal ;plan1
  initial-smartgov ;plan2
  initial-smarteco ;plan3
  initial-bestgov ;plan4
  initial-besteco ;plan5

  per-wtp-u-sg-0 ;percent of universal users with wtp-u-sg = 0
  per-wtp-u-sg-1
  per-wtp-u-sg-2
  per-wtp-u-sg-3
  per-wtp-u-sg-4
  per-wtp-u-sg-5
  per-wtp-u-sg-6

  per-wtp-u-se-0 ;percent of universal users with wtp-u-se = 0
  per-wtp-u-se-1
  per-wtp-u-se-2
  per-wtp-u-se-3
  per-wtp-u-se-4
  per-wtp-u-se-5
  per-wtp-u-se-6
```

per-wtp-sg-bg-0 ;percent of universal users with wtp-sg-bg = 0
per-wtp-sg-bg-1
per-wtp-sg-bg-2
per-wtp-sg-bg-3
per-wtp-sg-bg-4
per-wtp-sg-bg-5
per-wtp-sg-bg-6

per-wtp-sg-se-0
per-wtp-sg-se-1
per-wtp-sg-se-2
per-wtp-sg-se-3
per-wtp-sg-se-4
per-wtp-sg-se-5
per-wtp-sg-se-6

per-wtp-se-be-0
per-wtp-se-be-1
per-wtp-se-be-2
per-wtp-se-be-3
per-wtp-se-be-4
per-wtp-se-be-5
per-wtp-se-be-6

per-wtp-bg-be-0
per-wtp-bg-be-1
per-wtp-bg-be-2
per-wtp-bg-be-3
per-wtp-bg-be-4
per-wtp-bg-be-5
per-wtp-bg-be-6

per-wtp-u-feature1-0 ;Not Interested
per-wtp-u-feature1-1 ;<40
per-wtp-u-feature1-2 ;40
per-wtp-u-feature1-3 ;60
per-wtp-u-feature1-4 ;80
per-wtp-u-feature1-5 ;100

per-wtp-u-feature2-0 ;Not Interested
per-wtp-u-feature2-1 ;<40
per-wtp-u-feature2-2 ;40
per-wtp-u-feature2-3 ;60
per-wtp-u-feature2-4 ;80
per-wtp-u-feature2-5 ;100

per-wtp-u-feature3-0 ;Not Interested
per-wtp-u-feature3-1 ;<40
per-wtp-u-feature3-2 ;40
per-wtp-u-feature3-3 ;60
per-wtp-u-feature3-4 ;80
per-wtp-u-feature3-5 ;100

per-wtp-u-feature4-0 ;Not Interested
per-wtp-u-feature4-1 ;<40
per-wtp-u-feature4-2 ;40
per-wtp-u-feature4-3 ;60
per-wtp-u-feature4-4 ;80
per-wtp-u-feature4-5 ;100

per-wtp-sg-feature5-0
per-wtp-sg-feature5-1
per-wtp-sg-feature5-2
per-wtp-sg-feature5-3
per-wtp-sg-feature5-4
per-wtp-sg-feature5-5

per-wtp-se-feature5-0
per-wtp-se-feature5-1
per-wtp-se-feature5-2
per-wtp-se-feature5-3
per-wtp-se-feature5-4
per-wtp-se-feature5-5

per-wtp-sg-feature6-0
per-wtp-sg-feature6-1
per-wtp-sg-feature6-2
per-wtp-sg-feature6-3
per-wtp-sg-feature6-4
per-wtp-sg-feature6-5

per-wtp-se-feature6-0
per-wtp-se-feature6-1
per-wtp-se-feature6-2
per-wtp-se-feature6-3
per-wtp-se-feature6-4
per-wtp-se-feature6-5

per-wtp-sg-feature7-0
per-wtp-sg-feature7-1
per-wtp-sg-feature7-2
per-wtp-sg-feature7-3
per-wtp-sg-feature7-4
per-wtp-sg-feature7-5

per-wtp-se-feature7-0
per-wtp-se-feature7-1
per-wtp-se-feature7-2
per-wtp-se-feature7-3
per-wtp-se-feature7-4
per-wtp-se-feature7-5

per-wtp-sg-feature8-0
per-wtp-sg-feature8-1
per-wtp-sg-feature8-2
per-wtp-sg-feature8-3
per-wtp-sg-feature8-4
per-wtp-sg-feature8-5

per-wtp-se-feature8-0
per-wtp-se-feature8-1
per-wtp-se-feature8-2
per-wtp-se-feature8-3
per-wtp-se-feature8-4
per-wtp-se-feature8-5

revenue-plans
revenue-features

count-p1

```
count-p2
count-p3
count-p4
count-p5
count-f1
count-f2
count-f3
count-f4
count-f5
count-f6
count-f7
count-f8


]

turtles-own [
  plan
  wtp-u-sg ; code for willingness to pay 0=NI, 1<p-80, 2=p-80, 3=p-60, 4=p-40, 5=p-20, 6=p where p is
price for plan moving to
  wtp-u-se
  wtp-sg-bg
  wtp-sg-se
  wtp-se-be
  wtp-bg-be

  feature ;if feature is not selected then 0

  wtp-f1
  wtp-f2
  wtp-f3
  wtp-f4
  wtp-f5
  wtp-f6
  wtp-f7
  wtp-f8
]

;;;
;;; SETUP PROCEDURES
;;;

to setup
  clear-all
  setup-globals
  setup-people
  reset-ticks
end

to setup-globals
  set revenue-plans 0
  set revenue-features 0

  set std-price-sg 120
  set std-price-se 170
  set std-price-bg 170
  set std-price-be 250

  set upgrade-percent 1
```

```
set initial-clients 9307
set initial-universal 7888
set initial-smartgov 679
set initial-smarteco 458
set initial-bestgov 167
set initial-besteco 115

set per-wtp-u-sg-0 20.79 ;percent of universal users with wtp-u-sg = 0
set per-wtp-u-sg-1 52.69
set per-wtp-u-sg-2 5.38
set per-wtp-u-sg-3 3.94
set per-wtp-u-sg-4 2.51
set per-wtp-u-sg-5 3.23
set per-wtp-u-sg-6 11.47

set per-wtp-u-se-0 30.25;percent of universal users with wtp-u-se = 0
set per-wtp-u-se-1 56.63
set per-wtp-u-se-2 2.85
set per-wtp-u-se-3 2.14
set per-wtp-u-se-4 2.14
set per-wtp-u-se-5 0
set per-wtp-u-se-6 8.13

set per-wtp-sg-bg-0 10.53;percent of universal users with wtp-sg-bg = 0
set per-wtp-sg-bg-1 18.46
set per-wtp-sg-bg-2 13.16
set per-wtp-sg-bg-3 10.53
set per-wtp-sg-bg-4 10.53
set per-wtp-sg-bg-5 13.63
set per-wtp-sg-bg-6 23.16

set per-wtp-sg-se-0 16.67
set per-wtp-sg-se-1 38.89
set per-wtp-sg-se-2 25
set per-wtp-sg-se-3 2.78
set per-wtp-sg-se-4 8.33
set per-wtp-sg-se-5 2.78
set per-wtp-sg-se-6 5.56

set per-wtp-se-be-0 35
set per-wtp-se-be-1 40
set per-wtp-se-be-2 10
set per-wtp-se-be-3 5
set per-wtp-se-be-4 0
set per-wtp-se-be-5 0
set per-wtp-se-be-6 10

set per-wtp-bg-be-0 28.57
set per-wtp-bg-be-1 47.84
set per-wtp-bg-be-2 7.14
set per-wtp-bg-be-3 2.31
set per-wtp-bg-be-4 0
set per-wtp-bg-be-5 0
set per-wtp-bg-be-6 14.14

set per-wtp-u-feature1-0 11.76
set per-wtp-u-feature1-1 67.65
set per-wtp-u-feature1-2 8.82
set per-wtp-u-feature1-3 8.82
set per-wtp-u-feature1-4 2.94
```

set per-wtp-u-feature1-5 0

set per-wtp-u-feature2-0 26.87;Not Interested
set per-wtp-u-feature2-1 64.18;<40
set per-wtp-u-feature2-2 4.85;40
set per-wtp-u-feature2-3 2.24;60
set per-wtp-u-feature2-4 1.49;80
set per-wtp-u-feature2-5 0.37;100

set per-wtp-u-feature3-0 41.18
set per-wtp-u-feature3-1 50
set per-wtp-u-feature3-2 5.88
set per-wtp-u-feature3-3 2.94
set per-wtp-u-feature3-4 0
set per-wtp-u-feature3-5 0

set per-wtp-u-feature4-0 55.56
set per-wtp-u-feature4-1 38.89
set per-wtp-u-feature4-2 2.78
set per-wtp-u-feature4-3 2.78
set per-wtp-u-feature4-4 0
set per-wtp-u-feature4-5 0

set per-wtp-sg-feature5-0 46.15
set per-wtp-sg-feature5-1 46.16
set per-wtp-sg-feature5-2 0
set per-wtp-sg-feature5-3 0
set per-wtp-sg-feature5-4 7.69
set per-wtp-sg-feature5-5 0

set per-wtp-se-feature5-0 25
set per-wtp-se-feature5-1 25
set per-wtp-se-feature5-2 50
set per-wtp-se-feature5-3 0
set per-wtp-se-feature5-4 0
set per-wtp-se-feature5-5 0

set per-wtp-sg-feature6-0 42.86
set per-wtp-sg-feature6-1 42.86
set per-wtp-sg-feature6-2 14.28
set per-wtp-sg-feature6-3 0
set per-wtp-sg-feature6-4 0
set per-wtp-sg-feature6-5 0

set per-wtp-se-feature6-0 50
set per-wtp-se-feature6-1 25
set per-wtp-se-feature6-2 25
set per-wtp-se-feature6-3 0
set per-wtp-se-feature6-4 0
set per-wtp-se-feature6-5 0

set per-wtp-sg-feature7-0 46
set per-wtp-sg-feature7-1 38
set per-wtp-sg-feature7-2 14
set per-wtp-sg-feature7-3 0
set per-wtp-sg-feature7-4 0
set per-wtp-sg-feature7-5 0

set per-wtp-se-feature7-0 50
set per-wtp-se-feature7-1 50

```
  set per-wtp-se-feature7-2 0
  set per-wtp-se-feature7-3 0
  set per-wtp-se-feature7-4 0
  set per-wtp-se-feature7-5 0

  set per-wtp-sg-feature8-0 0
  set per-wtp-sg-feature8-1 0
  set per-wtp-sg-feature8-2 100
  set per-wtp-sg-feature8-3 0
  set per-wtp-sg-feature8-4 0
  set per-wtp-sg-feature8-5 0

  set per-wtp-se-feature8-0 75
  set per-wtp-se-feature8-1 25
  set per-wtp-se-feature8-2 0
  set per-wtp-se-feature8-3 0
  set per-wtp-se-feature8-4 0
  set per-wtp-se-feature8-5 0



end


to setup-people
  crt initial-clients
    [ setxy random-xcor random-ycor
      set shape "factory"

      set wtp-u-sg 0
      set wtp-u-se 0
      set wtp-sg-bg 0
      set wtp-sg-se 0
      set wtp-se-be 0
      set wtp-bg-be 0
      set feature 0

      if (who < initial-universal) [assign-universal]
      if ((who >= initial-universal) and (who < (initial-universal + initial-smartgov))) [assign-smartgov]
      if ((who >= (initial-universal + initial-smartgov)) and (who < (initial-universal + initial-smartgov +
initial-smarteco))) [assign-smarteco]
      if ((who >= (initial-universal + initial-smartgov + initial-smarteco)) and (who < (initial-universal +
initial-smartgov + initial-smarteco + initial-bestgov))) [assign-bestgov]
      if (who >= (initial-universal + initial-smartgov + initial-smarteco + initial-bestgov)) [assign-
besteco]
    ]
end

to go
      ask n-of (round ((upgrade-percent * initial-clients) / 100)) turtles
      [
      if (plan = 1) [check-upgrades-universal]
      if (plan = 2) [check-upgrades-smartgov]
      if (plan = 3) [check-upgrades-smarteco]
      if (plan = 4) [check-upgrades-bestgov]
      ]

      set revenue-plans (((count turtles with [plan = 2]) * price-sg) + ((count turtles with [plan = 3]) *
price-se) + ((count turtles with [plan = 4]) * price-bg) + ((count turtles with [plan = 5]) * price-be))
```

```
     set revenue-features ((count turtles with [feature = 1] * price-f1) + (count turtles with [feature = 2] * price-f2) + (count turtles with [feature = 3] * price-f3) + (count turtles with [feature = 4] * price-f4) + (count turtles with [feature = 5] * price-f5) + (count turtles with [feature = 6] * price-f6) + (count turtles with [feature = 7] * price-f7) + (count turtles with [feature = 8] * price-f8))

      set count-p1 count turtles with [plan = 1]
  set count-p2 count turtles with [plan = 2]
  set count-p3 count turtles with [plan = 3]
  set count-p4 count turtles with [plan = 4]
  set count-p5 count turtles with [plan = 5]
  set count-f1 count turtles with [feature = 1]
  set count-f2 count turtles with [feature = 2]
  set count-f3 count turtles with [feature = 3]
  set count-f4 count turtles with [feature = 4]
  set count-f5 count turtles with [feature = 5]
  set count-f6 count turtles with [feature = 6]
  set count-f7 count turtles with [feature = 7]
  set count-f8 count turtles with [feature = 8]


     if (ticks > 65) [stop]
     tick

end


to check-upgrades-universal
  let upgraded 0
  if (wtp-u-se != 0)
  [
    if (wtp-u-se = 1 and upgraded = 0) [
     if (price-se < (std-price-se - 80)) [
      assign-smarteco
      set upgraded 1 ]]
     if (wtp-u-se = 2 and upgraded = 0) [
      if ((price-se >= (std-price-se - 80)) and (price-se < (std-price-se - 60))) [
      assign-smarteco
      set upgraded 1 ]]
     if (wtp-u-se = 3 and upgraded = 0) [
      if ((price-se >= (std-price-se - 60)) and (price-se < (std-price-se - 40))) [
      assign-smarteco
      set upgraded 1]]
     if (wtp-u-se = 4 and upgraded = 0) [
      if ((price-se >= (std-price-se - 40)) and (price-se < (std-price-se - 20))) [
      assign-smarteco
      set upgraded 1 ]]
     if (wtp-u-se = 5 and upgraded = 0) [
      if ((price-se >= (std-price-se - 20)) and (price-se < (std-price-se))) [
      assign-smarteco
      set upgraded 1 ]]
     if (wtp-u-se = 6 and upgraded = 0) [
      if (price-se = std-price-se) [
      assign-smarteco
      set upgraded 1 ]]

     if (upgraded = 1) [set feature 0]
  ]

  if (wtp-u-sg != 0 and upgraded = 0)
  [
```

```
  if (wtp-u-sg = 1 and upgraded = 0) [
    if (price-sg < (std-price-sg - 80)) [
      assign-smartgov
      set upgraded 1 ]]
    if (wtp-u-sg = 2 and upgraded = 0) [
     if ((price-sg >= (std-price-sg - 80)) and (price-sg < (std-price-sg - 60))) [
      assign-smartgov
      set upgraded 1 ]]
    if (wtp-u-sg = 3 and upgraded = 0) [
     if ((price-sg >= (std-price-sg - 60)) and (price-sg < (std-price-sg - 40))) [
      assign-smartgov
      set upgraded 1 ]]
    if (wtp-u-sg = 4 and upgraded = 0) [
     if ((price-sg >= (std-price-sg - 40)) and (price-sg < (std-price-sg - 20))) [
      assign-smartgov
      set upgraded 1 ]]
    if (wtp-u-sg = 5 and upgraded = 0) [
     if ((price-sg >= (std-price-sg - 20)) and (price-sg < (std-price-sg))) [
      assign-smartgov
      set upgraded 1 ]]
    if (wtp-u-sg = 6 and upgraded = 0) [
     if (price-sg = std-price-sg) [
      assign-smartgov
      set upgraded 1 ]]

    if (upgraded = 1) [set feature 0]
]

if (upgraded = 0 and feature = 0) ;f1 check
[
  if (wtp-f1 = 2 and upgraded = 0) [
    if ((price-f1 >= 40) and (price-f1 < 60)) [
      set feature 1
      set upgraded 1 ]]
   if (wtp-f1 = 3 and upgraded = 0) [
    if ((price-f1 >= 60) and (price-f1 < 80)) [
      set feature 1
      set upgraded 1 ]]
   if (wtp-f1 = 4 and upgraded = 0) [
    if ((price-f1 >= 80) and (price-f1 < 100)) [
      set feature 1
      set upgraded 1 ]]
   if (wtp-f1 = 5 and upgraded = 0) [
    if ((price-f1 = 100)) [
      set feature 1
      set upgraded 1 ]]
]

  if (upgraded = 0 and feature = 0) ;f4 check
[
  if (wtp-f4 = 2 and upgraded = 0) [
    if ((price-f4 >= 40) and (price-f4 < 60)) [
      set feature 4
      set upgraded 1 ]]
   if (wtp-f4 = 3 and upgraded = 0) [
    if ((price-f4 >= 60) and (price-f4 < 80)) [
      set feature 4
      set upgraded 1 ]]
   if (wtp-f4 = 4 and upgraded = 0) [
    if ((price-f4 >= 80) and (price-f4 < 100)) [
```

```
      set feature 4
      set upgraded 1 ]]
    if (wtp-f4 = 5 and upgraded = 0) [
     if ((price-f4 = 100)) [
      set feature 4
      set upgraded 1 ]]
  ]

    if (upgraded = 0 and feature = 0) ;f3 check
  [
    if (wtp-f3 = 2 and upgraded = 0) [
     if ((price-f3 >= 40) and (price-f3 < 60)) [
      set feature 3
      set upgraded 1 ]]
    if (wtp-f3 = 3 and upgraded = 0) [
     if ((price-f3 >= 60) and (price-f3 < 80)) [
      set feature 3
      set upgraded 1 ]]
    if (wtp-f3 = 4 and upgraded = 0) [
     if ((price-f3 >= 80) and (price-f3 < 100)) [
      set feature 3
      set upgraded 1 ]]
    if (wtp-f3 = 5 and upgraded = 0) [
     if ((price-f3 = 100)) [
      set feature 3
      set upgraded 1 ]]
  ]

     if (upgraded = 0 and feature = 0) ;f2 check
  [
    if (wtp-f2 = 2 and upgraded = 0) [
     if ((price-f2 >= 40) and (price-f2 < 60)) [
      set feature 2
      set upgraded 1 ]]
    if (wtp-f2 = 3 and upgraded = 0) [
     if ((price-f2 >= 60) and (price-f2 < 80)) [
      set feature 2
      set upgraded 1 ]]
    if (wtp-f2 = 4 and upgraded = 0) [
     if ((price-f2 >= 80) and (price-f2 < 100)) [
      set feature 2
      set upgraded 1 ]]
    if (wtp-f2 = 5 and upgraded = 0) [
     if ((price-f2 = 100)) [
      set feature 2
      set upgraded 1 ]]
  ]



end


to check-upgrades-smartgov
  let upgraded 0
  if (wtp-sg-bg != 0)
  [
    if (wtp-sg-bg = 1 and upgraded = 0) [
     if (price-bg < (std-price-bg - 80)) [
```

```
      assign-bestgov
      set upgraded 1 ]]
    if (wtp-sg-bg = 2 and upgraded = 0) [
     if ((price-bg >= (std-price-bg - 80)) and (price-bg < (std-price-bg - 60))) [
      assign-bestgov
      set upgraded 1 ]]
    if (wtp-sg-bg = 3 and upgraded = 0) [
     if ((price-bg >= (std-price-bg - 60)) and (price-bg < (std-price-bg - 40))) [
      assign-bestgov
      set upgraded 1]]
    if (wtp-sg-bg = 4 and upgraded = 0) [
     if ((price-bg >= (std-price-bg - 40)) and (price-bg < (std-price-bg - 20))) [
      assign-bestgov
      set upgraded 1 ]]
    if (wtp-sg-bg = 5 and upgraded = 0) [
     if ((price-bg >= (std-price-bg - 20)) and (price-bg < (std-price-bg))) [
      assign-bestgov
      set upgraded 1 ]]
    if (wtp-sg-bg = 6 and upgraded = 0) [
     if (price-bg = std-price-bg) [
      assign-bestgov
      set upgraded 1 ]]

if (upgraded = 1) [set feature 0]
]

if (wtp-sg-se != 0 and upgraded = 0)
[
  if (wtp-sg-se = 1 and upgraded = 0) [
    if (price-se < (std-price-se - 80)) [
      assign-smarteco
      set upgraded 1 ]]
    if (wtp-sg-se = 2 and upgraded = 0) [
     if ((price-se >= (std-price-se - 80)) and (price-se < (std-price-se - 60))) [
      assign-smarteco
      set upgraded 1 ]]
    if (wtp-sg-se = 3 and upgraded = 0) [
     if ((price-se >= (std-price-se - 60)) and (price-se < (std-price-se - 40))) [
      assign-smarteco
      set upgraded 1 ]]
    if (wtp-sg-se = 4 and upgraded = 0) [
     if ((price-se >= (std-price-se - 40)) and (price-se < (std-price-se - 20))) [
      assign-smarteco
      set upgraded 1 ]]
    if (wtp-sg-se = 5 and upgraded = 0) [
     if ((price-se >= (std-price-se - 20)) and (price-se < (std-price-se))) [
      assign-smarteco
      set upgraded 1 ]]
    if (wtp-sg-se = 6 and upgraded = 0) [
     if (price-se = std-price-se) [
      assign-smarteco
      set upgraded 1 ]]

   if (upgraded = 1) [set feature 0]
]

if (upgraded = 0 and feature = 0) ;f8 check
[
  if (wtp-f8 = 2 and upgraded = 0) [
    if ((price-f8 >= 30) and (price-f8 < 40)) [
```

```
      set feature 8
      set upgraded 1 ]]
    if (wtp-f8 = 3 and upgraded = 0) [
     if ((price-f8 >= 40) and (price-f8 < 50)) [
      set feature 8
      set upgraded 1 ]]
    if (wtp-f8 = 4 and upgraded = 0) [
     if ((price-f8 >= 50) and (price-f8 < 60)) [
      set feature 8
      set upgraded 1 ]]
    if (wtp-f8 = 5 and upgraded = 0) [
     if ((price-f8 = 60)) [
      set feature 8
      set upgraded 1 ]]
]

  if (upgraded = 0 and feature = 0) ;f5 check
[
  if (wtp-f5 = 2 and upgraded = 0) [
    if ((price-f5 >= 30) and (price-f5 < 40)) [
      set feature 5
      set upgraded 1 ]]
   if (wtp-f5 = 3 and upgraded = 0) [
    if ((price-f5 >= 40) and (price-f5 < 50)) [
      set feature 5
      set upgraded 1 ]]
   if (wtp-f5 = 4 and upgraded = 0) [
    if ((price-f5 >= 50) and (price-f5 < 60)) [
      set feature 5
      set upgraded 1 ]]
   if (wtp-f5 = 5 and upgraded = 0) [
    if ((price-f5 = 30)) [
      set feature 5
      set upgraded 1 ]]
]

  if (upgraded = 0 and feature = 0) ;f7 check
[
  if (wtp-f7 = 2 and upgraded = 0) [
    if ((price-f7 >= 40) and (price-f7 < 40)) [
      set feature 7
      set upgraded 1 ]]
   if (wtp-f7 = 3 and upgraded = 0) [
    if ((price-f7 >= 40) and (price-f7 < 50)) [
      set feature 7
      set upgraded 1 ]]
   if (wtp-f7 = 4 and upgraded = 0) [
    if ((price-f7 >= 50) and (price-f7 < 60)) [
      set feature 7
      set upgraded 1 ]]
   if (wtp-f7 = 5 and upgraded = 0) [
    if ((price-f7 = 60)) [
      set feature 7
      set upgraded 1 ]]
]

    if (upgraded = 0 and feature = 0) ;f6 check
[
  if (wtp-f6 = 2 and upgraded = 0) [
    if ((price-f6 >= 30) and (price-f6 < 40)) [
```

```
      set feature 6
      set upgraded 1 ]]
    if (wtp-f6 = 3 and upgraded = 0) [
     if ((price-f6 >= 40) and (price-f6 < 50)) [
      set feature 6
      set upgraded 1 ]]
    if (wtp-f6 = 4 and upgraded = 0) [
     if ((price-f6 >= 50) and (price-f6 < 60)) [
      set feature 6
      set upgraded 1 ]]
    if (wtp-f6 = 5 and upgraded = 0) [
     if ((price-f6 = 60)) [
      set feature 6
      set upgraded 1 ]]
  ]

end


to check-upgrades-smarteco
  let upgraded 0
  if (wtp-se-be != 0)
  [
    if (wtp-se-be = 1 and upgraded = 0) [
     if (price-be < (std-price-be - 80)) [
      assign-besteco
      set upgraded 1 ]]
     if (wtp-se-be = 2 and upgraded = 0) [
      if ((price-be >= (std-price-be - 80)) and (price-be < (std-price-be - 60))) [
      assign-besteco
      set upgraded 1 ]]
     if (wtp-se-be = 3 and upgraded = 0) [
      if ((price-be >= (std-price-be - 60)) and (price-be < (std-price-be - 40))) [
      assign-besteco
      set upgraded 1]]
     if (wtp-se-be = 4 and upgraded = 0) [
      if ((price-be >= (std-price-be - 40)) and (price-be < (std-price-be - 20))) [
      assign-besteco
      set upgraded 1 ]]
     if (wtp-se-be = 5 and upgraded = 0) [
      if ((price-be >= (std-price-be - 20)) and (price-be < (std-price-be))) [
      assign-besteco
      set upgraded 1 ]]
     if (wtp-se-be = 6 and upgraded = 0) [
      if (price-be = std-price-be) [
      assign-besteco
      set upgraded 1 ]]

     if (upgraded = 1) [set feature 0]
  ]

  if (upgraded = 0 and feature = 0) ;f8 check
  [
    if (wtp-f8 = 2 and upgraded = 0) [
     if ((price-f8 >= 30) and (price-f8 < 40)) [
      set feature 8
      set upgraded 1 ]]
    if (wtp-f8 = 3 and upgraded = 0) [
     if ((price-f8 >= 40) and (price-f8 < 50)) [
      set feature 8
```

```
      set upgraded 1 ]]
    if (wtp-f8 = 4 and upgraded = 0) [
     if ((price-f8 >= 50) and (price-f8 < 60)) [
      set feature 8
      set upgraded 1 ]]
    if (wtp-f8 = 5 and upgraded = 0) [
     if ((price-f8 = 60)) [
      set feature 8
      set upgraded 1 ]]
]

  if (upgraded = 0 and feature = 0) ;f5 check
[
  if (wtp-f5 = 2 and upgraded = 0) [
    if ((price-f5 >= 30) and (price-f5 < 40)) [
      set feature 5
      set upgraded 1 ]]
    if (wtp-f5 = 3 and upgraded = 0) [
     if ((price-f5 >= 40) and (price-f5 < 50)) [
      set feature 5
      set upgraded 1 ]]
    if (wtp-f5 = 4 and upgraded = 0) [
     if ((price-f5 >= 50) and (price-f5 < 60)) [
      set feature 5
      set upgraded 1 ]]
    if (wtp-f5 = 5 and upgraded = 0) [
     if ((price-f5 = 30)) [
      set feature 5
      set upgraded 1 ]]
]

  if (upgraded = 0 and feature = 0) ;f7 check
[
  if (wtp-f7 = 2 and upgraded = 0) [
    if ((price-f7 >= 30) and (price-f7 < 40)) [
      set feature 7
      set upgraded 1 ]]
    if (wtp-f7 = 3 and upgraded = 0) [
     if ((price-f7 >= 40) and (price-f7 < 50)) [
      set feature 7
      set upgraded 1 ]]
    if (wtp-f7 = 4 and upgraded = 0) [
     if ((price-f7 >= 50) and (price-f7 < 60)) [
      set feature 7
      set upgraded 1 ]]
    if (wtp-f7 = 5 and upgraded = 0) [
     if ((price-f7 = 60)) [
      set feature 7
      set upgraded 1 ]]
]

    if (upgraded = 0 and feature = 0) ;f6 check
[
  if (wtp-f6 = 2 and upgraded = 0) [
    if ((price-f6 >= 30) and (price-f6 < 40)) [
      set feature 6
      set upgraded 1 ]]
    if (wtp-f6 = 3 and upgraded = 0) [
     if ((price-f6 >= 40) and (price-f6 < 50)) [
      set feature 6
```

```
        set upgraded 1 ]]
     if (wtp-f6 = 4 and upgraded = 0) [
      if ((price-f6 >= 50) and (price-f6 < 60)) [
        set feature 6
        set upgraded 1 ]]
     if (wtp-f6 = 5 and upgraded = 0) [
      if ((price-f6 = 60)) [
        set feature 6
        set upgraded 1 ]]
  ]

end


to check-upgrades-bestgov
  let upgraded 0
  if (wtp-bg-be != 0)
  [
    if (wtp-bg-be = 1 and upgraded = 0) [
      if (price-be < (std-price-be - 80)) [
        assign-besteco
        set upgraded 1 ]]
      if (wtp-bg-be = 2 and upgraded = 0) [
       if ((price-be >= (std-price-be - 80)) and (price-be < (std-price-be - 60))) [
        assign-besteco
        set upgraded 1 ]]
      if (wtp-bg-be = 3 and upgraded = 0) [
       if ((price-be >= (std-price-be - 60)) and (price-be < (std-price-be - 40))) [
        assign-besteco
        set upgraded 1]]
      if (wtp-bg-be = 4 and upgraded = 0) [
       if ((price-be >= (std-price-be - 40)) and (price-be < (std-price-be - 20))) [
        assign-besteco
        set upgraded 1 ]]
      if (wtp-bg-be = 5 and upgraded = 0) [
       if ((price-be >= (std-price-be - 20)) and (price-be < (std-price-be))) [
        assign-besteco
        set upgraded 1 ]]
      if (wtp-bg-be = 6 and upgraded = 0) [
       if (price-be = std-price-be) [
        assign-besteco
        set upgraded 1 ]]



  ]

end

to assign-universal
  set color white
  set plan 1
  let ran random 10000

  ;;assign wtp-u-sg
  if (ran < (per-wtp-u-sg-0 * 100)) [set wtp-u-sg 0]
  if (ran >= (per-wtp-u-sg-0 * 100)) and (ran < ((per-wtp-u-sg-0 * 100)+(per-wtp-u-sg-1 * 100))) [set
wtp-u-sg 1]
  if (ran >= ((per-wtp-u-sg-0 * 100)+(per-wtp-u-sg-1 * 100))) and (ran < ((per-wtp-u-sg-0 * 100)+(per-
wtp-u-sg-1 * 100)+(per-wtp-u-sg-2 * 100))) [set wtp-u-sg 2]
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 if (ran >= ((per-wtp-u-sg-0 * 100)+(per-wtp-u-sg-1 * 100)+(per-wtp-u-sg-2 * 100))) and (ran < ((per-wtp-u-sg-0 * 100)+(per-wtp-u-sg-1 * 100)+(per-wtp-u-sg-2 * 100)+(per-wtp-u-sg-3 * 100))) [set wtp-u-sg 3]
 if (ran >= ((per-wtp-u-sg-0 * 100)+(per-wtp-u-sg-1 * 100)+(per-wtp-u-sg-2 * 100)+(per-wtp-u-sg-3 * 100))) and (ran < ((per-wtp-u-sg-0 * 100)+(per-wtp-u-sg-1 * 100)+(per-wtp-u-sg-2 * 100)+(per-wtp-u-sg-3 * 100)+(per-wtp-u-sg-4 * 100))) [set wtp-u-sg 4]
 if (ran >= ((per-wtp-u-sg-0 * 100)+(per-wtp-u-sg-1 * 100)+(per-wtp-u-sg-2 * 100)+(per-wtp-u-sg-3 * 100)+(per-wtp-u-sg-4 * 100))) and (ran < ((per-wtp-u-sg-0 * 100)+(per-wtp-u-sg-1 * 100)+(per-wtp-u-sg-2 * 100)+(per-wtp-u-sg-3 * 100)+(per-wtp-u-sg-4 * 100)+(per-wtp-u-sg-5 * 100))) [set wtp-u-sg 5]
 if (ran >= ((per-wtp-u-sg-0 * 100)+(per-wtp-u-sg-1 * 100)+(per-wtp-u-sg-2 * 100)+(per-wtp-u-sg-3 * 100)+(per-wtp-u-sg-4 * 100)+(per-wtp-u-sg-5 * 100))) [set wtp-u-sg 6]

 set ran random 10000

  ;;assign wtp-u-se
  if (ran < (per-wtp-u-se-0 * 100)) [set wtp-u-se 0]
  if (ran >= (per-wtp-u-se-0 * 100)) and (ran < ((per-wtp-u-se-0 * 100)+(per-wtp-u-se-1 * 100))) [set wtp-u-se 1]
  if (ran >= ((per-wtp-u-se-0 * 100)+(per-wtp-u-se-1 * 100))) and (ran < ((per-wtp-u-se-0 * 100)+(per-wtp-u-se-1 * 100)+(per-wtp-u-se-2 * 100))) [set wtp-u-se 2]
  if (ran >= ((per-wtp-u-se-0 * 100)+(per-wtp-u-se-1 * 100)+(per-wtp-u-se-2 * 100))) and (ran < ((per-wtp-u-se-0 * 100)+(per-wtp-u-se-1 * 100)+(per-wtp-u-se-2 * 100)+(per-wtp-u-se-3 * 100))) [set wtp-u-se 3]
  if (ran >= ((per-wtp-u-se-0 * 100)+(per-wtp-u-se-1 * 100)+(per-wtp-u-se-2 * 100)+(per-wtp-u-se-3 * 100))) and (ran < ((per-wtp-u-se-0 * 100)+(per-wtp-u-se-1 * 100)+(per-wtp-u-se-2 * 100)+(per-wtp-u-se-3 * 100)+(per-wtp-u-se-4 * 100))) [set wtp-u-se 4]
  if (ran >= ((per-wtp-u-se-0 * 100)+(per-wtp-u-se-1 * 100)+(per-wtp-u-se-2 * 100)+(per-wtp-u-se-3 * 100)+(per-wtp-u-se-4 * 100))) and (ran < ((per-wtp-u-se-0 * 100)+(per-wtp-u-se-1 * 100)+(per-wtp-u-se-2 * 100)+(per-wtp-u-se-3 * 100)+(per-wtp-u-se-4 * 100)+(per-wtp-u-se-5 * 100))) [set wtp-u-se 5]
  if (ran >= ((per-wtp-u-se-0 * 100)+(per-wtp-u-se-1 * 100)+(per-wtp-u-se-2 * 100)+(per-wtp-u-se-3 * 100)+(per-wtp-u-se-4 * 100)+(per-wtp-u-se-5 * 100))) [set wtp-u-se 6]

  set ran random 10000

  ;;assign wtp-f1
  if (ran < ( per-wtp-u-feature1-0 * 100 ) ) [set wtp-f1 0]
  if (ran >= (per-wtp-u-feature1-0 * 100)) and (ran < ((per-wtp-u-feature1-0 * 100)+(per-wtp-u-feature1-1 * 100))) [set wtp-f1 1]
  if (ran >= ((per-wtp-u-feature1-0 * 100)+(per-wtp-u-feature1-1 * 100))) and (ran < ((per-wtp-u-feature1-0 * 100)+(per-wtp-u-feature1-1 * 100)+(per-wtp-u-feature1-2 * 100))) [set wtp-f1 2]
  if (ran >= ((per-wtp-u-feature1-0 * 100)+(per-wtp-u-feature1-1 * 100)+(per-wtp-u-feature1-2 * 100))) and (ran < ((per-wtp-u-feature1-0 * 100)+(per-wtp-u-feature1-1 * 100)+(per-wtp-u-feature1-2 * 100)+(per-wtp-u-feature1-3 * 100))) [set wtp-f1 3]
  if (ran >= ((per-wtp-u-feature1-0 * 100)+(per-wtp-u-feature1-1 * 100)+(per-wtp-u-feature1-2 * 100)+(per-wtp-u-feature1-3 * 100))) and (ran < ((per-wtp-u-feature1-0 * 100)+(per-wtp-u-feature1-1 * 100)+(per-wtp-u-feature1-2 * 100)+(per-wtp-u-feature1-3 * 100)+(per-wtp-u-feature1-4 * 100))) [set wtp-f1 4]
  if (ran >= ((per-wtp-u-feature1-0 * 100)+(per-wtp-u-feature1-1 * 100)+(per-wtp-u-feature1-2 * 100)+(per-wtp-u-feature1-3 * 100)+(per-wtp-u-feature1-4 * 100))) [set wtp-f1 5]

  set ran random 10000
  ;;assign wtp-f2
  if (ran < ( per-wtp-u-feature2-0 * 100 ) ) [set wtp-f2 0]
  if (ran >= (per-wtp-u-feature2-0 * 100)) and (ran < ((per-wtp-u-feature2-0 * 100)+(per-wtp-u-feature2-1 * 100))) [set wtp-f2 1]
  if (ran >= ((per-wtp-u-feature2-0 * 100)+(per-wtp-u-feature2-1 * 100))) and (ran < ((per-wtp-u-feature2-0 * 100)+(per-wtp-u-feature2-1 * 100)+(per-wtp-u-feature2-2 * 100))) [set wtp-f2 2]
  if (ran >= ((per-wtp-u-feature2-0 * 100)+(per-wtp-u-feature2-1 * 100)+(per-wtp-u-feature2-2 * 100))) and (ran < ((per-wtp-u-feature2-0 * 100)+(per-wtp-u-feature2-1 * 100)+(per-wtp-u-feature2-2 * 100)+(per-wtp-u-feature2-3 * 100))) [set wtp-f2 3]
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  if (ran >= ((per-wtp-u-feature2-0 * 100)+(per-wtp-u-feature2-1 * 100)+(per-wtp-u-feature2-2 * 100)+(per-wtp-u-feature2-3 * 100))) and (ran < ((per-wtp-u-feature2-0 * 100)+(per-wtp-u-feature2-1 * 100)+(per-wtp-u-feature2-2 * 100)+(per-wtp-u-feature2-3 * 100)+(per-wtp-u-feature2-4 * 100))) [set wtp-f2 4]
  if (ran >= ((per-wtp-u-feature2-0 * 100)+(per-wtp-u-feature2-1 * 100)+(per-wtp-u-feature2-2 * 100)+(per-wtp-u-feature2-3 * 100)+(per-wtp-u-feature2-4 * 100))) [set wtp-f2 5]

  set ran random 10000
  ;;assign wtp-f3
  if (ran < ( per-wtp-u-feature3-0 * 100 ) ) [set wtp-f3 0]
  if (ran >= (per-wtp-u-feature3-0 * 100)) and (ran < ((per-wtp-u-feature3-0 * 100)+(per-wtp-u-feature3-1 * 100))) [set wtp-f3 1]
  if (ran >= ((per-wtp-u-feature3-0 * 100)+(per-wtp-u-feature3-1 * 100))) and (ran < ((per-wtp-u-feature3-0 * 100)+(per-wtp-u-feature3-1 * 100)+(per-wtp-u-feature3-2 * 100))) [set wtp-f3 2]
  if (ran >= ((per-wtp-u-feature3-0 * 100)+(per-wtp-u-feature3-1 * 100)+(per-wtp-u-feature3-2 * 100))) and (ran < ((per-wtp-u-feature3-0 * 100)+(per-wtp-u-feature3-1 * 100)+(per-wtp-u-feature3-2 * 100)+(per-wtp-u-feature3-3 * 100))) [set wtp-f3 3]
  if (ran >= ((per-wtp-u-feature3-0 * 100)+(per-wtp-u-feature3-1 * 100)+(per-wtp-u-feature3-2 * 100)+(per-wtp-u-feature3-3 * 100))) and (ran < ((per-wtp-u-feature3-0 * 100)+(per-wtp-u-feature3-1 * 100)+(per-wtp-u-feature3-2 * 100)+(per-wtp-u-feature3-3 * 100)+(per-wtp-u-feature3-4 * 100))) [set wtp-f3 4]
  if (ran >= ((per-wtp-u-feature3-0 * 100)+(per-wtp-u-feature3-1 * 100)+(per-wtp-u-feature3-2 * 100)+(per-wtp-u-feature3-3 * 100)+(per-wtp-u-feature3-4 * 100))) [set wtp-f3 5]

 set ran random 10000
  ;;assign wtp-f4
  if (ran < ( per-wtp-u-feature4-0 * 100 ) ) [set wtp-f4 0]
  if (ran >= (per-wtp-u-feature4-0 * 100)) and (ran < ((per-wtp-u-feature4-0 * 100)+(per-wtp-u-feature4-1 * 100))) [set wtp-f4 1]
  if (ran >= ((per-wtp-u-feature4-0 * 100)+(per-wtp-u-feature4-1 * 100))) and (ran < ((per-wtp-u-feature4-0 * 100)+(per-wtp-u-feature4-1 * 100)+(per-wtp-u-feature4-2 * 100))) [set wtp-f4 2]
  if (ran >= ((per-wtp-u-feature4-0 * 100)+(per-wtp-u-feature4-1 * 100)+(per-wtp-u-feature4-2 * 100))) and (ran < ((per-wtp-u-feature4-0 * 100)+(per-wtp-u-feature4-1 * 100)+(per-wtp-u-feature4-2 * 100)+(per-wtp-u-feature4-3 * 100))) [set wtp-f4 3]
  if (ran >= ((per-wtp-u-feature4-0 * 100)+(per-wtp-u-feature4-1 * 100)+(per-wtp-u-feature4-2 * 100)+(per-wtp-u-feature4-3 * 100))) and (ran < ((per-wtp-u-feature4-0 * 100)+(per-wtp-u-feature4-1 * 100)+(per-wtp-u-feature4-2 * 100)+(per-wtp-u-feature4-3 * 100)+(per-wtp-u-feature4-4 * 100))) [set wtp-f4 4]
  if (ran >= ((per-wtp-u-feature4-0 * 100)+(per-wtp-u-feature4-1 * 100)+(per-wtp-u-feature4-2 * 100)+(per-wtp-u-feature4-3 * 100)+(per-wtp-u-feature4-4 * 100))) [set wtp-f4 5]


end

to assign-smartgov
 set color 85
 set plan 2
 let ran random 10000

 ;;assign wtp-sg-bg
 if (ran < (per-wtp-sg-bg-0 * 100)) [set wtp-sg-bg 0]
  if (ran >= (per-wtp-sg-bg-0 * 100)) and (ran < ((per-wtp-sg-bg-0 * 100)+(per-wtp-sg-bg-1 * 100))) [set wtp-sg-bg 1]
  if (ran >= ((per-wtp-sg-bg-0 * 100)+(per-wtp-sg-bg-1 * 100))) and (ran < ((per-wtp-sg-bg-0 * 100)+(per-wtp-sg-bg-1 * 100)+(per-wtp-sg-bg-2 * 100))) [set wtp-sg-bg 2]
  if (ran >= ((per-wtp-sg-bg-0 * 100)+(per-wtp-sg-bg-1 * 100)+(per-wtp-sg-bg-2 * 100))) and (ran < ((per-wtp-sg-bg-0 * 100)+(per-wtp-sg-bg-1 * 100)+(per-wtp-sg-bg-2 * 100)+(per-wtp-sg-bg-3 * 100))) [set wtp-sg-bg 3]
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  if (ran >= ((per-wtp-sg-bg-0 * 100)+(per-wtp-sg-bg-1 * 100)+(per-wtp-sg-bg-2 * 100)+(per-wtp-sg-bg-3 * 100))) and (ran < ((per-wtp-sg-bg-0 * 100)+(per-wtp-sg-bg-1 * 100)+(per-wtp-sg-bg-2 * 100)+(per-wtp-sg-bg-3 * 100)+(per-wtp-sg-bg-4 * 100))) [set wtp-sg-bg 4]
  if (ran >= ((per-wtp-sg-bg-0 * 100)+(per-wtp-sg-bg-1 * 100)+(per-wtp-sg-bg-2 * 100)+(per-wtp-sg-bg-3 * 100)+(per-wtp-sg-bg-4 * 100))) and (ran < ((per-wtp-sg-bg-0 * 100)+(per-wtp-sg-bg-1 * 100)+(per-wtp-sg-bg-2 * 100)+(per-wtp-sg-bg-3 * 100)+(per-wtp-sg-bg-4 * 100)+(per-wtp-sg-bg-5 * 100))) [set wtp-sg-bg 5]
  if (ran >= ((per-wtp-sg-bg-0 * 100)+(per-wtp-sg-bg-1 * 100)+(per-wtp-sg-bg-2 * 100)+(per-wtp-sg-bg-3 * 100)+(per-wtp-sg-bg-4 * 100)+(per-wtp-sg-bg-5 * 100))) [set wtp-sg-bg 6]

set ran random 10000
 ;;assign wtp-sg-se
 if (ran < (per-wtp-sg-se-0 * 100)) [set wtp-sg-se 0]
  if (ran >= (per-wtp-sg-se-0 * 100)) and (ran < ((per-wtp-sg-se-0 * 100)+(per-wtp-sg-se-1 * 100))) [set wtp-sg-se 1]
  if (ran >= ((per-wtp-sg-se-0 * 100)+(per-wtp-sg-se-1 * 100))) and (ran < ((per-wtp-sg-se-0 * 100)+(per-wtp-sg-se-1 * 100)+(per-wtp-sg-se-2 * 100))) [set wtp-sg-se 2]
  if (ran >= ((per-wtp-sg-se-0 * 100)+(per-wtp-sg-se-1 * 100)+(per-wtp-sg-se-2 * 100))) and (ran < ((per-wtp-sg-se-0 * 100)+(per-wtp-sg-se-1 * 100)+(per-wtp-sg-se-2 * 100)+(per-wtp-sg-se-3 * 100))) [set wtp-sg-se 3]
  if (ran >= ((per-wtp-sg-se-0 * 100)+(per-wtp-sg-se-1 * 100)+(per-wtp-sg-se-2 * 100)+(per-wtp-sg-se-3 * 100))) and (ran < ((per-wtp-sg-se-0 * 100)+(per-wtp-sg-se-1 * 100)+(per-wtp-sg-se-2 * 100)+(per-wtp-sg-se-3 * 100)+(per-wtp-sg-se-4 * 100))) [set wtp-sg-se 4]
  if (ran >= ((per-wtp-sg-se-0 * 100)+(per-wtp-sg-se-1 * 100)+(per-wtp-sg-se-2 * 100)+(per-wtp-sg-se-3 * 100)+(per-wtp-sg-se-4 * 100))) and (ran < ((per-wtp-sg-se-0 * 100)+(per-wtp-sg-se-1 * 100)+(per-wtp-sg-se-2 * 100)+(per-wtp-sg-se-3 * 100)+(per-wtp-sg-se-4 * 100)+(per-wtp-sg-se-5 * 100))) [set wtp-sg-se 5]
  if (ran >= ((per-wtp-sg-se-0 * 100)+(per-wtp-sg-se-1 * 100)+(per-wtp-sg-se-2 * 100)+(per-wtp-sg-se-3 * 100)+(per-wtp-sg-se-4 * 100)+(per-wtp-sg-se-5 * 100))) [set wtp-sg-se 6]

 set ran random 10000

  ;;assign wtp-f5
  if (ran < ( per-wtp-sg-feature5-0 * 100 ) ) [set wtp-f5 0]
  if (ran >= (per-wtp-sg-feature5-0 * 100)) and (ran < ((per-wtp-sg-feature5-0 * 100)+(per-wtp-sg-feature5-1 * 100))) [set wtp-f5 1]
  if (ran >= ((per-wtp-sg-feature5-0 * 100)+(per-wtp-sg-feature5-1 * 100))) and (ran < ((per-wtp-sg-feature5-0 * 100)+(per-wtp-sg-feature5-1 * 100)+(per-wtp-sg-feature5-2 * 100))) [set wtp-f5 2]
  if (ran >= ((per-wtp-sg-feature5-0 * 100)+(per-wtp-sg-feature5-1 * 100)+(per-wtp-sg-feature5-2 * 100))) and (ran < ((per-wtp-sg-feature5-0 * 100)+(per-wtp-sg-feature5-1 * 100)+(per-wtp-sg-feature5-2 * 100)+(per-wtp-sg-feature5-3 * 100))) [set wtp-f5 3]
  if (ran >= ((per-wtp-sg-feature5-0 * 100)+(per-wtp-sg-feature5-1 * 100)+(per-wtp-sg-feature5-2 * 100)+(per-wtp-sg-feature5-3 * 100))) and (ran < ((per-wtp-sg-feature5-0 * 100)+(per-wtp-sg-feature5-1 * 100)+(per-wtp-sg-feature5-2 * 100)+(per-wtp-sg-feature5-3 * 100)+(per-wtp-sg-feature5-4 * 100))) [set wtp-f5 4]
  if (ran >= ((per-wtp-sg-feature5-0 * 100)+(per-wtp-sg-feature5-1 * 100)+(per-wtp-sg-feature5-2 * 100)+(per-wtp-sg-feature5-3 * 100)+(per-wtp-sg-feature5-4 * 100))) [set wtp-f5 5]

  set ran random 10000
  ;;assign wtp-f6
  if (ran < ( per-wtp-sg-feature6-0 * 100 ) ) [set wtp-f6 0]
  if (ran >= (per-wtp-sg-feature6-0 * 100)) and (ran < ((per-wtp-sg-feature6-0 * 100)+(per-wtp-sg-feature6-1 * 100))) [set wtp-f6 1]
  if (ran >= ((per-wtp-sg-feature6-0 * 100)+(per-wtp-sg-feature6-1 * 100))) and (ran < ((per-wtp-sg-feature6-0 * 100)+(per-wtp-sg-feature6-1 * 100)+(per-wtp-sg-feature6-2 * 100))) [set wtp-f6 2]
  if (ran >= ((per-wtp-sg-feature6-0 * 100)+(per-wtp-sg-feature6-1 * 100)+(per-wtp-sg-feature6-2 * 100))) and (ran < ((per-wtp-sg-feature6-0 * 100)+(per-wtp-sg-feature6-1 * 100)+(per-wtp-sg-feature6-2 * 100)+(per-wtp-sg-feature6-3 * 100))) [set wtp-f6 3]
  if (ran >= ((per-wtp-sg-feature6-0 * 100)+(per-wtp-sg-feature6-1 * 100)+(per-wtp-sg-feature6-2 * 100)+(per-wtp-sg-feature6-3 * 100))) and (ran < ((per-wtp-sg-feature6-0 * 100)+(per-wtp-sg-feature6-
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1 * 100)+(per-wtp-sg-feature6-2 * 100)+(per-wtp-sg-feature6-3 * 100)+(per-wtp-sg-feature6-4 * 100))) [set wtp-f6 4]
  if (ran >= ((per-wtp-sg-feature6-0 * 100)+(per-wtp-sg-feature6-1 * 100)+(per-wtp-sg-feature6-2 * 100)+(per-wtp-sg-feature6-3 * 100)+(per-wtp-sg-feature6-4 * 100))) [set wtp-f6 5]

  set ran random 10000
  ;;assign wtp-f7
  if (ran < ( per-wtp-sg-feature7-0 * 100 ) ) [set wtp-f7 0]
  if (ran >= (per-wtp-sg-feature7-0 * 100)) and (ran < ((per-wtp-sg-feature7-0 * 100)+(per-wtp-sg-feature7-1 * 100))) [set wtp-f7 1]
  if (ran >= ((per-wtp-sg-feature7-0 * 100)+(per-wtp-sg-feature7-1 * 100))) and (ran < ((per-wtp-sg-feature7-0 * 100)+(per-wtp-sg-feature7-1 * 100)+(per-wtp-sg-feature7-2 * 100))) [set wtp-f7 2]
  if (ran >= ((per-wtp-sg-feature7-0 * 100)+(per-wtp-sg-feature7-1 * 100)+(per-wtp-sg-feature7-2 * 100))) and (ran < ((per-wtp-sg-feature7-0 * 100)+(per-wtp-sg-feature7-1 * 100)+(per-wtp-sg-feature7-2 * 100)+(per-wtp-sg-feature7-3 * 100))) [set wtp-f7 3]
  if (ran >= ((per-wtp-sg-feature7-0 * 100)+(per-wtp-sg-feature7-1 * 100)+(per-wtp-sg-feature7-2 * 100)+(per-wtp-sg-feature7-3 * 100))) and (ran < ((per-wtp-sg-feature7-0 * 100)+(per-wtp-sg-feature7-1 * 100)+(per-wtp-sg-feature7-2 * 100)+(per-wtp-sg-feature7-3 * 100)+(per-wtp-sg-feature7-4 * 100))) [set wtp-f7 4]
  if (ran >= ((per-wtp-sg-feature7-0 * 100)+(per-wtp-sg-feature7-1 * 100)+(per-wtp-sg-feature7-2 * 100)+(per-wtp-sg-feature7-3 * 100)+(per-wtp-sg-feature7-4 * 100))) [set wtp-f7 5]

 set ran random 10000
  ;;assign wtp-f8
  if (ran < ( per-wtp-sg-feature8-0 * 100 ) ) [set wtp-f8 0]
  if (ran >= (per-wtp-sg-feature8-0 * 100)) and (ran < ((per-wtp-sg-feature8-0 * 100)+(per-wtp-sg-feature8-1 * 100))) [set wtp-f8 1]
  if (ran >= ((per-wtp-sg-feature8-0 * 100)+(per-wtp-sg-feature8-1 * 100))) and (ran < ((per-wtp-sg-feature8-0 * 100)+(per-wtp-sg-feature8-1 * 100)+(per-wtp-sg-feature8-2 * 100))) [set wtp-f8 2]
  if (ran >= ((per-wtp-sg-feature8-0 * 100)+(per-wtp-sg-feature8-1 * 100)+(per-wtp-sg-feature8-2 * 100))) and (ran < ((per-wtp-sg-feature8-0 * 100)+(per-wtp-sg-feature8-1 * 100)+(per-wtp-sg-feature8-2 * 100)+(per-wtp-sg-feature8-3 * 100))) [set wtp-f8 3]
  if (ran >= ((per-wtp-sg-feature8-0 * 100)+(per-wtp-sg-feature8-1 * 100)+(per-wtp-sg-feature8-2 * 100)+(per-wtp-sg-feature8-3 * 100))) and (ran < ((per-wtp-sg-feature8-0 * 100)+(per-wtp-sg-feature8-1 * 100)+(per-wtp-sg-feature8-2 * 100)+(per-wtp-sg-feature8-3 * 100)+(per-wtp-sg-feature8-4 * 100))) [set wtp-f8 4]
  if (ran >= ((per-wtp-sg-feature8-0 * 100)+(per-wtp-sg-feature8-1 * 100)+(per-wtp-sg-feature8-2 * 100)+(per-wtp-sg-feature8-3 * 100)+(per-wtp-sg-feature8-4 * 100))) [set wtp-f8 5]

end

to assign-smarteco
 set color 95
 set plan 3
 let ran random 10000

 ;;assign wtp-se-be
 if (ran < (per-wtp-se-be-0 * 100)) [set wtp-se-be 0]
  if (ran >= (per-wtp-se-be-0 * 100)) and (ran < ((per-wtp-se-be-0 * 100)+(per-wtp-se-be-1 * 100))) [set wtp-se-be 1]
  if (ran >= ((per-wtp-se-be-0 * 100)+(per-wtp-se-be-1 * 100))) and (ran < ((per-wtp-se-be-0 * 100)+(per-wtp-se-be-1 * 100)+(per-wtp-se-be-2 * 100))) [set wtp-se-be 2]
  if (ran >= ((per-wtp-se-be-0 * 100)+(per-wtp-se-be-1 * 100)+(per-wtp-se-be-2 * 100))) and (ran < ((per-wtp-se-be-0 * 100)+(per-wtp-se-be-1 * 100)+(per-wtp-se-be-2 * 100)+(per-wtp-se-be-3 * 100))) [set wtp-se-be 3]
  if (ran >= ((per-wtp-se-be-0 * 100)+(per-wtp-se-be-1 * 100)+(per-wtp-se-be-2 * 100)+(per-wtp-se-be-3 * 100))) and (ran < ((per-wtp-se-be-0 * 100)+(per-wtp-se-be-1 * 100)+(per-wtp-se-be-2 * 100)+(per-wtp-se-be-3 * 100)+(per-wtp-se-be-4 * 100))) [set wtp-se-be 4]
  if (ran >= ((per-wtp-se-be-0 * 100)+(per-wtp-se-be-1 * 100)+(per-wtp-se-be-2 * 100)+(per-wtp-se-be-3 * 100)+(per-wtp-se-be-4 * 100))) and (ran < ((per-wtp-se-be-0 * 100)+(per-wtp-se-be-1 *
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100)+(per-wtp-se-be-2 * 100)+(per-wtp-se-be-3 * 100)+(per-wtp-se-be-4 * 100)+(per-wtp-se-be-5 * 100))) [set wtp-se-be 5]
  if (ran >= ((per-wtp-se-be-0 * 100)+(per-wtp-se-be-1 * 100)+(per-wtp-se-be-2 * 100)+(per-wtp-se-be-3 * 100)+(per-wtp-se-be-4 * 100)+(per-wtp-se-be-5 * 100))) [set wtp-se-be 6]

 set ran random 10000

  ;;assign wtp-f5
  if (ran < ( per-wtp-se-feature5-0 * 100 ) ) [set wtp-f5 0]
  if (ran >= (per-wtp-se-feature5-0 * 100)) and (ran < ((per-wtp-se-feature5-0 * 100)+(per-wtp-se-feature5-1 * 100))) [set wtp-f5 1]
  if (ran >= ((per-wtp-se-feature5-0 * 100)+(per-wtp-se-feature5-1 * 100))) and (ran < ((per-wtp-se-feature5-0 * 100)+(per-wtp-se-feature5-1 * 100)+(per-wtp-se-feature5-2 * 100))) [set wtp-f5 2]
  if (ran >= ((per-wtp-se-feature5-0 * 100)+(per-wtp-se-feature5-1 * 100)+(per-wtp-se-feature5-2 * 100))) and (ran < ((per-wtp-se-feature5-0 * 100)+(per-wtp-se-feature5-1 * 100)+(per-wtp-se-feature5-2 * 100)+(per-wtp-se-feature5-3 * 100))) [set wtp-f5 3]
  if (ran >= ((per-wtp-se-feature5-0 * 100)+(per-wtp-se-feature5-1 * 100)+(per-wtp-se-feature5-2 * 100)+(per-wtp-se-feature5-3 * 100))) and (ran < ((per-wtp-se-feature5-0 * 100)+(per-wtp-se-feature5-1 * 100)+(per-wtp-se-feature5-2 * 100)+(per-wtp-se-feature5-3 * 100)+(per-wtp-se-feature5-4 * 100))) [set wtp-f5 4]
  if (ran >= ((per-wtp-se-feature5-0 * 100)+(per-wtp-se-feature5-1 * 100)+(per-wtp-se-feature5-2 * 100)+(per-wtp-se-feature5-3 * 100)+(per-wtp-se-feature5-4 * 100))) [set wtp-f5 5]

  set ran random 10000
  ;;assign wtp-f6
  if (ran < ( per-wtp-se-feature6-0 * 100 ) ) [set wtp-f6 0]
  if (ran >= (per-wtp-se-feature6-0 * 100)) and (ran < ((per-wtp-se-feature6-0 * 100)+(per-wtp-se-feature6-1 * 100))) [set wtp-f6 1]
  if (ran >= ((per-wtp-se-feature6-0 * 100)+(per-wtp-se-feature6-1 * 100))) and (ran < ((per-wtp-se-feature6-0 * 100)+(per-wtp-se-feature6-1 * 100)+(per-wtp-se-feature6-2 * 100))) [set wtp-f6 2]
  if (ran >= ((per-wtp-se-feature6-0 * 100)+(per-wtp-se-feature6-1 * 100)+(per-wtp-se-feature6-2 * 100))) and (ran < ((per-wtp-se-feature6-0 * 100)+(per-wtp-se-feature6-1 * 100)+(per-wtp-se-feature6-2 * 100)+(per-wtp-se-feature6-3 * 100))) [set wtp-f6 3]
  if (ran >= ((per-wtp-se-feature6-0 * 100)+(per-wtp-se-feature6-1 * 100)+(per-wtp-se-feature6-2 * 100)+(per-wtp-se-feature6-3 * 100))) and (ran < ((per-wtp-se-feature6-0 * 100)+(per-wtp-se-feature6-1 * 100)+(per-wtp-se-feature6-2 * 100)+(per-wtp-se-feature6-3 * 100)+(per-wtp-se-feature6-4 * 100))) [set wtp-f6 4]
  if (ran >= ((per-wtp-se-feature6-0 * 100)+(per-wtp-se-feature6-1 * 100)+(per-wtp-se-feature6-2 * 100)+(per-wtp-se-feature6-3 * 100)+(per-wtp-se-feature6-4 * 100))) [set wtp-f6 5]

  set ran random 10000
  ;;assign wtp-f7
  if (ran < ( per-wtp-se-feature7-0 * 100 ) ) [set wtp-f7 0]
  if (ran >= (per-wtp-se-feature7-0 * 100)) and (ran < ((per-wtp-se-feature7-0 * 100)+(per-wtp-se-feature7-1 * 100))) [set wtp-f7 1]
  if (ran >= ((per-wtp-se-feature7-0 * 100)+(per-wtp-se-feature7-1 * 100))) and (ran < ((per-wtp-se-feature7-0 * 100)+(per-wtp-se-feature7-1 * 100)+(per-wtp-se-feature7-2 * 100))) [set wtp-f7 2]
  if (ran >= ((per-wtp-se-feature7-0 * 100)+(per-wtp-se-feature7-1 * 100)+(per-wtp-se-feature7-2 * 100))) and (ran < ((per-wtp-se-feature7-0 * 100)+(per-wtp-se-feature7-1 * 100)+(per-wtp-se-feature7-2 * 100)+(per-wtp-se-feature7-3 * 100))) [set wtp-f7 3]
  if (ran >= ((per-wtp-se-feature7-0 * 100)+(per-wtp-se-feature7-1 * 100)+(per-wtp-se-feature7-2 * 100)+(per-wtp-se-feature7-3 * 100))) and (ran < ((per-wtp-se-feature7-0 * 100)+(per-wtp-se-feature7-1 * 100)+(per-wtp-se-feature7-2 * 100)+(per-wtp-se-feature7-3 * 100)+(per-wtp-se-feature7-4 * 100))) [set wtp-f7 4]
  if (ran >= ((per-wtp-se-feature7-0 * 100)+(per-wtp-se-feature7-1 * 100)+(per-wtp-se-feature7-2 * 100)+(per-wtp-se-feature7-3 * 100)+(per-wtp-se-feature7-4 * 100))) [set wtp-f7 5]

 set ran random 10000
  ;;assign wtp-f8
  if (ran < ( per-wtp-se-feature8-0 * 100 ) ) [set wtp-f8 0]
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  if (ran >= (per-wtp-se-feature8-0 * 100)) and (ran < ((per-wtp-se-feature8-0 * 100)+(per-wtp-se-feature8-1 * 100))) [set wtp-f8 1]
  if (ran >= ((per-wtp-se-feature8-0 * 100)+(per-wtp-se-feature8-1 * 100))) and (ran < ((per-wtp-se-feature8-0 * 100)+(per-wtp-se-feature8-1 * 100)+(per-wtp-se-feature8-2 * 100))) [set wtp-f8 2]
  if (ran >= ((per-wtp-se-feature8-0 * 100)+(per-wtp-se-feature8-1 * 100)+(per-wtp-se-feature8-2 * 100))) and (ran < ((per-wtp-se-feature8-0 * 100)+(per-wtp-se-feature8-1 * 100)+(per-wtp-se-feature8-2 * 100)+(per-wtp-se-feature8-3 * 100))) [set wtp-f8 3]
  if (ran >= ((per-wtp-se-feature8-0 * 100)+(per-wtp-se-feature8-1 * 100)+(per-wtp-se-feature8-2 * 100)+(per-wtp-se-feature8-3 * 100))) and (ran < ((per-wtp-se-feature8-0 * 100)+(per-wtp-se-feature8-1 * 100)+(per-wtp-se-feature8-2 * 100)+(per-wtp-se-feature8-3 * 100)+(per-wtp-se-feature8-4 * 100))) [set wtp-f8 4]
  if (ran >= ((per-wtp-se-feature8-0 * 100)+(per-wtp-se-feature8-1 * 100)+(per-wtp-se-feature8-2 * 100)+(per-wtp-se-feature8-3 * 100)+(per-wtp-se-feature8-4 * 100))) [set wtp-f8 5]


end

to assign-bestgov
 set color 25
 set plan 4
 let ran random 10000

 ;;assign wtp-bg-be
 if (ran < (per-wtp-bg-be-0 * 100)) [set wtp-bg-be 0]
  if (ran >= (per-wtp-bg-be-0 * 100)) and (ran < ((per-wtp-bg-be-0 * 100)+(per-wtp-bg-be-1 * 100))) [set wtp-bg-be 1]
  if (ran >= ((per-wtp-bg-be-0 * 100)+(per-wtp-bg-be-1 * 100))) and (ran < ((per-wtp-bg-be-0 * 100)+(per-wtp-bg-be-1 * 100)+(per-wtp-bg-be-2 * 100))) [set wtp-bg-be 2]
  if (ran >= ((per-wtp-bg-be-0 * 100)+(per-wtp-bg-be-1 * 100)+(per-wtp-bg-be-2 * 100))) and (ran < ((per-wtp-bg-be-0 * 100)+(per-wtp-bg-be-1 * 100)+(per-wtp-bg-be-2 * 100)+(per-wtp-bg-be-3 * 100))) [set wtp-bg-be 3]
  if (ran >= ((per-wtp-bg-be-0 * 100)+(per-wtp-bg-be-1 * 100)+(per-wtp-bg-be-2 * 100)+(per-wtp-bg-be-3 * 100))) and (ran < ((per-wtp-bg-be-0 * 100)+(per-wtp-bg-be-1 * 100)+(per-wtp-bg-be-2 * 100)+(per-wtp-bg-be-3 * 100)+(per-wtp-bg-be-4 * 100))) [set wtp-bg-be 4]
  if (ran >= ((per-wtp-bg-be-0 * 100)+(per-wtp-bg-be-1 * 100)+(per-wtp-bg-be-2 * 100)+(per-wtp-bg-be-3 * 100)+(per-wtp-bg-be-4 * 100))) and (ran < ((per-wtp-bg-be-0 * 100)+(per-wtp-bg-be-1 * 100)+(per-wtp-bg-be-2 * 100)+(per-wtp-bg-be-3 * 100)+(per-wtp-bg-be-4 * 100)+(per-wtp-bg-be-5 * 100))) [set wtp-bg-be 5]
  if (ran >= (per-wtp-bg-be-0 * 100)+(per-wtp-bg-be-1 * 100)+(per-wtp-bg-be-2 * 100)+(per-wtp-bg-be-3 * 100)+(per-wtp-bg-be-4 * 100)+(per-wtp-bg-be-5 * 100)) [set wtp-bg-be 6]
end

to assign-besteco
 set color 15
 set plan 5
end
```