Sustainability of the Service-Profit Chain

by

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Abstract

Managers in organizations make investment decisions all the time. These decisions have an impact on the bottom-line profits and on the market penetration of the organization. Some decisions have more impact than others do and not all such decisions are evaluated for their impact. The Service-Profit Chain (SPC) framework brings together several components like operational attributes, customer perceptions, customer behavioral intentions and customer loyalty to evaluate the service operation. This research augments the SPC with another component – uncontrollable factors (environmental variables and competition) that are exogenous to the operation but definitely have an effect on the service delivery process. Further, this research develops a dynamic model to evaluate investments made in operational attributes (e.g. number of tellers in a bank, number of airline flight options to a particular city available to customers) and determine the behavior of customer perceptions, customer intentions, customer loyalty, profit, market penetration and marginal rate of return over time.

The above is accomplished by incorporating a hill-climbing algorithm into the dynamic SPC model. This hill-climbing algorithm senses the current state of the system and compares it to a certain goal to determine the discrepancies and make additional interventions. The objective is to determine an optimal path to steady state and to evaluate if certain goals are realistic. Next, the Service Sustainability Chain is developed to be applicable to training services. This is accomplished by building key relationships specific to training services into separate modules. The Dynamic SPC module is based on the SPC framework. The Customer Base Growth module captures the structure for referrals and how this enables the growth of the customer base mimicking the infectious model for epidemic diseases in the literature.

A methodology based on Chi-Square Automatic Interaction Detection (CHAID) and Structural Equation Modeling (SEM) developed to explore, uncover and identify relationships and mathematical equations is used to determine the structural input-output representation of the SPC. Next, the model and the methodology developed are applied to a case study in a training services organization, simulated and validated.

To my parents

Acknowledgements

Rightfully, I am very happy to have come to the end of a long journey in my life. To start with the process has been the biggest decision and the end has been the biggest achievement in my life so far. Looking back, I enjoyed the journey as much if not more than the destination. This has been an interesting ride with various joyous moments and frustrations. Thinking of myself as a river meandering down the terrain, several people's lives have intersected and crossed my path, some with major and significant impacts and others with minor exchanges. I'm glad I have the opportunity to express my thanks to the people whose contribution has been valuable toward my achievement.

I believe one main factor that kept me going down this path was the importance of education that my parents, especially my Dad instilled in us (my brother and I). He always used to tell us that the only thing that a person can take to the grave is educational achievement. My Mom and Dad have been a great moral support with the process.

I tell my friends that one person that would have been the happiest with this achievement is my Granddad. He knew I was starting with this endeavor but I feel sad that he is not around to hear the positive outcome. He is survived by my Grandmom who shares similar views. They are also my parents and in fact, I have spent more time with them than my parents. I have learned a lot from my parents and grandparents alike.

My brother, Arrvind has been more of a friend to me. We continue to argue with differences of opinions and views on real life issues. Sometimes, I feel he takes the opposite side to bring forth an argument. He has been very helpful in hosting and putting up with me for over a week during late December of 2004. I stayed at his place and worked on model validation. That visit not only took me out of the stress with my job at the American Red Cross, but also ended up being very productive in terms of analysis and writing part of Chapters 5 and 6.

My committee has been patient with me while ensuring that I am doing proper research grounded in theory and staying on the right path. Each member of my committee had expertise in different areas and this enabled me to make sure that my research was solid from all perspectives. In fact, my advisor Dr. Triantis, Dr. Hoopes and Dr. Koelling served on my master's thesis committee. We all had such a good working relationship that they agreed to stay on my dissertation committee. Dr. Triantis is first a friend, then an advisor. He is known to mentor his students in a unique way. I have not come across or heard of another professor that neither gets too involved nor stays far from the research, but keeps the flame of enthusiasm burning inside the students. He facilitated the theoretical and mathematical rigor in my research.

Dr. Hoopes always found time in her very tight schedule to give me constructive feedback all the way along. She brought the real world perspective while developing models and applying theory. Dr. Koelling has expertise in simulation and model validation and he always challenged the simulation techniques that I used. He also insisted that model validation was done appropriately.

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My two little friends, Felipe and Camile whom, now that I think about it, I have known for quite a few years were always cheerful to lighten up my life. "Buddy-beladon" as they used to call me, they are now concerned that they would have to refer to me as "Dr. Beladon." What more power is required than two innocent hearts wishing that I complete my dissertation and praying for me every night? Anytime I am stressed, either because of work, research or anything else, I could always spend time talking with them listening to their innocent ideas, yet not innocent at all. What more can anyone want to endure such a journey?

Alex has been not only a friend, philosopher and guide, but also "MS Project" to me, keeping me on my toes and pushing me to keep going. I have had so many discussions about my research, model and application with you some that were fruitful and led to more ideas for our future research endeavors and others to very heated discussions. You were also my boss, being accommodative with my research meetings and on the work side, providing opportunities for growth. You were also my mentor at work. I learned so much from you. I always liked the way you said things from your heart, not to think twice if it was "politically correct." I remember moments when you tried to make up things and I have news for you – it will never come out right. Even thinking about it now, makes me laugh. You probably made a few enemies, nevertheless your comments were constructive for me. One thing, I will never forget about you is the way you bring in passion and emotions into everything, rightfully so with your Latin background. I still believe that without you, I would not have been able to complete my dissertation. Thank you, Alex. I hope to continue working with you on several research initiatives.

With such people around me, I would not hesitate one moment to take upon me a similar journey yet again.

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1 Introduction

"We can do anything we want as long as we stick to it long enough."

- Helen Keller

1.1 BACKGROUND

Service organizations account for a substantial part of the output of a growing number of economies. Several authors have argued that evaluating service delivery operations and their impact on the behavior of service recipients is more relevant than ever in the new global market (Lengnick-Hall et al. 2000; O'Neill et al., 2003; Aigbedo and Parameswaran, 2004). With the advent of e-commerce, evaluating services and investigating approaches that can help organizations identify service features is ever more important not only to satisfy customer demands, but also to ensure repeated business and ultimately increase the business bottom line – profit.

As suggested by Gronroos (1988) and Parasuraman et al. (1985), it is becoming increasingly clear that the nature of service operations has distinctive features that set them apart from manufacturing operations. For instance, one of those distinctions is the inseparability of production and consumption in services. For services, both of them occur at the same time. Another distinctive feature is the importance that service quality enjoys in the overall satisfaction of the customer receiving the service, yet, contrary to the quality of a tangible product; service quality is an "elusive and indistinct construct" (Parasuraman et al. 1985).

The definition of service quality has been the object of numerous research initiatives (e.g. Parasuraman et al., 1985; Zeithaml, 1987; Gronroos, 1988; Triantis and Medina-Borja, 1996a; 1996b; Medina-Borja, 2002). There is agreement that service quality is based on customer's perceptions and expectations of both, service characteristics and provider of service. The SERVQUAL framework is to date the most widely used service quality framework. SERVQUAL is used by both academicians and managers (e.g. Carman, 1990; Babakus and Boller, 1992; Lam, 1997; Lam and Woo, 1997). To find a way to evaluate the features and attributes of the service that turns a customer into a satisfied customer, and makes the customer come back to the same organization (i.e. to have repeated business), is an additional and relevant research problem. In addition, identifying service characteristics that make a customer come back to the same place is imperative. This is especially important since repeated business increases an organization's sales, therefore increasing a organization's profit. The study of service operations features even has application for trying to evaluate the reasons of repeated business in e-commerce, an important issue as the "information society" increasingly moves towards on-line transactions.

Further, organizations do not want to only experience excessive one time profit, but to do so in a sustained fashion over time so that the organization can survive. For that, organizations need to gauge their market and competition and make wise investment decisions in operational attributes[1] to ensure that they will remain current and become the preferred choice for business of their current and potential customers.

1.2 THE SERVICE-PROFIT CHAIN (SPC)

Several models that approach the evaluation of services are described in the service operations and marketing bodies of literature. One of them, the service-profit chain (SPC) has been the seminal work for a large number of papers in the service evaluation field. The original framework was presented in 1994 by Heskett et al. who hypothesized that revenues are driven by service quality perceptions, which in turn are driven by operational inputs and employee efforts. Thus, the SPC is a framework for linking service operations to customer's assessments and in turn linking those customers' assessments to the organization's bottom line – profitability in most cases (Heskett et al., 1994). The objective of the SPC is to provide an integrated framework for understanding how an organization's operational investments in service quality are linked to customer perceptions[2] and behaviors, and how these translate into profits. Investments in operational inputs are categorized as any of the organization's interventions for improving the way services are delivered (i.e. investments in technology, additional points of delivery, more waiters in a restaurant, more cashiers in a supermarket, more ATMs in bank branches, etc.) Hence, the SPC framework can provide guidance about the complex interrelationships among operational infrastructure, customer perceptions, and the bottom line (Kamakura et al., 2002). Moreover, the SPC framework can become useful in helping organizations improve their operations.

Another similar framework developed to deal with factors that affect the profitability or survivability of service operations is that of "Return on Quality" (Rust et al., 1995) that explicitly models the cost and benefits of quality related investments. Both frameworks attempt to drive the organization's operations and strategic decisions based on statistical analysis of customer's surveys (Kamakura et al., 2002).

While there is extensive research linking attribute-level performance perceptions to service quality (Parasuraman et al., 1988), service quality perceptions to customer behaviors (Bolton 1998) and customer behaviors to revenues (Carr, 1999), Soteriou and Zenios (1999) noted that no study has comprehensively modeled the SPC and most studies have only tested the links among factors in isolation, giving inconsistent findings. Further, according to Kamakura et al (2002), these studies have been unable to identify the causal and mediating mechanisms that managers need to understand to implement the SPC.

The idea of 'profit' that has been introduced seeks to ascertain that the revenue generated is greater than the expenses incurred by the organization as of today. It does not talk about the future. Profitability, taking into consideration today's constraints, does not guarantee tomorrow's profits. Further, profitability is not the only outcome that today's managers need to be concerned about. Other outcomes such as the extent to which the market is penetrated and marginal return on the investment made are also important. And any investments being made at present not only has an impact on tomorrow's profits but also on tomorrow's market penetration with varying marginal rates

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[1] Operational attributes are features or characteristics of the internal operations of a service organization that enable service delivery to the customers.

[2] Customer perceptions are views/assessment of the customer about the operational attributes used during the service delivery process.

of return. So, how can today's manager know or decide when and how much to invest in operational attributes and whether such investments will sustain the operation?

1.3 RESEARCH PROBLEM

The service industry has grown considerably in the last century. Services can be as varied as those provided in the area of banking, health care, education and training, management consulting, communications, human services, and e-commerce, to name a few. Each of these has unique characteristics. Many of them are slowly migrating to the use of technologies, mainly the internet, as an additional option offered to their customers instead of traditional face-to-face service delivery (Curran et al., 2003). This increases the service delivery outreach to geographically distant and previously remote parts of the world. Thus creating global competition and setting organizations at the verge of constant drive for more accurate, timely and relevant decisions.

Managers in organizations make investment decisions all the time. These investment decisions have an impact on the bottom-line profits and the market penetration of the organization. Not all such decisions are evaluated for their impact. Some have more impact than others do. The Service-Profit Chain (SPC) (Heskett et al., 1994) is a theoretical approach that brings together several components of the service delivery system to evaluate investments. These components are,

- operational attributes like number of tellers in a bank, number of flight schedule options to a particular city available to customers;
- customer perceptions like service quality, value, satisfaction;
- customer behavioral intentions[3] to refer/recommend and/or return;
- customer loyalty[4] including referrals/recommendations that were fruitful and actual behavior (e.g. returns) that indicate loyalty and finally,
- financial component including expenses, revenue, surplus/profits.

While the SPC approach adopted by subsequent authors (e.g. Kamakura et al., 2002) appear to solve most of the problems associated with the evaluation of service operations, two major shortcomings seem apparent.

- Most of the strategic analyses of the factors that affect the bottom line emerge from the statistical analysis of the complex relationships in the chain at a given point in time. This approach does not address the issue of what will happen in subsequent time periods and in particular the long-term dynamic behavior of the organization and its customers.
- Other exogenous factors such as market size, dispersion, competition, etc. that might influence the SPC are not considered.

Hence, the following research questions arise.

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[3] Customer behavioral intentions are the intentions that the customer forms about his/her future behavior based on the perceptions of the service received.

[4] Customer loyalty is the dependability or faithfulness of the customer to act in a manner that is beneficial to the organization.

1.4 RESEARCH QUESTIONS

Q1: How do investments in operational attributes affect the long-term sustainability[5] of the organization?

Q2: Is the system dynamics methodology suitable to assess the dynamic achievement of service operations sustainability over the long-term? What are the key factors and variables associated with the SPC framework and what kind of relationships among these factors and variables need to be established and integrated into a system dynamics paradigm so as to dynamically assess the SPC framework?

Q3: For any given investment in services, is the dynamic model capable of providing an answer as to how much can one invest in operational attributes over a period of time and expect to get an adequate financial return (bang for the buck)?

Q4: Similarly, can the model identify the point in time beyond which the marginal rate of return decreases over time?

1.5 RESEARCH OBJECTIVES

To answer the above questions, the following research objectives are pursued:

O1: To develop a conceptual dynamic model of the Service-Profit Chain (SPC) including operational attributes, customer perceptions and behaviors, market and growth.

O2: To operationalize the conceptual model developed above.

O3: To develop an evaluation methodology of service operations sustainability using system dynamics theory.

O4: To incorporate the evaluation methodology in the operational model (SSC: Service-Sustainability Chain).

O5: To customize the Service-Sustainability Chain for training services.

O6: To establish relationships between the variables in the SSC as it applies to a research case study.

O7: To simulate the behavior and answer questions in the case study.

1.6 RESEARCH PREPOSITIONS

To start with the research, the following research prepositions are formulated:

P1: Sustainability is required for the existence of organizations.

P2: The Service-Profit Chain (SPC) can be extended to a Service-Sustainability Chain (SSC) to evaluate service operations.

P3: The SSC can be modeled in a system dynamics framework.

[5] Sustainability is the ability of an organization to uphold its state in the market place.

1.7 RESEARCH HYPOTHESES

The relationships between the components of the SPC are well documented in the literature. To answer research questions Q3 and Q4, the case study will be modeled using SSC. For this, the relationships should be tested for the specific case study in training services. Hence the following research hypotheses are formulated and tested:

H1: Improvements in operational attributes (inputs) have a positive impact on customer perceptions of service.

H2: Positive customer perceptions of service have a positive impact on behavioral intentions.

H3: Positive behavioral intentions have a positive impact on customer loyalty to the organization.

1.8 RESEARCH CONTRIBUTIONS

The main theme that runs as part of this research is *decision making* – collecting all of the available facts, weaving a well-knit relationship, gaining knowledge of the operations and then making a well-informed decision.

One of the main contributions of this research is to provide the decision maker with a dynamic framework to evaluate the sustainability of service operations in an organization. By that, the decision maker will be able to answer questions like, how the variables in SPC are related, how they affect one another, how should the investments be phased in order to attain certain goals over a period of time to ensure sustainability of the organization. While providing this framework, there were additional contributions which are discussed below.

This research modifies the conceptual model for the SPC presented originally by Heskett et al. in 1994 and modified by many others (e.g. Rucci et al., 1998) by including exogenous components or "uncontrollable factors" (e.g. market size, competition, other environmental factors like age, gender, etc.). These factors can influence the impact of investments on the market penetration and surplus. Another factor that is included in the modified conceptual model of the SPC is competition that affects the "value" within the customer perceptions component of the SPC. Thus a modified conceptual model of the SPC is provided for the research. This is a contribution to the service operations literature.

The operational model, which is also generalizable to any service industry, uses a system dynamics framework and is based on the above conceptual model. Within the operational dynamic SPC model, the hill-climbing algorithm (Sterman, 2000) is used to identify the steady state of the system. This is done through a search pattern by sensing whether there is too much or too little of the components of the system structure. The hill-climbing algorithm has been used by Vaneman (2002) to identify optimal path while evaluating the production efficiency. This research replaces the empirical production frontier in Vaneman (2002) with an actual structural input-output representation of the SPC. This is a contribution to the production/service operations and performance literature.

The Susceptible-Infectious (SI) epidemic model in Sterman (2000) captures the structure of the epidemic of infectious diseases. The SI model is modified in this research to depict the relationships between potential customers and actual customers. The operational model is also expanded to handle multiple operational attributes. By using this model, a decision-maker will be able to evaluate the impact of simultaneous investments with respect to multiple attributes. Further, the applicability of the operational model is illustrated by developing a full-blown system dynamics model as it applies to training services. Predictive analytics and structural equation modeling are used to formulate quantitative relationships in a system dynamics modeling framework. These are contributions to the system dynamics literature.

And finally, a case study is conducted in the Health & Safety Services department for First Aid CPR training at a humanitarian organization. For this, the model is simulated to answer questions related to the case study. Application to the case study illustrates to managers how the model and the methodology can be used to answer business-related questions elsewhere.

1.9 ORGANIZATION OF THIS DOCUMENT

Chapter 1 introduced the SPC, framed the research problem and identified the research questions. Then the research objectives and hypotheses were stated and contributions discussed. The next chapter reviews the Service Profit Chain, some of the existing performance measurement frameworks, fundamentals of decision making, system dynamics methodology, predictive analytics and structural equation modeling. Chapter 3 develops the conceptual model and operationalizes the same by identifying variables for each of the components in the chain.

Chapter 4 uses system dynamics to develop the Service-Sustainability Chain and describes the methodology to identify relationships in the structure. Chapter 5 launches the case study, applies the model and methodology developed in this research and discusses validation. Finally, Chapter 6 presents the results of the research hypotheses, answers to the research questions, concludes the research and sets the direction for future research.

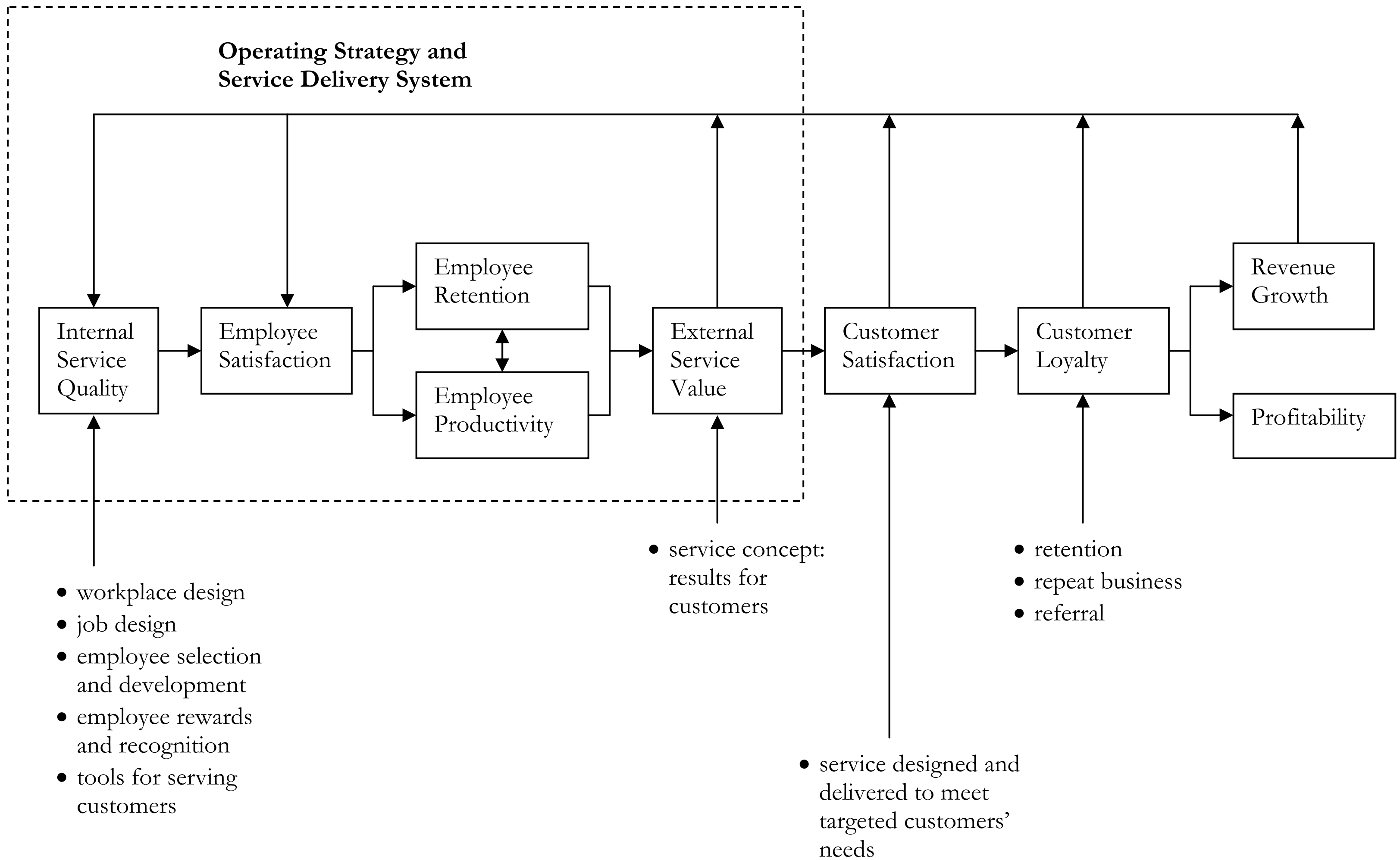
2 Literature Review

This chapter reviews the Service-Profit Chain, some of the existing performance measurement frameworks, fundamentals of decision making, system dynamics methodology, predictive analytics and structural equation modeling.

2.1 THE SERVICE-PROFIT CHAIN

Heskett et al. (1994) establish relationships between profitability, customer loyalty, employee satisfaction, employee loyalty, and productivity. The authors call this the Service-Profit Chain and propose several links. They say that profit and growth are simulated primarily by customer loyalty. Loyalty is a direct result of customer satisfaction, which in turn is largely influenced by the value of services provided to customers. This value is created by satisfied, loyal and productive employees. Employee satisfaction results primarily from high quality support services and policies that enable employees to deliver results to customers. The links proposed by the authors in the Service-Profit Chain can be seen in Figure 2-1.

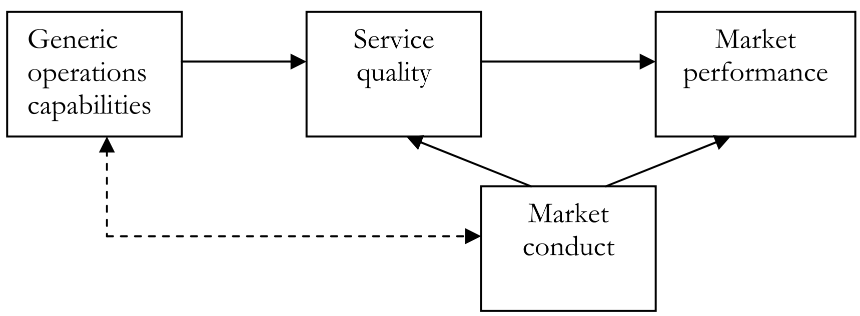
Figure 2-1. The Links in the Service-Profit Chain



Source: Heskett et al. (1994, p.166)

Roth and Jackson (1995) propose a new service management strategy based on an operations capabilities-service quality-performance (C-SQ-P) triad paradigm, see Figure 2-2. Unlike Heskett et al. (1994), Roth and Jackson (1995) have more of a market-focused model where they look at market performance and market conduct. According to the authors, market conduct is defined as an index of the degree of competition in the market, from pure competition to monopoly. They ask three related questions; what are the operational capabilities that determine service quality, does service quality have an effect on market performance and how is market conduct related to the three items in the triad. Some of the answers from this research are generic; operations' capabilities affect service quality and performance, service quality and total factor productivity are negatively correlated, and market conduct affects operations capabilities more than market performance, with all else being equal. Roth and Jackson (1995) do not explicitly look at employee motivation, satisfaction and behavior within the organization that affect service quality as demonstrated by Heskett et al. (1994).

Figure 2-2. The Capabilities-Service-Quality-Performance (C-SQ-P) Triad



Adapted from Roth and Jackson (1995, p.1721)

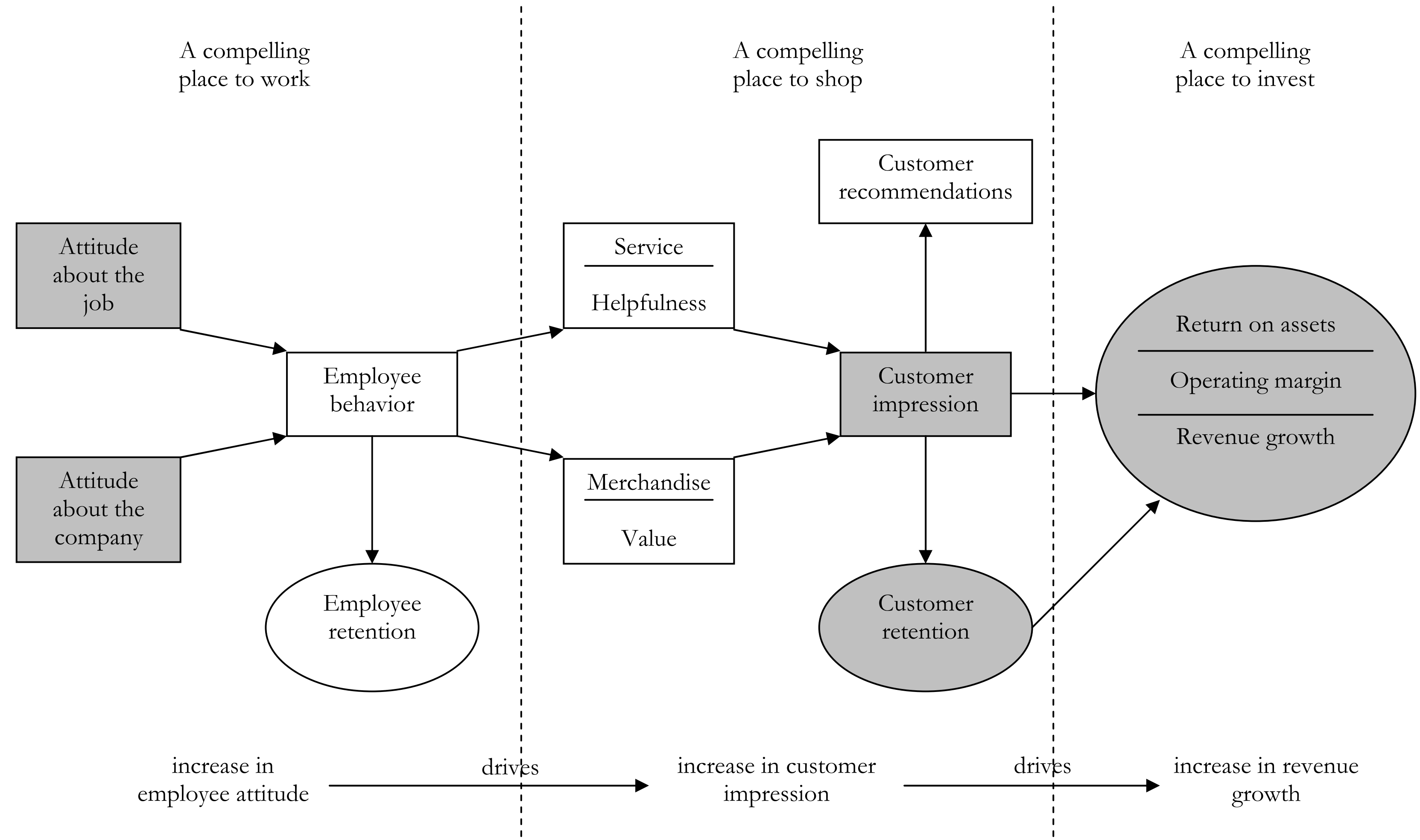
Later, Rucci et al (1998) studied the employee-customer model, which emphasizes the optimization of employee skills to satisfy customers. The authors claim that this study brought about a change in the business culture at Sears, Roebuck and Company and brought the organization from big losses to big profits. The authors use total performance indicators to analyze, model and experiment on employee-customer relations. The authors talk about how employee attitudes affect employee retention, which affects the drivers of customer satisfaction, and finally how the financial performance is affected. The operational strategy evolves from the concept. For Sears to be a compelling place to invest, it had to be both – a compelling place to work and a compelling place to shop, not just one, or the other. The authors express that rule as the following formula:

Work x Shop = Invest

Source: Rucci et al. (1998, p.88)

The relationships in the employee-customer-profit chain and the total performance indicators can be seen in Figure 2-3.

Figure 2-3. The Revised Model: The Employee-Customer-Profit Chain



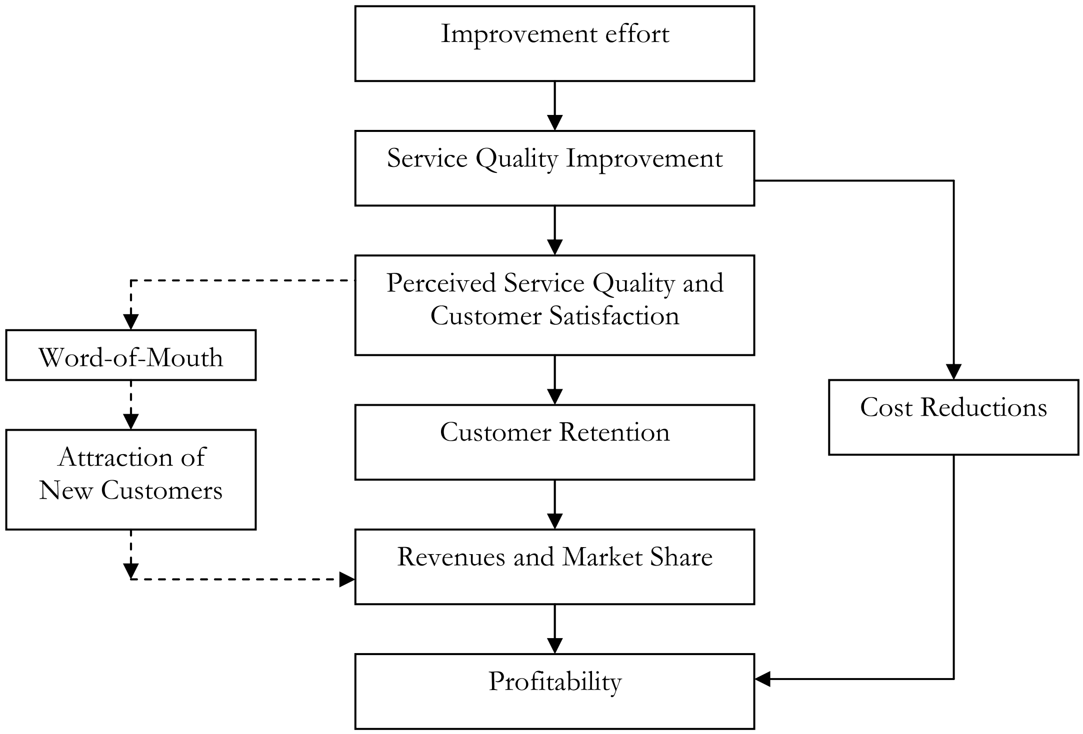
Guide: Rectangles – survey information; ovals – hard data; measures in gray – Sears Total Performance Indicators

Source: Adapted from Rucci et al. (1998, p.91)

Conceptually speaking, both Heskett et al. (1994) and Rucci et al. (1998) have the same theory behind the models and in fact, both the models are strikingly similar. Both capture aspects internal to the organization, like the job of the individual employees, the workplace, rewards and recognition, etc., and the effect of these on both employee satisfaction and the behavior that drives employee retention and productivity. Such a motivated employee in either model has high productivity and has increased service value to customers. This increased service value in turn drives customer satisfaction and prompts the customer to refer or recommend the service. Furthermore, this behavior can be translated into customer loyalty/retention, which is converted into revenue growth and profits. However speaking from a methodology standpoint, Heskett et al. (1994) do not explain how the various links are quantified or validated. Rucci et al. (1998) on the other hand, talk about *causal pathway modeling* which is used in analyzing the causal links. Causal pathway modeling also known as Path analysis as opposed to multiple regression analysis seeks causal pathways and not just correlations without causations.

Rust et al. (1995) developed the concept of Return on Quality (ROQ) to guide quality improvement efforts (Figure 2-4). The authors base the approach on legitimate assumptions, (1) quality is an investment, (2) quality efforts must be financially accountable, (3) it is possible to spend too much on quality and (4) not all quality expenditures are equally valid. This model proposed by Rust et al. (1995) is similar to the C-SQ-P triad by Roth and Jackson (1995) except that, while the former does explicitly consider customer satisfaction, recommendation and retention, the latter does not. On the other hand, the latter does consider competition in the market. The authors term this as market conduct.

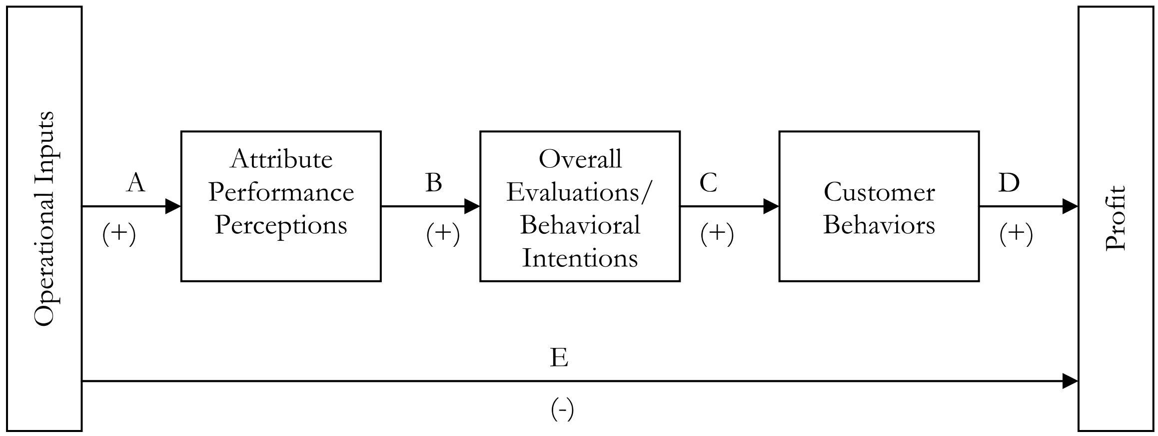
Figure 2-4. A Model of Service Quality Improvement and Profitability



Source: Rust et al. (1995, p.60)

More recently, Kamakura et al. (2002) built on the Service-Profit chain model proposed by Heskett et al. (1994) and came up with the model shown in Figure 2-5. The operational inputs include employee perceptions, attitudes, and satisfaction. Attribute performance perceptions are actually the perceived service quality. The authors include behavioral intentions between the perceived service quality and the actual behavior of the customers. Whereas the other models look at just customer satisfaction driving the behavior, Kamakura et al. (2002) combine the overall evaluations (assumed to the equivalent of overall customer satisfaction) with behavioral intentions. Overall evaluations are measures of overall consumers' evaluations of the service (overall service quality rating, overall satisfaction rating, or an overall behavioral intent rating). Behavioral intent rating is the customers stated intention to come back for repeated business in the future. The letters A, B, C and D represent the links between the two successive components of the chain.

Figure 2-5. The Service-Profit Chain



Source: Kamakura et al. (2002, p.295)

2.2 COMPARISON OF THE MODELS

Among the above models, Heskett et al. (1994), Rust et al. (1995) and Kamakura et al. (2002) analyze the effects of interventions or investments guided at improving inputs with the bottom-line (profitability) explicitly. Roth and Jackson (1995) and Rucci et al. (1998) focus more on retention and revenue maximization. As Rust et al. (1995) points out, this does not effectively capture the bottom-line (profitability) since it is possible to spend too much on quality and not all quality expenditures are equally valid.

All of the five models described above look at the intangibles ("soft" variables) in service delivery – service quality and how this affects the customer satisfaction and finally the profits. These models consider the profitability (or revenue growth) because of increased investments in operational attributes by way of service quality, customer satisfaction, and retention. There is a missing link between how investments in operational inputs are in many cases transformed into more outputs and not just better service quality perceptions. Further, the link between more outputs leading to more profits is also missing. However, this is not something that will be explored as part of this research.

Several questions need to be answered under the umbrella of Service-Profit Chain. These questions were initially raised as the research problem in Chapter 1. There are a number of frameworks and techniques in performance measurement literature that attempt to answer similar questions for service industries but from different perspectives. Some of these frameworks are discussed in the ensuing sections of this chapter. Also discussed are the comparisons of these frameworks that need to be looked at before answering the research problem.

2.3 STAGE-BY-STAGE FRAMEWORKS

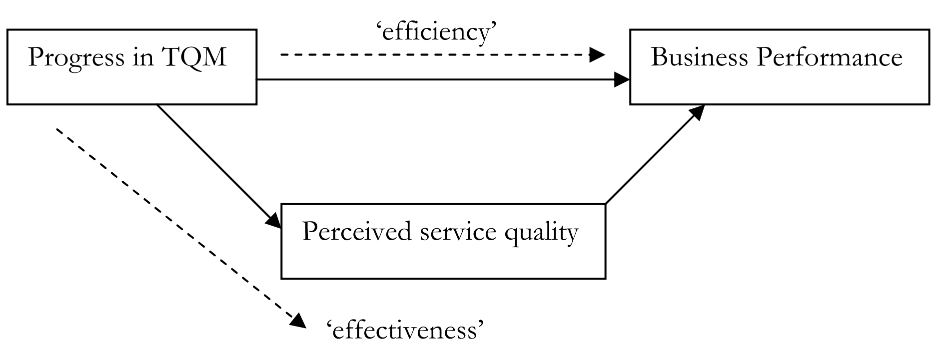
Based on Heskett el al.'s paper, several approaches to model several aspects of the SPC have been presented. In fact, Athanassopoulos (1999) and Soteriou and Zenios (1999) both applied a similar approach to evaluate the service–profit chain of financial institutions using a cascade of DEA models. More recently, Kamakura et al. (2002) present what they call a "comprehensive diagnosis and assessment" of the service organization that has the potential to identify and quantify the benefits of implementing a service strategy, especially for organizations having multiple units. These authors attempt to put all the pieces of the puzzle together for a single organization. They do this through a two-stage approach in which the first stage is called a "*strategic model*," which identifies the attributes or factors of service that pay-off in terms of customer ratings and repeated business. They utilize statistical techniques to prove the relationships. The second stage is called the "*operational model,*" in that they use the identified factors from the first stage, as the inputs to a Data Envelopment Analysis (DEA) framework to evaluate the efficiency in translating the Decision Making Unit's (DMU) investments in quality inputs and resources into repeated business and ultimately, profits. These authors mimic Athanassopoulos' DEA framework of a cascade of non-radial models to accomplish this, but contrary to Athanassopoulos, they do not use the projections of the first node as inputs to the second node, but simply use the actual output values. The DEA evaluation is used to assess how well each DMU in the sample is transforming the inputs into profit. This approach is the same used by other authors (e.g. Medina-Borja, 2002) to evaluate DMUs in different aspects of the service delivery chain. They do this in an attempt to integrate all the pieces of the puzzle, by joining data at the unit level, coming from different sources, such as financial statements, customer satisfaction surveys, and even employees' evaluations of the organization.

According to the above authors, the focus of their empirical approach is not to test the nature of each link in these complex relationships but to illustrate a comprehensive modeling approach from an implementation perspective. To stress this fact, Kamakura et al. (2002) say:

> *"By undertaking such an exercise, a clearer picture of the strategic and operational blueprint of the firm's service strategy emerges. This can be used to set action priorities for top management as well as front-line managers." pp. 296*

Kunst and Lemmink (2000) present their results of a study that identifies and evaluates success parameters of high (quality) performance and their possible interrelationships. The authors adapted the SERVQUAL instrument (developed by Parasuraman et al., 1985; 1988) to hospitals and concluded that environmental variables play an important role in how performance dimensions are correlated and that perceived service quality by customers have only a limited degree of positive effect on business performance (efficiency). They also concluded that progress in Total Quality Management (TQM) implementation leads to higher business performance of hospitals (efficiency/cost effectiveness) and to higher perceived service quality by patients, which in turn increases effectiveness. Figure 2-6 describes the results from the authors.

Figure 2-6. Explanatory power of progress in TQM and service quality in relation to business performance



Adapted from Kunst and Lemmink (2000, p.1132)

Any organization needs to gain more market penetration, battle against the competitors, grow and make money. To accomplish the former, a manufacturing industry for example, needs to give a lot of importance to the quality of the product. In the case of the service industry, better service to the customers is imperative to create customer loyalty. It is expected that higher quality in the products will generate greater customer loyalty and larger market penetration. The larger the market penetration, given constant or reduced costs, the higher the profitability. In short, profitability is the bottom line performance metric or indicator, and all others are aspects of performance that lead to profitability. All of them are important for the absence or under-performance of one of them will undermine the accomplishment of profits.

Hence, performance of an organization is a construct with many dimensions to it. There is lot of literature supporting this fact, (e.g. Sink, 1985; Kaplan and Norton 1992; Brown 1996, Medina-Borja, 2002). Though different authors have different number of dimensions of performance, conceptually they all agree to consider the main dimensions, namely, profitability (in the case of the profit sector), some sort of innovation (to track the organization's learning/growth), internal operations (whatever is going on inside the organization) and customer focus (to satisfy the customer). For instance Sink (1985) and Sink and Morris (1995) present seven interrelated and interdependent performance criteria for an organizational system, namely, effectiveness, efficiency, productivity, quality, quality of work life, innovation and profitability. Kaplan and Norton (1992; 1996) developed the concept of a balanced scorecard covering four areas: financial, learning and growth, internal business process and customer focus as the key perspectives.

Brown (1996) looks at performance and identifies six different categories of data for the measurement system to address:

- Financial performance – related to profitability or sustainability of the firm or organization.
- Product/service quality – related to the actual characteristics of the product or service produced by the organization.
- Supplier performance – related to the different desirable characteristics of the organizations suppliers and partners.
- Customer satisfaction – related to the outcome of the transaction with the customer: level of satisfaction or dissatisfaction.
- Process and operational performance – mainly related to efficiency, wise use of resources, timeliness and other process related measures.
- Employee satisfaction – the outcome of the relationship of the organization's employees with the organization (i.e. their level of satisfaction due to the quality of work life, Quality of Work Life (QWL) and other variables).

Brown also examines two approaches to design performance measurement systems, namely the top-down approach and the by unit/location approach. Brown suggests applying one of these approaches depending on the culture and the type of organization. The top-down approach is effective where the top management has a great amount of control over the entire organization. On the other hand, the unit/location approach seems to fit best where branch offices tend to operate on their own and administer themselves.

Work has also been done in a purely analytical framework to address the dimensions of performance. Medina-Borja (2002) examines a four-node focus to determine the performance of non-profit service industries. The author considers financial, capacity creation, service delivery and customer effectiveness as the four nodes and addresses the transformation process of the inputs at the beginning to intermediate inputs/outputs and finally produce the end outputs and outcomes. Of course, the framework can easily be modified and adapted to examine the profit industry sector as well.

A performance measurement system that considers as a part of its framework, all of these important dimensions of performance, is called a *balanced performance system*. The balanced scorecard[6] by Kaplan and Norton (1992) is one such approach. One would consider such performance measurement system as balanced because it does not provide too much emphasis to any one of the areas that constitute an organization, instead *balances* all aspects of organizational performance.

These dimensions, namely growth, customer perspective, innovation, etc. are not measurable at this level of abstraction. One cannot quantify performance based on these terms. To be able to determine the performance using the various dimensions, one needs to come up with measurable variables or indicators that represent each of these dimensions. These indicators are also termed as metrics. Examples of metrics are WIP levels, inventory, rework, on-time delivery, product defects, etc. These metrics or indicators can be used to determine the overall performance.

Once we have the different indicators, we need to analyze and understand how they relate to one another. The next section provides definitions for the terms leading and lagging indicators.

2.3.1 Leading indicators

As the name suggests, a leading indicator is something that happens '*before*' or in the beginning of the time period of analysis. If we were to consider an organization, anything that happens within the organization has an effect on the service and/or product provided to the customer, which in turn affects the perspective that the customer holds for the organization. Since the internal business operations cause the type of customer perspective (the effect), indicators relating to internal operations are termed leading indicators or *driver metrics*. These are also called as *performance measures* in the literature, see Norreklit (2000). Examples of leading indicators are WIP levels, inventory, etc.

2.3.2 Lagging indicators

A lagging indicator is something that happens '*after*' or in the end. If we were to go back to our manufacturing organization example, indicators relating to the end-result fall under this category (Norreklit, 2000). The service and/or product provided to the customer affect the perception that the customer holds for the organization. This customer perspective is the effect, which has some cause as the driver. Indicators relating to customer perspective are termed lagging indicators or *end-result metrics*. Examples of lagging indicators are on-time delivery to customer, defects in product, etc.

Let us now concentrate our efforts in understanding how the leading and the lagging indicators are related.

2.3.3 Relationship between leading and lagging indicators

'Many managers believe they are using a Balanced Scorecard, when they supplement traditional financial measures with generic, non-financial measures about customers, processes, and employees. But the best Balanced Scorecards are more than ad hoc collections of financial and non-financial measures… A scorecard should contain outcome measures and the performance drivers of those outcomes, linked together in cause and effect relationships'.

- Kaplan and Norton (1996*b*, p. 4).

As the above quote suggests, this prerequisite of cause-and-effect relationships between outcome measures and performance drivers is essential for the balanced scorecard performance measurement framework. However, this essential condition is not unique to the balanced scorecard. We could conceivably look at other forms of measuring performance, not necessarily a balanced scorecard and in many instances; the literature requires some type of causal relationships.

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[6] Balanced Scorecard (Kaplan and Norton 1992; 1996) is an approach that tracks the performance of an organization in four perspectives. This framework will be discussed in the later sections of this chapter.

Norreklit (2000) stresses the importance of having both leading and lagging indicators to have a good balanced scorecard. These leading and lagging indicators have cause-and-effect relationships horizontally within areas and vertically between areas and these relationships exist for sure in reality. Further, one can argue that there are actually circular relationships and not just cause-and-effect relationships. The lagging indicator in the current time period can become the cause for the leading indicator for the next time period. Thus, the effect becomes the cause of the cause and the cause becomes the effect of the effect, thus making it circular. For instance, it is intuitive that organizational growth and learning causes improved internal business processes, which cause greater customer satisfaction and finally better financial measures. These better financial measures aid for future investments in growth and learning.

There is lot more research analyzing the relationships between indicators from a systems perspective of how inputs are converted into outputs. Looking at the non-profit service sector, Medina-Borja (2002) considers the fund raising effort put in by the organization as input that affects the outputs, revenue to the organization. This revenue generated in the financial node affects capacity created by the organization. The capacity in turn has a cause-and-effect relationship with the service delivery and service delivery with customer effectiveness, down the line. The author uses effectiveness to explain the extent of outcome achievement of the service. The author assumes a linear relationship between indicators and convexity for the transformation process. One can easily question the convexity, and linearity assumptions especially between outputs and outcomes.

Figure 2-7. Cause-and-Effect relationship between Leading and Lagging indicators

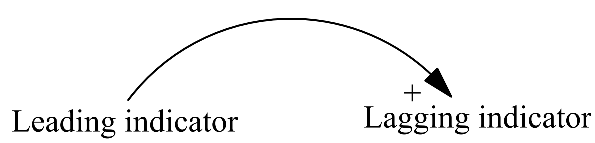


Figure 2-7 represents diagrammatically the cause-and-effect relationship[7] between the leading and lagging indicators. The '+' sign at the head of the arrow indicates that as the leading indicator increases, the lagging indicator increases more than what it otherwise would have been, holding all else equal (Sterman, 2000). To what extent is not evident as of now but part of this research is to explore and put a quantitative value to the extent of cause-and-effect. It symbolically represents our discussion so far.

Figure 2-8. Effect of Rework on On-time delivery

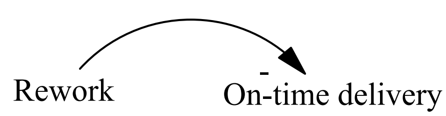


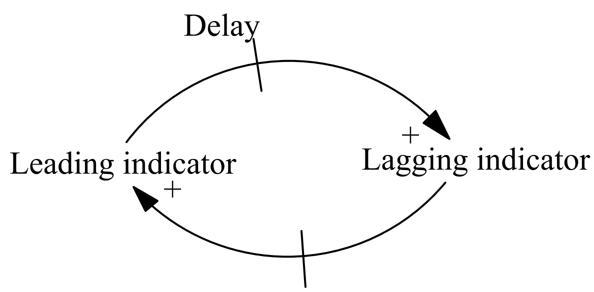
Figure 2-8 shows how a driver metric (rework) affects an end-result metric (on-time delivery). Increase in rework reduces the on-time delivery.

[7] A detailed discussion of System Dynamics as an approach for evaluation and explanation of cause-and-effect will be conducted in the later sections of chapter 2.

This causal relationship is not unidirectional. For instance, in the causal relationship above, the organizational growth and learning in the first place needs good financial results. Again, for innovative ventures and improvement of the internal business, more capital is required, which is possible only in the presence of satisfactory financial numbers. These relationships are circular and there are feedback loops across areas between measures. Figure 2-9 illustrates the feedback loop structure for the bi-directional causality.

The balanced scorecard framework does not address this bi-directional causal relationship. There have been some attempts made to link the balanced scorecard with the notion of feedback, but again, they do not explicitly capture the circular relationship in the structure. Neither does Medina-Borja (2002) look into the bi-directional causality or feedback. One cannot ignore the existence of a feedback loop from the satisfaction of customers back to the financial indicators. These types of relationships are also explored in this research.

Figure 2-9. Bi-directional causality with time delays



Another aspect of the causal-and-effect relationship is the time dimension. Causes and effects of the indicators will occur in different points in time where the lag (outcome) indicators follow the lead (performance) indicators with a time delay. One could assume that any initiative taken by the organization to improve its internal business processes will cater better to the needs of the customer, improve service or product quality and consequently increase customer satisfaction and finally end up with better financial results. All these events will happen with time delays. Typical examples are quality improvement efforts. Results from these interventions do not take place instantaneously without any time delay. Figure 2-9 shows the existence of time delay in the relationship.

Medina-Borja (2002) recognizes the existence of a time lag in the fund raising effort of the organization. The author considers the fund raising efforts put in by the organization in the previous time period to affect the revenue generated in the current time period under analysis. The author captures the effectiveness indicators and addresses the outcomes that are generated after the outputs are created. However, other authors (Brown, 1996; Sink, 1985) leave the time lag as an implicit assumption, without really addressing the issue.

In the previous section, we discussed some of the terminology pertinent to performance measurement. Now with that understanding of performance measurement, indicators and metrics let us move on to the issue of how many of these indicators do we need and their importance.

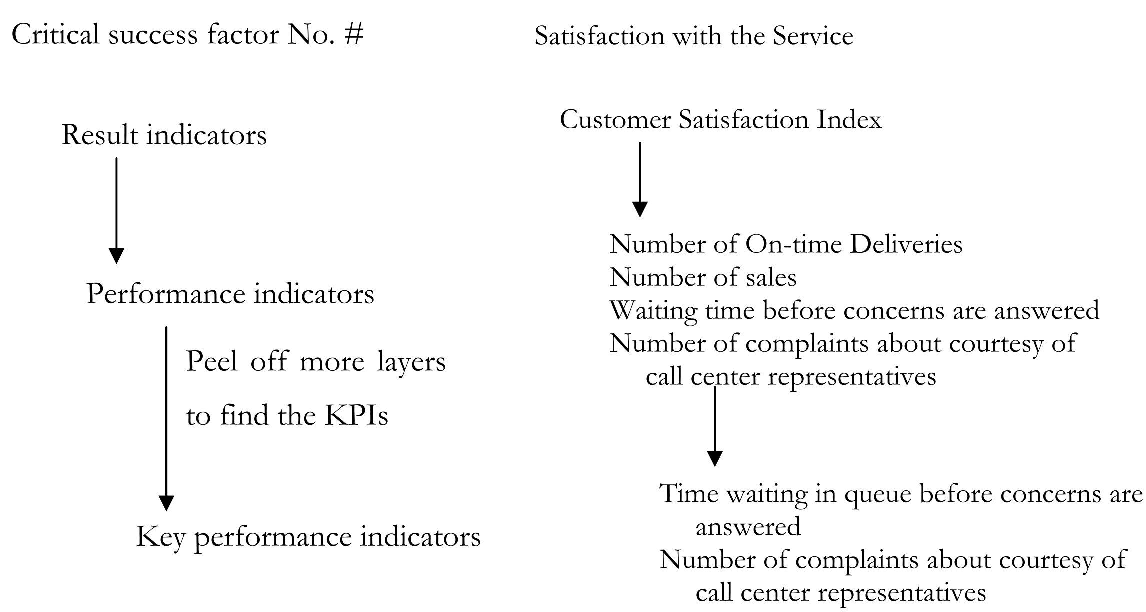
2.3.4 Key Performance Indicators:

An organization can come up with a number potential driver metrics and end-result metrics. More is not better. Having more than required number of indicators and metrics can turn out to be more disastrous than not having any indicators at all (Parmenter, 2002). Hence, it is imperative to narrow down the many potential driver metrics into those that are most important and meaningful. Here it is important to discuss indicators called key performance indicators.

Figure 2-10 shows the hierarchy of the various indicators and a real life example of selecting key performance indicators. According to Parmenter (2002) what is superficial and obvious to the eye are the result indicators, because they are easy to find out. The next level constitutes performance indicators that relate to the internal business operations of the organization.

Key performance indicators are those driver metrics that are most important and meaningful to the organization. They are the main drivers of performance and have maximum leverage on the end-results. They lay many layers beneath the result indicators. There are several ways to select Key Performance Indicators. Some authors talk about Key Performance Areas (KPAs), such as financial, customers, internal, etc. From there, a group of key variables or indicators that provide clues on the situation of the key performance area are identified. From those KPIs statistical analysis such as correlation analysis with the result indicators or factor analysis of all the indicators deemed important is performed. Finally, few KPIs per KPA are selected.

Figure 2-10. Example of the hierarchy of performance measures



Source: Modified from Parmenter (2002, p.49)

The following section discusses in detail the balanced scorecard model and approach to evaluate organizational performance.

2.4 THE BALANCED SCORECARD MODEL AND APPROACH

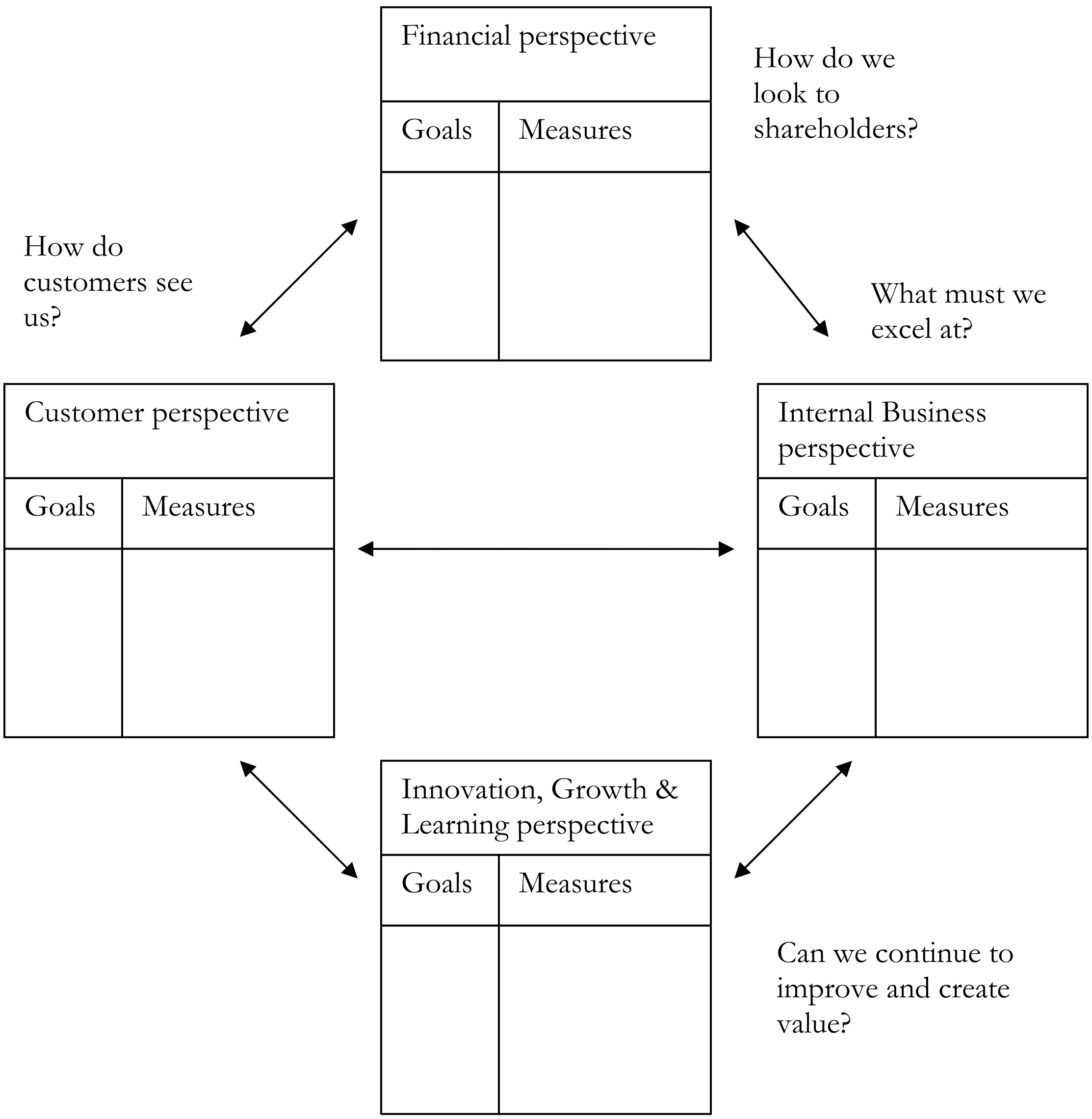
One of the latest "buzz-word"s in management, "balanced scorecard", is a performance measurement model or blueprint developed in the Harvard Business School by Kaplan and Norton (1991). This model was developed to overcome the drawbacks presented by accounting/financial measures traditionally used to evaluate the performance of organizations. These financial/accounting measures such as return-on-investment and earnings per share can be totally false and misleading signals of key areas such as the organization's improvement and innovative activities, Kaplan and Norton (1992). The basic concept of the balanced scorecard is simple. It was presented as a management approach to measure the performance of an organization considering four different perspectives within the organization and the relationship with the environment (customers and competition). It integrates financial and non-financial measures with strategic measures, Norreklit (2000).

As such, the balanced scorecard helps the managers to look at the business from four different perspectives in balance, without putting too much emphasis in any single area. The term "balanced scorecard" reflected the balance between short- and long-term objectives, financial and non-financial measures, lagging and leading indicators and external and internal performance perspectives, Hepworth (1998).

As can be seen in Figure 2-11, the four perspectives are:

- Customer perspective
- Internal Business perspective
- Innovation and Learning perspective
- Financial perspective

Figure 2-11. The Balanced Scorecard links Performance measures



Source: Kaplan and Norton (1992)

The balanced scorecard helps to understand the activities and answer the questions shown in Figure 2-11. According to Kaplan and Norton (1992), the mission statements need to be converted into customer-related measures to reflect the factors that matter to the customer the most, like, time, quality, performance, service, and cost. These measures then feed as input to what the organization must do internally to meet the expectations of the customers. The internal business measures should be based on business processes that have the greatest impact on the satisfaction of the customers. These two types of measures are sufficient if the expectations of the customers and the competition were static and the goals and targets were fixed over time. However, in truth, everything is dynamic. Hence, the organization needs to have the ability to constantly innovate, improve and learn. The measures set for these types of goals fall under the Internal Business perspective. Finally, any organization needs to contribute to the bottom line improvement, related to profitability, growth and shareholder value. The measures set forth for such goals are financial in nature.

Since the inception of the balanced scorecard, other authors have suggested other areas of measurement. For example, in addition to the four above, The Performance Measurement Action Team[8] identified and included "employee empowerment" as an additional balanced scorecard focus (Hepworth, 1998). In all the discussions hereon, only the four main original perspectives or measurement areas of the balanced scorecard will be referred to and employee empowerment will not be one of those.

Kaplan and Norton (1992) also consider the example of an organization to illustrate the application of the balanced scorecard. Since its initial publication, hundreds of organizations worldwide have attempted to implement the balance scorecard concept to measure performance. However, other authors claim that the original concept behind the balanced scorecard is in reality nothing novel. In fact, a French system that was used well before 1992 called the Tableau de Bord, resembles Kaplan and Norton's framework. Epstein and Manzoni (1997) give an elaborate comparison of the two performance measurement systems.

In the literature, one can find both advantages and criticisms of the BSC. Two advantages of using the balanced scorecard as mentioned by Kaplan and Norton (1992). Firstly, it has the capability to bring together many different aspects of the organization like customer focus, internal strategic activities, growth and financial perspective in the same report. Secondly, the authors claim that the balanced scorecard prevents sub-optimization of any of the areas within the organization. How exactly it prevents sub-optimization is not discussed in the literature. These are probably the main two advantages of implementing this framework. Some others will also argue that it is elegant and simple, easy to understand by the average manager.

The criticisms are presented next.

2.4.1 Unidirectional causality

The balanced scorecard assumes that there exist cause-and-effect relationships between the various measures. Thus, the key requirement of the balance scorecard is to establish a cause-and-effect relationship between the various measures across the four perspectives. According to Kaplan and Norton (1992), organizational growth and learning causes improved internal business processes, which cause greater customer satisfaction and finally better financial measures. However, their model does not address the effect of financial measures again on organizational growth and learning. As Norreklit (2000) points out, there is lot of interdependency and in the real world the causality is not unidirectional. For instance, in the causal relationship above, the organizational growth and learning in the first place needs good financial results. And again, for innovative ventures and improvement of the internal business, more capital is required, which is possible only in the presence of satisfactory financial numbers.

Thus, we see that there is lot more dependency and cause-and-effect relationships than the ones described in Figure 2-11. The relationships are circular and there are feedback loops across areas, between measures that the balanced scorecard framework does not address.

[8] The Performance Measurement Action Team is a US governmental body formed to consider government-wide procurement practices.

2.4.2 Inability to distinguish delays between actions and their impact on performance

The delay mentioned here refers to the time delay (or time lag) between the cause and the effect. In our A and B indicators case, now indicators A and B are also separated in time. A happens or occurs before B in time. 'Actions' are steps or interventions taken by the organization to change processes or activities to improve business.

According to Kaplan and Norton (1996*a*), the strategic objectives need to be broken down into targets to be achieved over time. Norreklit (2000) acknowledges this disadvantage:

'… it is problematic that the time dimension is not a part of the scorecard. … still a static section which does not solve the time lag problem', p.71

Causes and effects will occur in different points in time where the lag (outcome) indicators follow the lead (performance) indicators with a time delay. Still, the model does not account for the time delay.

Any initiative taken by the organization to improve its internal business processes will cater better to the needs of the customer, improve service or product quality and consequently increase customer satisfaction and finally end up with better financial results, all with time delays. Typical examples are quality improvement efforts. These relationships cannot be effectively captured on the balanced scorecard without a time dimension.

Norreklit (2000) further notices that measuring the effect of an action related to new and complex activities is particularly problematic since it is difficult or impossible to establish performance measures for activities with which the organization has no or very little experience.

2.4.3 Inability to easily validate results

Kaplan and Norton (1992) as mentioned above assume a cause-and-effect relationship between the measures across various perspectives. Further, the relationships are unidirectional. These assumptions help to make predictions for the financial performance based on non-financial measures. However, the validity of the entire balanced scorecard model relies on the assumptions that such cause-and-effect relationships exist between these areas, Norreklit (2000). When the cause-and-effect relationships are under so much criticism, the validity of the model and the results are in question.

Further, the validity of the model will also depend on the variables selected (indicators) by the organization to be part of the scorecard. It is possible that the organization does not make the best selection of indicators and that they are not related in a cause-and-effect sense, which in turn will invalidate the model.

Kaplan and Norton (1996*a*) also mention that the balanced scorecard is a strategic control system to align the strategy in action to the strategy in the plan. Norreklit (2000) raises a research question here on the validity of the scorecard as a strategic management control approach. This author argues that the balanced scorecard is static in nature and does not take into consideration the external environment such as the competition and the market. In that sense, the metrics will remain the same regardless potential threats that will in turn, affect the relationships. Thus, the strategy will fail to account for those dynamics, invalidating the strategic nature that Kaplan and Norton adjudicate to their framework.

2.4.4 Inability to sufficiently integrate strategy with operational measures

Butler *et al.* (1997) feel that the balanced scorecard is too general, may not fit the organizational culture and jargon and may ignore corporate missions. They also feel that it might be better to build metrics on mission that employees believe in rather than internalize an unfamiliar concept from outside. In such cases, it might be very difficult to integrate the strategic and operational measures.

Even before getting to integrate strategy with operational measures, Epstein and Manzoni (1997) have a problem with the ability of organizations to agree on a strategy in such clear terms that it would enable construction of a balanced scorecard.

The idea of linking measures to strategy[9] is not unique to the balanced scorecard. McNair *et al.* (1990); Beischel and Smith (1991) and Grady (1991) have also dealt with this. Further, Malmi (2001) notes that the claimed link between strategy and measures appears weak in most organizations. These authors arrived at this conclusion by interviewing people at different levels, right from top-level executives to managers to supervisors to direct reports in various organizations.

In most organizations, targets are set for the balanced scorecard measures. Then the managers are held responsible to achieve those targets, which is not quite different from Management by Objectives. Through this, non-financial measures and targets are used along with financial measures to direct managerial emphasis on issues thought to have strategic relevance. In other organizations, no targets are set for these measures and hence the balanced scorecard is more of an information system, (Malmi, 2001). There seems to be no link between the strategy and the operational measures.

Ahn (2001), while applying the balanced scorecard to the strategic business unit of ABB Industries AG, experienced most of the problems as a result of insufficient recommendations concerning the elaboration of the balanced scorecard concept. Further, the author feels that there is a lack of decision-making aids for organizations both when generating the strategic goals and when linking these goals to activities.

2.4.5 Definition of measures that are too internally (within the organization) focused

Vaivio (1995) questions the idea that a handful of quantitative measures can portray the various facets of an organization's strategy.

According to Atkinson *et al.* (1997), the balanced scorecard fails to consider the extended value chain, which is an essential element of today's networked organizations. It does not highlight employee and supplier's contributions. Further, the balanced scorecard fails to identify the role of the community in defining the environment within which the organization operates.

Norreklit (2000) argues that the balanced scorecard does not monitor the competition or technological developments. During the planning stage, the measures may be benchmarked against those of the competitors, but the scorecard does not presuppose any continuous observation of the competitors' actions and results or the monitoring of the technological developments in the field. There might be sudden events in the market that greatly affect the present strategy. Simons (1995) clearly pictures this by saying that, asking what has to be done well in order to realize the planned strategy is not sufficient, rather, it is also important to ask what the external shocks may prevent the realization of the organization's vision.

As the scorecard has had evolutionary improvement over time, it focuses entirely on subjects of internal interest and the customer's interest areas seem to be inadequately integrated into the grand scheme, Lawton (2002).

2.4.6 Other criticisms

Hepworth (1998) mentions that there have been pitfalls and problems in the application of the balanced scorecard as it requires a comprehensive understanding of the principles involved and significant commitment towards accepting the new philosophy and implementing the necessary

[9] According to the Webster dictionary, strategy is defined as an adaptation or complex of adaptations (as of behavior, metabolism, or structure) that serves or appears to serve an important function in achieving evolutionary success.

change. Further, though the balanced scorecard has received lot of appreciation and some applications here in the United States, the concept is still untouched in the United Kingdom.

Finally, as Atkinson *et al.* (1997) note, the balanced scorecard approach is more of a top-down performance measurement and fails to identify the measurement as a two-way process, i.e. both top-down and bottom-up.

The main theme that runs as part of this research is *decision making* – collecting all of the available facts, weaving a well-knit relationship, gaining knowledge of the operations and then making a well-informed decision. All of the models and frameworks discussed thus far have decision making as the common urge. So to be able to make a well-informed decision and answer the research questions, let us start from some basics.

2.5 DECISION MAKING

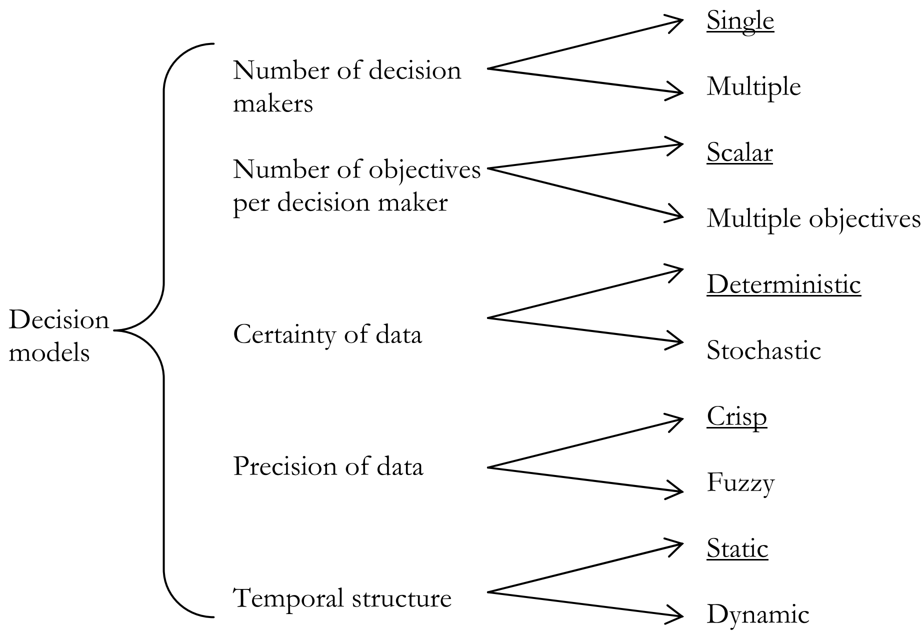
"Setting a goal is not the main thing. It is deciding how you will go about achieving it and staying with that plan."

- Tom Landry

The main characteristic that distinguishes humans from animals is the ability to make rational decisions keeping in mind the long-term consequences (of course, the assumption here is that, given a choice, humans will make rational decisions). The person that makes the decision, *decision maker* is posed with certain needs and preferences and at least two options. Considering these, the decision maker makes a choice to satisfy his/her needs. All of the needs, the preferences and the options available put together constitute a *decision problem*. To be able to arrive at a decision certain analyses need to be done. For this purpose, the real-life decision problem should be represented in a mathematical framework called a *decision model* (Dinkelbach, 1990).

The decision models can be classified based on various criteria, Glaser (2002). As illustrated in Figure 2-12, each decision model has several attributes based on which they are classified. In each classification, the default type is <u>underlined</u>.

Figure 2-12. Classification of Decision Models



Source: Glaser (2002)

2.6 NOTATION

All decision models have an *objective function* and a set of feasible alternatives. Let z be the objective function which represents the preference relation '$\succ$' and has d mutually exclusive alternatives in the set of feasible solutions D. The decision maker assigns objective function values to the alternatives and then will be able to order the alternatives. Then z maps d to the set of real values $\Re$.

$$z : D \to \Re; d \mapsto z(d) \qquad \textbf{Eq 2-1}$$

If the preference is to have higher objective function values, the operator that will be used in the decision model is '*max*' for maximization. The other similar operator is the '*min*' (for minimization) where lower objective function values are preferred.

Glaser (2002) gives the form of a basic decision model as below. The following has the simple attributes – single decision maker, scalar, deterministic, crisp and static.

$$\begin{aligned} &(DM) \\ &\max_{d} \{ z(d) | d \in D \} \qquad \textbf{Eq 2-2} \\ &with \quad z : D \to \Re; d \mapsto z(d) \end{aligned}$$

Each mutually exclusive alternative d is represented a set of L *decision variables*. d_l is a decision variable for all $l \in \{1,2,...,L\}$. Each alternative is given by *N* decision variables. These decision variables can be distinguished into *independent variables* and *dependent variables*. The dependent variables, as the name suggests, can only be affected indirectly through the use of the independent variables. In Dynamic Decision Models (to be discussed in the next section), the independent variables are the *control variables* that are used to cause a change in the *state variables* (dependent variables). The state variables determine the state of the dynamic system at a given point in time.

2.7 DYNAMIC DECISION MODELS

Organizations having so many changes occurring and they grow and evolve over a period of time. Because of these temporal changes, decisions cannot be made just based on analyses done at a snapshot in time. Dynamics as opposed to statics is something that changes over a period of time. According to Machlup (1963), there is a fine line dividing statics and dynamics and Samuelson (1983) argues that statics could be considered as a degenerate case of dynamics. According to Luenberger (1979), "The term dynamic refers to the phenomenon that produces time-changing patterns, the characteristics of the pattern at one time being interrelated with those at other times."

Any decision that needs to be made should include certain factors as part of the decision analysis and exclude certain others. This defines a *boundary*. Anything that is considered as part of the analysis is part of what is called a *system*.

"A system is an assemblage or combination of elements or parts forming a complex or unitary whole."

- Blanchard and Fabrycky (1990, p.1)

Samuelson (1947, p.314) defines a system as being dynamical "if its behavior over time is determined by functional equations in which 'variables at different points in time' are involved in an essential way." Vaneman (2002) defines the relationship between inputs and outputs in an "essential way" by including the results from the past actions to influence or control future actions via a feedback mechanism.

A *planning horizon* is the time period (from start to end) during which the analysis is conducted and the decision made. Let the planning horizon consist of *T* periods and represented by $t(t = 0,1,...,T)$ for *discrete-time systems* and $t(t \in [0,T])$ for *continuous-time systems*. A discrete-time system has countable time periods. For example, in the case of a manufacturing industry, the daily sales are looked at from a discrete-time standpoint, where one can count the number of days in the planning horizon (month, quarter, fiscal year, etc.). An altimeter of a flying aircraft, on the other hand, measures the altitude from the sea level on a continuous-time basis. Let $T_d := \{0,...T\}$ and $T_c := [0,T]$denote the discrete and continuous time horizons respectively.

For a planning horizon of *T* periods, let the state variables that determine the state of the system be represented as below:

$$
\begin{aligned}
x_{l,t} &\in \Re^L \times \Re^{T+1} \quad \textit{where } t \in T_d \quad (\textit{discrete time}) \\
x_l(t) &\in C(T_c)^L \quad \textit{where } t \in T_c \quad (\textit{continuous time})
\end{aligned}
\qquad \textbf{Eq 2-3}
$$

$C(T_c)^L$ is the L-dimensional vector space of continuous real-valued functions on the set $[0,T]$. The vector of the state variables along the time-line will represent the vector-valued *trajectory* (or *path*), called the *vector of state trajectories* or *state trajectory*, Glaser (2002).

In addition, for a planning horizon of T periods, let the control variables be represented as below:

$$\begin{aligned} u_{p,t} &\in \Re^P \times \Re^T \quad \textit{where } t \in T_d \quad (\textit{discrete time}) \\ u_p(t) &\in C(T_c)^P \quad \textit{where } t \in T_c \quad (\textit{continuous time}) \end{aligned} \qquad \textbf{Eq 2-4}$$

$C(T_c)^P$ is the P-dimensional vector space of continuous real-valued functions on the set $[0,T]$. The vector of the control variables along the time-line will represent the *vector of control trajectories* referred to as the *control trajectory*, Glaser (2002).

Dynamical systems can be classified into three distinct types: (1) dynamic and historical; (2) dynamic and causal (Samuelson, 1947); and (3) dynamic, causal and closed (Vaneman and Triantis, 2003). Dynamic and historical systems exhibit a great degree of correlation between the variables at time $t = 0$ and time $t = T$. Neither the structure of the system nor the passage of time is considered in the analysis. Thus, *intermediate variables*, ones that become active in the due course are not considered. Dynamic and causal systems consider the initial variables and the passage of time where intermediate variables can be added. These two systems can be termed as open systems where the feedback loops are ignored. Dynamic, causal and closed systems take the results of the past actions to influence future actions.

Vaneman (2002) looks at the dynamic, causal and closed system from an input-output standpoint. The author explores production theory and builds a model that evaluates the dynamic productive efficiency. This efficiency measure determines how well the organization is doing in producing outputs using the given inputs. It ensures that the organization does not waste any of its resources and ensures that for any given amounts of input, the organization produces optimal amounts of outputs. Conversely, for any given amounts of outputs, the model determines the optimal amounts of inputs that need to be used. The author's research looks closely at the transient state and measures how soon the organization reaches the steady state or equilibrium.

Consider the example of the author where a farmer adds fertilizer to the crops. In the dynamic and historical system case, the farmer plants the crops in spring and returns to harvest in autumn, without caring for the crop during the growing season. In the dynamic and casual system case, the farmer intervenes to add fertilizer, water and pesticides during the growing season irrespective of the crop needing it or not. In other words, there are no feedback mechanisms for the farmer to know if the crops need any intervention. In the dynamic, causal and closed system case, the farmer intervenes only as needed by the crops. Fertilizers, water and pesticides added are based on the crops needing them.

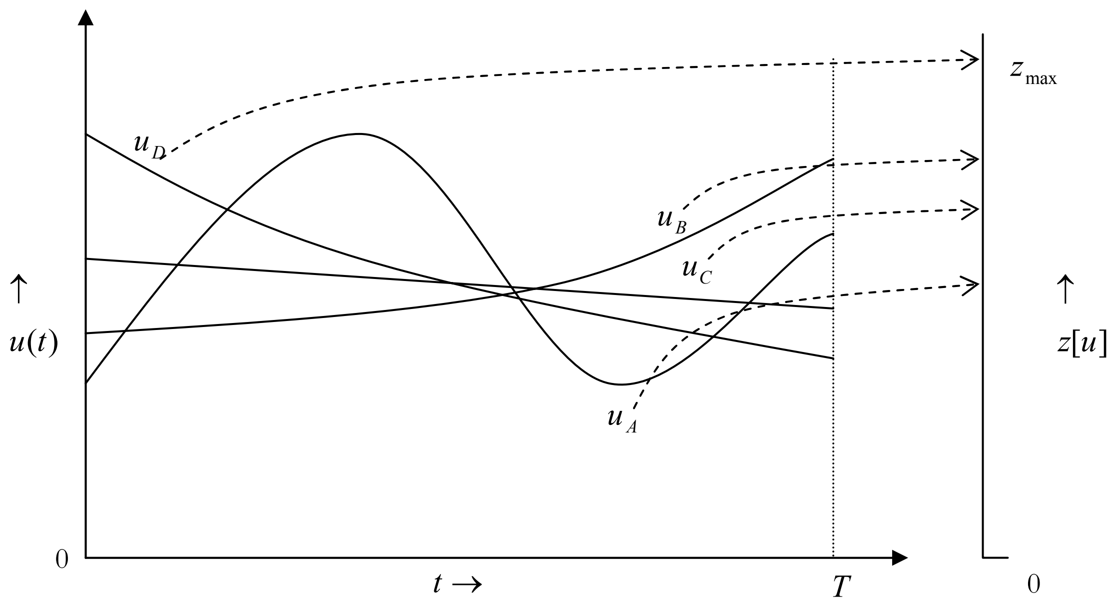
The farmer's only concern is the output from the crops during harvest season that happens once a year. The goal is at the end of the planning horizon. Often, this is not the case. The goal is not just the end of the planning horizon. Every point in the time horizon may be equally important. Even in farming, there are a number of non-seasonal crops and fruits that yield all-year around; the goal is not to wait until the end of the year but make sure to have a good yield during each harvest. Alternatively, consider a farmer with a chicken farm. This farmer needs to be equally concerned about the nutrition of the chickens as well as medicines to cure any diseases as and when the chickens need them. However, his goal is not to wait until the end of the year to collect all the eggs but an everyday day job of collecting and selling them. As Glaser (2002) puts it, destination is not what matters, but journey is the goal.

Another relevant problem is the usage of resources. Considering the most general of systems defined by Vaneman (2002), dynamic, causal and closed system case example, the farmer really only needs to care about maximizing the yield to the greatest possible extent extracting as much nutrients from the soil as required, even if that means none to be left for the subsequent year. This could leave the farmer with a land that is totally void of nutrients in the soil. The author's model does not account for the consumption or determining the production based on the consumption of the outputs or the needs of the customer.

Understanding the examples above, two types of objectives can be defined: (1) scalar objectives and (2) trajectorial objectives, Glaser (2002). Scalar objectives concern one single value of interest in the planning horizon that can be either at the beginning or the end or at any point of time within the planning horizon. Whereas, the trajectorial objectives concern every point of time within the planning horizon. In other words, the object of interest is a trajectory of values.

With the scalar objectives, the task is to map each of the control trajectories to their associated trajectories of states and then onto the scalar value z on the real line and to maximize its value at a certain point in time $\hat{t}$ within the planning horizon. Glaser (2002) represents this graphically as shown in Figure 2-13. Consider a single scalar objective in hand and having four possible control trajectories A, B, C and D over a period of time. These are mapped onto the real line using a function $z[u]$. The control trajectory, which is mapped to the maximum value, is the solution to the decision making problem. In Figure 2-13, when the control trajectories u_A, u_B, u_C and u_D are mapped onto the real number line $z[u]$, with the corresponding objection function values, $z_{\max}$ represents the maximum objection value mapped by the control trajectory u_D. Hence, u_D is the solution to the decision making problem.

Figure 2-13. Mapping control trajectories to a scalar objective



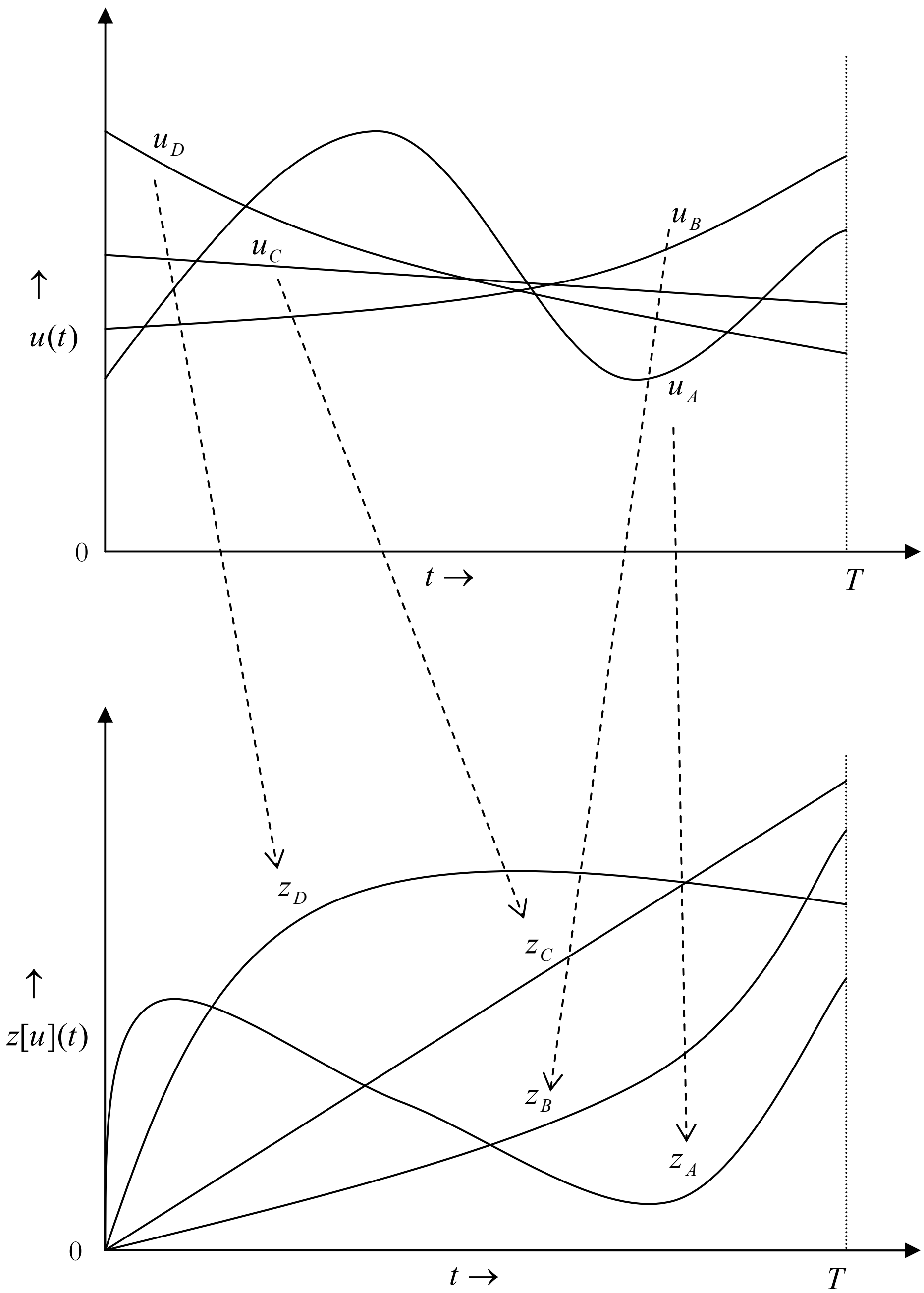
Source: Glaser (2002)

What is the overall objective and how we go about evaluating the achievement of objectives are two very relevant and interesting questions. In the next section, we will discuss the dominance based approach.

2.7.1 Dynamic dominance

Dynamic decision models with a different objective for every point in time have a set of objective values. These objective values over the entire time horizon form a *trajectory of objective values* or an *objective trajectory*, Glaser (2002). As can be seen in Figure 2-14, the control trajectories are mapped to not just real values but objective trajectories. The solution to the decision making problem is the control trajectory that *dynamically dominates* the other control trajectories. The term is defined in the next section.

Figure 2-14. Mapping of control trajectories to trajectorial objectives



Source: Glaser (2002)

For two control trajectories $u', u'' \in X$, control trajectory u' *dynamically dominates* u'' with respect to z, if (Glaser 2002)

$$z[u']_t \geq z[u'']_t \, \forall t \in T'_d \qquad \text{and}$$

$$\exists \tau \in T'_d : z[u']_\tau > z[u'']_\tau \qquad \textbf{Eq 2-5}$$

This research is borrowing the concept of sustainability and applying it to the business world. The ability to meet the needs is translated into meeting the objectives set forth for the organization. For any organization, the objective is to *sustain* itself over a trajectory of aspiration values over the period of interest. Aspiration trajectory ($\bar{y}$) was a term introduced by Glaser (2002). Aspiration trajectory is the vector of profit over time. The object of interest (e.g. profit) can be sustained to maintain a certain desirable *level*. Or the *change* of its level over time can be sustained or further, the *change* of its change can be sustained. This aspect ensures growth of the organization at a certain rate. The form can be of any type depending on the application and the indicator to be sustained. These objects can be defined with aspiration trajectories over a period of time.

Ideally, the object of interest shall be sustained over the entire time horizon. This can be defined by the term strong sustainability.

2.7.2 Strong sustainability:

Given an aspiration trajectory $\bar{y}$, a trajectory pair (consisting of control trajectory u and its associated state trajectory x with $\left(x^T, u^T\right)^T \in X$ is called (strongly) $\bar{y}$-sustaining (Glaser 2002), if

$$y_d(x_t, u_t, t) \geq \bar{y} \quad \forall t \in T'_d \qquad \text{and}$$

$$y_c(x(t), u(t), t) \geq \bar{y} \quad \forall t \in T_c \qquad \textbf{Eq 2-6}$$

which can be represented as

$$y \geq \bar{y} \qquad \textbf{Eq 2-7}$$

or further,

$$\mu \geq 0 \qquad \textbf{Eq 2-8}$$

The set of (strongly) $\bar{y}$-sustaining alternatives is defined by

$$X_{sust}(\bar{y}) := \left\{ \left(x^T, u^T\right)^T \in X \middle| y \geq \bar{y} \right\} \qquad \textbf{Eq 2-9}$$

If $X_{sust}(\bar{y})$ is a non-empty set, then $\bar{y}$ is (*strongly*) *sustainable* with respect to X and the given yield function $y_d\left(x_t, u_t, t\right)$ and $y_c\left(x(t), u(t), t\right)$ respectively and every control trajectory u_{sust} with $\left({x_{sust}}^T, {u_{sust}}^T\right)^T \in X_{sust}(\bar{y})$ ensures the *sustainability* of $\bar{y}$.

In the case of an infinite planning horizon $T = \infty$, if the set $X_{sust}(\bar{y})$ is non-empty, then $\bar{y}$ is called *permanently sustainable*.

However, it may not be possible to attain strong sustainability of the aspiration trajectory $\bar{y}$ over the entire time horizon. For such cases, Glaser (2002) introduces a general relaxation with a threshold point of time $\tau > 0$ with $\tau \in T'_d$ and, respectively, $\tau \in T_c$ to start the phase in which the aspiration must be met, which takes us to the definition of weak sustainability.

2.7.3 Weak sustainability:

Given an aspiration trajectory $\bar{y}$, a trajectory pair (consisting of control trajectory u and its associated state trajectory x with $(x^T, u^T)^T \in X$ is called (*weakly*) $\bar{y}$ *-sustaining* (Glaser 2002), if for a *threshold* point of time $\tau > 0$ with $\tau \in T'_d$ and, respectively, $\tau \in T_c$ the inequalities

$$y_d(x_t, u_t, t) \geq \bar{y} \quad \forall t \in \{\tau, ..., T-1\} \qquad \text{and}$$

$$y_c(x(t), u(t), t) \geq \bar{y} \quad \forall t \in [\tau, T] \qquad \textbf{Eq 2-10}$$

which can be represented as

$$y \overset{\tau}{\geq} \bar{y} \qquad \textbf{Eq 2-11}$$

or further,

$$\mu \overset{\tau}{\geq} 0 \qquad \textbf{Eq 2-12}$$

The set of (weakly) $\bar{y}$ -sustaining alternatives is defined by

$$X_{sust}(\bar{y}, \tau) := \left\{ \left(x^T, u^T\right)^T \in X \,\middle|\, y \overset{\tau}{\geq} \bar{y} \right\} \qquad \textbf{Eq 2-13}$$

If $X_{sust}(\bar{y}, \tau)$ is a non-empty set, then $\bar{y}$ is (*weakly*) *sustainable with threshold* τ with respect to X and the given yield function $y_d(x_t, u_t, t)$ and $y_c(x(t), u(t), t)$ respectively and every control trajectory u_{sust} with $\left(x_{sust}{}^T, u_{sust}{}^T\right)^T \in X_{sust}(\bar{y}, \tau)$ ensures the *weak sustainability* of $\bar{y}$.

The extreme case, with $\tau = 0$, the weak sustainability collapses and one has strong sustainability again,

$$y \overset{\tau=0}{\geq} \bar{y} \Leftrightarrow y \geq \bar{y} \qquad \textbf{Eq 2-14}$$

Up to this point, we have looked at decision modeling, dynamic decision making and the concept of dominance as it is documented in the literature.

To be able to model the Service-Profit Chain, there is a need for an approach that can capture the structure and the interrelationships between the various components of the chain. The next section describes one such approach in detail.

2.8 SYSTEM DYNAMICS

> *"[System dynamics] is an approach that should help in important top management problems … Many predetermine mediocre results by setting initial goals too low. The attitude must be one of enterprise design. The expectation should be for major improvement … The attitude that the goal is to explain behavior, which is fairly common in academic circles, is not sufficient. The goal should be to find management policies and organizational structures that lead to greater success."*
>
> - Jay W. Forrester (Industrial Dynamics, 1961, p. 449)

System dynamics modeling is a methodology that captures complex and non-linear relationships between components of a closed boundary system over time (dynamic) and provides solution to problems for better decision making. System dynamics was born in the form of Industrial Dynamics (Forrester, 1961), Urban dynamics (Forrester, 1969) and World dynamics (Forrester, 1971).

System dynamics is more of a top-down approach different from complex adaptive approaches like agent-based modeling for instance, which are built bottom-up. Agent based modeling simulates the behavior of the system based on the relationships between agents (or entities in the real world). These agents capture the belief, knowledge and objectives of their real-world counterparts by means of simple rules and norms they will follow under certain circumstances (Collings et al. 2000; Macy and Willer 2002; Chiva-Gomez 2003). The whole process of modeling using system dynamics, validation, gathering insights, revisiting the results and going back to the model to make changes makes it a learning model.

The agent based modeling approach will be more useful if the research problem were to focus solely on the customer perspective and to analyze how they behave to referrals and recommendations. In such a scenario, the customers will be modeled as agents. However, in the current research problem, there is also an organization perspective, where investments are made in operational attributes and the customers do not come in direct contact with these investments. Further, this research also aims to answer whether the chain is sustainable. Hence, for this research, system dynamics modeling approach will be more useful than agent based modeling.

A decision-making problem can be modeled using system dynamics. System dynamics models the problem and helps in understanding the system and doing things. System dynamics is not a performance measurement framework but an approach that enables decision-making. It is an approach that helps one understand the dynamic behavior of systems. System dynamics cannot substitute the balanced scorecard or any other performance measurement system. Instead, it can be used in conjunction with one of the measurement frameworks to better understand the internal structure of the system that includes the technology, the transformation processes, relationships with the environment, feedback mechanisms that determine the behavior over time.

System dynamics has been used to model problems in various fields and understand the systems better, see for instance Forrester 1961, 1969, 1971; Sterman 2000; Vaneman 2002. Santos et al. (2002) use system dynamics along with multi-criteria decision analysis to approach management processes to measure performance. The authors illustrate the applicability in the health services sector. The research conducted here will not try to cover all the literature available on system dynamics, but instead focus only on those concepts needed to build a model and to answer the research questions.

System dynamics is built on the premise that the behavior of the system is consequence of the system structure (Richardson and Pugh, 1981). Further, system dynamics models have two attributes in common: (1) they involve quantities that change over time; and (2) they have control or feedback loops. Hence, actions taken in one time period influence the actions taken in subsequent periods (Richardson and Pugh, 1981).

The results from decisions may be immediately apparent or may be dormant and surface up after a delay in space and/or time. This delay is due to the characteristic of the closed loops and the feedback structures. The feedback structures can be broken down into a hierarchy of feedback elements. The elements of this hierarchy are variables, linkage, feedback loop and a feedback system (Roberts, 1978).

Quantities that change over time are called *variables* (Roberts, 1978). Variables can be one of three types – *level*, *rate* or *auxiliary*. The state of the system is described by the *level variables* with accumulations. The *rate variables* change the accumulations of the level variables and control the flow. System policies control the rate variables, (Drew, 1994). The assumption used to build the system dynamics model is that the structure can be represented using a series of level and rate variables (Forrester, 1961).

The level and rate variables are interlinked with a series of cause and effect relationships that determine the underlying flows within a system. These relationships and the flow bring the various components together to be viewed as a single holistic entity as opposed to having a bunch of individual components (Roberts, 1978). Forrester (1961) identified six flows within the system to be material, money, people, capital equipment, orders and information.

Levels (also known as stocks, state variables, integrals) are accumulations of inflows and outflows over a period of time. The mathematical representation of a level variable is given by the following integral (Forrester, 1961 and 1968; Richardson and Pugh, 1981).

$$Level(t) = Level(t_0) + \int_{t_0}^{t} (Inflow - Outflow)dt \qquad \textbf{Eq 2-15}$$

where,

$Inflow$ is the quantity that flows into the $level$

$Outflow$ is the quantity that flows out of the $level$

$Level(t_0)$ is the initial value of the level in the system at time t_0

$Level(t)$ is the value of the level in the system at time t

VENSIM (1998), software used to run the system dynamics simulations, gives the initial value of the level at time t_0 as below:

$$Level(t_0) = f\left(levels(t_0), auxiliaries(t_0), data(t_0), cons\tan ts\right) \qquad \textbf{Eq 2-16}$$

Examples of level variables are inventory levels, balance sheet items, number of professors/teachers, etc. All of these variables will have values at any given point in time. When the system is stopped for an instant, level variables will have a value that determines the state at that instant.

The rate of change of the level can be determined by differentiating with respect to time as below (Sterman, 2000):

$$\frac{d}{dt}(Level) = Net\ Change\ in\ Stock = Inflow(t) - Outflow(t) \qquad \textbf{Eq 2-17}$$

The rate variables (also known as flows, rates of change, derivatives) determine how fast a system is changing. The rate equation recognizes the system goal, compares the goal with the current state of the system and makes corrections to narrow the discrepancy and get closer to the goal (Forrester, 1961 and 1968). VENSIM (1998) represents a rate variable as below:

$$Rate(t) = f\left(levels(t), auxiliaries(t), data(t), constants\right) \qquad \textbf{Eq 2-18}$$

where,

f is an arbitrary, non-linear, time varying vector function.

Examples of rate variables are throughput, income statement items, etc.

Sterman (2000) gives a table with different terminologies used in various disciplines to describe levels (stocks) and rates (flows).

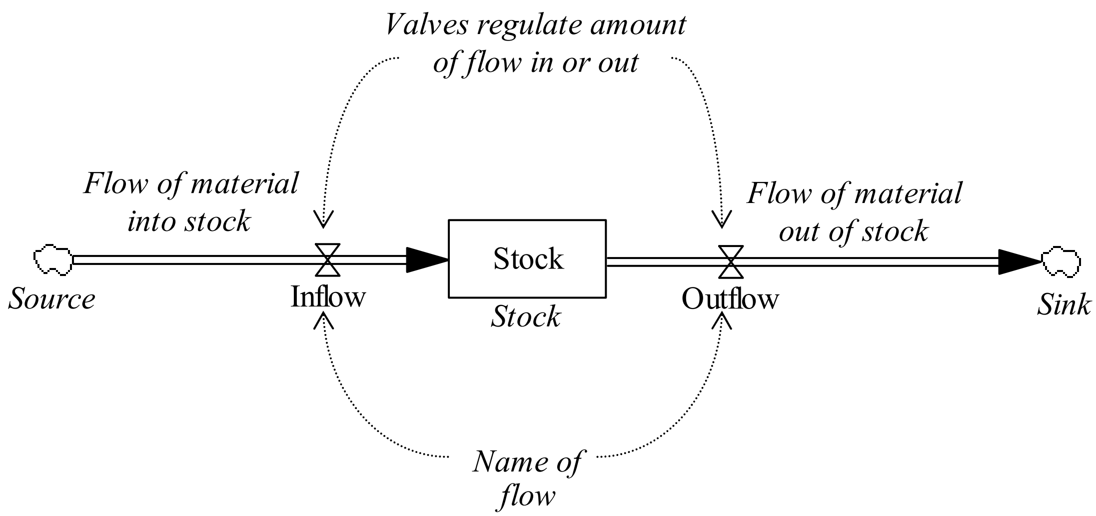
Table 2-1. Terminology to describe stocks and flows

Field	Stocks	Flows
Mathematics, physics and engineering	Integrals, states, state variables, stocks	Derivatives, rates of change, flows
Chemistry	Reactants and reaction products	Reaction rates
Manufacturing	Buffers, inventories	Throughput
Economics	Levels	Rates
Accounting	Stocks, balance sheet items	Flows, cash flow, income statement items
Biology, physiology	Compartments	Diffusion rates, flows
Medicine, epidemiology	Prevalence, reservoirs	Incidence, infection, morbidity and mortality rates

Source: Sterman (2000, p.198)

In VENSIM, stocks are represented by rectangles and flows (inflow and outflow) are represented by arrows into or out of the stock respectively. Valves control the flows. A diagram that graphically represents the relationships between stocks and flows is called a *stock and flow diagram* (or SFD for short). The following figure shows the diagrammatic representation of stocks and flows.

Figure 2-15. Representation of stocks and flows

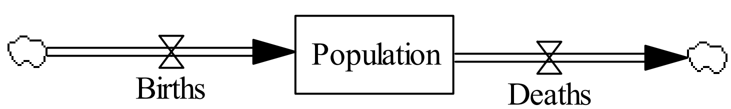


Source: Sterman (2000, p.193)

For example,

Births add to population and deaths reduce the population.

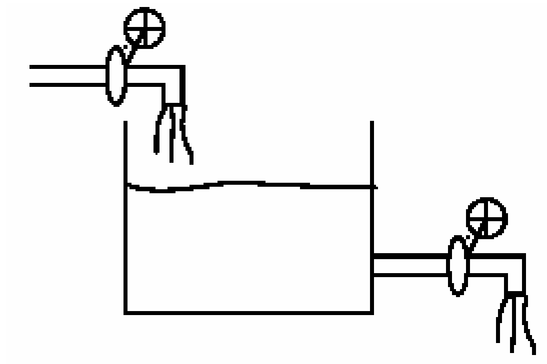
Figure 2-16. Example of stock and flow



One of the day-to-day life examples of stocks and flows is a hydraulic metaphor. Water flowing in and out of a reservoir (stock) can be considered as flows (Forrester, 1961). Sterman (2000) gives the four equivalent representation of the stock and flow structure.

Figure 2-17. Equivalent representations of stocks and flow

Hydraulic metaphor:



Stock and Flow Diagram:

Integral Equation:

$$Level(t) = Level(t_0) + \int_{t_0}^{t} (Inflow - Outflow)dt \qquad \textbf{Eq 2-19}$$

Differential Equation:

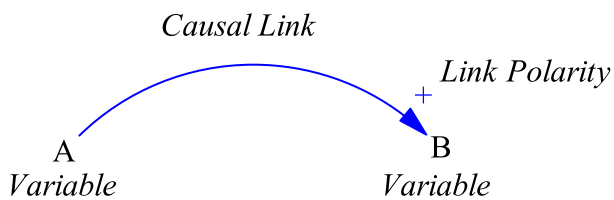
$$\frac{d}{dt}(Level) = Net\ Change\ in\ Stock = Inflow(t) - Outflow(t) \qquad \textbf{Eq 2-20}$$

Source: Sterman (2000, p.194)

A *linkage* is a cause-and-effect relationship between variables (Roberts, 1978). Sterman (2000) refers to this linkage as a *causal link*. Two variables are said to have a cause-and-effect relationship if at least one of the two variables affect the other. The cause can have either a positive effect or a negative effect. If neither holds true, then the two variables do not have a causal link. The *link polarity* shows the type of effect, positive or negative.

Two variables, A and B that have a positive cause-and-effect relationship can be graphically represented as below:

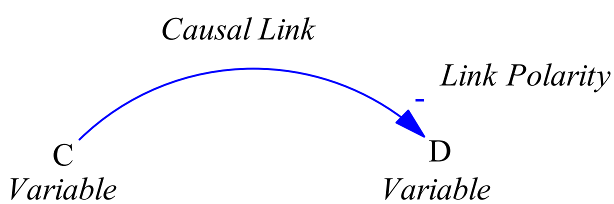
Figure 2-18. Positive cause-and-effect relationship



The positive link polarity means that if the cause (variable A) increases, the effect (variable B) increases above what it would otherwise have been, and if the cause (variable A) decreases, the effect (variable B) decreases below what it would otherwise have been (Sterman, 2000).

Similarly, two variables C and D that have a negative cause-and-effect relationship can be graphically represented as below:

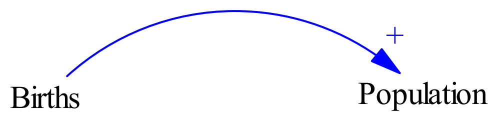
Figure 2-19. Negative cause-and-effect relationship



The negative link polarity means that if the cause (variable C) increases, the effect (variable D) decreases below what it would otherwise have been, and if the cause (variable C) decreases, the effect (variable D) increases above what it would otherwise have been (Sterman, 2000).

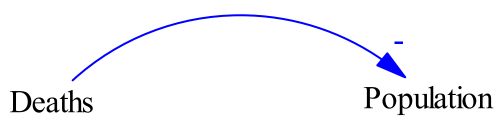
An example is the relationship between births and population. An increase (or decrease) in births increases (or decreases) the population above (or below) what it otherwise would have been. Here, the variable births has a positive effect on the variable population.

Figure 2-20. Example of a positive cause-and-effect relationship



Similarly, the variable deaths has a negative effect on the variable population. An increase (or decrease) in deaths decreases (or increases) population below (or above) what it otherwise would have been.

Figure 2-21. Example of a negative cause-and-effect relationship



A *feedback loop* is a collection of two or more linkages where one can start at a variable, go around the loop and end at the original variable. Feedback loops are the basic structure of system dynamics problems and contain stock and flow variables. According to Forrester (1968), every decision and all actions in a system occur within the feedback loop. Feedback loops can be characterized as positive or negative, called the *loop polarity*. A feedback loop is positive (or negative) if it has even (or odd) number of negative linkages (zero negative linkages being considered even), Richardson and Pugh (1981).

Sterman (2000) gives the mathematical way of deducing the type of feedback loop.

Figure 2-22. Given feedback loop

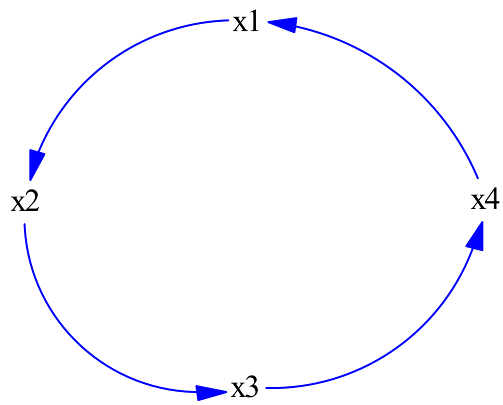
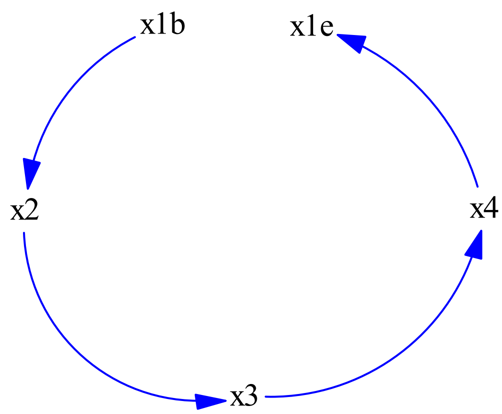


Figure 2-23. Deducing loop polarity



Source: Sterman (2000, p.146)

Any given feedback loop as in Figure 2-22 can be broken and represented as in Figure 2-23. Sterman (2000) defines the polarity of the loop as

$$Polarity\ of\ loop = \partial x1(e) / \partial x1(b) \qquad \textbf{Eq 2-21}$$

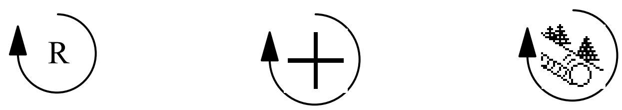
where:

$$\partial x1(e) / \partial x1(b) = \left[(\partial x1(e) / \partial x4)(\partial x4 / \partial x3)(\partial x3 / \partial x2)(\partial x2 / \partial x1(b)) \right] \qquad \textbf{Eq 2-22}$$

From equation above, it is clear that the polarity of the loop is the product of all the partial derivatives. Hence, an even (or odd) number of negative signs will results in a positive (or negative) loop polarity (Sterman, 2000).

Positive feedback loops are shown with a '+' or an 'R' (for Reinforcing) inside a circular arrow within the loop and the arrow pointing in the direction of flow (Sterman, 2000). Another way of representing a positive feedback loop is with a graphic of a snowball hurtling down a steep slope inside a circular arrow.

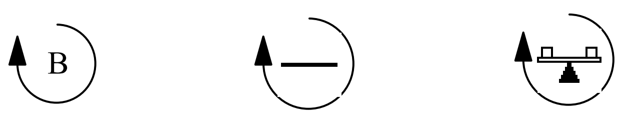
Figure 2-24. Equivalent ways of representing positive feedback loops



Positive feedback loops generate growth, amplify deviations and reinforce change (Sterman 2000, p.111). Feedback loops with positive loop polarity are *self-reinforcing* in nature as they keep building up (Senge, 1990).

Negative feedback loops are shown with a '-' or a 'B' (for Balancing) inside a circular arrow within the loop and the arrow pointing in the direction of flow. Such loops seek balance, equilibrium and stasis (Sterman, 2000). Another way of representing a negative feedback loop is with a graphic of a balance with two weights on a fulcrum inside a circular arrow.

Figure 2-25. Equivalent ways of representing negative feedback loops



Feedback loops with negative loop polarity are *self-balancing* in nature (Senge, 1990).

A *feedback system* is a series of two or more feedback loops with common variables between them. Causes in one of the loops affect another loop through the cause-and-effect relationship between variables. Typical organizational and industrial problems can be described by a feedback system (Forrester 1961, 1968, 1971; Sterman 2000). Most information can be derived from areas where multiple feedback loops converge (Roberts, 1978).

The feedback system describes the structure by capturing all the relationships between the variables and feedback loops through linkages. This structure determines the behavior of the system. The behavior over time is depicted on charts called *behavior over time charts* or BOT charts, for short (Sterman, 2000). The next section will research some of the fundamental behaviors and find out how these structures determine the behavior over time.

2.9 FUNDAMENTAL MODES OF DYNAMIC BEHAVIOR

A different structure can give rise to a different behavior. With all possible combinations of variables, linkages and loops, it is likely to end up with very many different types of structures which will give rise that many different behaviors. The most fundamental modes of behavior are exponential growth, goal seeking and oscillation. Other modes of behavior like S-shaped growth, S-shaped growth with overshoot, and overshoot and collapse arise from nonlinear interactions of the fundamental feedback structures (Sterman, 2000). To make it complete, equilibrium and exponential decay will be included along with the three most fundamental modes and the three additional modes of behavior (Vaneman, 2002).

2.9.1 Equilibrium:

Equilibrium is the most basic type of system behavior. When a system is in equilibrium, it is said to have attained steady state. There are two types of equilibrium – static and dynamic. In a static equilibrium, there is no change in the system. The system is idle. All flows are zero and all stocks are constant.

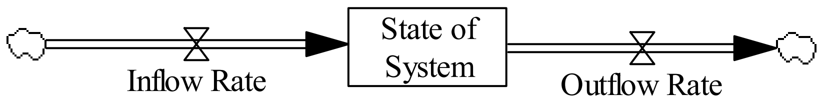
A system is said to be in dynamic equilibrium if the net flow is zero. In other words, the net inflow equals the net outflow. However, all the stocks remain constant. The model is shown in Figure 2-26 using a stock and flow diagram. The two types of equilibrium hold with different conditions as shown below. In either case, the behavior of the system is at a constant level over time.

2.9.2 Exponential growth:

Such a behavior is exhibited by a single positive reinforcing feedback loop. Consider a feedback loop with two variables – one flow and one state of the system. Let a constant c determine the flow rate. Further, let the two variables have a positive impact on one another. Hence, an increase in the rate increases the state of the system above what it would otherwise have been and an increase in the state of the system increases the rate above what it would otherwise have been. The causal loop diagram, stock and flow diagram and the behavior are shown in Figure 2-27. Pure exponential growth has a remarkable property where the *doubling time* is constant, i.e. the state of the system doubles itself (no matter how large) in a fixed period of time (Sterman, 2000).

Figure 2-26. Structure and behavior of equilibrium

Structure



Static equilibrium	Dynamic equilibrium
Inflow Rate = Outflow Rate = 0	Inflow Rate = Outflow Rate
State of System = constant	State of System = constant

Behavior

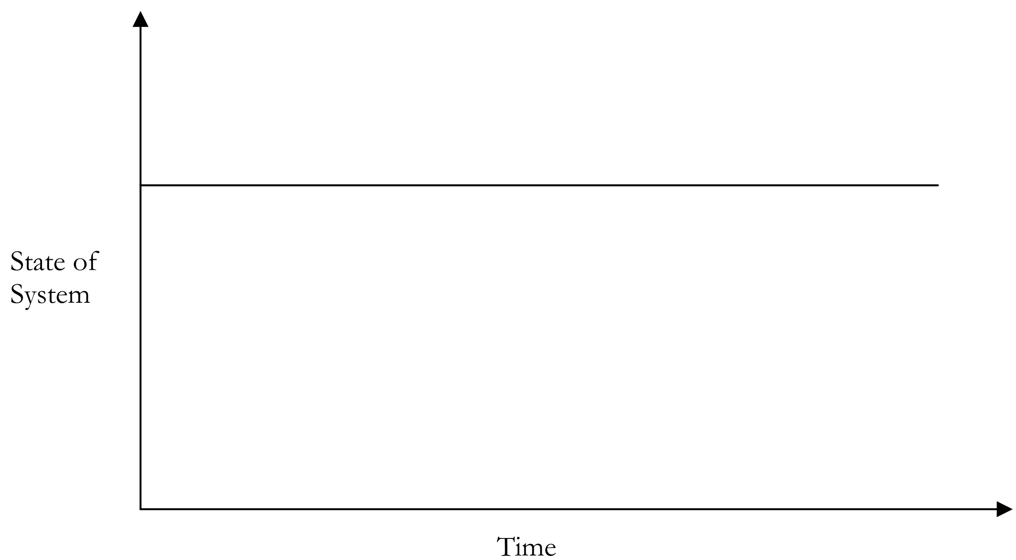
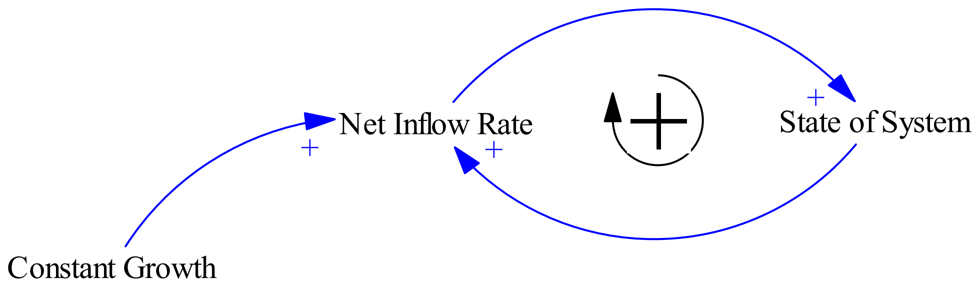
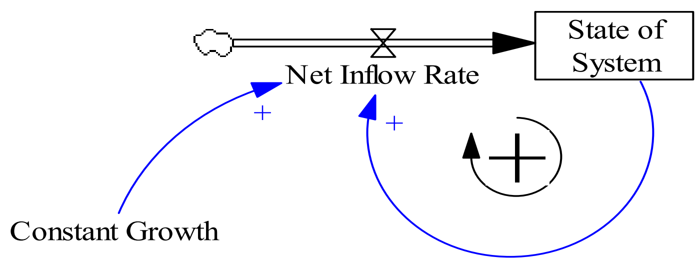


Figure 2-27. Structure and behavior of exponential growth

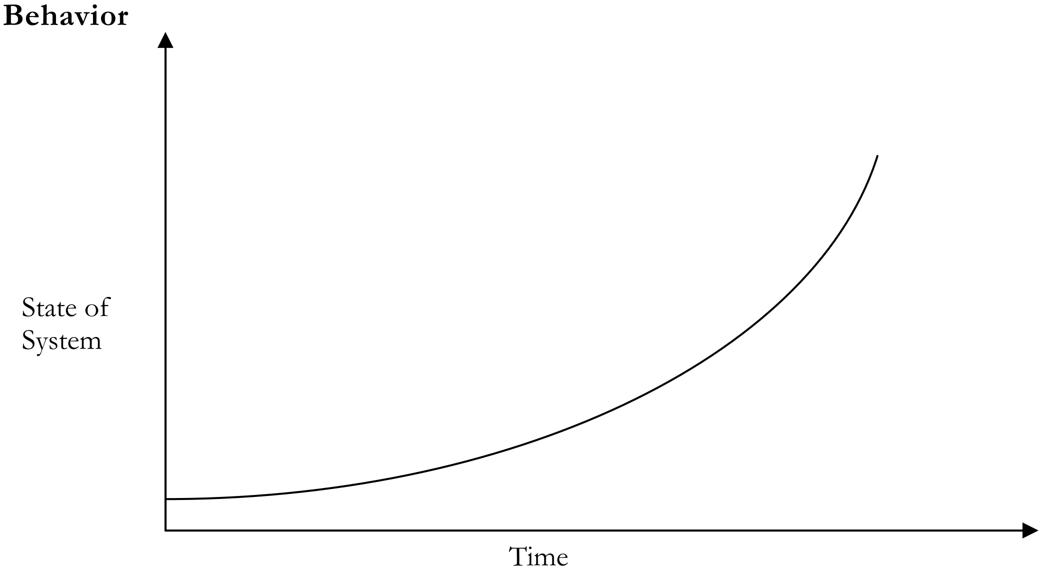
Structure – Causal loop diagram



Structure – Stock and flow diagram



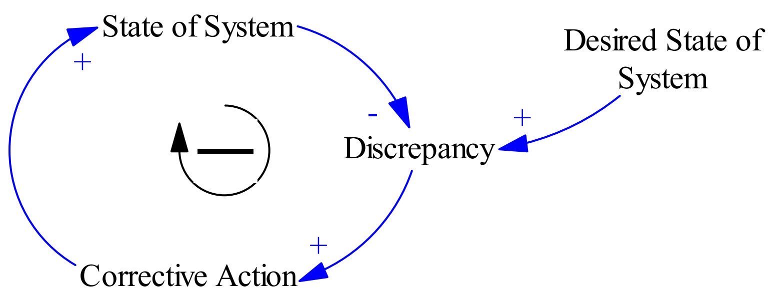
Behavior



Source: Based on Sterman (2000, p.109)

Figure 2-28. Structure and behavior of goal seeking

Structure



Behavior

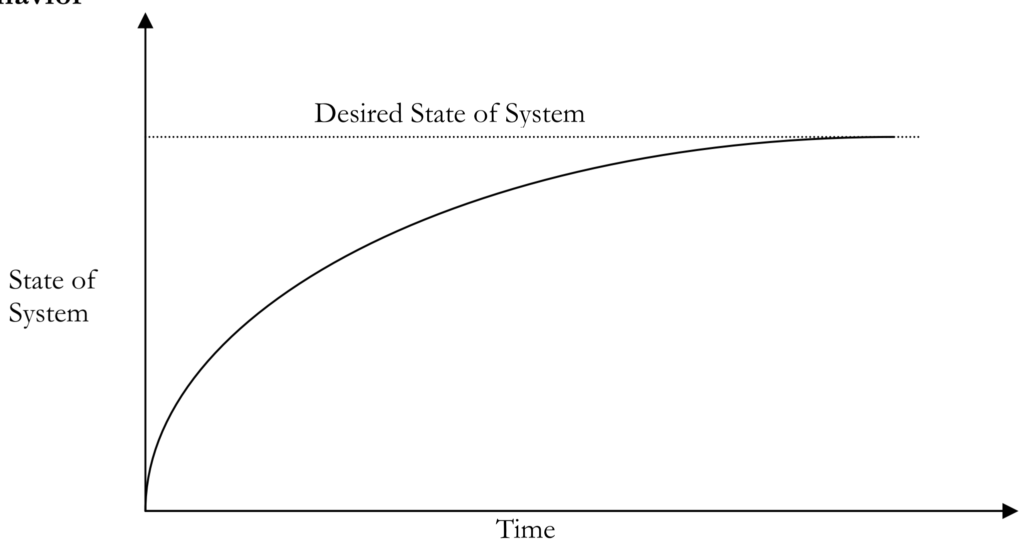
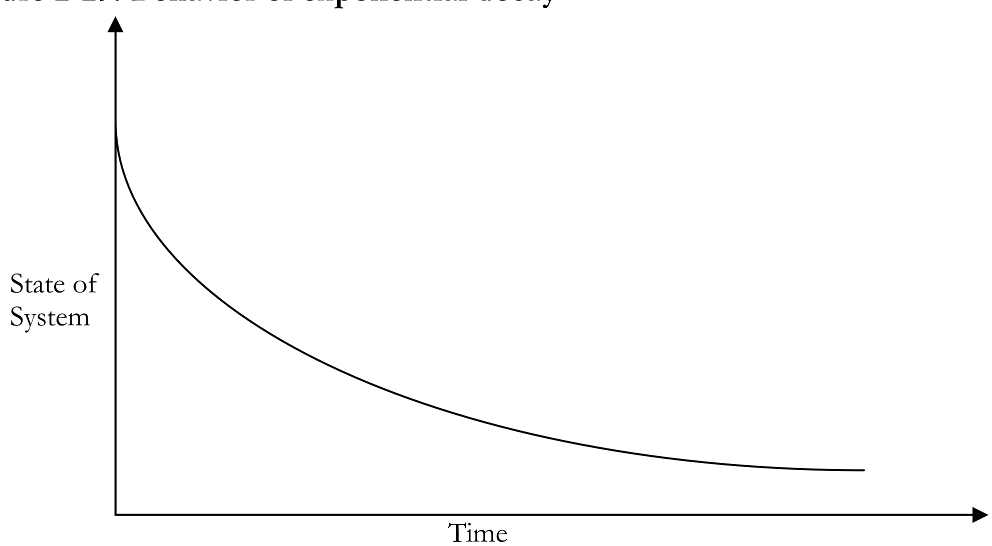


Figure 2-29. Behavior of exponential decay



Source: Sterman (2000, p.111)

2.9.3 Goal seeking:

A goal seeking structure brings the system to a desired state or goal. For every time period, the state of the system is compared with the desired state of the system. Based on the difference or the discrepancy, extent of the corrective action is determined (here, the net inflow rate). This will affect the state of the system in the next time period. The further the state of the system from the desired state, the more the discrepancy, the more will be the corrective action. As the state approaches the desired state, the difference will reduce and so will the corrective action. The structure (causal loop diagram) and behavior are shown in Figure 2-28 (Sterman, 2000).

2.9.4 Exponential decay:

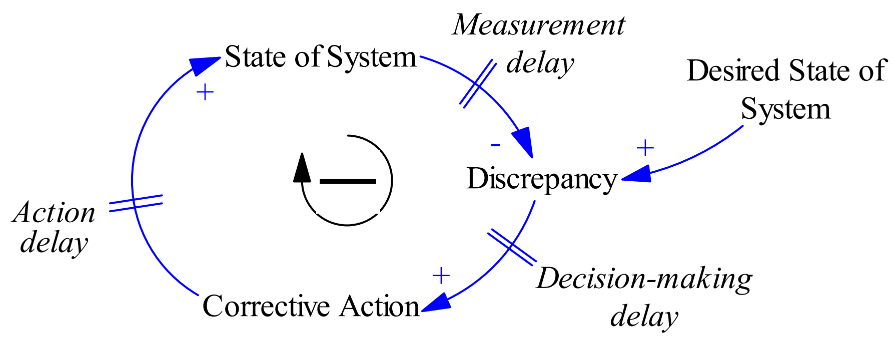
Exponential decay is a special case of goal seeking where the relationship between the size of the gap and the corrective action is linear. An interesting characteristic of the exponential decay structure is its *half-life*. This is the time required for half of the gap to be eliminated (Sterman, 2000). The structure is similar to the one for goal seeking in Figure 2-28, except that instead of the state growing to reach the goal, its diminishing and the linear relationship above holds true. The exponential decay behavior is shown in Figure 2-29.

2.9.5 Oscillation:

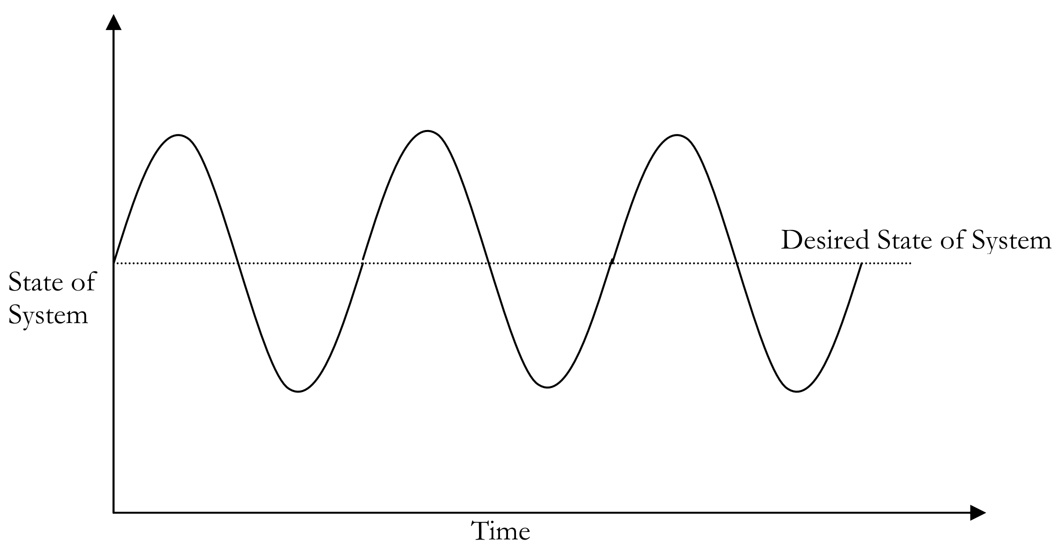
Oscillation is the third most fundamental mode of behavior, which are also caused by negative feedback loops where a corrective action tries to bring the state of the system to its goal. However, what brings about the oscillation is the presence of *time delays* in one or more of the causal linkages in the negative feedback loop. When there is a discrepancy between the actual and the desired states, the corrective action is applied only after a time delay, which results in the actual state overshooting the desired state and further increasing the discrepancy, which is again measured, and/or decision made and/or acted upon with a time delay. Thus, the resultant behavior is an oscillation. The structure and behavior are shown in Figure 2-30 (Sterman, 2000).

Figure 2-30. Structure and behavior of oscillation

Structure



Behavior



Source: Sterman (2000, p.114)

Interactions of the three most fundamental modes – exponential growth, goal seeking and oscillation give rise to the next three modes – S-shaped growth, S-shaped growth with overshoot and overshoot and collapse.

2.9.6 S-shaped growth:

An S-shaped growth is produced by a positive and negative loop interacting with one another. The structure is shown in Figure 2-31. For this mode, two conditions must be satisfied: 1) the system must not contain any time delays; and 2) the system capacity must be fixed (Sterman, 2000). Initially the positive (or reinforcing) loop is dominant and tends to have an exponential growth behavior. Then the negative (or balancing) loop takes over and produces a goal-seeking behavior. The overall behavior is seen in Figure 2-31 as a stretched out S with the initial exponential growth and the subsequent goal seeking to reach the system capacity.

When the first condition is relaxed one or more delays are introduced into the negative loop, we get the S-shaped growth with overshoot.

2.9.7 S-shaped growth with overshoot:

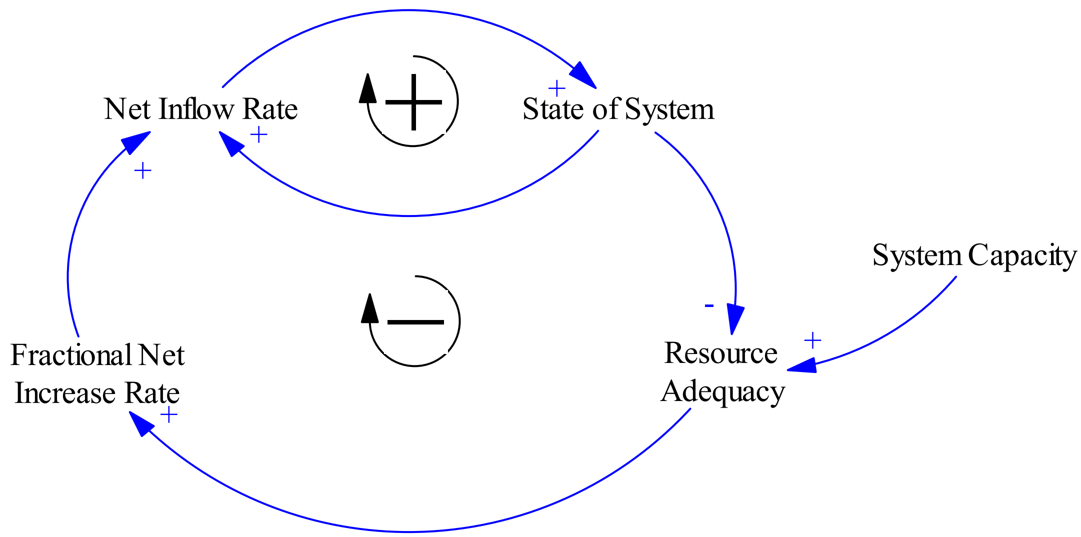
As before, the positive feedback loop is dominant at the beginning, giving rise to the exponential growth behavior. When the negative loop takes over, the system tries to reach the system capacity. However, the presence of one or more delays in the balancing loop gives the oscillatory behavior around the system capacity. The structure and the behavior are shown in Figure 2-32 (Sterman, 2000).

2.9.8 Overshoot and collapse:

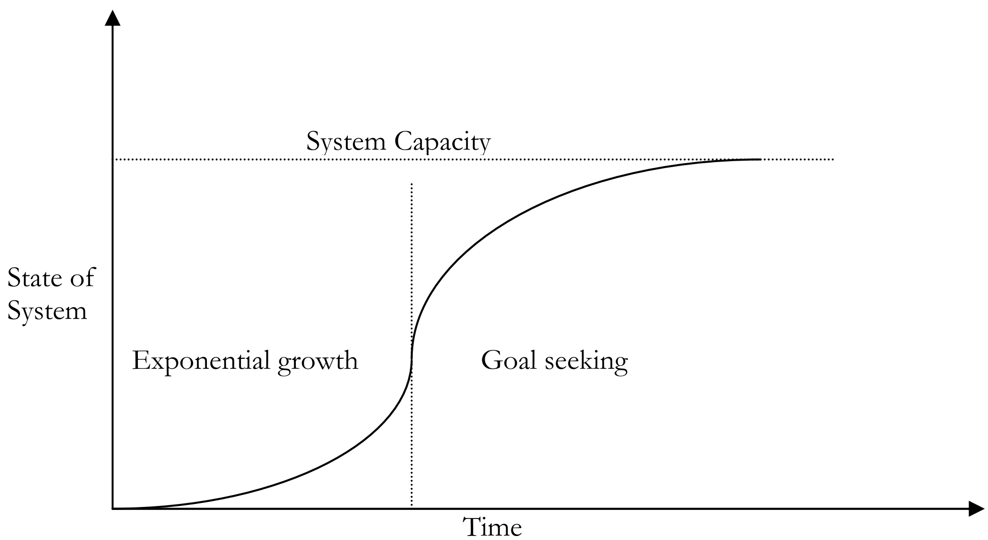
The second condition in the S-shaped growth mode assumes that the system capacity over time is fixed. This is often not the case. As the state of the system grows, the system capacity is eroded by the consumption. Hence, the system capacity drops after a certain point in time. What this does to the system structure is it brings a second negative feedback loop into play. The consumption of the system capacity erodes the system capacity and eventually brings down the state of the system. The structure and behavior are shown in Figure 2-33 (Sterman, 2000).

Figure 2-31. Structure and behavior of S-shaped growth

Structure



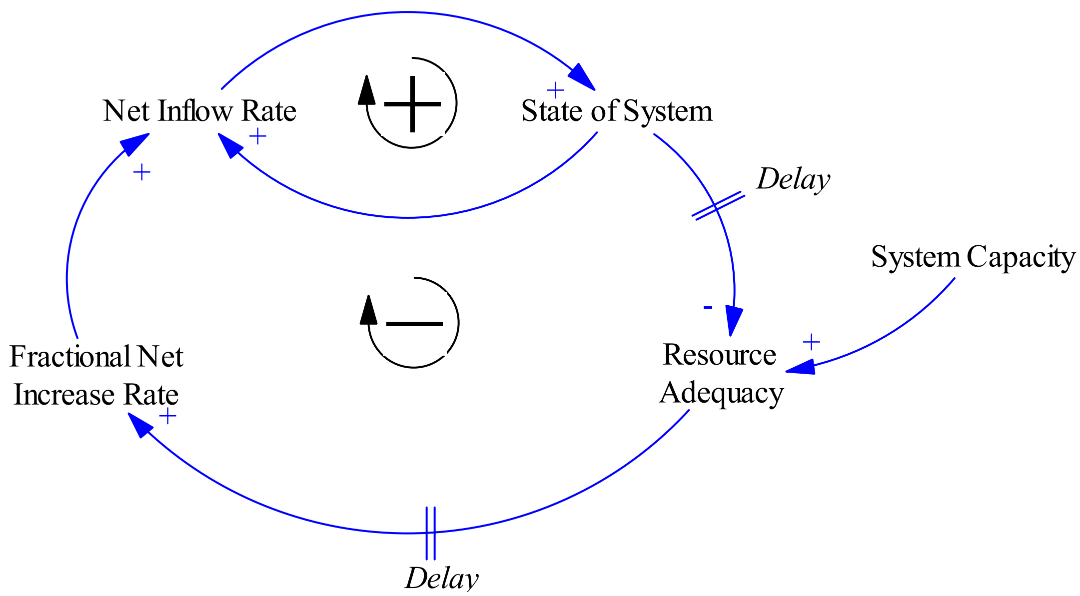
Behavior



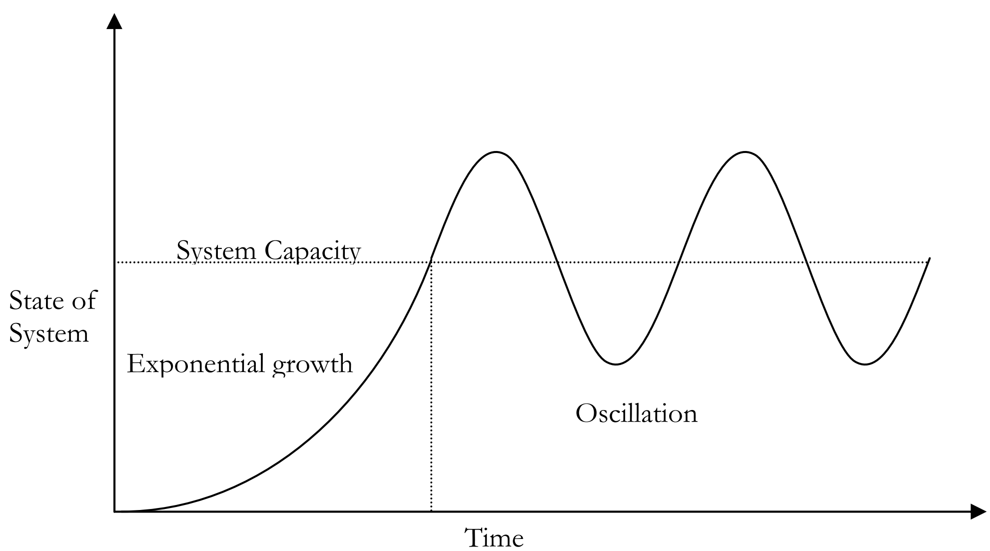
Source: Sterman (2000, p.118)

Figure 2-32. Structure and behavior of S-shaped growth with overshoot

Structure



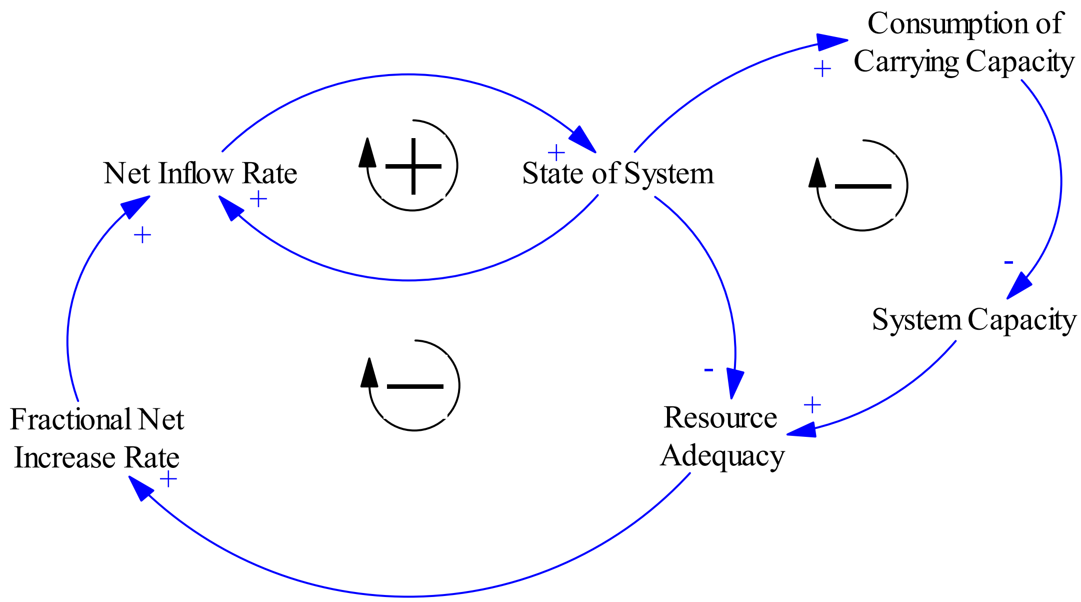
Behavior



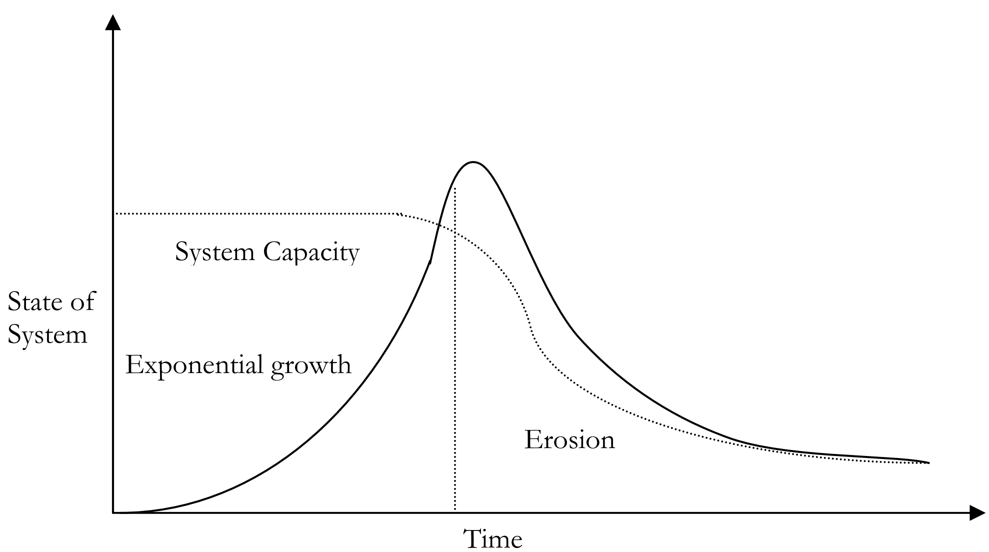
Source: Sterman (2000, p.121)

Figure 2-33. Structure and behavior of overshot and collapse

Structure



Behavior



Source: Sterman (2000, p.123)

We have discussed what is system dynamics, what are the feedback elements and how they come together to give rise to various modes of behavior. System dynamics is a very good approach to model the structure and predict the behavior of the system and base policies on such analysis. Normal applications of system dynamics include problem formulation, selection of variables, defining time step and then the model parameters and structure are adjusted manually until the model attains the desired objective (Wolstenholme, 1990). However, this does not ensure the optimality of the system going into the future. To optimize the system, an optimization heuristic needs to be incorporated into the system dynamics model (Keloharju, 1983). The next section will discuss explore how such a heuristic can be incorporated to optimize the system. The concept is based on replacing the manual model revisions by an optimization heuristic that will automatically determine the optimal solution to the model (Wolstenholme, 1990).

2.9.9 Optimization in System Dynamics:

The following three entities are required to perform a SD optimization (Wolstenholme, 1990):

1. Objective function that represents the desired model behavior.
2. Parameters, which represent constraints with feasible ranges.
3. Number of iterations of the model.

Wolstenholme (1990) gives the differences between traditional SD and optimized SD in Figure 2-34. As can be seen from the figure, the traditional SD needs manual intervention to make changes to the SD model before the next iteration. However, in the case of the optimized SD, the model runs iteratively to optimize the system and arrive at an optimal solution.

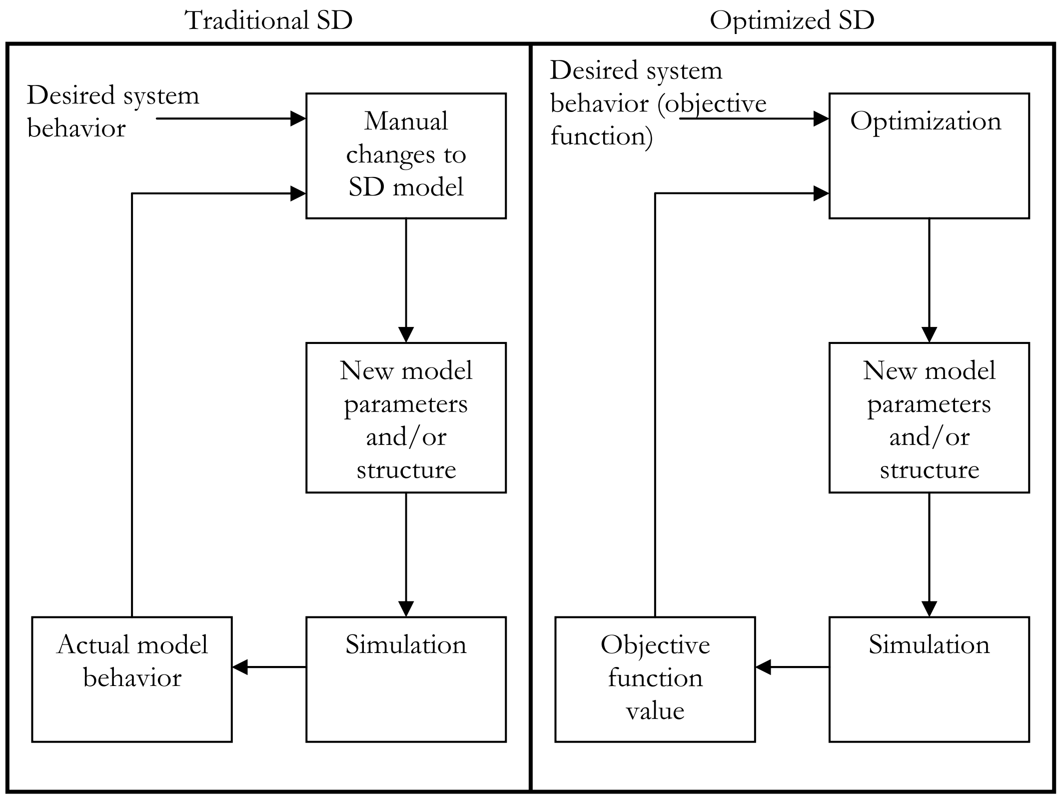
The objective function can be built with level variables. Coyle (1996) implies that these level variables do not necessarily need to have a physical meaning in the real world. Of course, one can argue that physical interpretations can be given to these level variables, for instance, inventory. Coyle (1985) suggests developing a performance index to measure efficiency of the system.

Constraints can be build around auxiliary or rate variables (Wolstenholme, 1990). The constraints and the ranges for the variables used make sure that the model searches for the solution within the feasible region. The constraints and the ranges define the boundary and the characteristic (size and shape) of the feasibility set. This is again represented by the combination of several variables.

The number of iterations to be included for the running of the model is a very tricky issue. Having a great number of iterations is good to ensure all of the feasible region is searched for the optimal solution but might take a lot of computing time. On the other hand, having too few iterations will run faster but may not search all of the feasibility space.

Such an optimization is achieved through a hill climbing algorithm. The idea is to systematically alter the variables in the objective function in order to find the desired value (maximum or minimum) (Fletcher and Powell, 1963; Vanderplaats, 1984).

Figure 2-34. Differences between traditional SD and optimized SD

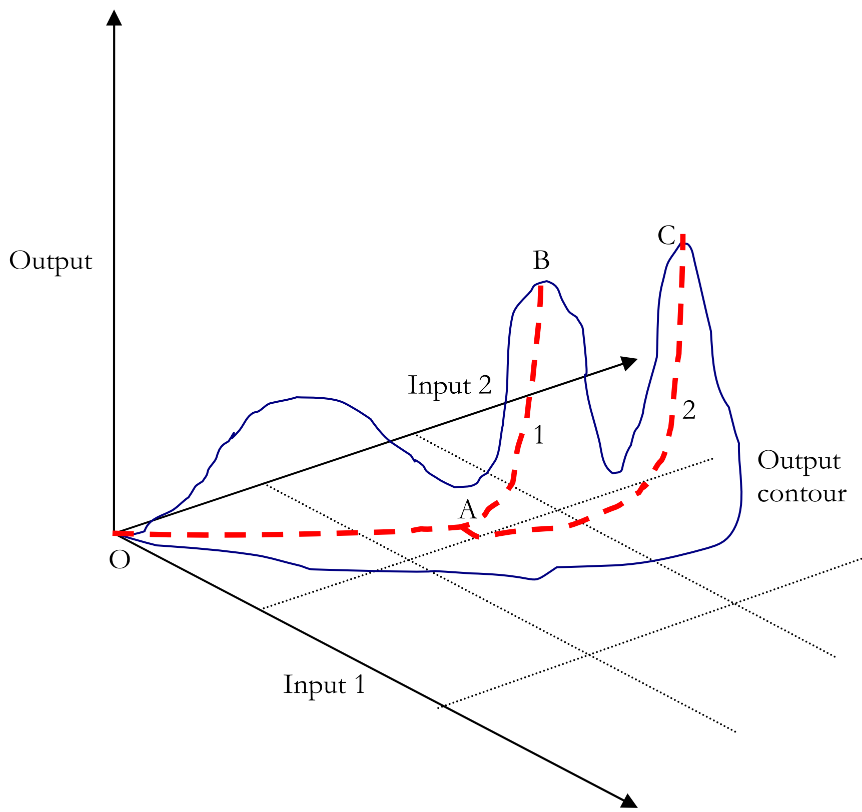


Source: Coyle (1996)

To explain the SD optimization heuristic, Coyle (1996) uses the analogy of a blind man trying to climb a hill. The man's objective is to get to the highest point on the hill. He starts at the foot of the hill. He feels the ground around him in all directions and makes a slight move in the direction that is the steepest. This is equivalent to one iteration in the model. The blind man repeats this process until he has no more energy to continue. The point that he ends up at before his energy is depleted represents the highest point he found on the hill. This may not be the highest point on the hill. Similarly, the model might have run out of iterations before getting to the objective. Hence, it is advisable to test the model with different iterations (Coyle, 1996).

Coyle (1996) also explains the three-dimensional hill-climbing search graphically as shown in Figure 2-35. Consider a blind man starting at the foot of the hill at point O (the origin in the graph in Figure 2-35). In the model, this is characterized by the state variables with specific values. The man senses the slope of the terrain around him in all directions and takes a slight step in the direction with the steepest slope. Thus, he moves along the path depicted by the dotted line and gets to point A. At point A, he has the option of taking path 1 or 2. He decides to take path 1 since that direction has a steeper slope and gets to point B. If he has any energy left in him (equivalent to having more iterations left in the model simulation), he will go back to point A, take path 2 and reach point C, which is the *global optimum*. Such a point is the highest point on the hill and the optimal of all solutions in the feasibility space to the decision making problem. If the man did not have sufficient energy to move back from point B, he would be stuck in a point called the *local optimum*. Such a point is at the top of a small mound on the hill. It is the highest point in its neighborhood and all points around it are lower in height.

Figure 2-35. Hill-climbing optimization – an illustration



Source: Coyle (1996)

Now that we have introduced an optimization heuristic, the next section will present a generic hill-climbing structure using system dynamics.

2.9.10 Generic optimization hill-climbing structure:

The generic hill-climbing optimization structure, Figure 2-36 developed by Sterman (2000) has two feedback loops – one positive and one negative. The positive loop adjusts the goal of the system and the negative loop tries to reduce the discrepancy between the actual state of the system (L) and the desired state of the system (L^*). The external pressures influence the desired state of the system and also represent the slope or gradient of the hill that the man desires to climb and what direction to take to reach the optimal value, Sterman (2000). The hill-climbing optimization procedure is done through three equations.

$$L = L_{t_o} + \int_0^{t_0} R dt$$ **Eq 2-23**

where, L_{t_0} is the initial state of the system

The desired state of the system is influenced by external factors represented by

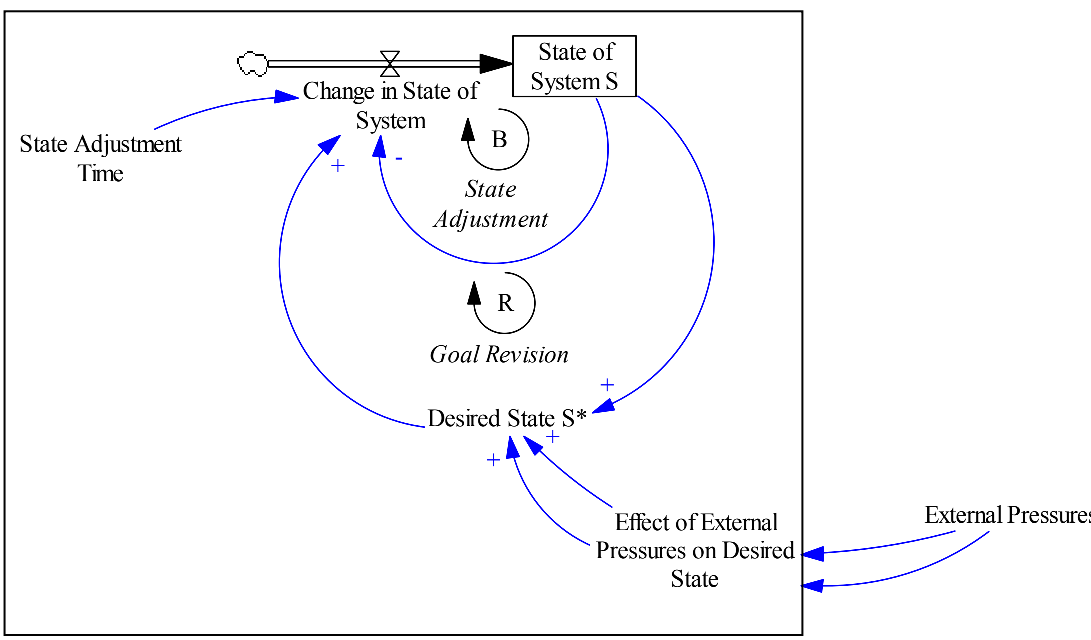
$$L^* = f(L, effect\ of\ X_1\ on\ L^*, ..., effect\ of\ X_n\ on\ L^*)$$ **Eq 2-24**

where, X_i is the external pressure on the system and $i = 1,2,...n$

$$Effect\ of\ X_i\ on\ L^* = f(X_i / X_i^*)$$ **Eq 2-25**

where, X_i^* is the base value, Sterman (2000).

Figure 2-36. Structure for hill-climbing search



Source: Sterman (2000, p.539)

Sterman (2000) defines the change in the system R as how fast the state of the system is changing. R is a rate variable and is given by

$$R = \frac{L^* - L}{SAT} \qquad \textbf{Eq 2-26}$$

where, SAT is the state adjustment time

When the external pressures influence the desired state of the system and $L^* > L$ (or $L^* < L$), the state of the system will increase (or decrease) and the negative loop will try to get the state to equilibrium at the desired level. In addition, when $L^* = L$, equilibrium is achieved.

System dynamics captures the relationships in the structure of a system to predict the behavior over time. The relationships are not always evident and might need to be uncovered from data using other techniques. Two such techniques are discussed next.

2.10 BASIC ALGORITHM FOR DECISION TREES

Automatic tree classification methods are a family of methods that use recursive partitioning to find patterns in large data sets. As other nonparametric methods created to find patterns in the data, automatic decision trees try to overcome the limitations of parametric methods that assume linearity and therefore, can be used in a wider array of applications. All automatic tree methods follow the same algorithm:

i. Split into nodes

ii. Grow branches

iii. Terminate growth

Starting with the whole population in the data concentrated in a starting node (dependent variable), the algorithm looks for the best way to split the cases into a series of "parent" nodes and "child" nodes. A pre-determined splitting criterion is followed systematically. In that way, cases are classified into branches and leaves. Through a series of termination rules, a node is declared either "undetermined" meaning that there is potential for growth and further classification, or "terminal" node, meaning that there is no additional value in continuing the splitting.

When continuous or integer variables are part of the data set, there is potential for a huge number of data split interactions. Any point can split the data. Because of this, splitting rules have been developed that partition continuous data in categorical sub-sets. The following sections discuss one such technique.

2.10.1 Chi-Square Automatic Interaction Detection (CHAID)

Morgan and Sonquist (1963) proposed a simple method for fitting trees to predict a quantitative variable. They called their original algorithm Automatic Interaction Detection (AID) because it naturally incorporates interaction among predictors. Talking about Interaction, Wilkinson says:

"Interaction is not correlation. It has to do instead with conditional discrepancies. In the analysis of variance, interaction means that a trend within one level of a variable is not parallel to a trend within another level of the same variable. In the ANOVA model, interaction is represented by cross-products between predictors. In the tree model, it is represented by branches from the same node which have different splitting predictors further down the tree." P.4

The algorithm performs stepwise splitting by computing the within-cluster sum of squares about the mean of the cluster on the dependent variable.

CHAID is a type of decision tree method originally proposed by Kass (1980). According to Ripley, 1996, the CHAID algorithm is a descendent of THAID developed after AID by Morgan and Messenger, (1973). It is also an exploratory method used to study the relationship between a dependent variable and a series of predictor variables.

Categorical predictors that are not ordinal (such as race classification or nominal options of type of service provided) require a different approach. Since categories are unordered, all possible splits between categories must be considered. For deciding on one split of *k* categories into two groups, this means that 2 *k* -1 possible splits must be considered (Wilkinson, 1992).

CHAID modeling selects a set of predictors and their interactions that optimally predict the dependent measure. The developed model shows how major "types" formed from the independent (predictor or splitter) variables differentially predict a criterion or dependent variable. Any given node in CHAID can be partitioned in more than two groups.

CHAID is a combinatorial algorithm since it goes over all possible variable combinations in the data to partition the node. The CHAID algorithm is particularly well suited for the analysis of larger datasets because the CHAID algorithm will often effectively yield many multi-way frequency tables (e.g., when classifying a categorical response variable with many categories, based on categorical predictors with many classes). One of the most common uses of CHAID has been in market segmentation to uncover customer characteristics for response modeling.

CHAID facilitates the development of predictive models, screen out extraneous predictor variables, and produce easy-to-read population segmentation subgroups. The splitting criteria are given by the Chi-square test of independence, entropy measures and cross-validation differences. A larger Chi-square statistic suggests a more significant partition. Adjusted p-value measures of significance (using Bonferroni) are used to determine the best value of the partition, or the best split. Further, measures of entropy within the groups (a measure of information content within the split) are used. An extensive explanation of how the CHAID algorithm works can be found in Wilkinson (1992). Pasupathy and Medina-Borja (2005)[10] propose that the same can be used to identify or confirm important predictors of any given variable in system dynamics modeling.

For the purpose of this research, CHAID will be run using a software package, AnswerTree 3.1. A detailed explanation of the procedure to use the software is given in SPSS (2001).

2.11 FROM RELATIONSHIPS TO MATHEMATICAL EQUATIONS

CHAID, as a decision tree method would help us determine whether a relationship exists, and the direction of the relationship. However, if we were to run the simulation model, we would be facing a problem since we do not know exactly how these categorical variables that are part of a construct (for example, service quality) interact to affect customer loyalty, specially since they are measured in a Likert-type of scale. Again, Pasupathy and Medina-Borja (2005) propose using structural equation modeling to uncover the mathematical equation of the relationship uncovered by CHAID.

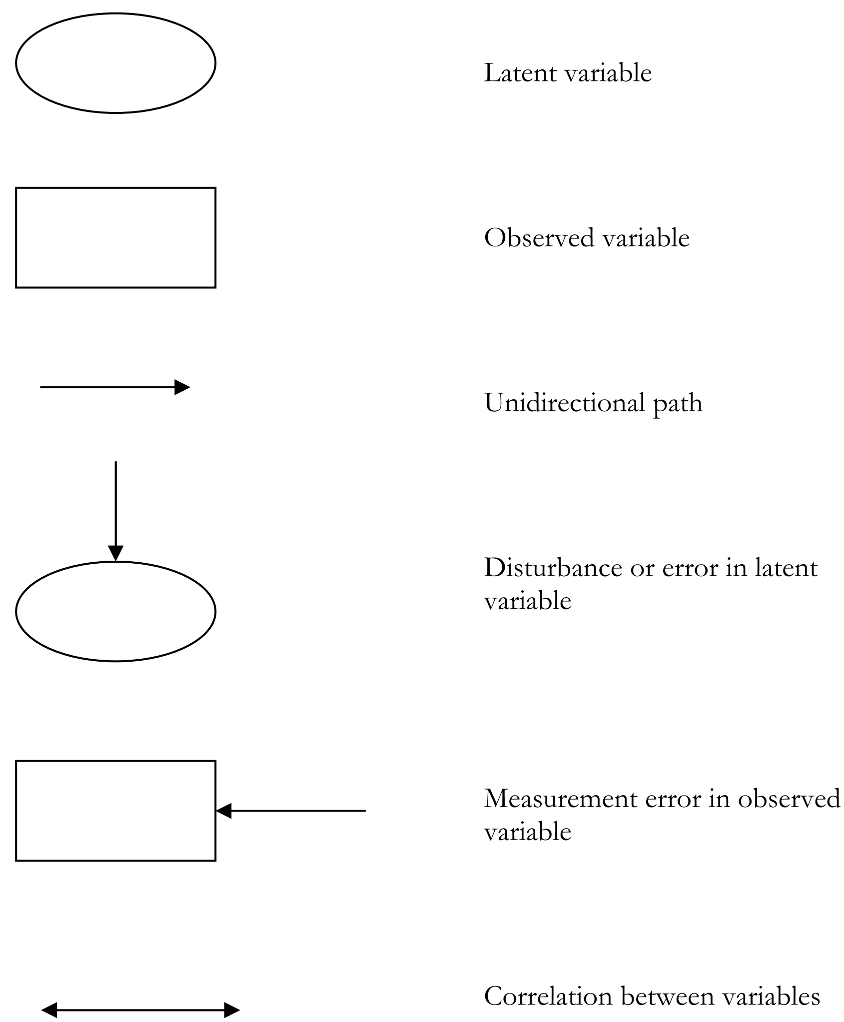
2.11.1 Structural Equation Modeling

[10] Article submitted to System Dynamics Review included in Appendix A.

Structural equation modeling (SEM) is a methodology used to model interactions, nonlinearities, multiple latent independents measured by multiple indicators, and one or more latent dependents also each with multiple indicators. SEM is a major component of applied multivariate statistical analysis and used by biologists, economists, market researchers, and other social and behavioral scientists, see for instance (Hayduk, 1985; Bollen, 1989; Schumacker and Lomax, 1996; Pugesek et al. 2003). Some of the elements of SEM are indicators, latent variables, error terms and structural coefficients.

Indicators are variables that are measured. They are also called manifest variables or reference variables, such as items in a survey instrument. The observed variables are the indicators. These indicators are used to measure unobserved variables or constructs or factors which are called *latent variables*. Error terms are associated with indicators and are explicitly modeled in SEM to capture the measurement error. Structural coefficients are the cause-and-effect sizes calculated by SEM that are used to formulate the structural equations. The symbols used for SEM models in path diagrams are shown in Figure 2-37.

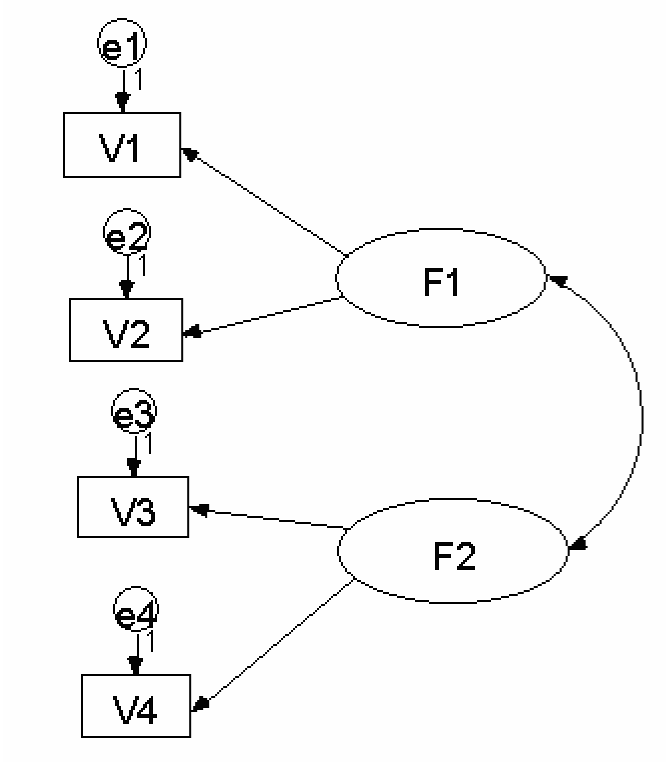
Figure 2-37. Symbols used for SEM models in path diagrams



Source: Raykov and Marcoulides (2000, p.9)

Using these symbols, Figure 2-38 gives an example of a simple path diagram. Consider two latent variables, F1 and F2. F1 is measured by indicators V1 and V2 and F2 is measured by indicators V3 and V4. There is also a correlation link between the two latent variables F1 and F2. Each of the indicators V1, V2, V3 and V4 has an error term associated with them, e1, e2, e3 and e4, respectively. Each error term captures the amount of residue due to measurement error. There are no error terms associated with the latent variables because all the variation will be captured by the respective indicators and by the covariance between them. The '1' on the link from each error term to the respective indicator represents the weight and is related to model identification. Identification relates to whether or not there is a unique set of parameters consistent with the data. This depends on the transposition of the variance-covariance matrix of the observed variables into the structural parameters of the model under study. If a unique solution can be found then the model is said to be identified. Under such a scenario, the parameters can be estimated. But on the other hand, if the model cannot be identified, then a unique set of values for the parameters cannot be estimated. Thus, setting the value makes the model just-identified and parameters estimable. For a detailed explanation, please refer to Bollen (1989), Raykov and Marcoulides (2000) and Byrne (2000).

Figure 2-38. Example of a path diagram



Then the model equations can be written as below:

$V1 = \lambda_1 F1 + e1$

$V2 = \lambda_2 F2 + e2$ **Eq 2-27**

$V3 = \lambda_3 F3 + e3$

$V4 = \lambda_4 F4 + e4$

where, λ_1, λ_2, λ_3, λ_4 are coefficients to be determined. V1, V2, V3, V4 are all measured. The coefficients are determined based on the variance in data set and how the variables are related in the path diagram.

Bentler (1995) gives the following six rules for determining model parameters:

1. All variances of independent variables are model parameters
2. All co-variances between independent variables are model parameters
3. All factor loading connecting the latent variables with their indicators are model parameters
4. All regression coefficients between observed or latent variables are model parameters

5. The variances and co-variances between dependent variables and the co-variances between dependent and independent variables are never model parameters
6. For each latent variable included in a model, the metric of its latent scale needs to be set

The parameters are estimated using the correlation and co-variance matrices. To estimate the parameters, four laws of variance and co-variance are used (Hays, 1994; Raykov and Marcoulides, 2000). They are:

$$Law1: Cov(X, X) = Var(X) \qquad X - random\ variable$$

$$Law2: Cov(aX + bY, cZ + dU) = acCov(X, Z) + adCov(X, U) + bcCov(Y, Z) + bdCov(Y, U)$$

$$X, Y, Z, U - random\ variables; a, b, c, d - constants$$

$$\begin{aligned} Law3: Var(aX + bY) &= Cov(aX + bY, aX + bY) \\ &= a^2Cov(X, X) + b^2Cov(Y, Y) + 2abCov(X, Y) \\ &= a^2Var(X) + b^2Var(Y) + 2abCov(X, Y) \end{aligned}$$

$$X, Y - random\ variables; a, b - constants$$

$$Law4: Var(aX + bY) = a^2Var(X) + b^2Var(Y)$$

$$X, Y - random\ variables; a, b - constants$$

For an explanation and proof, the reader is directed to Raykov and Marcoulides (2000).

Structural Equation Modeling (SEM) is usually used as a confirmatory approach rather than an exploratory procedure. A causal model based on theory is first proposed and then tested for the data set. For instance, it is used to test how well a model fits the data only to be accepted as a not-invalidated model. Alternatively, several proposed models can be compared against each other and based on the goodness-of-fit measures, the best model is chosen. The causal model is based on exploratory methods such as CHAID (Pasupathy and Medina-Borja, 2005). In practice, a hybrid approach is used, where a proposed theoretical model is tested with data. Then the modeler goes back to make changes in the model based on the SEM indexes.

For the purpose of this research, SEM will be run using a software package, Amos 5.0. A detailed explanation of the procedure to use the software is given in Byrne (2000) and SmallWaters Corporation (1999, 2003).

This chapter researched the existing literature that deals with the service-profit chain, introduced the dynamic decision making theory, system dynamics as an approach to aid in decision making and introduced techniques like system dynamics modeling, predictive analytics and structural equation modeling. The next chapter will develop the conceptual and operational models.

3 Model Development

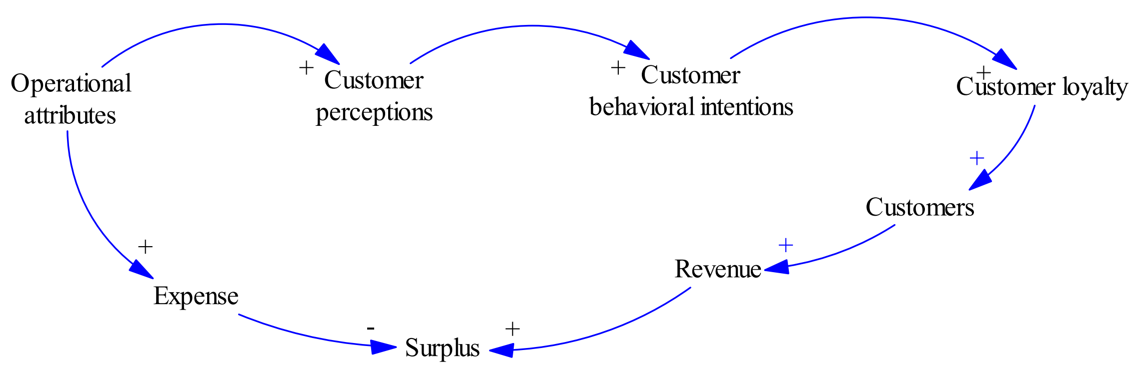
"Study the science of art and the art of science"

- Leonardo da Vinci

Modeling is partly art and partly science. It is the process of capturing what we observe to analyze it. We see the outside world through our mental models (Sterman, 2000). Mental models are the sum total of our life's experiences. And different people have varying experiences. For that reason, no two modelers working in parallel on the same problem within the same system will produce the same model. And the same modeler is likely to develop different models of the same system at different points in time.

The various relationships among components in the SPC are well documented in the literature (see for instance, Heskett et al., 1994; Rucci et al., 1998). Based on the review of the literature, Figure 3-1 gives the SPC in the literature.

Figure 3-1. Service-Profit Chain in the literature



3.1 THE CONCEPTUAL MODEL

The Service Profit Chain (SPC) originally formulated by Heskett et al. (1994) has had several modifications (Roth and Jackson, 1995; Rust et al., 1995; Rucci et al., 1998; Kamakura et al., 2002). Although different researchers concentrated on various components of the chain, the essence is to look at how revenues are driven by service quality perceptions, which in turn are driven by investments in operational attributes or enhancements. This section elaborates on each one of the components of the SPC and defines them as they are used in this research.

3.1.1 Operational Attributes

Operational attributes are features or characteristics of the internal operations of a service organization. These attributes can be related to the "internal perspective" in the balanced scorecard by Kaplan and Norton (1992). This component of the SPC includes all the attributes or characteristics of the internal operations that enable the organization to provide services to the customers. Kamakura et al. (2002) use the term "operational inputs" to refer to these attributes, e.g. number of employees, number of equipment, etc. Any interventions in these attributes are expected to enable the organization to provide better services. These interventions can be in the form of investments to hire more people, employee training, improving their quality of work, acquiring more tools or equipment, better workplace design, etc.

Other authors have looked at attributes inside the organization like employee satisfaction (Heskett et al., 1994), employee behavior (Rucci et al., 1998), employee retention (Heskett et al., 1994; Rucci et al., 1998). Roth and Jackson (1995) refer to operational attributes as operational capabilities. Rust et al. (1995) look specifically into service quality improvement efforts. Some operational attributes can be referred to as capacity or the capability or potential sitting within an organization to be used in providing services.

Interventions in operational attributes can be divided into two broad categories, namely, personnel efforts and equipment/material efforts (Kamakura et al., 2002). Personnel efforts include any interventions made inside the organization relating to personnel or employees. Recruiting additional employees, providing training, rewards and recognition, or any other efforts causing higher levels of employee motivation and satisfaction are perfect examples of personnel efforts. Equipment/material efforts, on the other hand, are interventions and investments made relating to any equipment or material, like more equipment, more ATMs in a bank branch, more materials for training, installation of long distance video-conferencing in educational settings, etc.

However, this research will not treat them separately but group all such interventions under improvement efforts. In those lines, Operational attributes are defined as all features or characteristics of the internal operations of a service organization that enable service delivery to the customers.

3.1.2 Customer Perceptions

Customers perceive the quality and the value of the services provided. This section discusses the literature in perceived service quality, perceived value and their relationship to customer satisfaction as it relates to the SPC.

Customer perceptions as it relates to the SPC could be seen as perceptions of the personnel and other attributes providing the service. Courteousness, helpfulness, knowledge, ability to answer questions are examples of perceptions a customer may have of the personnel. Quality of books used is an example of perception of materials used. In the case of education or training, convenience of times and locations and ease of registration are perceptions about service delivery logistics. The type of perceptions that apply to each type of service is dependent on the characteristics of the specific type of service, and on the "production" system put in place to deliver such service. Service quality is said to be the construct of the above customers' perceptions. Most researchers hypothesize that service quality (construct of above perceptions) leads to different degrees of customer satisfaction.

Oliver (1980), Anderson and Sullivan (1993), Taylor and Baker (1994) and Johnson (1995) claim service quality to be the main determinant of customer satisfaction. Customer satisfaction has been under the light of several marketing research studies since Drucker (1954) claimed it to be the driver of revenue. Drucker (1973) also posits that the mission and purpose of any business is to satisfy its customers. It is common in the literature to find perceived service quality and customer satisfaction grouped together like in Rust et al. (1995). Rucci et al. (1998) look at the service helpfulness of the employees and the value gained from the service. These dimensions feed into what they call customer impression which is more commonly known as "customer satisfaction" (Parasuraman et al. 1985, 1988; Medina-Borja, 2002). Medina-Borja (2002) uses perceived service quality as a predictor of overall satisfaction (of customers). Kamakura et al. (2002) refer to it as "attribute performance perceptions."

Interventions, and hence investments made in operational attributes will have no effect on the behavior of the customers and eventually on the revenues, if the customers do not perceive the changes in the operational attributes in the first place. Kamakura et al. (2002) reinforce this when they say that acquiring additional ATMs or more tellers and eventually achieving lesser waiting times should be perceived by the customer to have an effect on their satisfaction, and their positive intentions, etc. Hence, service quality is included as an important dimension of customer perceptions.

Another dimension of customer perceptions included in this research is value. Heskett et al. (1994) include external service value as part of their theoretical model. Most of the other research in the literature has not identified *perceived value* as a determinant of satisfaction and this inadequacy has been noted (Anderson et al. 1994; Ravald and Gronroos, 1996; Lemmink et al. 1998). Further, similar to service quality, perceived value has also been a difficult concept to define and measure (Holbrook, 1994; Zeithaml, 1988; Woodruff, 1997). Still, few definitions have been proposed in the literature:

'Value is the consumer's overall assessment of the utility of a product based on perceptions of what is received and what is given.'

- Zeithaml (1988, p. 14).

'Value in business markets [is] the perceived worth in monetary units of the set of economic, technical, service and social benefits received by a customer firm in exchange for the price paid for a product, taking into consideration the available suppliers' offerings and prices.'

- Anderson et al. (1993, p. 5).

In this research, perceived value will be used in a similar context as defined below. The reason for using this definition (impact of competition on value) as opposed to the two above is explained in detail in the subsequent section.

'… perceived value can be viewed as a relative measure of the costs and other monetary aspects of the service in comparison to competition.'

- McDougall and Levesque (2000, p. 394).

Zeithaml (1988) shows that customers who perceive that they received "value for money" are significantly more satisfied than customers who do not. Anderson et al. (1994) and Ravald and Gronroos (1996) argue that value has an effect on customer satisfaction. Value of the services provided has been identified as another determinant of satisfaction (Woodruff 1997; McDougall and Levesque 2000).

Concept of Value and Competition

Value, as mentioned before, is a dimension of customer perceptions and competition has an impact on value. This section discusses how competition can be used to measure relative value. With value being a vague concept, it is difficult to quantify value in absolute terms. Further, what constitutes value is personal, idiosyncratic and varies widely from one customer to another (Zeithaml, 1988; Holbrook, 1994; McDougall and Levesque, 2000). One way to work around this problem is to measure value in relative terms in the market. As proposed, relative value can be measured as the quality of the service received by the customer for the price paid in comparison to the quality of similar service offered by competitors for their price (McDougall and Levesque, 2000). Woodruff (1997) however, does not include competition as part of the definition of value. This could be a drawback because, for customers to be able to evaluate whether they are receiving "value for money," they need to know what constitutes "value for money." No other SPC model has explicitly included competition. This research includes competition in the conceptual model as a predictor of customer perceptions. In specific, competition is used to measure value in relative terms. Competition is one of the uncontrollable factors and the uncontrollable factors are discussed later.

In short, Customer perceptions are views/assessment of the customer about the operational attributes used during the service delivery process.

3.1.3 Customer Behavioral Intentions

Kamakura et al. (2002) add to the SPC a component on behavioral intentions. Based on the perceptions and the overall satisfaction levels, customers have certain intentions regarding their future relationship with the service, (Kamakura et al. 2002). However, these authors group the behavioral intentions with overall evaluations (which is the same as overall satisfaction). Several authors do not have this link in the SPC. Heskett et al. (1994), Rust et al. (1995) and Rucci et al. (1998) jump directly from perceptions to retention. Customer behavioral intentions is an important component of the SPC because the time lag between the end of the provision of the service and the actual return of the customer makes likely that not all customers who had the intention to return actually would.

The component customer behavioral intentions is a vital element of the SPC as it ties closely with customer perceptions. As Kamakura et al. (2002) explain, the behavioral intentions are the only way of determining if the positive perceptions end up in actual retentions. This element will remain in the conceptual model and defined as intentions that the customer forms about his/her future behavior based on the perceptions of the service received.

3.1.4 Customer Loyalty

This is a key component that ties what happens now to what can happen in the future. Customers that come back for more business and others that came because of referrals are measured by this component which ties to more revenues for the organization in the future. Reichheld (1996) study the relationship linking customer retention and profitability over a period of time. The author concludes that the ability of an organization to retain customers is what generates stronger cash flows. The balanced scorecard (Kaplan and Norton, 1992) puts all of the above three components of the SPC – customer perceptions, behavioral intentions and customer loyalty into one – the customer perspective.

Customer loyalty can be captured as retentions rates and referrals (Heskett et al., 1994). Although, Edvardsson et al. (2000) define loyalty as a customer's predisposition to repurchase from the same organization again and retention as whether the customer has actually repurchased from the organization. However, the definition by Heskett et al. (1994) will be followed. In other words, how many people are coming back for repeat business or how many were referred by others that have used the service. Heskett et al. (1994) look at both referrals and returns, while Rucci et al. (1998) restrict themselves to just customer retention. Customer loyalty remains in the conceptual model and is defined as the dependability or faithfulness of the customer to act in a manner that is beneficial to the organization.

3.1.5 Surplus

Having customer loyalty and attracting new customers will increase the revenue (Reichheld, 1996; Johnson, 1998). Greater customer retention rates have been claimed to have a significant positive effect on profits (Dawkins and Reichheld, 1990; Reichheld and Sasser, 1990; Rust et al. 1995). If the expenses are fixed, this will lead to a surplus (revenues-expenses) increase. The initial investments made in the operational attributes tend to decrease the surplus by increasing the expenses. This component of the SPC can be related to the financial perspective of the balanced scorecard, Kaplan and Norton (1992).

Greater customer satisfaction and customer loyalty leading to greater profits are thought to be a significant determinant of an organization's long term financial performance. Surplus remains as part of the conceptual model. Deficit will be measured as negative surplus. Hence this component is shown as 'Surplus' in the model.

3.1.6 Uncontrollable Factors

Uncontrollable factors (for instance the operating environment) are outside the control of the management, but have a substantial impact on the operation of the organization, Ruggiero (1996). There are uncontrollable factors that affect several components of the SPC. Ruggiero (1996), Fried et al. (1999), Blank and Valdmanis (2001) and Medina-Borja (2002) talk about the effect of the operating environment on the performance of the organization. Bradford et al. (1969) evaluate organizational performance by a two-stage model where the authors include the environmental variables. As an example, customer perception is affected by certain uncontrollable factors like the wealth in the community (Medina-Borja, 2002). Some uncontrollable factors are market size, wealth in the community, dispersion or spread, racial/ethnic diversity, age and gender.

In Figure 3-2, uncontrollable factors are shown to affect two components – customer perceptions and customers. Competition, as mentioned before affects value of the service received by the customer. In other words, competition is used to measure relative value. Other environmental variables that are also uncontrollable, like dispersion, age, gender, etc., also affect customer perceptions (service quality). Another uncontrollable factor, market size, affects one component – customers. Such factors are included as an exogenous component in the SPC.

This research also demonstrates a method using predictive analytics and structural equation modeling to determine the uncontrollable factors that affect service delivery and the extent to which they do so. This is illustrated for a specific case study in training services.

3.2 SUMMARY OF SYSTEM DIMENSIONS USED IN THIS RESEARCH

Table 3-1 maps the components of the SPC and the corresponding system dimensions incorporated in this research. This is a generic mapping for all service operations. Each of the components in the SPC (shown in the column on the left) have the corresponding dimensions (shown in the column on the right).

Table 3-1. System Dimensions

Component of SPC	System Dimension
Operational attributes	Improvement efforts
Customer perceptions	Service quality
	Value
	Overall satisfaction
Customer behavioral intentions	Referral/Recommendation intentions
	Return intentions
Customer loyalty	Referrals/Recommendations
	Retention
Surplus	Finance
Uncontrollable factors	Environment/market

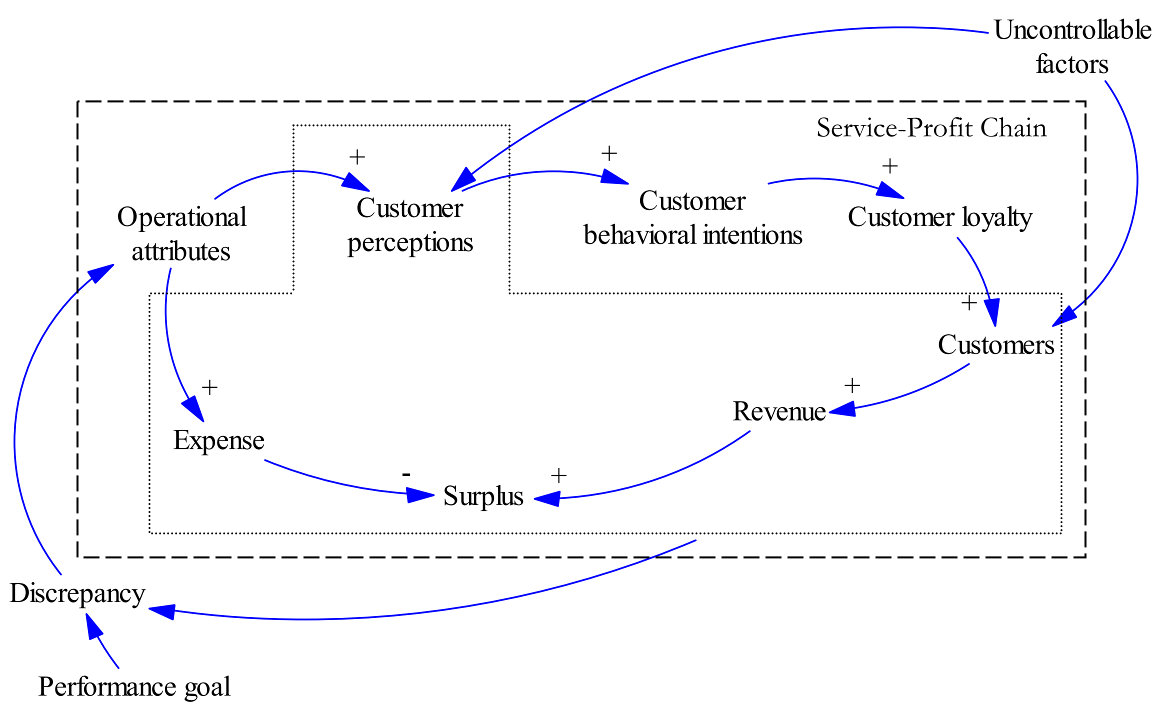
Figure 3-2 in comparison with Figure 3-1 shows the departure of this research in comparison to the SPC model in the literature. Elements inside the box with dashed lines are the components of the

SPC. Uncontrollable factors that are outside the box with dashed lines (exogenous to the SPC) affect certain components of the SPC. The other additional element in Figure 3-2 is the feedback loop that goes from customer perceptions-customers-revenue-expense-surplus (enclosed by the box with dotted lines) to discrepancy (where a comparison of the current state of the system is made against the performance goal). Based on the discrepancy, changes for the future are made in the operational attributes. Figure 3-2, termed as the Dynamic SPC is the conceptual research model for this research.

3.2.1 A Note about Feedback Mechanisms

The feedback mechanism is a way of comparing the current state of the system to performance goals to make changes in operational attributes. Performance goals are set forth by organizations based on past analysis, experience, mental models, etc. (Sterman, 2000). Performance goals, in this research, are measurable. An example of a performance goal is installing one ATM machine for every 100 customers in the community. Performance goal comparison is an inherent system dynamics feature. This is discussed further as part of the operational model.

Figure 3-2. Conceptual Research Model – Dynamic SPC



The next section takes the conceptual model forward and operationalizes various dimensions by determining the variables used to measure them.

3.3 THE OPERATIONAL MODEL

The conceptual model in Figure 3-2 is applicable to any service delivery industry. This section shows how the conceptual model is operationalized by identifying key observed variables. This model is again generalizable to any service delivery industry.

Improvement efforts can be varied depending on the type of industry. Examples of improvement efforts include increasing the number of tellers in a bank (banking services) or in a hotel (hospitality services) distributing candies to arriving guests or increasing course offerings (training services). Regardless of the service industry, by making such improvement efforts, the organization expects to have an impact on the perceptions by the customer (including service quality, value and satisfaction). Service quality is a construct that can be measured by the combination of several items (e.g. SERVQUAL by Parasuraman et al., 1985) included on a survey instrument targeted to a specific group of people that have something in common (here, customers receiving the same type of service). Improvements can be made in one or more of several operational attributes. More investments made in operational attributes will result in perceptions of an increased service quality of the operation.

The increased perceived service quality translates into better value and increased overall satisfaction. Ham and Hayduk (2003) statistically test hypotheses pertaining to correlations between service quality and customer satisfaction. They demonstrate the existence of a significant positive correlation in a higher educational setting.

Since value is a vague concept, it can be measured in relative terms (McDougall and Levesque 2000). Relative value for this research is defined as the quality of the service received by the customer for the price paid in comparison to the quality of similar service offered by competitors for their price. Thus, value can be measured by asking the customer on a survey instrument in relative (to competitor) terms. An example item on such an instrument would ask "how satisfied are you that the service offered a good value compared to competitors offering similar services?" Competition is measured by the quality of the service and the price offered by the competitor. If our organization offers better service (i.e. our quality perceived by customers is better than the competitor's quality perceived by the same customer), but the competitor's service is priced higher than our organization, then customers will perceive to be receiving better value for money from our organization. As the competitor increases the service quality without increasing the price, our relative value advantage will decrease. We can counter this and try to keep/gain relative value either by increasing our quality further or reducing the price. Because of this, competition (which can manifest itself as increased competitor's service quality and/or reduced competitor's price) has a negative effect on relative value. Increasing our service quality and/or reducing our price have a positive effect on relative value. However, our price has a positive impact on total revenue.

Ittner and Larcker (1998) validate claims of customer satisfaction as the leading indicator and having an impact on customer purchase behavior (retention, revenue and revenue growth). So, increase in customer satisfaction through increased service quality and value has a positive impact down the line on loyalty, customer base and revenues. But before we get to loyalty, let us look at customer behavioral intentions.

The customer behavioral intentions component of the SPC has one variable each corresponding to the two dimensions, referral/recommendation intentions and retention intentions. The two corresponding variables are 'Intend to refer' and 'Intend to return'. These variables capture the intention to refer/return of a customer that had the service delivered. Ham and Hayduk (2003) demonstrate the existence of a significant positive correlation between customer satisfaction and positive customer behavioral intentions in a higher educational setting. This higher level of satisfaction increases the intention to return for more service in the future and/or the intention to refer/recommend the service to others.

Because of these increased intentions to refer and/or return, we can expect to see more referrals and/or returns respectively. The actual 'Referrals' and the actual 'Returns' show loyalty (physical act of a referred person or of a returned person showing up for repeat business). Both of these effects tend to increase the number of customers, revenue and market penetration.

3.3.1 Market Penetration

According to Merriam-Webster dictionary, market share is the percentage of market for a service that an organization delivers. Hence, market shares of all competing organizations for a particular service will add up to 100%. Market penetration is a closely related term in the literature. An organization is said to penetrate the market either by gaining competitors' customers (part of competitors' market share) and/or attract new customers and/or convince current customers to use more (repeated use) of the service. Hence market penetration is a much broader term than market share. This research uses market penetration.

Having greater customer loyalty is claimed to have a positive effect on market penetration (Fornell and Wernerfelt, 1988; Rust and Zahorik, 1993). In essence, greater customer retention leads to bringing back more customers for repeat business which increases the customer base for the future and hence the market penetration. Customer referrals/recommendations bring additional customers and can also increase market penetration. But most SPC models do not include market penetration and refer only to revenue growth. Market penetration is added to the operational model.

Table 3-2 lists the components and dimensions of the SPC and the corresponding observed variables and Table 3-3 shows the polarity between pairs of variables that were derived from the literature, and will be tested for the case study. Figure 3-3 portrays the operational model using all the variables discussed and the respective polarities.

Table 3-2. Operationalization of the components of the SPC

Component of SPC	System Dimensions	Observed variables
Operational attributes	Improvement efforts	E.g. Increase in number of tellers in a bank, increase in course offerings in training
Customer perceptions	Service quality	Service quality (on a survey)
	Value	Relative value
	Overall satisfaction	Overall satisfaction (on a survey)
Customer behavioral intentions	Referral/Recommendation intentions	Intend to refer
	Retention intentions	Intend to return
Customer loyalty	Referrals/Recommendations	Referrals (actual)
	Retention	Returns (actual)
Surplus	Finance	Surplus
Uncontrollable factors	Environment/market	Market size Competition Other uncontrollable factors like dispersion or spread, racial/ethnic diversity, age, gender, etc.

Table 3-3. Cause and Effect variables and Polarities

Cause variable	Effect Variable	Polarity of effect
Operational attribute	Service quality	+
Operational attribute	Expenses	+
Price	Relative value	-
Price	Revenue	+
Service quality	Relative value	+
Competitor price	Relative value	+
Competitor service quality	Relative value	-
Service quality	Overall satisfaction	+
Relative value	Overall satisfaction	+
Overall satisfaction	Intend to refer	+
Overall satisfaction	Intend to return	+
Intend to refer	Referrals	+
Intend to return	Returns	+
Referrals/Recommendations	Customers	+
Retention	Customers	+
Market size	Customers	+
Customers	Market penetration	+
Market size	Market penetration	-
Customers	Revenue	+
Revenue	Surplus	+
Expense	Surplus	-

3.3.2 Feedback revisited

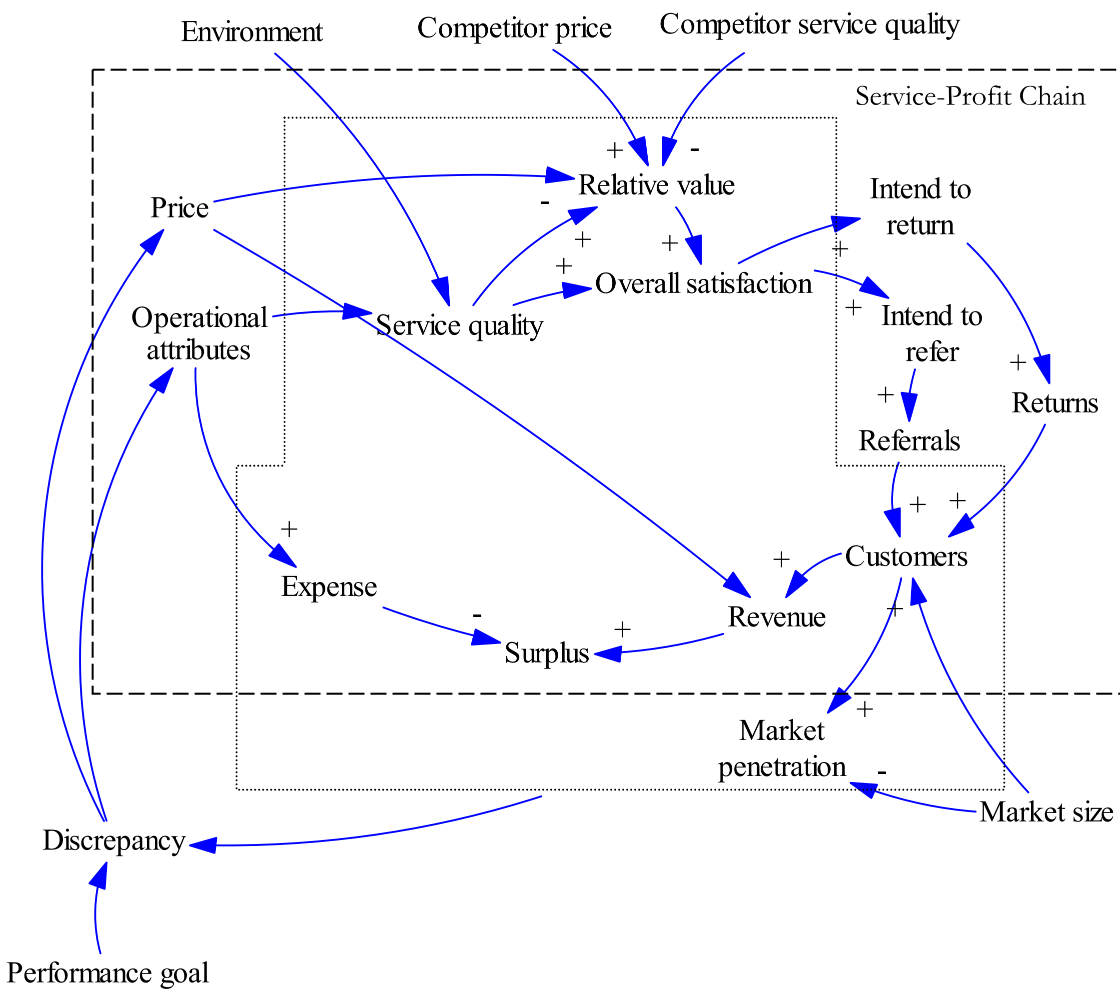
The feedback mechanism is a way of comparing the current state of the system to performance goals so as to make changes in operational attributes. Performance goals are set forth by organizations based on past analysis, experience, mental models, etc. (Sterman, 2000). Comparisons between goals and current state of the system are an inherent system dynamics feature and performance goals can be defined with respect to several performance dimensions. Few examples are provided here.

For instance, let us say that a bank has a policy to have an ATM machine for every 100 people in the community. This might be sufficient or not to satisfy the demand. Obviously, installing more ATMs will cost more, but at the same time will provide more convenience for customers. Do we have sufficient ATMs, or is it worth investing in more ATMs? If we do invest in more ATMs, to what extent would the customers perceive the convenience and would it increase our market penetration, by how much? What happens if the market conditions change? If the number of customers changes, how many ATMs do we need? The model developed in this research simulates current conditions, compares and makes necessary interventions in operational attributes if needed and then charts out the behavior of the system over time. This enables the organization to determine if the performance goals are realistic and satisfactory and investments in operational attributes are sufficient. If so, what is the outcome? If not, how should the performance goals be changed?

The above example describes a policy adjustment around operational attributes. There can be other kinds of policies for increasing the market penetration, for example, an increase of 20%; of new investments if service quality/satisfaction falls below a certain level or if the rate of return is insufficient; altering price when competition increases (relative value decreases), etc. The operational model is shown in Figure 3-3. As before, elements inside the box with dashed lines are part of the SPC. Any element enclosed by the box with dotted lines can be compared to make interventions in operational attributes and price.

The next chapter develops the model to evaluate the sustainability of investments in operational attributes using the hill-climbing optimization structure which is the evaluation methodology.

Figure 3-3. Operational model



4 Evaluation Methodology

Chapter 3 developed the conceptual and operational models to evaluate the Service-Profit Chain. Based on the current state of the SPC, managers make interventions for the future. This research restricts itself to interventions made in operational attributes and price. There are other kinds of interventions possible (e.g. advertising) which are not covered in this research. To be able to make such intervention decisions, managers need to be aware of the optimal path with regard to the operational attributes and price to best utilize and direct scarce resources. This entails incorporating an optimization algorithm to evaluate the SPC. In situations where the decision makers lack knowledge of the system structure to help identify the steady state of the system, a search heuristic called the hill-climbing optimization (Sterman, 2000) discussed in Chapter 2 is used. This chapter discusses the need to use the hill-climbing algorithm and then explains the heuristic to identify the steady state and thus evaluating the SPC.

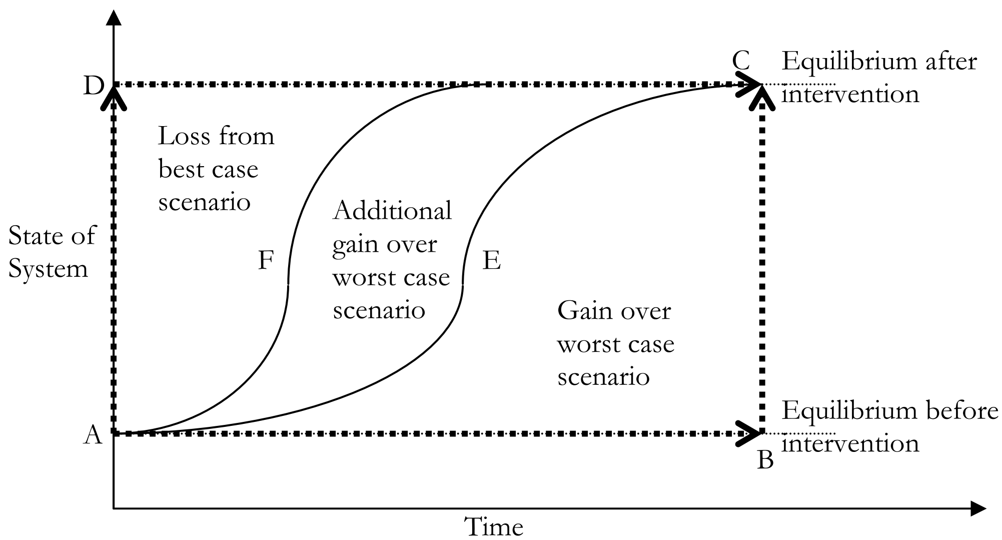
4.1 WHY IS OPTIMIZATION REQUIRED?

The law of nature governs systems to come to equilibrium and service systems are no exception to this. Whenever an intervention is made in a system to disturb from its current equilibrium, the system tries to attain a new equilibrium. The new equilibrium point is determined by the magnitude and direction of the intervention. Achieving this new equilibrium is not instantaneous and happens over time. Ideally, if the changes were to happen and the new equilibrium is achieved instantaneously, there would be no losses in the system performance (Vaneman, 2002). But this is far from reality and systems take time to get to this new equilibrium. More the time taken, more the loss in system performance. This concept is graphically illustrated as shown in Figure 4-1. Let us assume that the system is in equilibrium before intervention at point A. Let an intervention be made and the system tries to achieve a new equilibrium, say along the horizontal through point C. There are several ways to get to this new equilibrium. The ideal case would be if the system was highly responsive without any time lag and followed the path ADC. If that was the system performance, there would be no loss associated. But this is only an ideal case and not realistic. The worst case would be when the system never responds (intervention has no impact on the system performance) or the system takes an amount of time that is equal to or greater than the entire time horizon, say path ABC or path AB followed by a vertical path to the right of path BC. This would render maximum loss with system performance. Realistically speaking, the system would follow some path AEC that lies between path ADC and path ABC, where there is some gain over the worst case scenario and some loss from the best case scenario. The reason for optimization is to find some other path AFC (given the constraints of the system determined by the relationships in the SPC) that lies between path ADC and path AEC (both inclusive) such that there is additional gain over the worst case scenario and the loss from the best case scenario in system performance can be reduced.

Such a concept has been explored successfully in the past to identify the optimal path to the steady state for production systems and thus determining production efficiency (Vaneman, 2002). This research identifies a similar optimal path for service systems. Further, the empirical production frontier in Vaneman (2002) is replaced by an actual structural input-output representation of the

SPC. The next section explains how the hill-climbing algorithm can be used to identify the optimal operating path to steady state. In other words, this is the evaluation of the transformation function, the SPC.

Figure 4-1. System performance of response over time

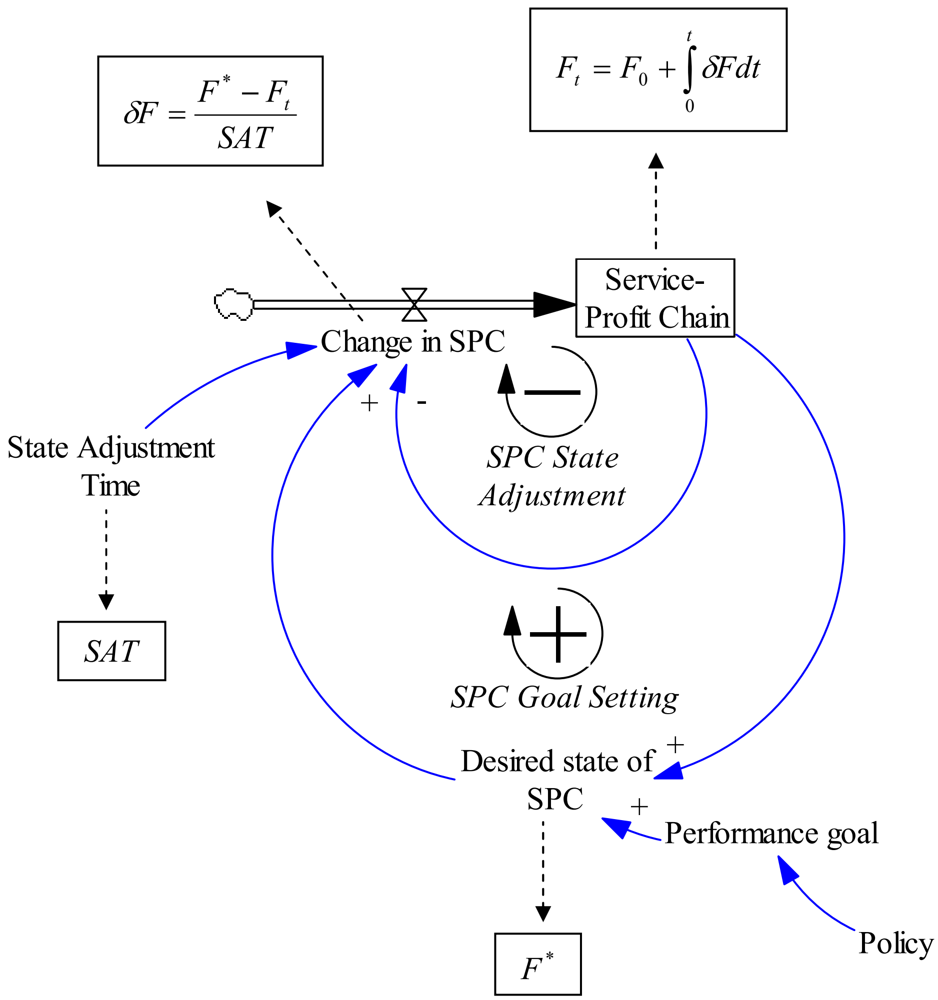


4.2 SERVICE SUSTAINABILITY CHAIN

Let F represent the transformation function formed because of the interactions between all the components of the SPC. Hence, F_t will represent the state of the SPC at any point in time t. Based on Sterman (2000), the system dynamics model for identifying the steady state of the transformation function F_t (here the SPC) is shown in Figure 4-2. The model consists of two loops, one balancing *SPC State Adjustment* loop and one reinforcing *SPC Goal Setting* loop. The balancing loop tries to correct for the discrepancy by closing the gap to get to the desired state. The reinforcing loop sets the desired state for the system. The desired state of the system is determined by performance goal that is affected by external factors like policy decisions.

Simulating this model will determine the *Change in SPC* required to alter the current state of the *Service-Profit Chain* to attain the *Desired state of SPC* and thus determining the steady state for the SPC. The *Change in SPC* includes all interventions that will be made by the decision maker to the operational attributes and price.

Figure 4-2. Evaluation of the transformation function

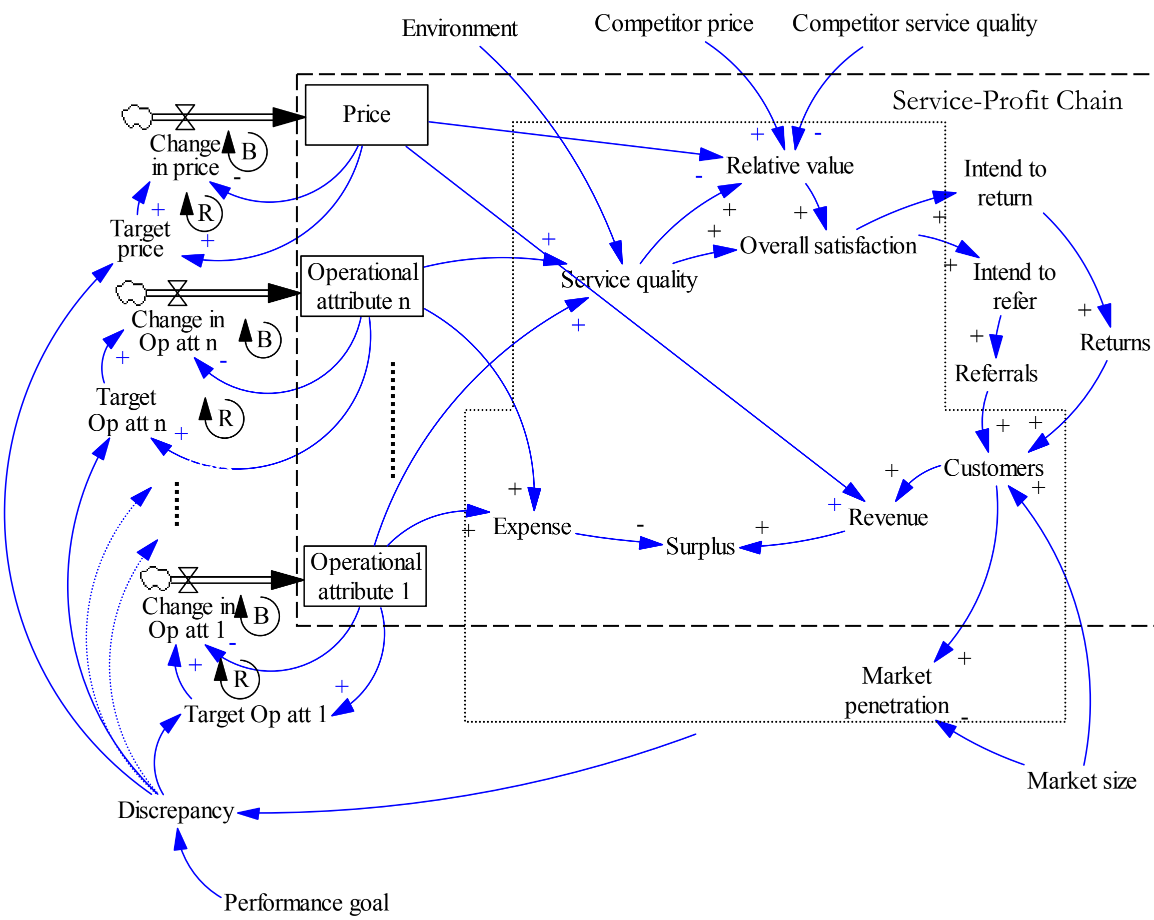


Then the above concept of identifying the steady state is used to develop the evaluation of the operational model of the SPC. The model is shown in Figure 4-3 and is still generalizable to all types of services. Figure 4-3 is similar to Figure 3-3 except for the additional optimization heuristic built around the operational attributes and price. Only operational attributes and price are shown as state variables because, those are the only variables where interventions are made in this research. Similar optimizations models can also be built where interventions are made in other variables (e.g. investment in advertising).

This generalized model can evaluate the overall impact on market penetration/revenue/surplus when simultaneous investments are made in multiple operational attributes (1, 2, … n). This is done through the search algorithm built around the multiple operational attributes. Price is another attribute that has a search algorithm and helps setting the price at the optimal level. The higher the price per customer, the more will be the overall revenue. But on the down side, higher priced services will tend customers to perceive lower value for money (all else being equal).

All optimizations which are heuristic search algorithms have similar structures. The outcome from the current state of the SPC is compared against the performance goal to set a target for the operational attribute (or price). This target which is part of the reinforcing loop sets the desired amount of operational attribute (or price). The balancing loop searches for the appropriate amount of the operational attribute (or price) by trying to close the gap (or discrepancy). Thus, the balancing loop acts together with the reinforcing loop to determine the optimal level, while simultaneously, determining the behavior of the system.

Figure 4-3. Service Sustainability Chain – Operational model with evaluation



Now that we have discussed the evaluation methodology for the operational model, let us see how it applies to a specific type of service. The next section looks at training services in specific and develops a full-blown system dynamics model.

4.3 TRAINING SERVICES

The Merriam-Webster dictionary gives the definition of *training* as 'to teach so as to make fit, qualified or proficient'. Training is a service that focuses on a specific topic and aims at making the student proficient. Educational institutions offer training services to students. Due to the students' intimate involvement with the educational process, students have traditionally been viewed as a product of an educational institution, Gold (2001). However, Wallace (1999) suggests that, although using the term 'customers' can arouse many emotions and misconceptions in academia, referring to students as customers does not mean that administration cannot or should not drive the educational agenda. Now, there is consensus that the student is the primary customer of educational services, Banwet and Dutta (2003). Ham and Hayduk (2003) claim that service quality improvement is important for educational services and university's administrators and business leaders should make investments for the same. Service quality, customer satisfaction and behavioral intentions are global issues that affect all organizations, and educational institutions are no exception to this, Ham and Hayduk (2003). The current research considers students as customers and evaluates such investments made in operational attributes to improve service quality, satisfaction, loyalty and eventually market penetration/surplus, etc.

4.4 SERVICE SUSTAINABILITY CHAIN FOR TRAINING SERVICES

This section builds a system dynamics model to evaluate the sustainability of investments in operational attribute improvements in the SPC as it relates to training services. The model is developed in modules. First is the Dynamic SPC module. This module builds further on the operational model in Figure 4-3.

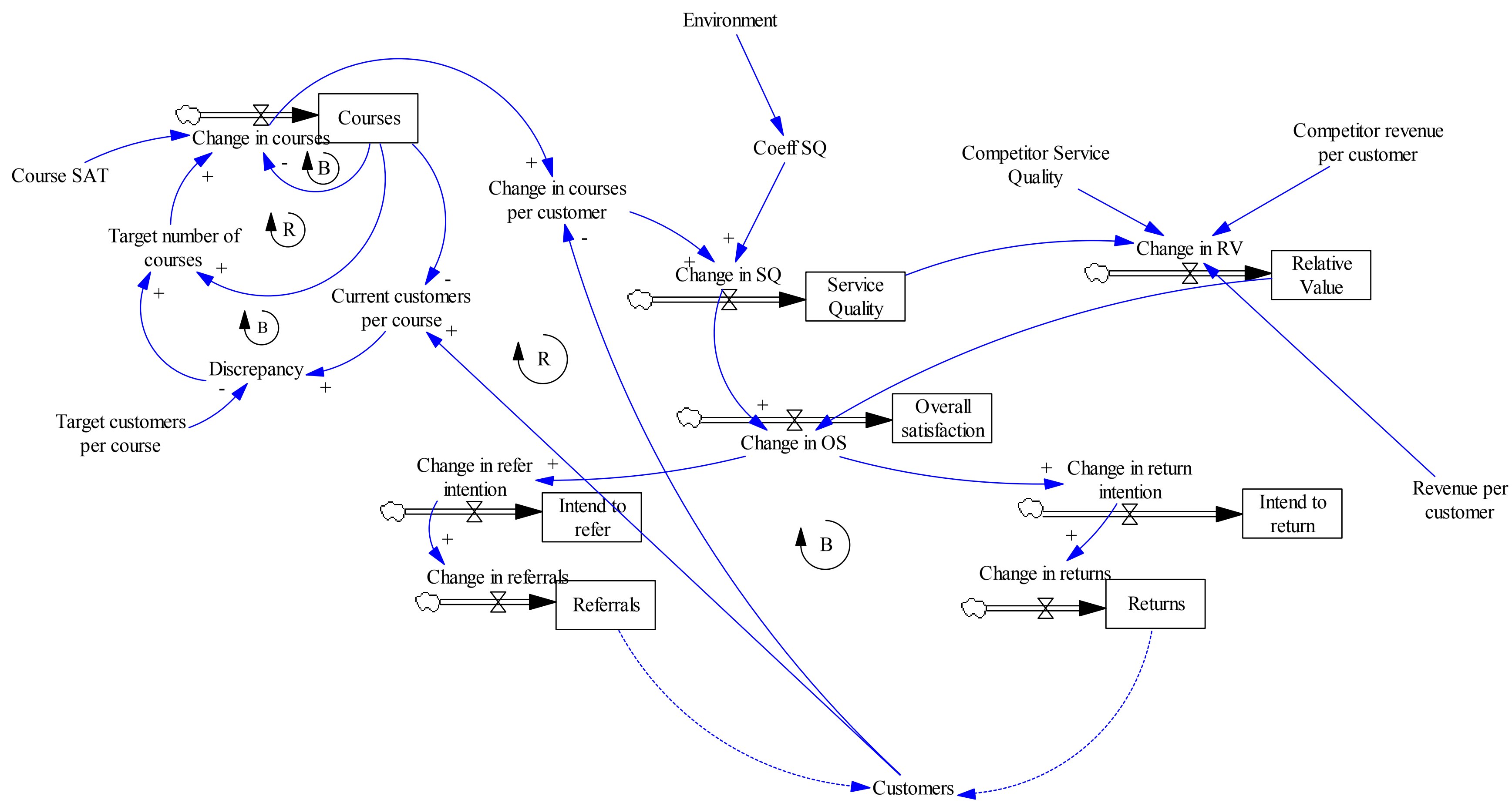
4.4.1 Dynamic SPC

The model includes one operational attribute – number of *Courses* offered. *Target customers per course* is a performance goal based on policy decisions made by the organization. Customers perceive this operational attribute based on the course to customer ratio. For any *Change in courses per customer* there is a change in service quality (*Change in SQ*). Change in the *Environment* affects a change in service quality through the coefficient of service quality (*Coeff SQ*). In this research, the coefficient of service quality is determined by a combination of CHAID and SEM. *Revenue per customer* (shown as Price in the operational model) and *Competitor revenue per customer* (shown as competitor price) both affect the *Relative value*. By offering more number of *Courses*, the organization presents more locations and schedule options for the customer. Because of this, the customer is expected to have an increase in the perceived *Service Quality*, *Overall satisfaction*, intentions and loyalty in terms of *Referrals* and *Returns*, thus increasing the number of *Customers*. Dashed arrows between *Referrals*/*Returns* and *Customers* show existence of other variables that affect the relationship and are explained in detail in the Customer Base Growth module. *Course SAT* stands for Course State Adjustment Time and determines how often the state variable *Courses* is adjusted. Or, how long it takes to make changes to number of *Courses*. The actual time depends on the type of operational attribute (e.g. changing number of courses offered is easier and can be done more often than changing the number of locations, hence the former will have a lower SAT than the latter), application and industry.

The *Current customers per course* is compared against the *Target customers per course*. Based on the comparison and the current number of *Courses*, the *Target number of courses* is set which alters the *Change in courses*. For a given *Target number of courses*, the closer the number of *Courses* to the target, the lower the *Change in courses* that is required. Thus the structure shown in Figure 4-4 determines the steady state for the system. Such a state is known to have reached when the system is in dynamic equilibrium. In other words, quantity that enters the system (inflow rate) is equal to the quantity that leaves the system (outflow rate) and the state variables have a constant amount. The system will continue to exhibit this steady state behavior until another intervention or a change in one of the exogenous factors is effected.

Next, the Customer Base Growth module is discussed.

Figure 4-4. Dynamic SPC Module



4.4.2 Customer Base Growth

This module of the system dynamics model is built around the number of *Customers* the organization is serving at any given time period. *Customers* is a stock variable and the units of measurement will be the number of people. *Potential Customers* is another stock variable indicating the number of people in the market that could become customers. *Customers* are replenished by the people from the *Potential Customers* by adoption. There are two types of adoption, *Normal Adoption* and *Referred Adoption*. *Normal Adoption* will be discussed later. *Referred Adoption* accumulates *Customers* with the number of people that had the need and decided to take the service based on a positive referral made for the organization under study. What percentage of the *Potential Customers* actually adopts the service is determined by *Referrals*, which is measured as a percentage. *Market size* is an exogenous factor that also affects the *Referred Adoption* rate.

The concept of customer referrals is analogous to the SI-model for infectious diseases (Kermack and McKendrick, 1927; Sterman, 2000). The SI-model captures the structure of spread of diseases where the infection is contagious. The disease spreads from one person (from the Infectious Population) to another (from the Susceptible Population) when they come in physical contact with one another. In the SI-model, *Contact Rate* (c measured as the number of people contacted per person per time period) is the rate at which people in the community interact. The *Susceptible Population* (S measured as the number of people) brings about Sc contacts. The probability that a randomly selected encounter is an encounter with an infectious person is I/N (I is the total of *Infectious Population* and N is the *Total Population*). The model assumes that infected people are not confined to bed or quarantined. This assumption is irrelevant to the Customer Base Growth module, since except for the duration of the training/course, which is a very negligible amount of time compared to the duration the infected people will be confined to bed or quarantined, *Customers* will interact with other people at the same rate as *Potential Customers*. Among the encounters in the SI-model, not every encounter with an infectious person leads to infection. Infectivity (i) of the disease is the probability that a person gets infected after contact with an infectious person. Thus, Sterman (2000) gives the *Infection Rate* (IR) as the total number of encounters, Sc multiplied by the probability that the encounter is with an infectious person, I/N multiplied by the probability i that an encounter with an infectious person results in infection:

$$IR = (ciS)(I/N)$$

Further, assuming that the *Total Population* remains constant,

$$S + I = N$$

Hence, the *Infection Rate* is

$$IR = (c)(i)I(1-I/N)$$

As we can see, the product c*i is the probability that any contact results in infection. The equivalent of this product for the Customer Base Growth module would be the percentage of the people that were referred and ended up coming to the organization. The reason why it is inappropriate to explicitly model the *Contact Rate* for the Customer Referrals model is because, unlike the SI-model, people do not need to come in physical contact with one another to refer. The population density or spread of the community does not affect the contact rate, since one can refer another even over the phone or internet. In other words, the Customer Referrals model aims to capture the proportion of people that got referred and ended up taking the course, which is a percentage, *Referrals*. The state variable *Referrals* is the link between the Customer Base Growth and the Dynamic SPC modules. The percentage of *Referrals* determined by the Dynamic SPC module for any given year feeds the Customer Base Growth module. Table 4-1 shows the analogy between the two models by listing out the corresponding variables.

Table 4-1. Analogy of Customer Referrals to SI-model

Customer Referrals	SI-model
Potential Customers	Susceptible Population
Referred Adoption	Infection Rate
Market Size	Total Population
Referrals	Contact Rate * Infectivity
Customers	Infectious Population

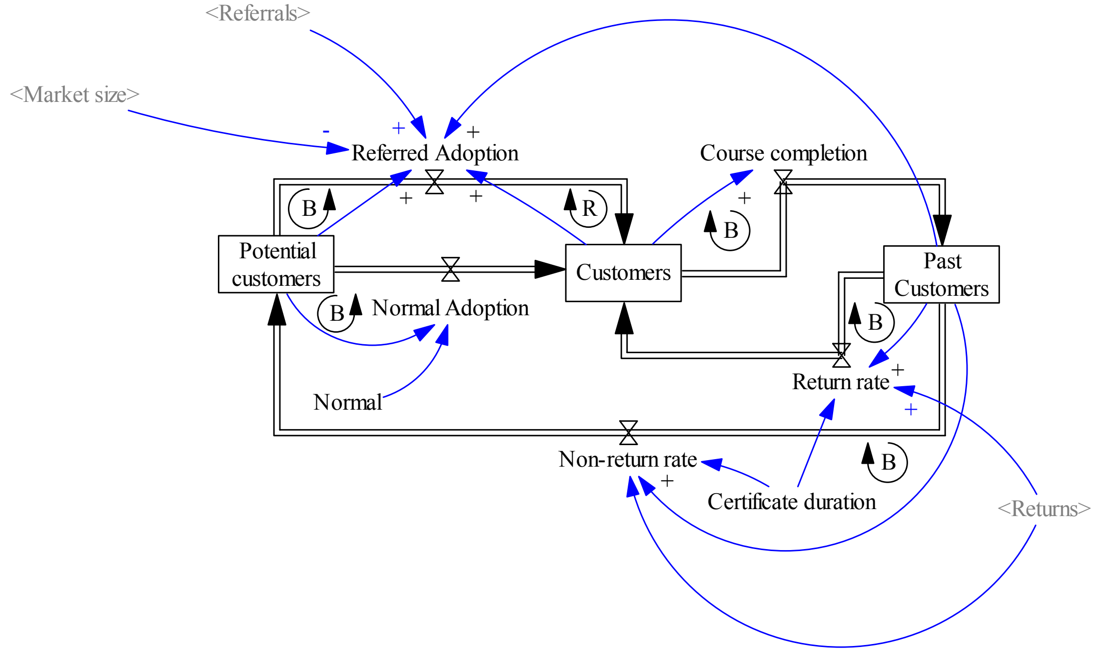
Customer referrals is one part of the overall "Customer Base Growth" module. There are other parts in the module, normal adoption and returns, which will be discussed now. *Normal Adoption* encompasses people that choose to take the training service because they have a need to do so but were not referred by former customers. *Normal* is the percentage of potential customers that take the course without referrals. The greater the *Potential Customers* are, the greater will be the *Normal Adoption* rate.

Past Customers is another stock variable that tracks the number of people from the moment they complete the course/training to when their training certification expires. *Certificate Duration* is the amount of time for which the certification is valid. The *Course Completion* rate depletes the current *Customers* and accumulates *Past Customers* as the people taking the training complete the requirements for the certification. As the number of people cannot exceed the market size, at any point in time, the sum of *Potential Customers, Customers* and *Past Customers* is always equal to the *Market Size*. Both *Customers* and *Past Customers* can refer people and hence, both affect the *Referred Adoption* rate.

Referrals is one type of customer loyalty and the other type is retention or the return of a prior customer for repeat business. *Past Customers*, based on their experience with the service, decide either to return back or not for more service once their certification expires. The ones that return replenish the *Customers* stock through *Return rate* and the ones that do not come back after the expiration of their certification feed in back to *Potential Customers* through *Non-return rate*. *Return rate* and *Non-return rate* are determined by *Returns* (measured as a percentage of people that come back) and *Certificate Duration* (measured as the number of time periods for which the certification is valid). *Returns* is a link between the Dynamic SPC module and the Customer Base Growth module. The percentage of *Returns* determined by the Dynamic SPC module feeds the Customer Base Growth module.

Market Size, *Referrals* and *Returns* are shown here as shadow variables because they are exogenous to the Customer Base Growth module. The module is shown in Figure 4-5. Change in Market module (which *Market Size* is a part of) will be discussed next.

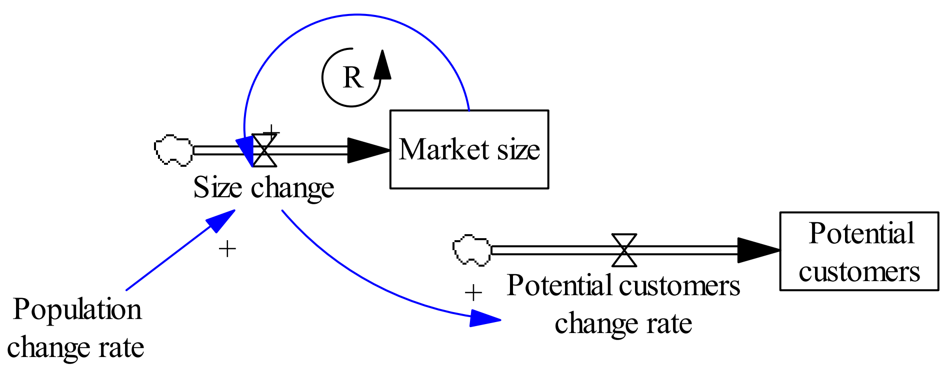
Figure 4-5. Customer Base Growth Module



4.4.3 Change in Market

Market Size, and hence the *Potential customers* can change because of several reasons like birth/death/immigration/emigration. There is a reinforcing loop, as *Market size* increases, the *Size change* also increases, further increasing the *Market size*. *Population change rate* affects the *Size change* rate which in turn alters the *Potential customers change rate*; eventually altering the *Potential customers* in the Customer Base Growth module. This is shown in Figure 4-6.

Figure 4-6. Change in Market



Putting together all the above modules, Figure 4-7 shows the full-blown system dynamics model and Table 4-2 lists the state and control variables modeled in the SSC.

Figure 4-7. Full-blown System Dynamics Model

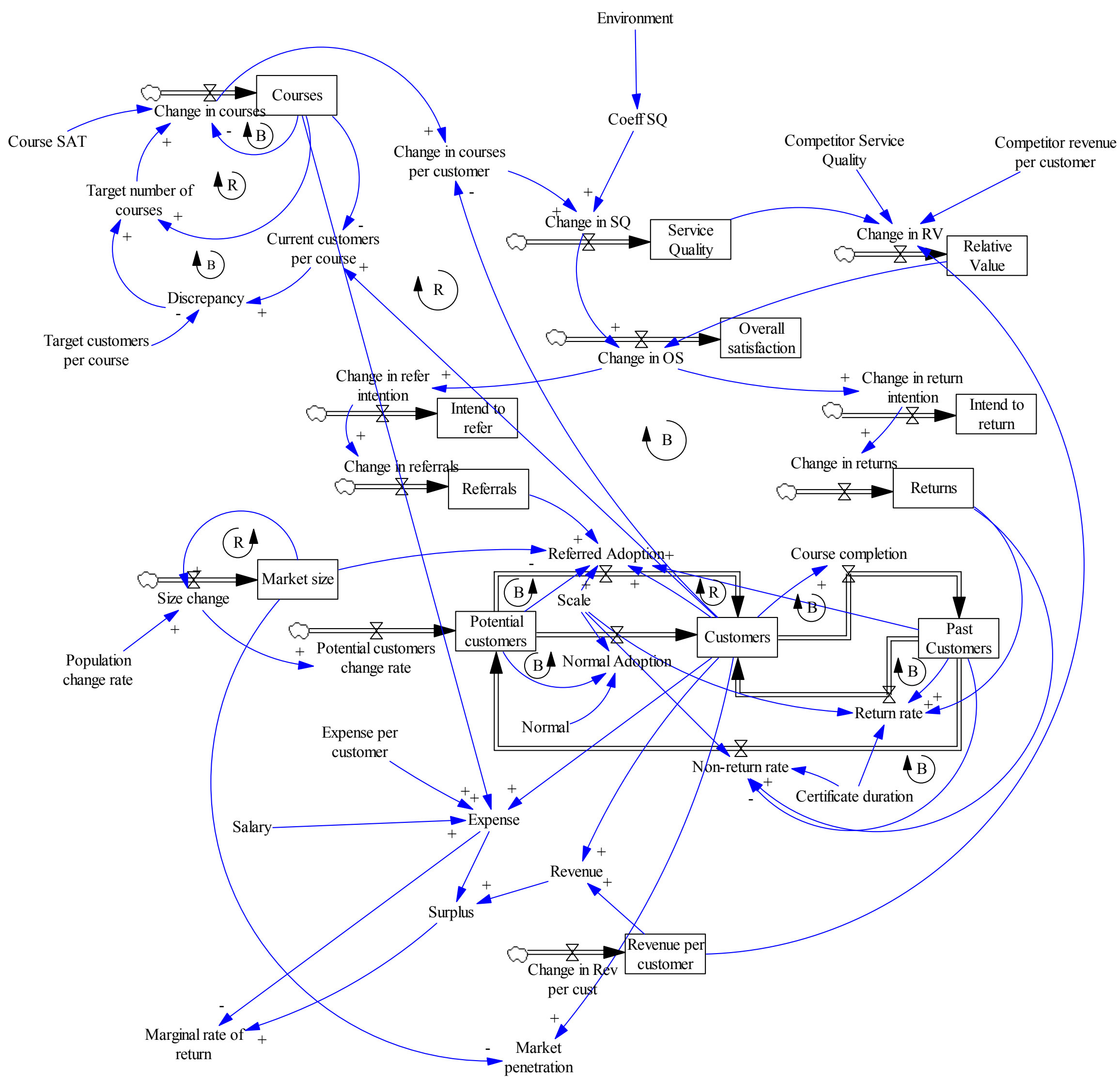


Table 4-2. State and Control variables in the SSC

Component of SSC	Dimension	State variables modeled as stocks	Control variables modeled as flows
Operational attribute	Improvement effort	Courses	Change in courses
Customer perceptions	Service quality	Service quality	Change in SQ
	Value	Relative value	Change in RV
	Overall satisfaction	Overall satisfaction	Change in OS
Customer behavioral intentions	Referral/Recommendation intentions	Intend to refer	Change in refer intention
	Retention intentions	Intend to return	Change in return intention
Customer loyalty	Referrals/Recommendations	Referrals	Change in referrals
	Retention	Returns	Change in returns
(additional state/control variables)		Potential customers Customers Past customers	Referred Adoption Normal Adoption Course completion Return rate Non-return rate
Uncontrollable factors	Environment/market	Market size	Size change

The variables used in the model shown in Figure 4-7 along with the definitions and units are listed in Appendix B.

The system dynamics model, both the general model and the one specific to training services have been developed. The full-blown system dynamics model can be applied to study behavior and answer business related questions in service operations. However, service operations do not have any specific mathematical equations between variables that exist, like the empirical production frontier in the case of production systems. Hence, a methodology needs to be used to represent the structure of the system by exploring service operations. Such a methodology would provide the following:

- Explore and identify measurable predictor environmental variables and profiles
- Determine structural coefficients for various environmental profiles
- Determine structural coefficients for various SPC components

The next section describes the methodology to identify patterns and relationships in the data. The methodology uses Chi-Square Automatic Interaction Detection (CHAID) and Structural Equation Modeling (SEM). Both the techniques are explained in Chapter 2 of this research. However, the relationships and structural coefficients identified using such a methodology are case specific and vary from one type of service to another.

4.5 CHI-SQUARE AUTOMATIC INTERACTION DETECTION (CHAID) AND STRUCTURAL EQUATION MODELING (SEM) METHODOLOGY

In the SD process, the modeler is tasked with putting together the relationships among variables with enough precision to make the model useful. The modeler does this based on literature, knowledge of experts and testing relationships using past data. In today's organizations, large amount of data collected is stored without any in depth analysis of changes and trends. If no one has the holistic approach of the organizational authorities of the past, finding an expert that will clarify the relationships or finding enough organizational documentation to point in the right direction is a challenging task. Intuitively, when data is abundant and no other sources of expert knowledge exist, one could expect that mathematics can settle the issue. A potential modeling strategy would be to confirm the relationships through some statistical method. CHAID can be used for this purpose (Pasupathy and Medina-Borja, 2005[11]).

CHAID is a type of decision tree method originally proposed by Kass (1980). CHAID is a combinatorial algorithm since it goes over all possible variable combinations in the data to partition them into nodes. Each node would give a specific profile that has a unique behavior that is represented by a corresponding unique equation later developed using SEM. It is also an exploratory method used to study the relationship between a dependent variable and a series of predictor variables. The CHAID algorithm is particularly well suited for the analysis of large datasets because the algorithm will often effectively yield many multi-way frequency tables (e.g., when classifying a categorical response variable with many categories, based on categorical predictors with many classes). One of the most common uses of CHAID has been in market segmentation to uncover customer characteristics for response modeling (see for example MacLennan and MacKenzie, 2000)

In addition if some of the variables can be classified as "constructs" of otherwise ambiguous perceptual concepts, such as service quality, customer satisfaction or political support, these are generally measured through survey items on some sort of scale (the most common one the Likert scale). Finding how these items are related to other variables in the problem, such as investment dollars is difficult. Ultimately, how can the exact mathematical representation of such a relationship be uncovered so that a model is built, run, and gives useful and credible results. SEM is suggested to be used for this purpose (Pasupathy and Medina-Borja, 2005).

Structural equation modeling (SEM) is a methodology used to model interactions, and nonlinearities among multiple latent independents[12] measured by multiple indicators, and one or more latent dependents[13] each with multiple indicators as well. SEM is a major component of applied multivariate statistical analysis and is used by biologists, economists, market researchers, and other social and behavioral scientists to study complex dependencies among variables in a causal framework. See for instance Hayduk (1985), Bollen (1989), Schumacker and Lomax (1996) and Pugesek et al. (2003). Contrary to CHAID, a causal model based on theory is first proposed and then tested for the data set. The model is used to test how well a model fits the data only to be accepted as a not-invalidated model. Alternatively, several proposed models can be compared against each other and based on the goodness-of-fit measures, the best model is chosen.

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[11] Article submitted to System Dynamics Review included in Appendix A.

[12] Latent independents are independent variables that are not observed.

[13] Latent dependents are dependent variables that are not observed.

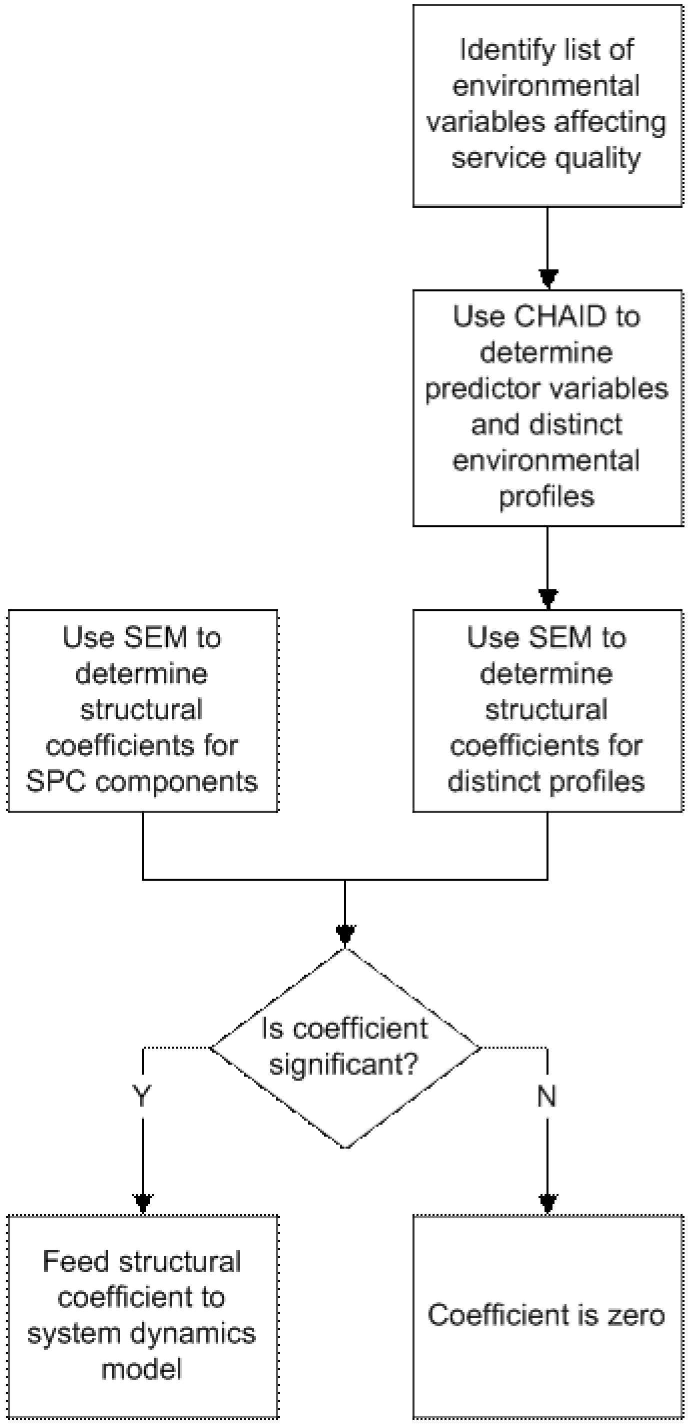
Pasupathy and Medina-Borja (2005) propose that the same can be used to identify or confirm important predictors of any given variable in system dynamics modeling.

Based on these discussions, the current research uses a combination of CHAID and SEM to uncover the relationships and determine the equations for system dynamics, Figure 4-8 shows the methodology in the form of a flowchart. To start with, the decision-maker turns to the literature and to experts to identify environmental variables that can potentially affect customer perceptions (in specific, service quality). Then, CHAID is used to determine which of the environmental variables more significantly predict service quality. CHAID also determines splits in the data that correspond to different environment profiles or segments that exhibit significantly different perceptions (service quality levels). Then for each of these profiles or segments, a SEM model is run to determine the structural coefficient.

With regard to relationships between the components in the SPC (customer perceptions-behavioral intentions-loyalty), variables have already been identified based on the literature and hence the decision-maker skips CHAID and uses SEM to determine the structural coefficients for the relationships between the variables.

In both the above cases, the structural coefficient is used in the system dynamics model if it is significant, else is deemed zero. This methodology is illustrated in the next chapter where the step-by-step procedure is followed to identify relationships and equations for a case study.

Figure 4-8. Methodology to uncover relationships and determine equations



5 Case Study, Application and Model Validation

5.1 RESEARCH CASE STUDY

The research case study was conducted at the national headquarters of a social service organization in Washington DC. The case study concentrated on Health & Safety training of First Aid and CPR (cardiopulmonary resuscitation) courses. The Health & Safety Services Department has a total of 12 million enrollees (or course takers or customers) per fiscal year, out of which six million enroll in First Aid and CPR training alone. The organization has approximately 900 field units across the United States providing services in the community. First Aid and CPR is one such service where the course is taught in the community for a fee.

5.1.1 The Problem

Field unit A of the organization has a policy establishing that they should register no more than ten customers in each course offering. This field unit is interested in knowing whether it is a sustainable policy. Is their customer base poised to increase? How do they need to phase in their investments in increasing course offerings over time? What is the exact impact on service quality, satisfaction and on customer loyalty which in turn affects the number of customer walk-ins? To what extent can the field unit increase the number of courses and expect an increase in market penetration? Is there a point in time beyond which the marginal rate of return decreases with investments?

All of these questions can be answered by applying the methodology and the model developed in this research. Field unit A of this organization is large and complex, with many departments and functions interacting. A problem of this sort involves various aspects like financial, capacity, service delivery, market research, etc. Knowledge of the entire operation is much diluted in several departments and no one person has a holistic view to address the questions identified previously. However, large amounts of data are being collected year after year. These large amounts of data can be used along with the model and the proposed methodology to answer the questions in the case study.

The field unit knows that the main competitor in the market provides a similar course for $60 (lower when compared with the field unit's course fee of $65) but they believe the contents are of lower quality. The relative value[14] of the course offered, based on a previous study, was rated at

[14] Relative value is defined as the value perceived by the customer based on the quality of the service received for the price paid in comparison to the quality of similar service offered by competitors for their price (McDougall and Levesque, 2000).

78.7%. Since service quality[15] itself was not a measured item in that study, it will be set arbitrarily at some percent and the changes will be modeled and analyzed. Service quality of the filed unit is set at 50% (meaning 50% of the customers rated the service as 'Excellent') and that of the competitor at 40% (lower since past study shows a lower service quality) based on input from experts.

5.1.2 Unit of Analysis

The unit of analysis will be a field unit. Field units have Health & Safety instructors employed to teach the courses and train the people. They use books, videos and other materials for providing these courses. Typical settings for teaching are the field unit office, schools and other office buildings. A lot of data is collected around this operation. Customers are surveyed about their perceptions. Responses to surveys were aggregated at the field unit level.

5.1.3 Source Data

Several sources of data were used for the purpose of this case study:

- Financial profile

  This data source has all data pertaining to the finances of the field unit, like revenue, expenses, investments made in specific attributes. Data was available for 980 field units.

- Service delivery and demographic profile

  This profile has data on enrollees (customers), number of courses and instructors, personnel, demographic variables, etc. Data was available for 991 field units.

- Customer profile

  This profile is available through a program that has been implemented in the past. Data is available on personnel efforts and on customers like perceptions and satisfaction, behavioral intentions and customer loyalty. 406 field units participated in the program, surveyed their customers, hence data was available from only these field units.

The data source and the instrument used for each of the dimensions are shown in Table 5-1.

Table 5-1. Data sources

Dimension	Instrument	Data source
Investment effort	Database system	Financial profile
Service quality	Survey of customers	Customer profile
Overall satisfaction	Survey of customers	Customer profile
Referral/Recommendation intentions	Survey of customers	Customer profile
Retention intentions	Survey of customers	Customer profile
Referrals/Recommendations	Survey of customers	Customer profile
Retention	Survey of customers	Customer profile
Finance	Database system	Financial profile
Environment/market	Database system	Demographic profile

[15] Service quality is the quality of the service provided by the organization to the customer and constitutes a set of items. Service quality is measured as it is perceived by the customer using these items on a survey instrument shown in Appendix C.

5.1.4 Survey Instrument

The survey instrument used for this research to profile the customers has the following four areas to collect the data: (see Appendix C for the survey instrument).

i. Perceived service quality and customer satisfaction items

ii. Outcome effectiveness items

iii. Demographic items

iv. Other related information

Survey items that are used as data for the corresponding observed variables are identified in Table 5-2. Survey item #11 is one question with several sub-questions and each of the sub-questions relate to one observed variable. The one-to-one mapping of these can also be seen in this table.

Table 5-2. Survey items for variables

Observed variables	Page	Survey item#	Survey item
Clarity	1	11	Instructor's ability to present information clearly
Knowledge	1	11	Instructor's knowledge: ability to answer questions
Courteousness	1	11	Availability/courtesy of staff to answer questions
Information	1	11	Inclusion of skills and information that you needed
Quality of materials	1	11	Quality of course books and videos
Helping to learn skills	1	11	Effectiveness in helping you learn skills
Convenience of times	1	11	Convenience of times offered in the course schedule
Convenience of locations	1	11	Convenience of the available course locations
Ease of course registration	1	11	Ease of course registration
Overall satisfaction	1	11	Overall satisfaction with this course
Intend to refer	2	12	I would recommend this course to a friend
Intend to return	1	10	Are you interested in using computer-based learning as part of your course in the future? "Yes"
Referrals	2	-	How did you first learn about this course (presentation)? "From a friend/family member"
Returns	1	2	How many times have you taken this course? Any answer other than "This is my first time"

Perceived service quality, customer satisfaction and outcome effectiveness items have a 6-point Likert scale. The instrument was piloted and tested and the perceived service quality items had a high reliability of alpha=0.9 with number of valid cases, N=101,623.

The items included as part of the service quality construct all grouped together in factor analysis[16] assuring the measurement of one construct. In other words, one factor was identified and all the items loaded onto this factor, service quality. The component values are shown in Table 5-3. Ease of course registration had to be dropped from the analysis because of excessive missing data

[16] Principal component analysis using Varimax rotation (Stevens, 2002) using SPSS 10.0

(less than 0.01% data available). This was because of the existence of different versions of the survey (one with and the other without the question). Almost all field units used the version without the question.

Table 5-3. Component matrix

Item	Component 1
Instructor's ability to present information clearly	0.813
Instructor's knowledge: ability to answer questions	0.813
Inclusion of skills and information that you needed	0.834
Quality of course books and videos	0.706
Effectiveness in helping you learn skills	0.840
Availability/courtesy of staff to answer questions	0.799
Convenience of the times offered in the course schedule	0.663
Convenience of the available course locations	0.672

5.1.5 Environmental Variables – Identification

The following uncontrollable factors and variables were originally identified[17] as those that can potentially affect components in the SSC. They are shown in Table 5-4.

Table 5-4. Environmental variables

Uncontrollable factor	Variable name	Variable code	Data source
Dispersion or spread	Population density	POP_DEN	Demographic profile
Wealth	Median household income	MEDHHI	Demographic profile
Racial/ethnic diversity	% minority	%MINO	Customer profile
Age	% below 25	BELOW25	Customer profile
	% above 25	ABOVE25	
Gender	% female	FEMALE	Customer profile
	% male	MALE	
Market size	Market size	POP	Demographic profile

All the variables that were identified as potential factors (shown in Table 5-4) that affect customer perceptions were included as part of the CHAID analysis. The outcome variable is service quality. But since service quality per se was not measured, overall satisfaction (OvSat) was used as the outcome variable. This is a valid proxy since overall satisfaction was highly correlated with the items that constitute service quality and also aligned well with these items in the factor analysis. Further, this was validated by the results from structural equation modeling where the coefficient of service

[17] Several internal documents show that previous studies had validated this notion of environmental influence on performance.

quality predicting overall satisfaction came out to be 0.98 (almost equal to one[18], significant at < 0.0005 level).

Population density is the spread of the population in the community served by the field unit and is measured in people per square mile. Median household income is the median of all the household incomes in the community[19] and is measured in US dollars. Diversity is measured as the percentage minority in the community. This is computed as the percentage of people that answered the "You consider yourself to be (FILL ONLY ONE):" question on page 2 of the survey in Appendix C as any answer other than "White." The ages were divided into two groups – kids/youth/young adult and adult/senior. These coincide with "below 25" and "above 25." "Below 25" is the percentage of people at the field unit level that answered to the question "Age Group:" as "12 or younger," "13to 18" or "19 to 25." "Above 25" is the percentage for the remaining three groups on that question.

When CHAID was run[20] including all the variables shown in Table 5-4, the tree shown in Figure 5-1 was obtained. Age group (ABOVE25) and median household income (MEDHHI) came out to be the most significant predictors of overall satisfaction in that order. Markets with more than 56% ABOVE25 customers are significantly (with p-value = 0.0002) more satisfied (with a mean of 75%) than those markets with lesser than 56% (with a mean of 68%). ABOVE25 less than 56% ended up being a terminal node, meaning, there are no more significant predictor variables for any subgroups of the 40 field units. On the other hand, ABOVE25 greater than 56% splits further and MEDHHI is the next most significant (with p-value = 0.0288) predictor. There are five (four valid and one missing) child nodes. These child nodes are also terminal nodes (with no further possible splits).

5.1.6 Effect of Environmental Variables – Calculation of Coefficient

Each of the terminal nodes has significantly different perception (satisfaction) levels. The next task is to find out to what extent these groups change with changes to the number of courses per customer (which is the operational attribute perceived by customers). Since SEM can handle constructs (measured by items) as latent variables (measured by indicators), there was not a need to use a proxy. A model with *Courses per customer* as the independent variable and *Service Quality* (with all its items identified in Table 5-3 as indicator variables) as the dependent variable was developed. The variable codes are shown in Table 5-5 and the structural equation model is shown in Figure 5-2.

Number of courses offered per customer (Coffenro) is an observed variable and hence is enclosed in a rectangle. Service Quality is a latent variable (enclosed in an oval) measured by indicators (that are observed and hence enclosed in rectangles) – clarity, knowledge, courteousness, information, quality of materials, helping to learn skills, convenience of times and convenience of locations. From the SSC, we know that any change in Courses per customer causes a change in Service Quality. Hence, the link from Courses per customer (independent variable) to Service Quality (dependent variable) and SEM will quantify the effect of this relationship and determine the significance. These indicator variables are those that constitute the service quality construct. Each of the variables has an associated error term. This error term accounts for any measurement error or any variation that remains unexplained in the relationships. These are shown in small circles feeding into the respective variable and are denoted by a lower case 'e' followed by an abbreviation for the variable.

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[18] A coefficient of one means that for a unit increase in service quality, overall satisfaction increases by one.

[19] Documented by the US Census Bureau

[20] Using AnswerTree 3.1 (SPSS, 2001)

The '1' on the link from each error term to the respective variable represents the weight and is related to model identification. Identification relates to whether or not there is a unique set of parameters consistent with the data. This depends on the transposition of the variance-covariance matrix of the observed variables into the structural parameters of the model under study. If a unique solution can be found then the model is said to be identified. Under such a scenario, the parameters can be estimated. But on the other hand, if the model cannot be identified, then a unique set of values for the parameters cannot be estimated. Thus, setting the value makes the model just-identified and parameters estimable. For a detailed explanation, please refer to Bollen (1989), Raykov and Marcoulides (2000) and Byrne (2000). The arrow leading from Service Quality to Clarity is also set to 1, as part of model identification.

Figure 5-1. Identification of environmental variables that affect customer perceptions

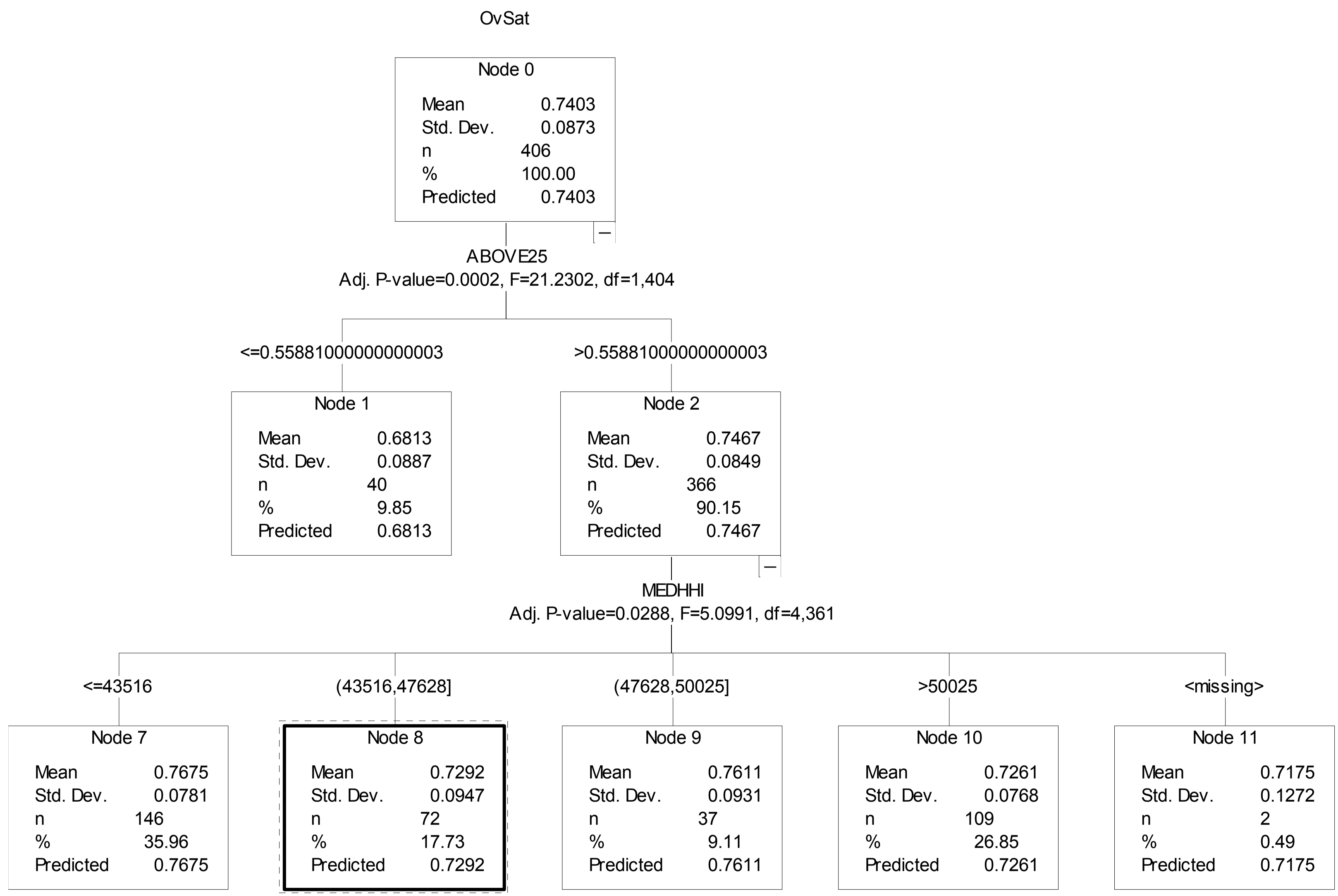
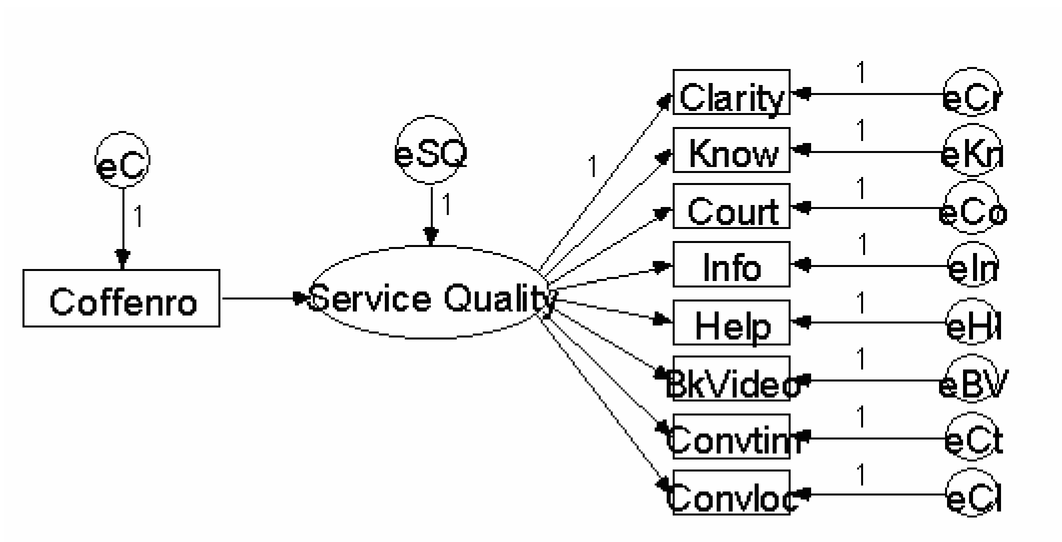


Table 5-5. Variable codes used in Structural Equation Modeling

Variable name	Variable code
Courses per customer	Coffenro
Clarity	Clarity
Knowledge	Know
Courteousness	Court
Information	Info
Quality of materials	BkVideo
Helping to learn skills	Help
Convenience of times	Convtim
Convenience of locations	Convloc
Overall satisfaction	OvSat
Intend to refer	IRefer
Intend to return	IReturn
Referrals	Refer
Returns	Return

Figure 5-2. Effect of change in number of courses on service quality



The model in Figure 5-2 is run[21] to compute structural coefficients between courses per customer (Coffenro) and service quality. The coefficients (obtained from SEM) for the various terminal nodes (identified by CHAID) along with the significance values are shown in Table 5-6. The last coefficient in the table is not significant (p-value = 0.734) and hence was not used in the system dynamics model.

[21] Using Amos 5.0 (Byrne, 2000)

Table 5-6. Coefficients for various environmental profiles

Age above 25	Median Household Income	Coefficient	P-value
<= 55.88%	-	0.63	0.095
> 55.88%	<= $43,516	0.28	< 0.0005
> 55.88%	> $43,516 and <=$47,628	0.57	0.021
> 55.88%	> $47,628 and <= $50,025	0.8	0.029
> 55.88%	> $50,025	-0.003	0.734*

*Not significant and hence will not be used in the model

All the significant coefficients were fed into the system dynamics model for the *Coeff SQ* variable (effect of environment on customer perceptions). Depending on the profile in which the field unit's environment fell (range of ABOVE25 and MEDHHI) at each time period the *Coeff SQ* will take on the corresponding value from Table 5-6.

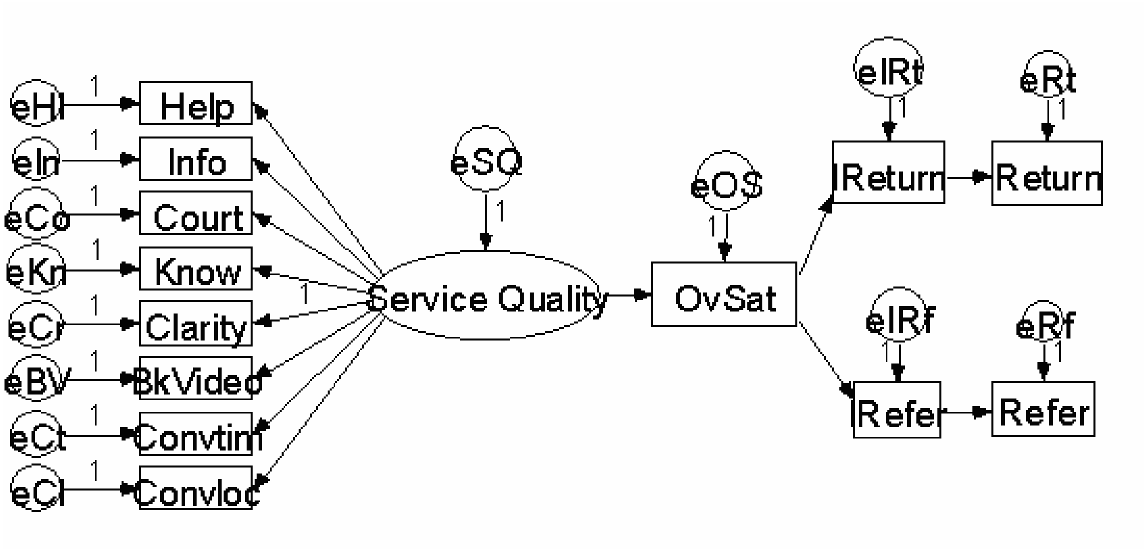
5.1.7 Structural coefficients for SPC

Next, the structural coefficients are quantified for the relationships in the SPC using SEM. For this, the relationships from service quality through overall satisfaction and return/refer intentions to actual returns/referrals are modeled, Figure 5-3. Service Quality was modeled as a latent independent variable measured by a group of indicators (on a survey instrument).

As before, Service Quality is enclosed in an oval to illustrate that it is a latent variable and set of eight indicators that are part of the survey instrument used to measure service quality – helpfulness, information, courteousness, knowledge, clarity, quality of materials, convenience of times and convenience of locations. Service Quality is linked to overall satisfaction (OvSat), which is a measured variable. Overall satisfaction is linked to both intend to return (IReturn) and intend to refer (IRefer).

Each of the variables has an associated error term. This error term accounts for any measurement error or any variation that remains unexplained in the relationships. These are shown in small circles feeding into the respective variable and are denoted by a lower case 'e' followed by an abbreviation for the variable. The arrow leading from Service Quality to Clarity is also set to 1, as part of model identification.

Figure 5-3. Structural model for SPC



The model in Figure 5-2 is run[22] to compute structural coefficients between the variables in the model. The coefficients (obtained from SEM) along with the significance values are shown in Table 5-7 below. The coefficient is the value by which an outcome variable increases for a unit increase in the predictor variable. For example, for every unit increase in Service Quality (predictor variable), OvSat (outcome variable) increases by 0.982. All of the coefficients were very significant, except one (IReturn ← OvSat), which was fairly significant. The coefficient for Clarity ← Service Quality is 1, which was set prior to running the model.

Table 5-7. Coefficients for variables in SSC

Relationship	Coefficient	P-value
OvSat ← Service Quality	0.982	< 0.0005
IReturn ← OvSat	0.03	0.068
IRefer ← OvSat	0.404	< 0.0005
Clarity ← Service Quality	1	< 0.0005
Know ← Service Quality	0.963	< 0.0005
Court ← Service Quality	1.026	< 0.0005
Info ← Service Quality	1.021	< 0.0005
Help ← Service Quality	1.065	< 0.0005
BkVideo ← Service Quality	1.023	< 0.0005
Convtim ← Service Quality	1.018	< 0.0005
Convloc ← Service Quality	1.016	< 0.0005
Return ← IReturn	0.651	< 0.0005
Refer ← IRefer	0.348	< 0.0005

[22] Using Amos 5.0 (Byrne, 2000)

All structural coefficients were fed into the SSC model in system dynamics. The list of variables, units and mathematical equations used in the simulation are given as part of the text model in Appendix D.

One of the assumptions is that the model can be simulated as long as the service quality of the field unit is greater than the competitor and the price (revenue per customer) of the competitor is lower than the field unit. The model cannot be used as it is under other conditions. This restriction could be relaxed by incorporating into the structure additional relationships between these variables and the impact on relative value under different assumptions. If this were to be done, SEM would have to be used for this purpose.

Two delays are used as part of the model, both as state adjustment times[23]. One is the *course state adjustment time* and equal to one year. This means that the number of courses can be changed once every year. This can be changed when using the model for another field unit, if need be. For instance, another field unit might be capable of making such an intervention more often, say every six months. In that case, the course state adjustment time will be six months. Further, the state adjustment time will vary for different operational attributes.

The other state adjustment is *certificate duration* which is set at 2 years. *Certificate duration* affects three state variables – *customers*, *potential customers* and *past customers*. *Certificate duration* affects *customers* through *return rate*, affects *potential customers* through *non-return rate* and affects *past customers* through both *return rate* and *non-return rate*. *Certificate duration* determines how long it takes to deplete the state variable *past customers* by the amount of customers whose certificate expired, through *return rate* and through *non-return rate*. Simultaneously, the amount of customers depleted by *return rate* replenishes *customers* and the amount of customers depleted by *non-return rate* replenishes *potential customers*. Both *return rate* and *non-return rate* are affected by both, *past customers* and *certificate duration*. Thus the time delay (certification validity time) of the customers is captured using the *certification duration* state adjustment time.

The time step of simulation in this case was originally set at one year. Later, the time step had to be reduced to 0.5 year (six months) based on the findings in model validation. The results shown are with a time step of six months. The time horizon was set at 20 years to illustrate the achievement of steady state in the long term. Data was available only on a yearly basis. However, if more frequent data were available, more realistic and accurate predictions of behavior can be made. Simulating the behavior under the data availability constraints, the next section describes the results obtained.

5.2 RESULTS OF THE SIMULATION

The behavior patterns obtained for certain key variables in the model follow. Figure 5-4 shows the behavior for *number of courses*, *change in number of courses* and *overall satisfaction*. The *number of courses* to be offered (measured in Courses, shown as Crse in the chart) follows almost an S-shaped curve with the lower leg rising more abruptly and attaining a steady state. The *change in number of courses* (measured in Courses/Year, shown as Crse/Year in the chart) follows a skewed bell-shaped curve and is positive for the entire time horizon indicating the need to increase course offerings (i.e. intervention by adding courses) every year for the next 20 years. The behavior starts to gradually rise from the initial value of approximately 50 courses per year to reach a maximum at the sixth year. For the first six years, courses are added at an increasing rate (every subsequent year more courses are added than the previous year). After the sixth year, the behavior drops to reach a steady state by the 20th year. Thus from the sixth year onward, courses are added at a decreasing rate (every subsequent year lesser

[23] State adjustment time is the time taken to make changes or adjustments to the state of the system.

courses are added than the previous year). *Overall satisfaction* (measured in percentage, shown as Per in the chart) rises only by a little amount to attain a steady state.

Figure 5-5 shows the behavior patterns for *surplus*, *market penetration* and *marginal rate of return*. *Surplus* (measured in $) and *market penetration* (measured as dimensionless, shown as Dmnl in the graph) follow S-shaped behaviors, although *surplus* is more of a goal-seeking behavior. *Marginal rate of return* (measured as dimensionless, shown as Dmnl in the graph) is defined as the return obtained for every additional dollar invested. *Marginal rate of return* peaks in the second year and starts to drop to attain a steady state.

Figure 5-4. Behavior of key attribute and perceptions

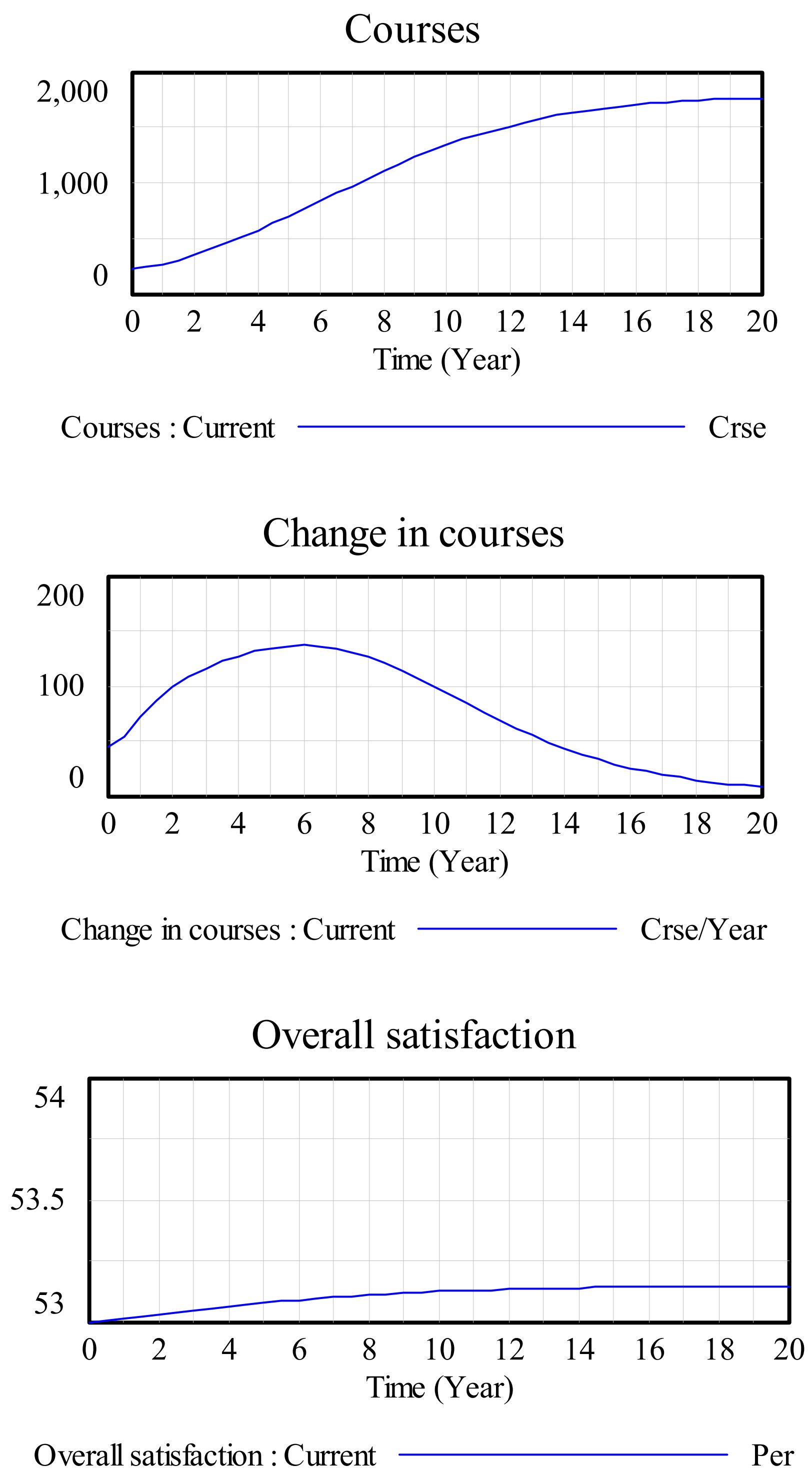
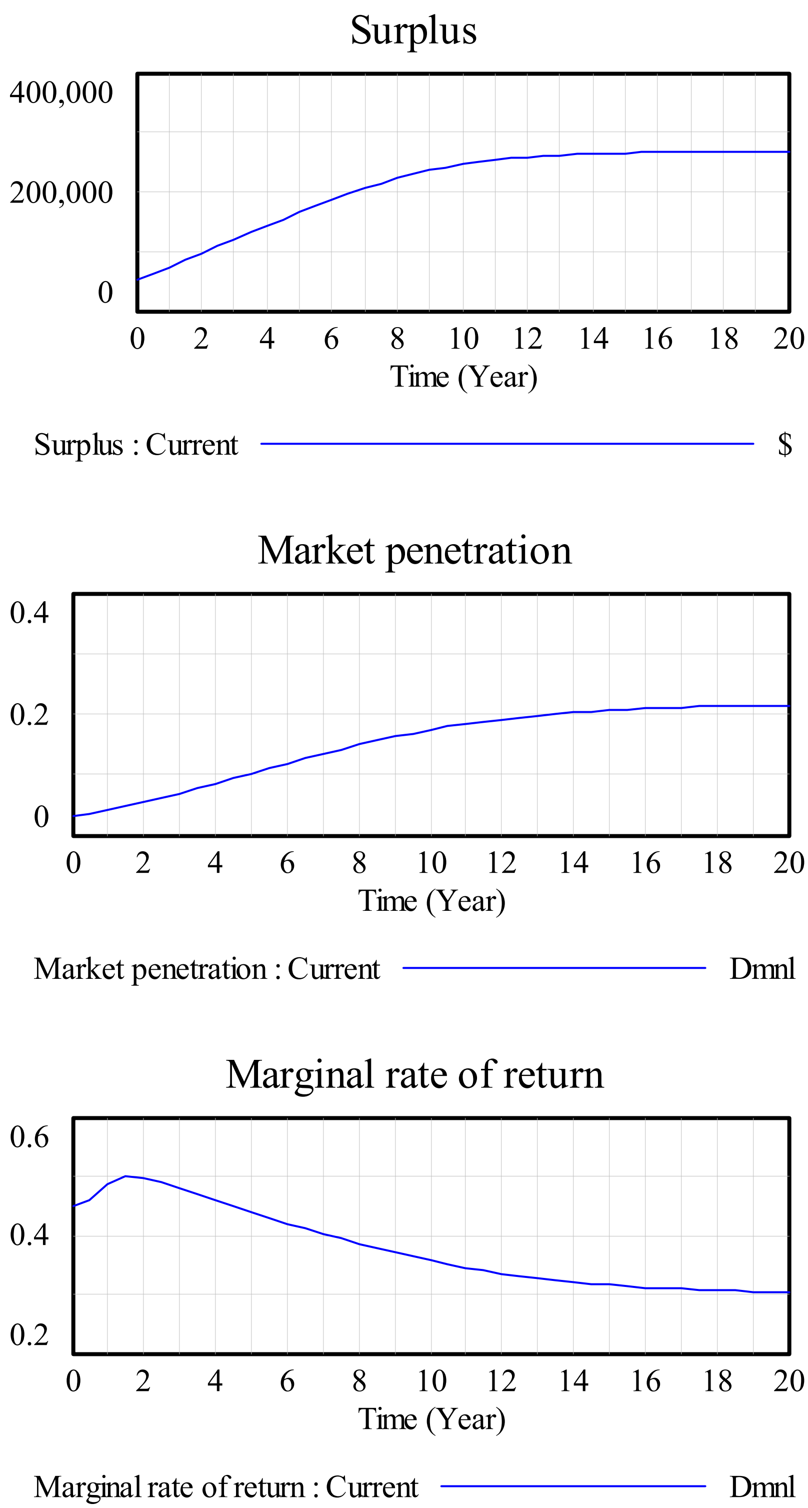


Figure 5-5. Behavior of surplus, market penetration and marginal rate of return



Steady state has been achieved. This was evident because, with no further interventions, the system continues to perform at the new equilibrium level. In other words the system is in dynamic equilibrium. Under dynamic equilibrium, the inflow equals the outflow with respect to corresponding state variables. Because of such equality, the net flow is zero. Hence, the state variable remains at the same level. This does not necessarily mean that the system is stationary (static equilibrium), however, static equilibrium is a special case of dynamic equilibrium. There is constant movement in the system but the values of all state variables remain constant.

To understand the state of dynamic equilibrium, consider a bath tub (state variable) containing a certain amount of water, and the faucet and drain are left open. Now, let us assume that the faucet fills up the tub with a certain amount of water, say per minute (inflow rate) and the drain empties the same amount of water per minute (outflow rate). Hence, the inflow and outflow rates are equal, which would mean that the tub would continue to have the same amount of water minute after minute. However, the faucet keeps bringing water and the drain keeps emptying. Such a bath tub system (combination of bath tub, faucet and drain) is said to be in a state of dynamic equilibrium.

The steady state values for key variables in the SSC are given below in Table 5-8.

Table 5-8. Steady state values for key variables

Variable	Initial value	Final/steady state value
Courses	220 courses	1,765 courses
Change in courses	45 courses	8 courses
Overall satisfaction	53%	53.15%
Customers	2,650 people	17,731 people
Surplus	$53,250	$268,374
Market penetration	0.032	0.215
Marginal rate of return	0.447	0.304

5.2.1 Answers to the Questions in the Case Study

Based on the behavior patterns and the results from the model, questions in the case study can be answered.

- The customer base does in fact increase from 2,650 people to 17,731 people over 20 years.
- The course offerings need to increase continuously from the current 220 courses to 1,765 courses in 20 years following a skewed bell-shaped curve shown in Figure 5-4.
- How the increase in customer base (market penetration captures increase in customer base) and course offerings (surplus and marginal rate of return account for expenses incurred due to additional courses offerings) above compare against changes in population and the environment in general are interesting questions that are discussed in detail as part of the sensitivity analysis under model validation. Behavior mode sensitivity discusses effect of changes in market size (population) on surplus. Numerical sensitivity explains the impact of realistic changes (inputs from experts) in environment (market size, age and wealth) on market penetration and marginal rate of return. Further, there is also discussion on the combined effect of policy and environment changes on these variables.
- The effects on service quality, satisfaction and customer loyalty are given in Table 5-7 and the overall satisfaction behavior pattern in Figure 5-4. The effect size of

these investments (i.e. increase in course offerings) is small but significant on service quality, satisfaction and other components in the SPC as can be seen from the overall satisfaction behavior which increases by less than 0.15% and attains a steady state. This increase is minimal but based on the results from SEM in Table 5-7, we know that it is highly significant (p-value < 0.0005). To the decision maker, this means that service quality is a key variable to make an impact on overall satisfaction. Intervening with the number of course offerings (as an operational attribute), for sure will cause an impact on overall satisfaction but will be minimal. If overall satisfaction is a main outcome variable that is of concern, the decision maker should turn to other operational attributes that might bring about greater impact.

- The field unit can increase the course offerings to 1,770 courses over 20 years and expect to increase the market penetration from 0.032 to a steady state of 0.215.
- Surplus will increase from $53,250 in the current time period to $268,374 after 20 years. Considering 20 years is a long period of time, the future surplus was adjusted to account for time value of money[24] to get a better sense of the comparison. The present value of $268,374 came out to be $134,876, which is still almost three times over the initial surplus. This conversion was done to illustrate the comparison. Other dollar amounts in this case study are shown without adjustments. Similar, adjustments can be made as deemed necessary for actual decision making.
- Additional investments do not always give increasing rate of returns. This is evident from the marginal rate of return behavior in Figure 5-5. The marginal rate of return increases and peaks during the second year, but, then on starts to drop to reach a steady state by year 20.
- Is the policy of no more than ten customers for each course offering sustainable? The answer to this question depends on how the field unit weighs its options. The field unit can currently cover all its expenses by the revenues generated. Investing in more course offerings, increases market penetration and surplus but at the same time brings in decreasing marginal rates of return. The model also identified that the steady state marginal rate of return can be increased to 0.379 by changing the policy to no more than eleven customers per course offering. This will keep the market penetration at the same level but increase the surplus at the end of 20 years to $316,502 (a gain of $48,128) with an increase of only 0.12% in overall satisfaction (a drop of 0.03%).

Such case studies can be conducted to answer similar real world questions using the model and the methodology developed in this research. Similarly, questions around setting a right price for the service, market penetration goals, surplus goals and investments in other operational attributes can also be evaluated.

All discussions in Chapters 3, 4 and 5 so far have focused on modeling. Modeling is a process of representing reality to comprehend, analyze and identify course of action. One of the dreams of any modeler, especially mathematical modeler, is probably to come up with a model that is virtually identical to the reality being modeled. This is not at all possible as there might be several unaccounted factors that might affect the system being modeled. Even if this were not the case,

[24] Considering an inflation rate of 3.5% compounded annually over the next 20 years.

developing an exact replica would cost a lot of time and money, and might end up being lot worse than not venturing into the modeling task at all. Further, trying to make the model very realistic might excessively complicate the model. On the other hand, very restricted and limited (bounded) models tend to get too far away from reality. So, how do we find out if the models and methodology developed in Chapters 3 and 4 meet the objectives and provide desired results or if they are useful? This is achieved by performing model validation. Ultimately, the model usefulness is demonstrated through the actual implementation.

"All models are wrong, but some models are useful"

- George Box

5.3 MODEL VALIDATION

If a model is valid, then the decisions made based on the results from the model should be similar to those that would be made with the real system (Fishman and Kiviat, 1968). Based on this, Law and Kelton (1991, p. 299) define model validation as "determining whether the conceptual simulation model is an accurate representation of the system under study." Furthermore, when a simulation model and its results are accepted by the decision-maker as being valid, and are used as an aid in making decisions, the model is credible (Carson, 1986; Law and Kelton, 1991). Model validation is demonstrating in part the degree of usefulness of a model. Model validation is neither something that is done by a modeler in isolation nor is done at the end of the modeling process. In fact, it is done by the modeler working closely with people that are familiar with the system and in parallel to the actual modeling process (Law and Kelton, 1991). Model validation consists of conceptual validation and results validation (Defense Modeling and Simulation Office, 1996). These will be discussed next.

5.3.1 Conceptual Validation

Conceptual validation ensures that the model accurately represents reality and captures the concept in the system structure. Conceptual validation typically includes tests for boundary adequacy, structure assessment, parameter assessment and dimensional consistency (Sterman, 2000).

Boundary adequacy, as the name implies ensures that all concepts necessary to address the problem are endogenous to the model. Structural assessment ensures that the model structure is consistent with relevant descriptive knowledge of the system and level of aggregation is appropriate (Sterman, 2000). Parameter assessment is to determine if all parameters have real world counterparts and dimensional consistency tests are to determine if the equations are dimensionally consistent without the use of parameters that do not have any real world meaning (Sterman, 2000).

Boundary adequacy, structure assessment and parameter assessment were done using a combination of procedures. Several sources were used – existing literature, conversations with subject matter experts, organizational knowledge, partitioning and cross-validation techniques. Subject matter experts included field unit executives, Health & Safety Services directors and national headquarters experts and evaluators in Health & Safety Services Training. There were several informal conversations with such experts. Organizational knowledge was obtained from reports of studies and analyses done for past projects and informal documents such as email communications.

The whole research endeavor started off with the Service-Profit Chain which is well documented in the literature. This was the basis for the conceptual model and other models developed in this research. Outcomes of questioning the boundaries, structure and parameters gave rise to inclusion of related concepts like competition and its effect on relative value. Another factor that was included is the environment (in specific, age and wealth in the community for this case study) and its effect on service quality perceptions. For the specific case study the unit of analysis was determined to be the field unit. It was also agreed that perceptions and other survey data collected at national headquarters should be aggregated at the field unit level as opposed to customer level. Customer level data would have been useful if specific profiles and segments in the market needed to be analyzed using agent based modeling or another methodology.

Going back to the methodology developed in this research, the relationships between variables are established using CHAID. Validation of the relationships is done through two validation techniques – partitioning and cross-validation. In the case of partitioning, the data set is split into two random samples. The first sample is the calibration or the training sample and the second, the validation or the testing sample. The calibration sample is used to "train" (teach the model how to behave by identifying the relationships). Then the model is evaluated by testing it on the validation sample to identify any idiosyncratic behavior specific to that sample but not to other data (SPSS, 2001). The training was done with 85% of the data set and tested on the remaining 15%. Further, risk estimates were calculated. A risk estimate, for scale variables, is the variance within each node about the corresponding mean, averaged across all nodes for the entire tree. In simpler terms, if the variables were categorical (nominal or ordinal) in nature, the risk estimate is analogous to the proportion of cases incorrectly classified. Such estimates were calculated both for the testing sample and the training sample. These are shown in Table 5-9 below. The low estimates for the testing sample also show that no considerable idiosyncratic behavior was picked up.

Table 5-9. Partitioning Risk Estimates

	Risk statistics	
	Training sample	**Testing sample**
Risk Estimate	0.0069	0.0048
Standard Error of Risk Estimate	0.0007	0.0018

In the case of cross-validation, the sample was randomly partitioned into *k* different groups or *folds* (SPSS, 2001). Then, *k* trees were built using the same growth criteria as the tree being evaluated. The first tree uses all folds except the first; the second tree uses all folds except the second, and so on until all folds have been excluded once. Then a risk estimate is calculated for each of the *k* trees. The cross-validated risk estimate for the entire tree being evaluated is the average of the *k* risk estimates for the *k* trees, weighted by number of cases in each fold.

Setting a value for *k* depends on the size of the whole data set. A very low value for *k* would make significant splits for each of the trees but fail to pick up any idiosyncratic behavior among smaller groups in the sample. On the other hand, a too high value will have several small groups to identify any anomalies (of course at the expense of additional computer time), but each individual tree may not have significant splits. Considering the above, for the size of the data set in this case study, ten was a fairly reasonable number of folds. This test was conducted with $k = 10$ and random seed = 2,000,000 (for the random partitioning) and the risk estimates are shown in Table 5-10 below. Again, low risk estimates, strongly validate the relationships explored.

Table 5-10. Cross-validation Risk Estimates

	Risk statistics	
	Overall tree	**Cross-validation**
Risk Estimate	0.0069	0.0070
Standard Error of Risk Estimate	0.0007	0.0007

Next, in the validation process is parameter assessment and dimensional consistency. *Change in courses per customer* is a variable that is not useful to the decision maker. *Change in courses per customer* was introduced in the SSC model to carry forth any changes in the number of *Courses* that impacts *Service Quality*. *Target number of courses* measured in courses is another variable that has no real world counterpart, but is introduced as part of the optimization structure. In reality, *Target number of courses* does not make sense. However in the SSC model, this variable is used to effect *Change in courses* based on current *Courses* and *Discrepancy* (which is another variable not useful to the decision maker). These two variables were introduced as part of the modeling exercise. *Discrepancy* is dimensionless and is a mere ratio.

On the other hand, *Course SAT* (Course State Adjustment Time) measured in Years does have a real world counterpart. It is the frequency with which decisions regarding changes in the state of the operational attribute can be made. In other words, *Course SAT* is the time needed to make changes to the state variable *Courses*. For instance, in the case study the number of *Courses* offered can be changed on a yearly basis. For the same case study decisions around change in number of course centers (another operational attribute) where courses are offered probably can be made only once in say, 3 years. Then *Center SAT* (if there was such a variable) would have been 3 years. Dimensional consistency was tested and all variables met the requirements.

Next, a construct validation was performed to ensure that the survey instrument measures one single construct. The instrument used for data collection was previously piloted and tested. The perceived service quality items had a high reliability of alpha=0.9 with number of valid cases, N=101,623.

The items included as part of the service quality construct also grouped together in factor analysis assuring the measurement of one construct. The component values are shown in Table 5-11. Ease of course registration had to be dropped from the analysis because of excessive missing data (less than 0.01% data available). This was because of existence of different versions of the survey (one with and the other without the question) and almost all field units used the version without the question.

Table 5-11. Component matrix

Item	Component 1
Instructor's ability to present information clearly	0.813
Instructor's knowledge: ability to answer questions	0.813
Inclusion of skills and information that you needed	0.834
Quality of course books and videos	0.706
Effectiveness in helping you learn skills	0.840
Availability/courtesy of staff to answer questions	0.799
Convenience of the times offered in the course schedule	0.663
Convenience of the available course locations	0.672

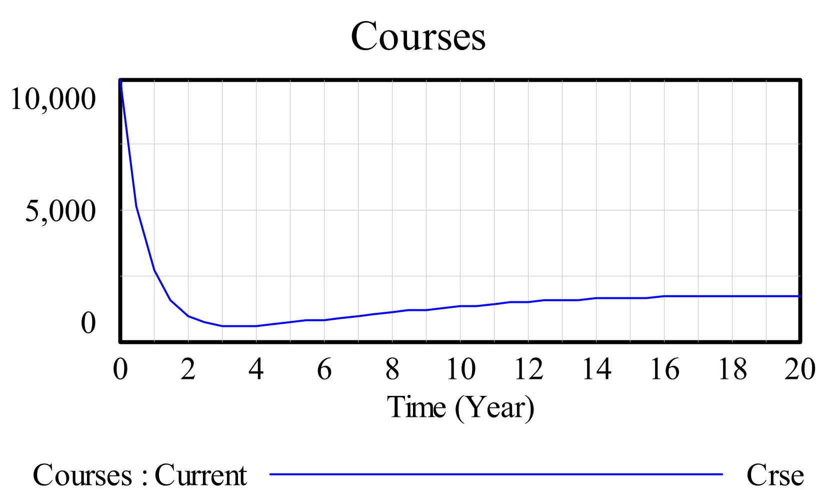
Additional factor analysis was conducted with two components and ease of course registration was the item that fell into a different component. The reason was then identified. Ease of course registration factored into a separate component because, this was the item with almost no data and hence was dropped. Other factor analyses demonstrated only a slight grouping of items related to personnel efforts (namely, instructor's ability to present information clearly, instructor's knowledge, effectiveness in helping you learn skills and availability/courtesy of staff to answer questions) separately. This test shows that if separate analysis of personnel perceptions and equipment perceptions are required, two distinct components in the factor analysis are necessary. Once the concepts and constructs were validated, the next step involved results validation.

5.3.2 Results Validation

Results validation includes tests around developed computer programs and simulation runs. Results validation is also referred to as model verification (Law and Kelton, 1991). Typically, tests for extreme conditions, integration errors, surprise behavior and sensitivity analysis are part of results validation (Sterman, 2000).

The model was tested for robustness under extreme conditions by altering several variables over a large range. For instance, initial number of *Courses* was varied over a range from 1 to 10,000. Of course, for the size of the field unit under study, 10,000 courses is a very extreme case. The model handled changes at either extreme well and this is evident from the behavior. The initial value is important in determining the starting point but does not interfere with the hill-climbing algorithm (as expected) to seek the optimal path and the equilibrium. The model corrects drastic changes of the initial values in the beginning time periods and exhibits similar smooth behavior patterns to attain the same steady state or equilibrium over time. One such extreme behavior pattern with the initial value of *Courses* = 10,000 is shown in Figure 5-6 below. A different behavior from the base case is obtained because of the change in the initial value.

Figure 5-6. Extreme condition behavior



Similar trends were noted with other variables in the model. This validates the robustness of the model under extreme conditions.

The model was then tested for integration errors using the time step method (Sterman, 2000). For this, the time step for the simulation was reduced to 0.5 years (six months) from the original one year. This gave similar behavior patterns but the sharp peaks and troughs were replaced by smooth curves. This is because, with a smaller time step, more accurate integrations and calculations were possible, with additional computing time and power. When the time step was further reduced to 0.25 years (three months), the behavior was more or less the same as those for a time step of 0.5 years. Hence, the appropriate time step for the simulation of the case study is 0.5 years (six months), since expending additional computing time and power for no additional benefit is meaningless.

One surprise behavior was identified during the simulation of the case study. Overall satisfaction increases only 0.15%. The original expectation was to observe a much higher increase. On further investigation of the structure and studies of several simulation runs, it was determined that number of *Course* offerings as an operational attribute, though significant, does not have a huge impact on service quality and subsequently value and overall satisfaction perceptions. Further, the impact is also diluted by the effect of the environment on service quality perceptions. These are important findings for the research per se and thus, reinforce the importance of model validation. For the decision maker, this means that the number of courses for sure is an operational attribute that has a significant impact on the perceptions of customers, but not necessarily one with a huge impact. The decision maker should consider other operational attributes to have a bigger impact on service quality and overall satisfaction.

Sensitivity analysis is another important step in results validation. It is related to robustness under extreme conditions in a sense that, extreme conditions test behavior at extreme points (such points are set very extreme such that there are no possible outer points) but sensitivity analysis tests behavior within the range. This is used to determine if the model behavior changes significantly when the input parameters are changed (Law and Kelton, 1991). According to Sterman (2000), sensitivity analysis is more than just changing the input values and there are three types of sensitivity analyses – policy, behavior mode and numerical. Policy sensitivity exists when a change in assumption reverses the impact or desirability of a policy. Behavior mode sensitivity exists when changes in assumptions in the model change the behavior pattern and finally, numerical sensitivity exists when changes in assumptions changes the numerical results of the model. As Sterman (2000) points out, all models exhibit numerical sensitivity, and the model developed in this research is no exception to this.

Policy sensitivity analysis was conducted over several components of the model. One policy sensitivity that the model (to be precise, this is a sensitivity of the methodology due to insufficient data) possesses is around relative value. The model can be simulated as long as the service quality of the field unit is greater than the competitor and the price (revenue per customer) of the competitor is lower than the field unit. Under other conditions, the relationships/equations between the environmental variables and service quality identified in this research are still valid. However, those between the components in the SPC (customer perceptions, customer behavioral intentions, customer loyalty) cannot be used. Of course, this sensitivity can be relaxed by incorporating into the structure, additional relationships between these variables (service quality, price, competitor's service quality and competitor's price) and the impact on relative value under different conditions. If this were to be done, SEM would have to be used for this purpose.

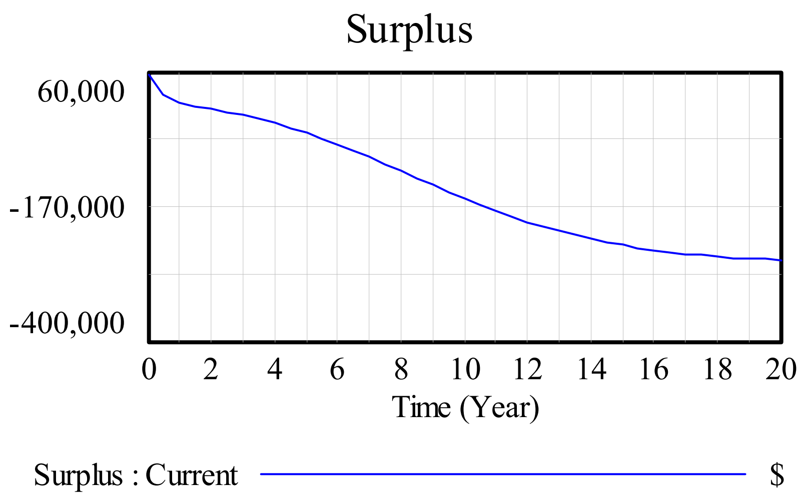
Dropping the policy of no more than ten customers per course to five, there was a reversal from a surplus to a deficit and a continuously dropping marginal rate of return to below zero, see Figure 5-7. The reason for such a behavior is under-utilization of the resources (here, ability of the instructor to train a certain number of customers in one course offering). Lesser customers are trained for each course offering who perceive the service provided to be of better quality and hence an increase in overall satisfaction by almost 0.5% (number of additional people that rated the service as 'Excellent' on the survey instrument) compared to the 0.15% in the base case scenario. On checking the results with experts and field unit managers, it was validated that even such slight increases in service quality and overall satisfaction are very hard to come by and are necessary for the field unit to flourish in the market. However, expenses are higher and hence the surplus plummets.

When the policy was increased to no more than 15 customers per course, both surplus and marginal rate of return shot up, see Figure 5-8. Such small changes in the policy in either direction make a very large displacement from a deficit of $261,000 (and marginal rate of return of -0.185) at steady state to a surplus of $445,000 (and a marginal rate of return of 0.63) at steady state. Here, although there is a huge surplus and a good marginal rate of return, overall satisfaction almost did not have any change from the initial 53%. Such reversal effects happened because changes in assumptions in policy are analogous to changes to a 'hand holding a bull-whip' exhibiting a bull-whip effect. When a hand holding a bull-whip is moved back and forth rapidly, even for small movements of the hand, the tip of the bull-whip has very large displacements.

What does this mean for the field unit? Is it good to have a deficit with an increase of 0.5% overall satisfaction or to have a surplus and no impact on overall satisfaction. Of course, there is a trade-off and the effects in this case study are enlarged to illustrate the point. Having immediate surplus, without improvements in overall satisfaction can be good during the short term, but is a recipe for the operation to fade away slowly. On the other hand, having deficits cannot sustain the operation. Hence the manager is forced to find a suitable compromise between either extreme; to have surplus and also have positive effects on overall satisfaction. With such a compromise, the model would suggest the optimal path to the steady state. This optimal path will determine necessary interventions at every point in time during the entire time horizon. As identified earlier, changing the policy to no more than 11 customers per course keeps surplus, marginal rate of return and also penetration at realistically (as validated by experts) high levels with an increase in overall satisfaction.

Change in other variables did not exhibit such large and dramatic displacements. This reinforces the importance of different variables in the model for the decision making process.

Figure 5-7. Policy sensitivity: No more than five customers per course



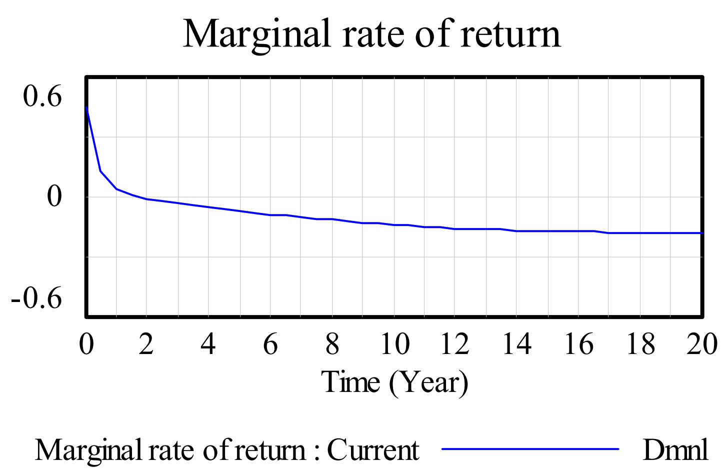
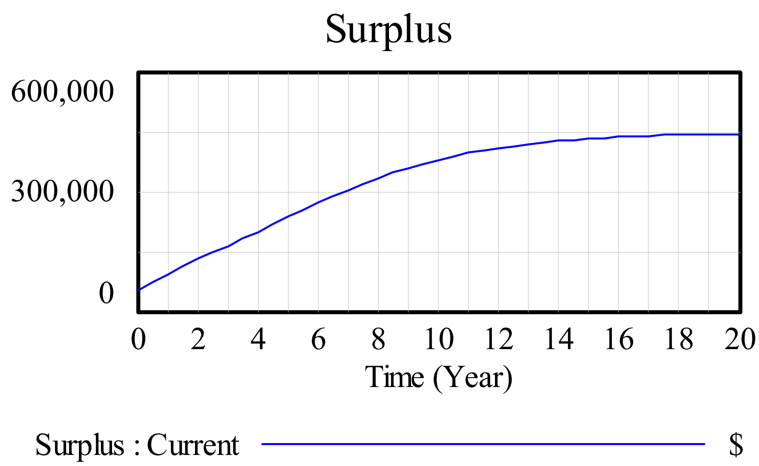
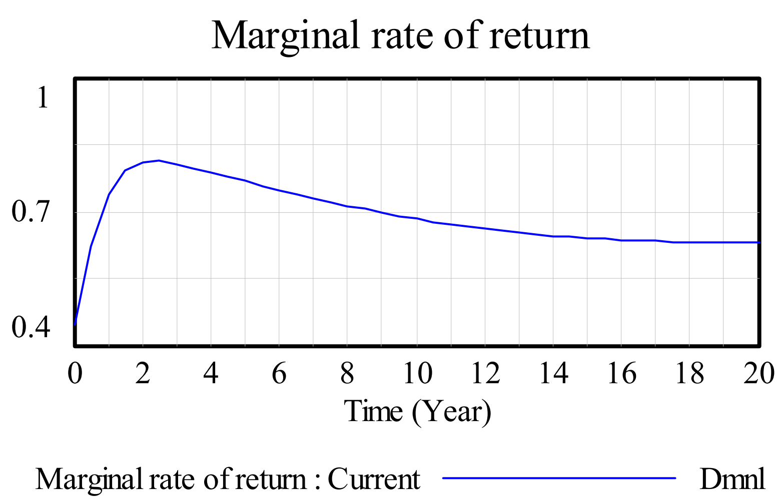


Figure 5-8. Policy sensitivity: No more than 15 customers per course





The model has slight behavior mode sensitivity as determined under changes in assumptions to the population change rate. When population was assumed to decrease at 10% per year, the behavior of surplus changed form the original goal-seeking behavior to an overshoot and collapse behavior, see Figure 5-9. On the other hand, when the assumption was changed to an increase of 10% per year, the behavior was exponential, see Figure 5-10. But all other variables had same behavior patterns under both scenarios. Such behavior was expected as 10% increase or decrease is a significant change to the assumption. However, there were no major reversals (for example from surplus to deficit or vice-versa) such as those discussed in policy sensitivity. This also illustrates that some parameters and assumptions have greater impact on the results and behavior than others. For instance, changes in policy were significant enough to decide a surplus vs. deficit. On the other hand, changes in market result in changes only in behavior pattern. Such parameters and assumptions are points of leverage where slight changes can make significant differences. More than just validations, these are also findings as part of the case study that can be used in decision-making.

Figure 5-9. Behavior mode sensitivity: Population decreasing at 10% per year

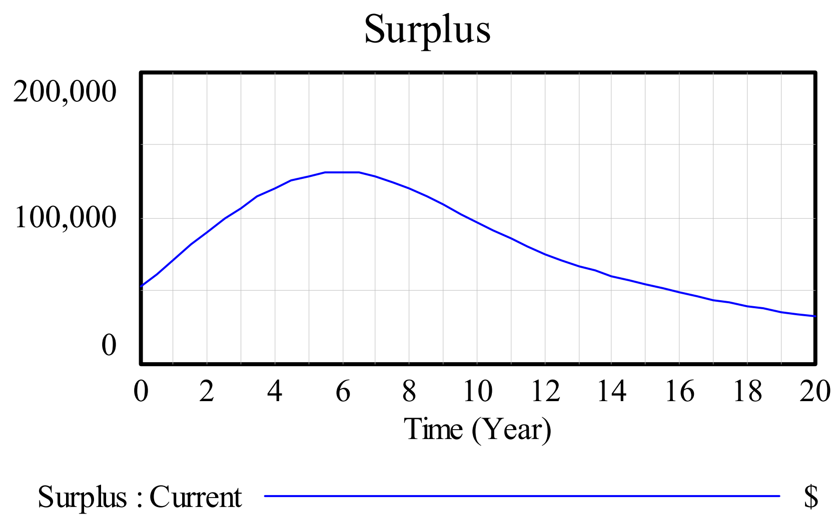
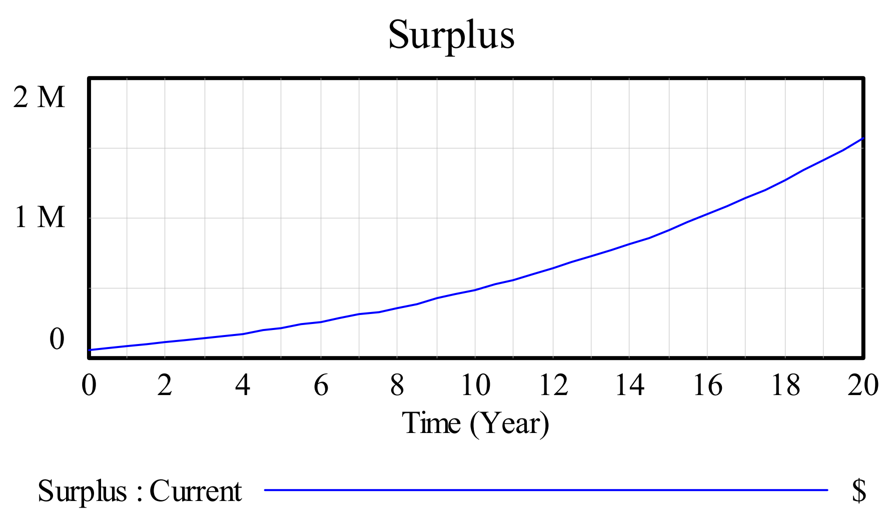


Figure 5-10. Behavior mode sensitivity: Population increasing at 10% per year

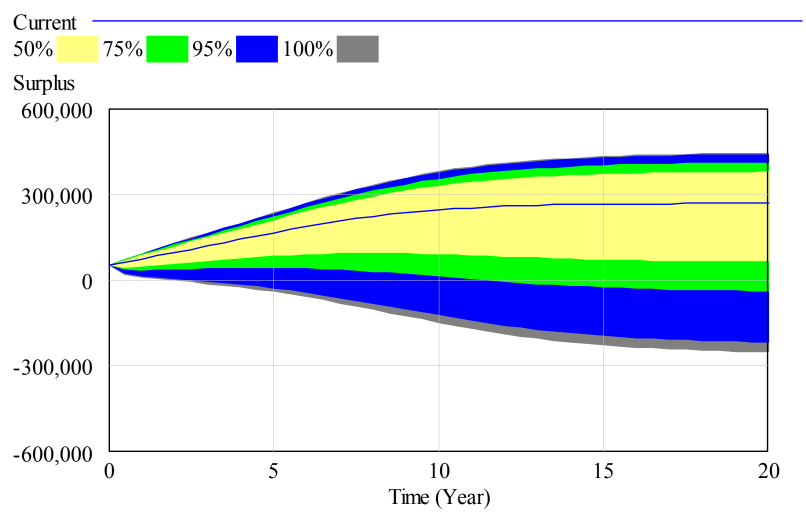


Numerical sensitivity analysis is typically done where the input values are altered based on random numbers generated by some distribution (Law and Kelton, 1991). Monte Carlo simulations, also known as multivariate sensitivity simulations change the parameters based on such random distributions to determine best, worst and most likely outcomes of the simulations (Sterman, 2000).

For this case study, such Monte Carlo simulations were used to perform sensitivity analysis and determine the confidence bounds for key variables – *Overall satisfaction*, *Surplus*, *Market penetration* and *Marginal rate of return*. Each scenario was simulated with 200 iterations. The graphs show the variability associated with the behaviors with changes in the parameters. The four bands have corresponding confidence bounds (as percentages). For instance, for a confidence bound of 95%, there is 95% likelihood (or probability) that the variable will have a behavior pattern within those boundaries (Vensim, 1998). Three scenarios were analyzed.

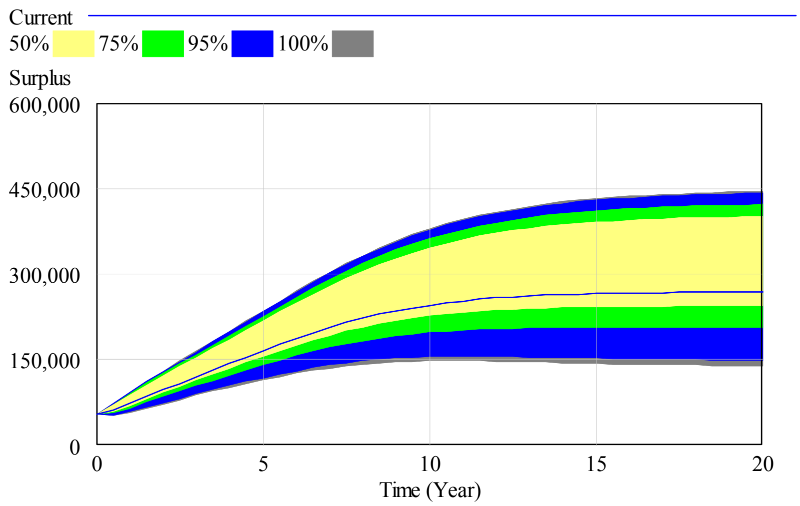
For scenario 1, the environment was held constant to better comprehend the effect of policy-making on the outcome. The policy was allowed to vary between no more than 5 customers per course and no more than 15 customers per course. For this, *Target customers per course* was allowed to vary uniformly with a minimum of 5 and a maximum of 15. The confidence bounds from the sensitivity analysis are shown in Figure 5-11 below. It can be seen that there is only 50% likelihood that there will be a surplus over the time horizon. Even moving to a slightly higher confidence bound of 75% has a chance of deficit. The behavior with 10 customers per course is also shown by the blue line corresponding to 'Current' discussed under the base scenario.

Figure 5-11. Confidence bounds: Major variation in policy



When a more realistic range of 8 to 15 was used for the *Target customers per course*, the confidence bounds changed drastically showing definite surplus with 100% confidence, see Figure 5-12. This gives valuable information to the decision-maker in terms of confidence in the profitability of the operation.

Figure 5-12. Confidence bounds: Realistic variation in policy



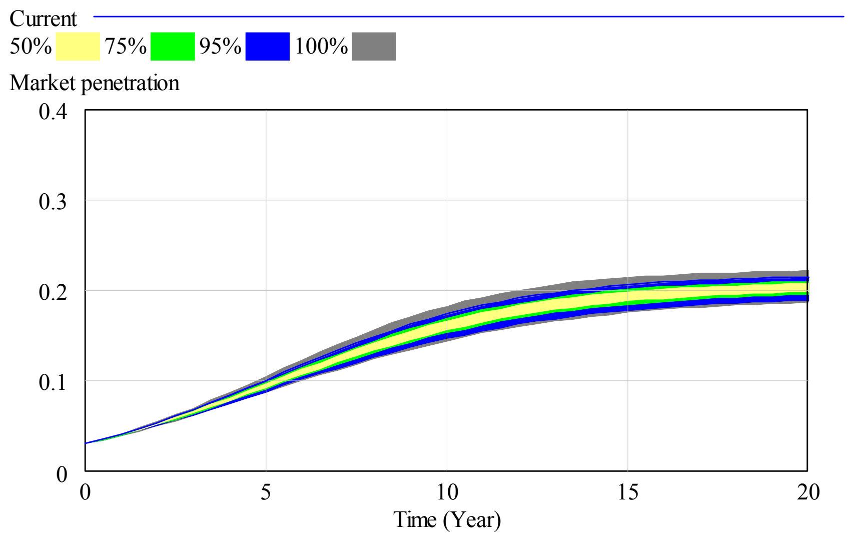
In scenario 2, policy (*Target customers per course*) was held constant and the environment was allowed to change. All three environmental variables – age, wealth and population change were allowed to vary normally based on the data available. The minimums, maximums, means and standard deviations used are given in Table 5-12.

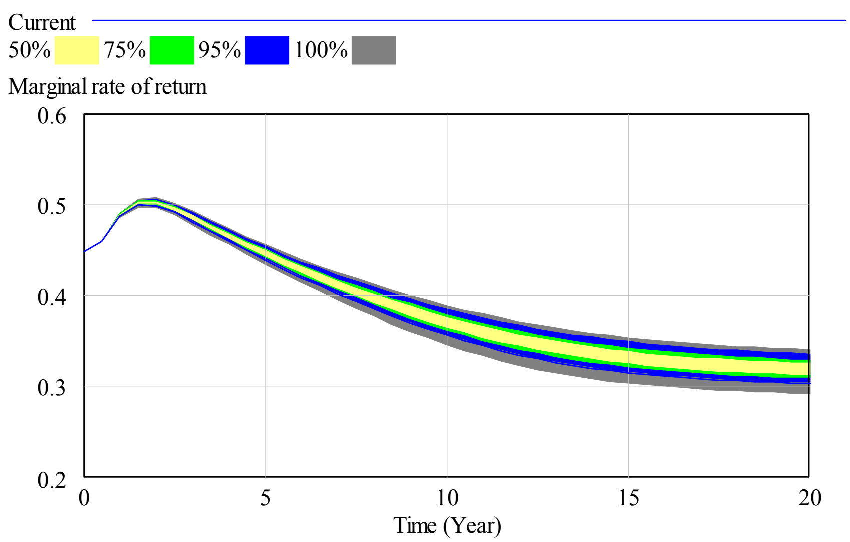
Table 5-12. Parameter distributions

Parameter	Minimum	Maximum	Mean	Standard Deviation
Age above 25	42%	68%	57%	7%
Median Household Income	$35,312	$50,025	$43,150	$985
Population change rate	-2%	7%	2%	1%

The dynamic confidence bounds obtained for *Market penetration* and *Marginal rate of return* are shown in Figure 5-13. It is evident that the bounds are thin. Thinner bounds give greater confidence in the behavior. Here, it is very likely that *market penetration* will be around 0.2 and *marginal rate of return* little over 0.3.

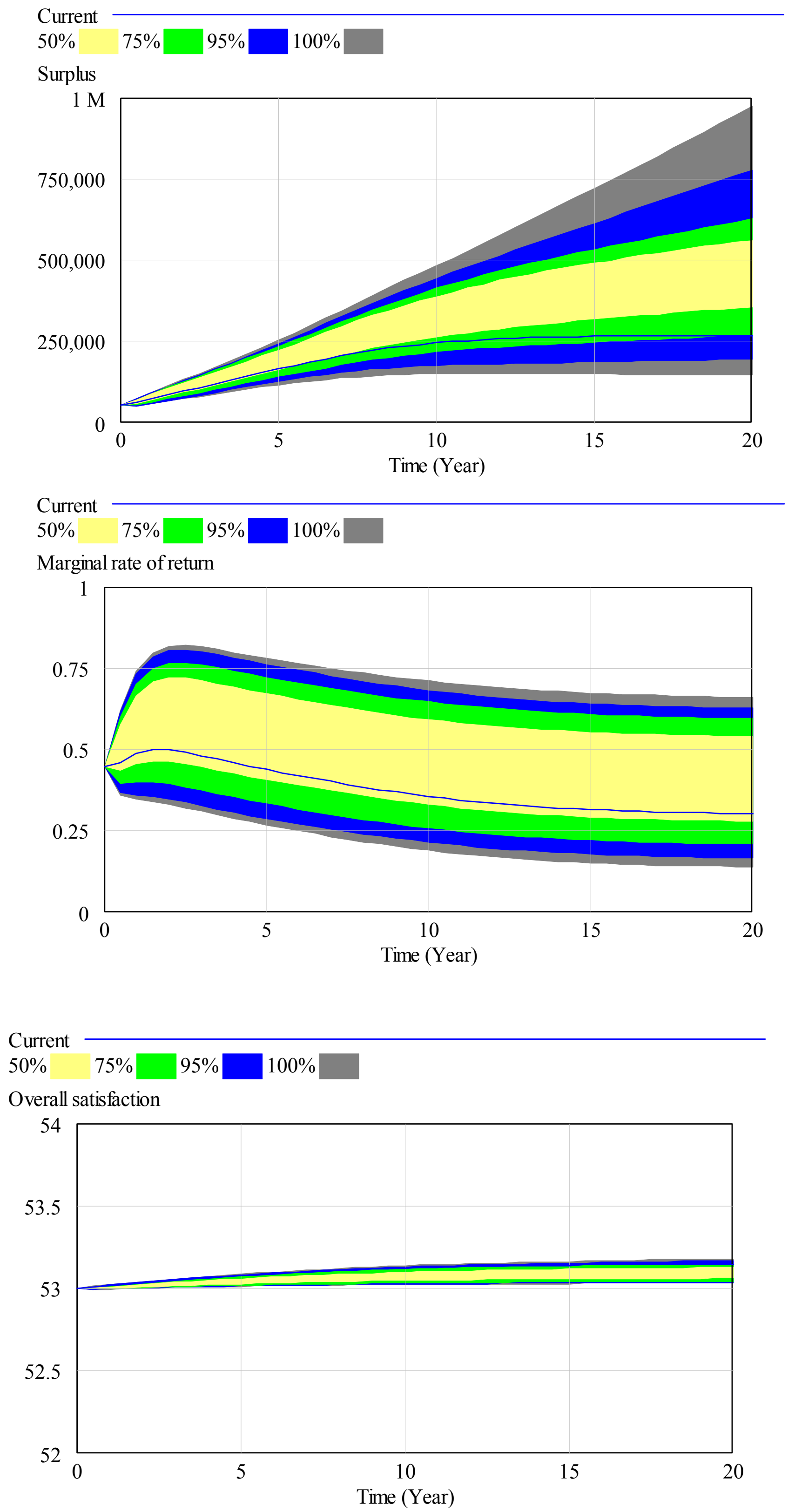
Figure 5-13. Confidence bounds: Variation in environment





Finally in scenario 3, both policy (*Target number of customers per course* – realistic) and environment were allowed to vary. The distributions used for each of the individual parameters were same as those used in scenarios 1 and 2 above. The resulting confidence bounds are shown in Figure 5-14. Bounds on *surplus* have widened to a great extent and this is due to too many variations. The bounds on *marginal rate of return* are wider than those in scenario 2, which tells us that policy changes impact *marginal rate of return* way more than environment changes. *Market penetration* under scenario 3 exhibited bounds similar to those in scenario 2 that were narrow. *Overall satisfaction* showed similar confidence bounds in all three scenarios. From all of these results, it is clear that there are some parameters that impact more than others, and have striking outcomes. And, there are some components that are least impacted. *Marginal rate of return* is sensitive to policy changes, *market penetration* is sensitive to environmental changes, *overall satisfaction* is sensitive to neither and *surplus* is sensitive to both.

Figure 5-14. Confidence bounds: Variation in policy and environment



5.3.3 Face Validation

One last step in the validation process is face validation. This step is used to find out if the model, methodology, results and the sensitivity analysis mean anything in real life. In other words, on the face of it, if there is potential for valuable information to be obtained. This is very important because, implementation of new tools and techniques (such as the model and methodology developed in this research) need the "buy-in" of the people involved with the operation. This includes both senior management and the decision makers close to the operation. Only then will such tools and techniques be understood, used and internalized within the culture of the organization. The approach and the findings were shared with employees that have in-depth knowledge and understanding of the training service operation in the humanitarian organization where the case study was conducted.

One main feedback obtained was the realistic nature of the behavior and results. There have been situations in the past where, national headquarters was capable of setting goals that are highly unrealistic and insensitive to the variability of the type of field units. Experts felt that the results and behavior similar to those shared with them could be obtained (by replicating the model and methodology) customized to specific field units. This could be done by taking into consideration, for instance, varying sizes of operations, different types of markets, etc. Further, sensitivity analysis results gave alternate options for courses of action as opposed to a hard iron-hand from national headquarters instructing what is to be done. The CHAID/SEM methodology developed was commended to be useful also for other analyses different from those done in this research. Employees suggested that such a methodology could be used to gain better understanding of customer profiles and market segmentation and target specific groups in the community (for example, groups by age, gender, etc.) differently. Such tools and techniques also empower the decision maker at the field unit level to play with different scenarios and gain deeper understanding of the operation. Employees also wanted to explore the effect changes in demographics (like internal migrations) might have on the model/results.

5.3.4 Final word about Validation

Validating such models is a very challenging task, to say the least. The results are not objective. However, model validation provides lot of subjectivity for the decision-maker to gain insights and better comprehend the operation being analyzed. Model validation is not a one time task that is done after model development. In fact, model validation was performed in parallel to the actual modeling process. Results from sensitivity analysis and other model validation techniques, along with validating the model, also provide additional insights to the results of the case study. Decision makers should make their decisions not only based on the results from the model, but simulate several scenarios and perform sensitivity analyses, accompanied by wise judgment to determine the best course of action.

6 Results, Conclusion and Discussion

Making investment decisions in special features (operational attributes) to enhance the service experience is one of the most essential roles played by management. Investment decisions in operational attributes have different levels of impact on customer perceptions, behavioral intentions, loyalty, market penetration and surplus. Thus managers who evaluate different policies and interventions must do it based on informed decisions. Frameworks available in the literature that evaluate service operations usually do not consider certain uncontrollable factors including the operating environment (age, gender, wealth, market size) and competition. Moreover, methodologies developed for this purpose are static in nature and only focus on looking at a certain point in time without regard to feedback and key interactions that may affect the future. The models and the methodology developed in this research attempt to overcome many of these drawbacks and enable managers to make informed decisions.

This last chapter summarizes the lessons learned during this research journey. First, the research hypotheses are revisited and followed by answers to research questions. Finally, the impact of this research is explained and recommendations for future research are suggested.

6.1 REVISITING THE RESEARCH HYPOTHESES

The research hypotheses set forth in Chapter 1 were tested based on the case study analysis and the results are discussed in detail below.

H1: Improvements in operational attributes (inputs) have a positive impact on customer perceptions of service.

The operational attribute considered for the case study was the number of course offerings made available to the customer. Improvement in this operational attribute entails mainly, increasing the number of course offerings. Customer perceptions of service include service quality, value and overall satisfaction. From the SSC model we know that there is a direct impact of operational attributes (number of course offerings) on service quality. The hypothesis H1, in other words states that, an increase in the number of course offerings (normalized based on number of customers) has a positive impact (increases) on customer perceptions of service (service quality).

From the application case study on training services, it became evident that an increase in the number of course offerings causes an increase in service quality. Further, it was also determined that the impact is varied for different environmental segments (by accounting for age and wealth in the case study). Table 6-1 below shows the extent of impact for each environmental segment and their corresponding significance levels.

Table 6-1. Impact of improvement in operational attributes on customer perceptions of service

Age above 25	Median Household Income	Coefficient	P-value
<= 55.88%	-	0.63	0.095
> 55.88%	<= $43,516	0.28	< 0.0005
> 55.88%	> $43,516 and <=$47,628	0.57	0.021
> 55.88%	> $47,628 and <= $50,025	0.8	0.029

Therefore, hypothesis H1 is accepted. A similar finding of positive impact has also been documented in the literature for banking services (Kamakura et al., 2002).

H2: Positive customer perceptions of service have a positive impact on behavioral intentions.

Customer perceptions of service include three dimensions – service quality, value and overall satisfaction. Similarly, the component *customer behavioral intentions* has two dimensions – refer/recommend intentions and retention intentions. The SSC model illustrates that overall satisfaction is directly linked to intend to refer and intend to return. Restating the hypothesis, an increase in the customer perceptions of service (overall satisfaction) has a positive effect (increases) on customer behavioral intentions (both intentions to refer/recommend and return).

From the case study on training services, it is clear that an increase in overall satisfaction (OvSat) contributes to an increase in intention to refer/recommend (IRefer) and in intention to return (IReturn). These coefficients are shown in Table 6-2 along with the respective significance levels.

Table 6-2. Impact of positive customer perceptions of service on behavioral intentions

Relationship	Coefficient	P-value
IReturn ← OvSat	0.03	0.068
IRefer ← OvSat	0.404	< 0.0005

Therefore, hypothesis H2 is accepted. Similar positive impact is found in the literature for service operations in higher educational setting (Ham and Hayduk, 2003).

H3: Positive behavioral intentions have a positive impact on customer loyalty to the organization.

The component customer behavioral intentions has two dimensions – refer/recommend intentions and retention intentions. Customer loyalty also has two dimensions – referrals and returns. From the SSC model, it is evident that refer/recommend intentions is directly linked to referrals and retention intentions is directly linked to returns. Restating the hypothesis, increases in refer/recommend intentions and retention intentions cause increases in referrals and returns respectively.

From the case study on training services, it is clear that increases in refer/recommend intentions (IRefer) and return intentions (IReturn) cause increases in referrals (Refer) and returns (Return) respectively. These coefficients are shown in Table 6-2 along with the respective significance levels.

Table 6-3. Impact of positive behavioral intentions of service on behavioral intentions

Relationship	Coefficient	P-value
Return ← IReturn	0.651	< 0.0005
Refer ← IRefer	0.348	< 0.0005

Therefore, hypothesis H3 is also accepted.

All the three hypotheses above have been tested using the results from the specific case study. Similar hypotheses can be formulated and tested for other service industries. And such results would be required to model and evaluate sustainability of those service operations.

6.2 ANSWERS TO RESEARCH QUESTIONS

The research questions posed in Chapter 1 were answered and a brief discussion follows:

Q1: How do investments in operational attributes affect the long-term sustainability of the organization?

Investments in operational attributes positively affect customer perceptions (service quality, value and satisfaction) which in turn positively affect customer behavioral intentions and customer loyalty. Customer loyalty is vital for both retaining (return) existing customers and attracting new customers through referrals. The corresponding hypotheses were tested for training services in a large humanitarian organization. The increased loyalty increases the customer base for the future and enables the organization to further penetrate the market. In the case study, the organization was able to meet all its expense obligations. Will the operation generate surplus? Yes, as can be seen from the results. But this relates exclusively to the financial aspect. Does that mean the operation is sustainable? Behaviors of other variables need to be considered as well to answer this question. There was a decrease (after an initial slight increase) in marginal rate of return for every additional dollar invested. Strategically speaking, for a particular organization it might be sustainable to penetrate the market with decreasing marginal rate of return. But for another organization, the stakeholders might be content with current surplus and returns. A third organization might want to explore investments in other operational attributes with certain trade-offs. So, investments in operational attributes do affect the long-term sustainability of the organization. However, such impact varies from one type of operational attribute to another. Some attributes have more impact than others on certain outcomes (for instance, surplus, market penetration, marginal rate of return). The model and methodology developed in this research can be used to evaluate the extent of the impact. Such an exercise enables the decision maker to compare multiple scenarios, where interventions are made to varying magnitudes and on different attributes. Based on these results, the decision maker can decide on the appropriate course of action that is sustainable when looking at making investments in operational attributes.

Q2: Is the system dynamics methodology suitable to assess the dynamic achievement of service operations sustainability over the long-term? What are the key factors and variables associated with the SPC framework and what kind of relationships among these factors and variables need to be established and integrated into a system dynamics paradigm so as to dynamically assess the SPC framework?

Yes, the system dynamics methodology was proven suitable to assess the dynamic achievement of sustainability over the long-term. More specifically, the hill-climbing algorithm was capable of identifying the steady state of the Service-Profit Chain as a system. This became evident when, without any additional interventions, the system continued to be in a state of dynamic equilibrium, where net flows were zero (inflow equal to outflow) and the state variables remained at a constant level. At every instant, the algorithm compared the current state of the SPC with a desired state (based on the policy) and corrected for the gap (taking into consideration other changes in factors) over time. By sensing the magnitude and direction of the gap and making appropriate corrections, the algorithm provided the optimal path to the steady state (Vaneman, 2000). This is important piece of information for the decision maker since not following the optimal path might lead to loss in system performance. This in real life is analogous to, for example, offering too many courses than required; or for having a given number of courses achieving a lower impact on overall satisfaction, surplus, market penetration, etc.

The conceptual model identified uncontrollable factors that affect components of the SPC. These factors and the components of the SPC were operationalized by identifying corresponding variables. Relationships among the factors and variables were established based on two sources. Some were based on the body of literature, for instance, impact of service quality on satisfaction. Others like the relationships of age with service quality were explored using CHAID. Those relationships that emerged from the literature review were generic enough such that they can be applied to any service operation. The relationships between the environmental variables (age and wealth) and service quality were explored from the specific data set in training services. These relationships were further validated. However, such relationships might differ for another case study in training services and for other service operations. The mathematical equations for the relationships were subsequently identified. SEM was used for identifying equations between surveys items and for the effect of the environment on service quality perceptions. Again, these mathematical equations were based on a specific data set. These relationships might also differ for other case studies in training services and other service operations. All of the relationships expressed as mathematical equations became the structure of the system dynamics framework. This system dynamics framework as a model represented the dynamic SPC framework.

Q3: For any given investment in services, is the dynamic model capable of providing an answer as to how much can one invest in operational attributes over a period of time and expect to get an adequate financial return (bang for the buck)?

Simulation of the system dynamics model along with model validation provided valuable insights into evaluation of the operation. Several scenarios and sensitivity analyses were simulated to study the financial return (surplus) behavior of investments in operational attributes. In addition, market penetration and marginal rate of return behaviors could also be obtained. The base case scenario provided results on the behavior of key variables linked to interventions in operational attributes (number of courses offered). Though, this could be useful information for the decision maker, this may not be sufficient. Decision makers need to know more about how the operation performs and gain further insights. These insights could emerge by conducting sensitivity analysis. As such, policy, behavior mode and numerical sensitivity were carried out. Findings of the sensitivity analysis illustrate that there was sensitivity of surplus and marginal rate of return, to policy changes. Surplus exhibited behavior mode sensitivity to changes in market size (uncontrollable factor). From numerical sensitivity analysis, it was found that marginal rate of return is sensitive to policy changes, market penetration to environment changes, overall satisfaction is sensitive to neither and surplus is sensitive to both. Confidence bounds were also identified for variables exhibiting certain kinds of behaviors. These bounds give the decision maker probabilities for certain kinds of outcomes (for example, generating surplus or achieving a certain market penetration). By modifying the model one can simulate investments in multiple operational attributes and also analyze their outcomes. Using the models developed during the course of this research, managers can better understand trade-offs, compromises and probabilities of success for making right investment decisions.

Q4: Similarly, can the dynamic model identify the point in time beyond which the marginal rate of return decreases over time?

Surplus and market penetration are important variables that were tracked during the study. Another important variable, especially when additional investments are made, is marginal rate of return. Every additional dollar invested not necessarily gives the same return as the previous dollar invested. As expected, this rate of return climbed in the beginning and began to decline until attaining a steady state. This dynamic model is able to capture this behavior by identifying the point in time where the marginal rate of return peaks (or reaches a maximum) and starts to decrease. This finding is important for managers to explore alternate courses of action if one scenario ends up with huge decreasing returns. Of course, this finding is specific to the case study. But similar findings can be obtained for other cases in training services and operations in other service industries to answer the same question.

6.3 GENERALIZABILITY OF THIS RESEARCH

The Service-Profit Chain (SPC) framework brought together several components, namely operational attributes, customer perceptions, behavioral intentions, customer loyalty and linked it back to revenues needed for investments in those operational attributes. These components are part of all service industries and as such the SPC could be generalized to any – training, banking, airlines, hospitality, etc.

The conceptual (dynamic SPC) model advanced in this research augments the SPC model as currently described in the literature by adding additional components – uncontrollable factors like operating environment and competition. Further, a feedback loop has been introduced linking outcomes (e.g. surplus, market penetration) to operational attributes. Both additions are applicable to any service industry. Different service industries have different environmental factors that are exogenous and affect the operations. Competition is another uncontrollable factor faced by all organizations to varying degrees. The feedback loop, irrespective of the type of industry, is the mechanism through which managers consider current status and make interventions for the future. Hence, the additions of new components are not specific to the type of service. The operational model operationalizes the conceptual model by identifying certain variables that are measurable and is still generic to all service operations.

The evaluation methodology includes a hill-climbing algorithm for the optimization of the service operation and a combination of CHAID and SEM for the actual structural input-output representation of the SPC. The hill-climbing algorithm and how it is incorporated to optimize the system are borrowed from the system dynamics and production efficiency literature and are generic to services. Hence, the Service Sustainability Chain (SSC – operational model with evaluation) developed by incorporating the hill-climbing algorithm into the operationalized SPC is generic to all service industries. Furthermore, the SSC was developed further (full-blown system dynamics model) by getting more into the details of the system dynamics model as it applies to training services. This model as needed has to be modified for other types of services.

CHAID and SEM are used to explore relationships and identify mathematical equations (structural coefficients). Relationships among the factors and variables were established based on two sources. Some were based on literature, for instance, impact of service quality on satisfaction. Others had to be explored using CHAID, like the relationships of age with service quality. Those relationships that were based on the literature are generic enough that they can be applied to any service operation. The relationships between the environmental variables (age and wealth) and service quality were explored from the specific data set in training services. These relationships were validated. However, such relationships might be different for another case study in training services and for other service operations. The mathematical equations for the relationships were then identified. SEM was used for identifying equations for relationships between survey items and for the effect of environment on service quality perceptions. Again, these mathematical equations were based on the specific data set. These might be different for another case study in training services and for other service operations. However, the same methodology of CHAID and SEM can be used to explore and uncover relationships and equations in another case study. Hence the methodology is generic to all service operations.

The generalizability of this research is also illustrated in the case study by applying the generalized CHAID/SEM methodology to explore and uncover relationships/equations from a specific data set and feeding the SSC model for training services (SSC model is generic, which is later developed into the full-blown system dynamics model, specific for training services). The results from the case study, behavior patterns, validation and sensitivity analysis are specific to the case study in training services. But the methodology of how this research can be used to optimize and simulate models to obtain results, understand behaviors, perform validation and sensitivity analysis to inform decision making is very general and applicable to all service industries.

6.4 IMPACT OF THIS RESEARCH

This research contributes with new insights to the literature in service operations, management systems, dynamic efficiency and system dynamics.

The research begins by looking at the problem of insufficient information for managers (or decision makers) who are in charge of making investment decisions. The impact of investment decisions on the outcomes and the bottom-line in service operations have not been fully evaluated and understood before such decisions were made. The Service-Profit Chain (SPC) is a framework that brought together several components like operational attributes, customer perceptions, behavioral intentions, customer loyalty and linked them back to revenues needed for investments in operational attributes in the first place.

This research builds on existing service operations literature – particularly on the SPC framework, by including exogenous components or "uncontrollable factors," like environmental factors (market size, age, wealth) and competition. Further, the SPC is rendered dynamic by comparing the outcomes occurring at present time in relation to a performance goal in order to formulate interventions for the future. Such interventions are made until a steady state is achieved.

This research also impacts the management systems literature by providing additional techniques for decision making. The SPC framework is analyzed from a systems perspective where adjacent pairs of components are considered to be part of an input-output relationship. Thus, each component is an input to the successor and an output to the predecessor. As such, the input-output relationships form a chain. This input-output relationship is also preserved in the operationalization and eventually in the Service Sustainability Chain model. With a systems perspective, the SPC framework is engineered by developing the model and the methodology to aid in decision making for managers. The model and the methodology provide the decision maker with a dynamic framework to evaluate the sustainability of service operations. Hence, the decision maker will be better suited to answer questions concerning the investments in such operations in organizations. Some of the questions managers may be better informed to answer are: which operational attributes will have a greater impact on the outcomes? how are the variables in the SPC related? how will they affect one another? how investments could be phased in order to achieve the performance goals over a period of time to ensure sustainability of the organization? Thereby, opening new venues of research in the management systems engineering literature.

The identification of the steady state is achieved by incorporating the hill-climbing algorithm (Sterman, 2000) into the operational model to arrive at the Service Sustainability Chain (SSC – operational model with evaluation). In doing so, this research uses knowledge from the literature, CHAID and SEM to capture the actual structural input-output representation of the SPC. Such an approach has never been explored before in the literature. This is possibly an area where this research is posed to contribute greatly to the dynamic efficiency literature. Vaneman (2002) used an empirical production frontier to evaluate dynamic efficiency for production systems. This research evaluates service operations using an actual structural input-output representation of the SPC.

Contributions to system dynamics are provided from different angles. First and foremost, the use of CHAID and SEM is illustrated while exploring, uncovering relationships and identifying mathematical equations. This in itself as a methodology is also a major contribution. Such an innovative methodology is helpful when knowledge of the operations and relationships is much diluted as it is in present day organizations. Particularly where there are several departments, where no individual can provide all necessary insights, bringing together a cross-functional team from all parts of the organization often times leads to overemphasizing selected aspects of the operation or pushing for certain participants' agenda. This in turn may also lead to conflicts of interest. The CHAID/SEM methodology described in this research provides an alternate source for such information by turning one's analysis efforts to the wealth of data being collected through systems like Customer Relationship Management, etc. Ideally, the best scenario would be to use a combination of existing relevant literature, expert advice and CHAID/SEM findings to formulate such relationships.

Another contribution to system dynamics are the Dynamic SPC module and the Customer Base Growth module of the SSC model for training services. The Dynamic SPC module gives a dynamic representation of the SPC framework. The Service-Profit Chain, as its name suggests is a chain. As part of this research, the chain was closed by taking the end around and connecting it to the beginning. The Customer Base Growth module builds on the Susceptible-Infectious (SI) model of infectious diseases (Kermack and McKendrick, 1927; Sterman, 2000). The Customer Base Growth module describes modeling of how referrals work in training services. The entire exercise of building and simulating the model (SSC for training services) for the case study shows the applicability of system dynamics to training services. Based on the Customer Base Growth module, formulations of other aspects as to how referrals work can also be explored.

For the service organization where the case study was conducted, there were several contributions. The results, behavior and the sensitivity analyses are very valuable for the managers in charge of the specific field unit. Findings from this research may enable the manager to make better informed decisions. This may include for instance, increasing the course offerings over the next few years. The model and the methodology could also be used by national headquarters for simulating behavior patterns for specific groups of field units (similar type field units grouped together). This would help to set more realistic goals for the field units. These results in addition to policy, behavior mode and numerical sensitivity analyses will provide information to ascertain which variables (e.g. market penetration) are more sensitive than others (e.g. marginal rate of return) as related to environmental changes. Moreover, the model and the methodology can also be used by the individual field unit managers to better understand the service operation in their unit. Managers can also look at probabilities of success (e.g. being able to sustain with surplus, market penetration and returns) with investments in one attribute as opposed to another and make necessary intervention decisions to achieve goals specified by higher management layers such as by national headquarters.

6.5 LESSONS LEARNED AND RECOMMENDATIONS FOR FUTURE RESEARCH

As part of this research, models and a methodology to evaluate investments in service operations were developed. The process of modeling in itself is dynamic. This is because service operations in organizations change over time and change is inevitable. Further, the modeler perceives the real world through the sum total of life's experiences. Even with the organization remaining unchanged, with time, the same modeler looks at it differently at different points in his/her life.

This research endeavor laid the groundwork for taking the evaluation of service operations (using the SPC) from a static realm to a dynamic perspective. Additional components were included in the SPC. Generic conceptual and operational models were developed, an evaluation methodology was formulated using the hill-climbing algorithm and a full-blown system dynamics model for training services was developed. The application of this research was illustrated through a case study in a large humanitarian organization engaged in training services. All of above set the perfect launch pad for future research endeavors.

The dynamic approach used to evaluate the service operations (using the SPC) can also be borrowed and applied in other frameworks that are used to evaluate service operations. Such an approach can also be explored with production operations by looking specifically at logistics or supply chain operations. It is worth exploring the use of predictive analytics and SEM to capture the actual structural input-output representation of such operations.

The policy sensitivity of the model/methodology in relation with assumptions around relative value could lend themselves to be relaxed. This can be accomplished by exploring additional relationships and equations around price, service quality, competitor's price, competitor's service quality and their impact on relative value when the assumptions used in this research are relaxed. However, to achieve this objective additional data about competitors in the market, their price and quality of service need to be gathered and analyzed using CHAID and SEM.

The full-blown system dynamics model developed in this research pertains to training services. Impact of other operational attributes on the outcomes can be modeled and studied. Similar models can be developed for other service operations based on the conceptual and operational models and variables specific to such services. Hypotheses similar to those here can be tested and results compared to gain insights on the importance of certain components in one type of service operation (training services here) vs. another (say banking services).

As for the empowerment of the manager for more informed decision making, behavior under alternate scenarios and more sensitivity analyses can be conducted to provide more information. One valuable piece of information for the manager would be the impact of investing in one operational attribute vs. another, for example in training, investing in increasing the number of courses vs. increasing the quality of the materials. Finally, modeling and validation is never completely done and as such there is always room for improvement. In that, this is a loop with a never ending cycle where trade-offs need to be considered between amounts of information that can be provided to the manager and the time, effort and resources required to provide such information.

From what I have learned during this research endeavor, I would like to explore the application of the models and the evaluation methodology to other service industries. I plan to investigate the health care industry (another service operation) looking at problems that can be addressed using this evaluation methodology. A similar approach as suggested by this research may offer a promising beginning. To start, the conceptual and operational models need to be revisited and the applicability of components ensured. Although the CHAID/SEM methodology is applicable, the mathematical equations formulated here cannot be used. This warrants collection of data around customer perceptions, intentions, loyalty, etc.

Other kinds of models and methodologies can be explored using a combination of other performance measurement techniques (perhaps Data Envelopment Analysis – DEA) along with system dynamics. DEA quantifies the best practice for a group of similar operating units. Such work has been done for a similar service operation (Medina-Borja et al. 2005). New research endeavors would take into account the quantified best practices to feed the system dynamics structure as an alternate to the current structural input-output representation. Alternatively, simulation results from the system dynamics model can be used in conjunction with DEA to perform window analysis to track the growth and performance of an organization over time.

Appendix A – CHAID and SEM

Uncovering Complex Relationships in System Dynamics Modeling: Exploring the Use of CART, CHAID and SEM

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Abstract

One of the premises of system dynamics is that the modeler would make relationship assumptions with enough precision to make the model useful. A common validation method is to consult with field experts, but with the advent of the internet, and automated data collection methods, knowledge is diluted as companies store abundant information without time to process it. Customers' dislikes perceptions, intentions, opinions, and service characteristics reside in data warehouses (e.g. survey data is stored as categorical, nominal, ordinal or qualitative without further analysis). Without experts, companies are data rich but not necessarily knowledge rich. We present an application of known nonparametric predictive methodologies to uncover/confirm significant variable relationships and build the equations to feed the model: Classification and Regression Trees (CART), Chi-Square Automatic Interaction Detection (CHAID) and Structural Equation Modeling (SEM). A developing application of CHAID/SEM to explore restructuring decisions in a large service organization will be briefly discussed.

Key words: System dynamics, service quality, satisfaction, loyalty, relationships, CART, CHAID, structural equation modeling.

Overview
Modeling strategies vary from person to person and from problem to problem. One of the premises of system dynamics is that the modeler would be able to make assumptions about the relationships among variables with enough precision to make the model useful. The system dynamics approach should facilitate understanding into the analysis of the model and suggest behavior, but the modeler is not always sure of the validity of the structure. In many circumstances, the modeler is able to identify the important variables but the identification does not provide enough information for the modeler to make valid assumptions about mathematical relationships. The most common method to solve the relationships puzzle is to gain support from the literature or from a specific set of data collected for that purpose as to the direction of the relationship. The modeler can also ask a group of experts in the field to clarify the same. Then, an iterative modeling process begins when a simulation is run, and in many cases, adjusted after more data is collected. When data is not readily available to confirm expert knowledge, the equations representing the relationships may lack understanding as to why they are put together in that way.

The founders of the discipline believed that most of the information available to the modeler comes from the "actor's heads" —their mental models or what Forrester (1994) called "mental databases." Forrester recognized the mental database as the most important and significant source of information, placing the written database in the mid-range and giving to the numerical database the least importance both in magnitude and information about structures and policies. As the mental and written database contains mostly qualitative data, other authors have presented methods and models to deal with qualitative sources (see Luna-Reyes and Andersen, 2003). We argue, however, that all of the above presumes that knowledge about the system resides in some place. Yet, for many twenty first century business cases, organizational knowledge is diluted in several functions and departments. Contrary to measurement dilemmas of the past, when knowledge was kept in a group of senior experts who had experienced the organization in different capacities over the years, but had little or no data to support their expert knowledge, we live in an era of rapidly changing work environments, with specialized areas but very few knowledge integrators. Organizations today, contrary to the past, have an enormous amount of hard data collected through automated means, such as internet-based customer relationship management (CRM) systems, e-commerce, automated financial and service delivery systems, scannable and on-line customer satisfaction surveys, etc. With abundant information collected at a reduced cost, business analysts perform specific tasks, such as checking correlations for a specific project and, in many cases, millions of data points are stored without major exploration. Companies are data rich, but not necessarily knowledge rich.

Data collected every day is stored without any particular person concentrating in the analysis of changes and trends. If no one has the holistic approach of the organizational authorities of the past, finding an expert that will clarify the relationships or finding enough organizational documentation to point in the right direction is a challenging task.

We are living what *RYGIELSKI* ET AL. *(2002)* call "the network economy" that has transformed business practices. Nonetheless, data today has always a "story to tell."

We are concentrating this paper on one special case in which the modeler does not find readily available support to his/her theories, hunches and/or mental models and has data available to confirm these relationships.

Purpose
Intuitively, when data is abundant and no other sources of expert knowledge exist, one could expect that mathematics can settle the issue. Given the abundant information on customers likes, dislikes, perceptions, behaviors and opinions, and the multitude of options, including diversity of products, and services, data mining techniques are needed for decision-making. These techniques extract hidden predictive information from large databases, so that organizations are able to identify

important patterns, predict future behaviors, and allow organizations to make proactive, knowledge driven decisions. This is especially the case when the empirical evidence of the direction of the relationship resides in data collected from customers in the form of surveys, and stored as categorical, ordinal or qualitative in large data warehouses.

In some cases, we do not even know whether a relationship exists, such as the case of a new introduced technology or gadget and the number of returning customers. Automated systems may collect enough data but it might require the intervention of the market research department to uncover the outcome of such new product features. However, even when the existence of a relationship is known, uncovering the exact mathematical form of the relationship of intangible concepts described by survey data is not easy. For instance, how specific service quality characteristics (e.g. timeliness, empathy, knowledge) relate to customer retention and loyalty is likely to be a modeling challenge. Knowing that customer retention has the same direction as that of timeliness is intuitive. Nevertheless, knowing how exactly a stock variable, *number of customers*, is affected by a concept named "service quality" which in turn is composed by the customer reactions to a number of attributes or service dimensions, of which one of them is being more or less timely, is a very difficult question to answer. Statistics (a branch of mathematics) can also determine a formula for each relationship, which can be used, updated, refined, and reused over again. However, a methodology is needed to uncover "the formula" that relates an easily quantifiable variable to an abstract quality perception of the customer.

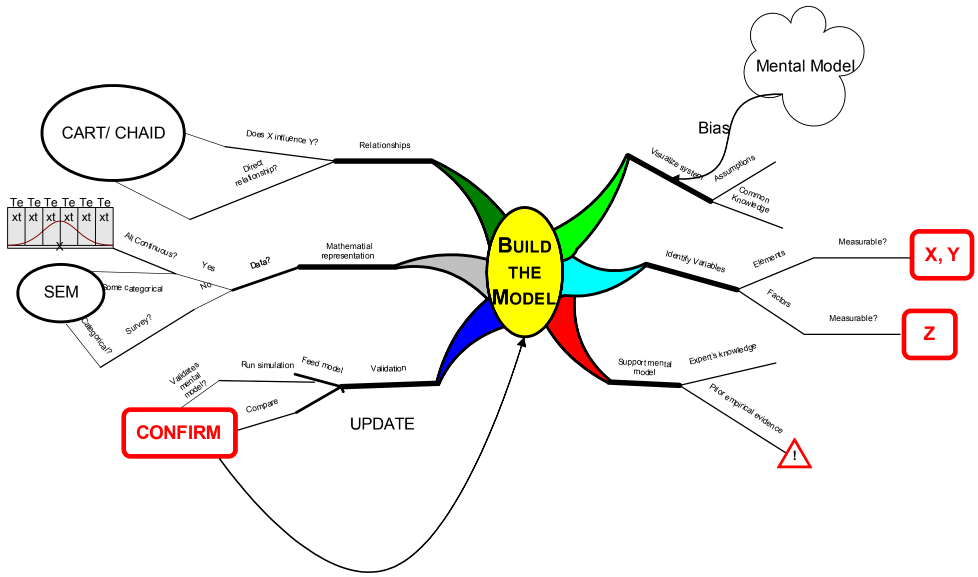
In this paper, we want to present a combination of three methodologies to uncover/confirm the significant relationships and build the equation to feed the model: Classification and Regression Trees (CART), Chi-Square Automatic Interaction Detection (CHAID) and Structural Equation Modeling (SEM). We offer the above as a potential solution for the problem of finding an adequate methodology to extract the relationships from a large data warehouse.

A Possible Modeling Strategy

While the system dynamics community is right in that the mental model of the researcher plays the most important role in the modeling process, it is undeniable that the "network society" has had an effect in the way modelers put together their systems. When abundant data resides in data warehouses, including customer data, the modeler needs to determine the relationships among variables that are sometimes abstract such as concepts, perceptions and opinions, collected through surveys. Figure 15 depicts what could be a mind map for such a situation. Here, the researcher has the main task of building a model. The first mental action is to retrieve a mental model with his/her biases, identify the issues, variables and factors and go to expert sources in search for support of his/her theories. This is a common process regardless of the nature of the problem, or the nature of the variables. Next, if expert knowledge is not available and data is, a potential modeling strategy would be to confirm the relationships through some statistical method. We propose that CART and CHAID can be used with this purpose.

However, once some of the variables can be classified as "constructs" of otherwise ambiguous perceptual concepts, such as marital happiness, service quality, customer satisfaction or political support, one would develop theories on how to measure such concepts creating a series of question items that are measured on some sort of ordinal scale (the most common one the Likert scale). But then, how these items are related to other variables in the problem, such as investment dollars, and ultimately, how can we uncover the exact mathematical representation of such a relationship so that a model is built, run, and gives useful and valid results. This is the scope of this paper.

Figure 15. Mind Map of the System Dynamics Modeling Process: Modeling Categorical Variables



Basic Algorithm for Decision Trees

Automatic tree classification methods are a family of methods that use recursive partitioning to find patterns in large data sets. As other nonparametric methods created to find patterns in the data, automatic decision trees try to overcome the limitations of parametric methods that assume linearity and therefore, can be used in a wider array of applications. Basically, all automatic tree methods follow the same algorithm:

1. Split into nodes
2. Grow branches
3. Terminate growth

Starting with the whole population in the data concentrated in a starting node (dependent or response variable), the algorithm looks for the best way to split the cases into a series of "parent" nodes and these cases into a series of "children" nodes. A pre-determined splitting criterion is followed systematically. In that way, cases are classified into branches and leaves. Through a series of termination rules, a node is declared either "undetermined" meaning that there is potential for growth and further classification, or "terminal" node, meaning that there isn't any further value in continuing the splitting.

When continuous or integer variables are part of the data set, there is potential for a huge number of data split interactions. Basically, any point can split the data. Because of this, splitting rules are developed that partition continuous data in categorical sub-sets.

The following sections discuss two of these methods, CART and CHAID in the context of SD modeling.

CART

CART is a binary decision tree whose proponents claim that it can automatically uncover the hidden structures in the data. CART was introduced originally by Freidman in 1977 and for those interested in details, an extensive methodological discussion is presented in Breiman *et al.* (1983).

In the literature, the main use of CART is that of identifying variables that are predictors of certain customer behavior. A set of rules or a profile is built based on the results, and whenever a new case arises the behavior is predicted based on the CART profile. The most common is of course that of credit decisions based on past customer data. While LOGIT and other parametric methods are also used, CART has been proved to be as or more efficient in cases where there is no assumption on the distribution of the variables (e.g. Galindo and Tamayo, 2000).

The algorithm divides the data in exactly two branches from each nonterminal node. The objective is to decrease heterogeneity. The response variable (dependent variable) can be quantitative or nominal (e.g. returned/ did not return, was satisfied with service or was dissatisfied, etc.) and the predictor variables can be nominal, ordinal, or continuous. Cross-validation and pruning are used to determine the size of the tree. Therefore, to build one such tree the modeler has to first grow the tree and then prune it.

In short, the algorithm divides the objects (data cases) in k different groups. The greatest amount of heterogeneity (or impurity) resides therefore at the top node. Then the data is split into sub-nodes that are significantly different. Each split contributes to the purity of the classification (i.e. to homogeneity of groups). Through this process, a set of important independent variables is revealed.

The validity of the model built through CART is done by cross-validating with another data set. There are issues around CART regarding the depth of the tree and pruning, but they are less worrisome than other assumptions in other methods. We are proposing that the same can be used to identify or confirm important predictors of any given variable in system dynamics.

For example, let's assume that an organization wants to re-engineer its operations by closing some of its branches in small towns, where apparently the presence of the company has no impact in the overall business. However, having wide presence might influence public opinion and brand image value. There are some not so obvious effects of having the branches in small places that are beyond pure financial numbers. It is hypothesized that having wide nation coverage would positively affect brand recognition, which in turn will positively affect both, customer retention and new customers. This is just one small piece of the system, as having more branches does have a financial effect, higher cost and perhaps not proportionately higher revenue generation. Customers from big branches were surveyed in the past and asked if nationwide coverage was important in their decision to do business with the company. They were also asked about their intention to continue. They answered Likert-scale type of questions from "strongly agree" to "strongly disagree" of the type: *I am satisfied with the number of branches*, *I do business in other cities*, *I feel a sense of security when I see a branch in a neighborhood other than mine.* Historic data on past closings and financial results were also available. Other satisfaction items were included in the survey.

CART was used to confirm the relationships and identify the most important predictors of customer retention. The tree in Figure 16 was created. The terminal nodes are shaded. According to the fictitious tree generated, brand recognition is the most important independent variable that affects customer retention. Customers who said that brand recognition is important or above will likely remain with the company in 55% of the cases. Affecting Brand recognition is convenience of branches. Those customers that said that branch convenience was very important or extremely important and for whom brand recognition was important have higher likelihood of continuing with the company. In fact, there is a probability close to 100% of that happening. Table 4 shows some of the potential rules associated with each terminal node.

For those who stated that convenience of branch availability was not as important (i.e. at the *important* or below rating in the Likert scale) but who also stated that they were extremely satisfied, the retention rate was high as well. This is confirmed by the other side of the coin, in which customers indifferent or dissatisfied had the lowest retention rate.

There are circumstances in which Chi-Square Automatic Interaction Detection, or CHAID, another nonparametric method, is more appropriate, such as when nominal variables are part of the data set or when the modeler wants to know how the independent variables interact with each level of the dependent variable (i.e. the researcher is interested in more than a dichotomous response). Like in the case when the dependent variable is customer satisfaction measured in a 5-point Likert scale and the modeler wants to see how Branch availability and Branch recognition interact to produce each of the five levels of measured satisfaction (from extremely dissatisfied to extremely satisfied). The next section explains the use of CHAID.

Figure 16. CART Results Identifying the Important Variables that Affect Customer Retention

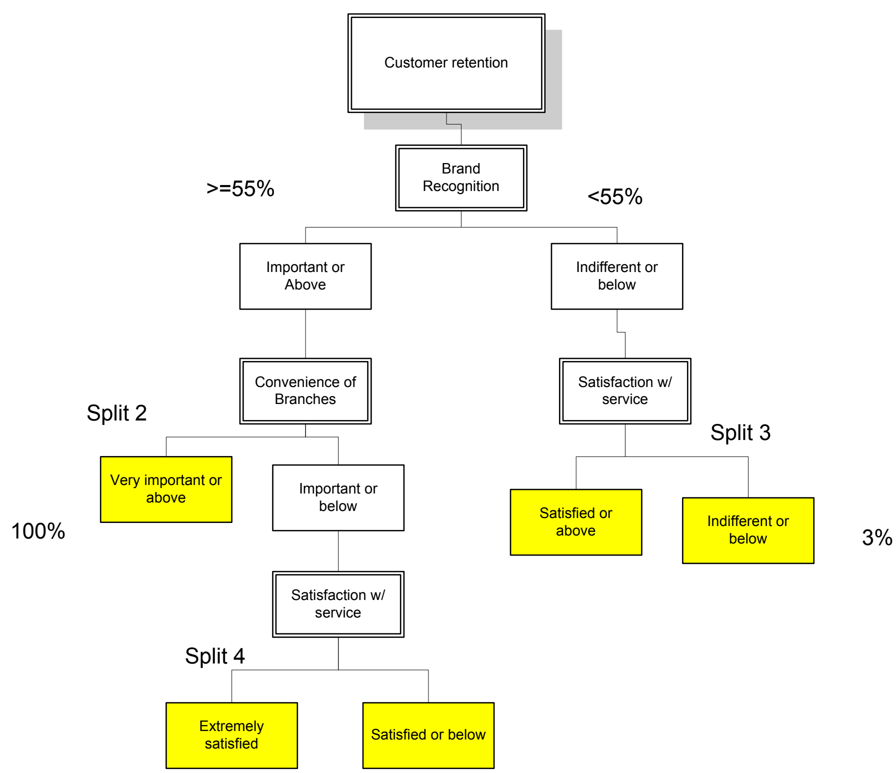


Table 4. Potential Rules Associated with each Terminal Node

Rules	*Potential response or outcome*	*Likelihood*
If the customer's rating for satisfaction with service is indifferent or less; and brand recognition is indifferent or below	Losing customer Retaining customer	97% 3%
If the customer's rating for satisfaction with service is very important or above; and brand recognition is important or above	Retaining customer	100%

CHAID

Morgan and Sonquist (1963) proposed a simple method for fitting trees to predict a quantitative variable. They called their original algorithm AID because it naturally incorporates interaction among predictors. Talking about Interaction, Wilkinson says:

> *"Interaction is not correlation. It has to do instead with conditional discrepancies. In the analysis of variance, interaction means that a trend within one level of a variable is not parallel to a trend within another level of the same variable. In the ANOVA model, interaction is represented by cross-products between predictors. In the tree model, it is represented by branches from the same node which have different splitting predictors further down the tree." p.4*

The algorithm performs stepwise splitting by computing the within-cluster sum of squares about the mean of the cluster on the dependent variable.

CHAID is another type of decision tree method originally proposed by Kass (1980). According to Ripley (1996), the CHAID algorithm is a descendent of THAID developed after AID and discussed by Morgan and Messenger, (1973). CHAID is a combinatorial algorithm since it goes over all possible variable combinations in the data to partition the node. It is also an exploratory method used to study the relationship between a dependent variable and a series of predictor variables.

Categorical predictors that are not ordinal —such as ethnicity or race classification, or nominal options of the type of service provided— require a different approach. Since these types of nominal categories are unordered, all possible splits between categories must be considered. For deciding on one split of k categories into two groups, this means that 2 k -1 possible splits must be considered (Wilkinson, 1992). CHAID modeling selects a set of predictors and their interactions that optimally predict the dependent measure. The developed model shows how major "types" formed from the independent (predictor or splitter) variables differentially predict a criterion or dependent variable. The main difference between CHAID and CART is that CHAID partitions the data in more than two groups, therefore, it discriminates more among categorical variables that are not necessarily binary. Any given node in CHAID can be partitioned in more than two groups.

The CHAID algorithm is particularly well suited for the analysis of larger datasets because the CHAID algorithm will often effectively yield many multi-way frequency tables (e.g., when classifying a categorical response variable with many categories, based on categorical predictors with many classes). One of the most common uses of CHAID has been in market segmentation to uncover customer characteristics for response modeling (see for example MacLennan and MacKenzie, 2000)

CHAID facilitates the development of predictive models, screen out extraneous predictor variables, and produce easy-to-read population segmentation subgroups. The splitting criteria are given by the non-parametric Chi-square test of independence, entropy measures and cross-validation differences. A larger Chi-square statistic suggests a more significant partition. Adjusted p-value measures of significance (using Bonferroni) are used to determine the best value of the partition, or the best split. Further, measures of entropy within the groups (a measure of information content within the split) are also used. An extensive explanation of how the CHAID algorithm works can be found in Wilkinson (1992).

Other than the differences pointed out above, the logic behind CHAID and CART are very similar. Both clarify relationships among variables.

From Relationships to Mathematical Equations

Let us assume that the problem in our example of how CART works is part of a more comprehensive modeling endeavor. Any of the decision tree methods would help us determine whether a relationship exists, and the direction of the relationship. In the example given, we were able to determine that brand value affects customer retention in a positive way, the same as customer satisfaction. We also determined interactions with other variables. However, if we were to run the simulation model, we would be facing a problem since we do not know exactly how these categorical variables included in the survey (as part of a larger construct, for example, service quality) interact to affect customer retention, specially since they are measured in a Likert-type of scale.

In the next section, we briefly review survey design methodologies to help readers that are not familiar with the subject to understand how survey data are processed and why SEM works better for this type of problem.

Designing a Customer Survey

One of our favorite ways to explain survey design is the example of measuring people's happiness. Happiness is a concept as abstract as service quality. Those who see it or experience it know it is there, but it is invisible, intangible and therefore subjective and difficult to measure. One cannot ask, "Are you happy?" "Yes or no." Happiness has different degrees, and different nuances, and to be truly objective it is better to rely on the symptoms of happiness than on the simple self-evaluation of it.

If the researcher would rely on personal observations about happy people, she would probably include questions related to things she observed every time she was happy, or others around her seemed to be happy. Perhaps her mother used to wear a red dress every time she was happy, and used to wear a smile, and soften her voice, also presenting a joyful demeanor. Therefore, if she decides not to check the literature on the construct "happiness", but to rely on her mental model, she would include the following items in the initial pilot survey:

I am wearing a bright color today
My voice is soft
I feel joyful
I am smiling

In an attempt to measure the degree of the respondents' happiness, the researcher would include a scale in the survey to allow the respondent to choose among nuances of each question item above. The scale could include the following potential answers:

Describes me totally
Describes me

Does not describe me
Does not describe me at all

A numerical value would be assigned to each possible answer, 4 being assigned to "Describes me totally" and 1 assigned to "Does not describe me at all".

A pilot test with at least 50 customers would provide enough data to test the reliability of the construct "happiness" as it was built by the researcher (i.e. whether the four items above truly measure one's happiness or not). A statistic to measure the reliability of the construct would be calculated (generally Alpha Cronchbach) and if the Alpha statistic is close to 1, the items in the construct are correlated and therefore, assumed to be consistent and measuring the same thing. One can also test what would happen with the statistic if each of the items were to be removed from the survey, one at a time. If the Alpha coefficient increases, then the construct is better off without the question item. That is, the item is not consistent with the underlying concept being measured.

Let's assume that 20 persons stated that the sentences:

My voice is soft
I feel joyful
I am smiling

describe them totally. Of those, only 3 were actually wearing a bright color. Of those stating the opposite (i.e. that the three items above does not describe them at all) at least 3 stated that they were wearing a bright color. Therefore, the dress color does not seem to be consistent with the other 3 items, or in other words, it does not correlate with the other items (inter item correlation). Therefore, the internal consistency of the construct is better off if that item is not included since most likely the Alpha Cronchbach coefficient will increase if the statement about the color of cloth is deleted. The final questionnaire to elicit one's happiness will only include voice, demeanor and smile.

Now that we have explained how researchers build survey questions to measure "constructs", we are ready to move to the use of SEM to uncover the hidden mathematical relationships among variables.

To make the link between the survey data and the hard data such as number of customers and service quality, Structural Equation Modeling or SEM could be used in conjunction with CHAID or CART. SEM is more of a confirmatory technique than an exploratory one. In fact, the two previous techniques discussed explore the potential relationships among variables in the data while SEM is more appropriate to confirm the relationships and build the mathematical model.

Structural Equation Modeling

Structural equation modeling (SEM) is a methodology used to model interactions, and nonlinearities among multiple latent independents measured by multiple indicators, and one or more latent dependents each with multiple indicators as well. SEM is a major component of applied multivariate statistical analysis and is used by biologists, economists, market researchers, and other social and behavioral scientists to study complex dependencies among variables in a causal framework. See for instance Hayduk, 1985; Bollen, 1989; Schumacker and Lomax, 1996; Pugesek *et al.* 2003.

Contrary to CHAID and CART, a causal model based on theory is first proposed and then tested for the data set. The model is used to test how well a model fits the data only to be accepted as a not-invalidated model. Alternatively, several proposed models can be compared against each other and based on the goodness-of-fit measures, the best model is chosen. We are proposing that the causal model could be based on exploratory methods such as CHAID and CART.

We now explain the main elements of SEM to familiarize the reader: indicators, latent variables, error terms and structural coefficients. *Indicators* are variables that are measured. They are also called as manifest variables or reference variables, such as items in a survey instrument. These indicators are used to measure unobserved variables or constructs or factors that represent an abstract concept, which are called *latent variables*. Error terms are associated with indicators and are explicitly modeled in SEM to capture the measurement error. *Structural coefficients* are the cause-and-effect sizes calculated by SEM and used to formulate the structural equations.

In practice, most researchers use a hybrid approach, where a proposed theoretical model is tested with data. Then the modeler goes back to make changes in the model based on the SEM indexes. The problem of generalizability of the model (because it was modified based on a specific data set) to any data set can be overcome by a cross-validation strategy. Here the model is developed using a calibration or training data sample and then confirmed with a validation or testing sample.

Latent variable models are appropriate for continuous and discrete observed variables. Thus, SEM is especially well suited for discrete and categorical survey data. One can understand this if the concept of *latent variable* is understood. Normally, survey researchers use accepted statistical artifacts to get to the overall evaluation of the abstract construct under study. In our 'happiness" example, to evaluate how happy a person is, the researcher could either calculate the average of the responses to all the three proven items in the construct *happiness,* or find the best item to represent it. If a respondent answered "Describes me totally" to *I feel joyful* and *I am smiling* and answered "Does not describe me at all" to *My voice is soft,* the overall "happiness rating" would be the average of the numerical values (i.e. (4 + 4 + 1)/3 = 3. If another respondent answered "Does not describe at all" to all three items his/her rating would be one (1). The first respondent would be considered happier than the second one.

The same researcher using SEM, will approach the evaluation of the construct "happiness" in a different way. "Happiness" will be deemed a *latent variable*. The survey items, qualifying voice, demeanor, and smile will be the indicators. In Table 5, the observed variables are the indicators. These indicators are used to measure the latent variable *happiness*.

Table 5. Latent and Indicator Variables

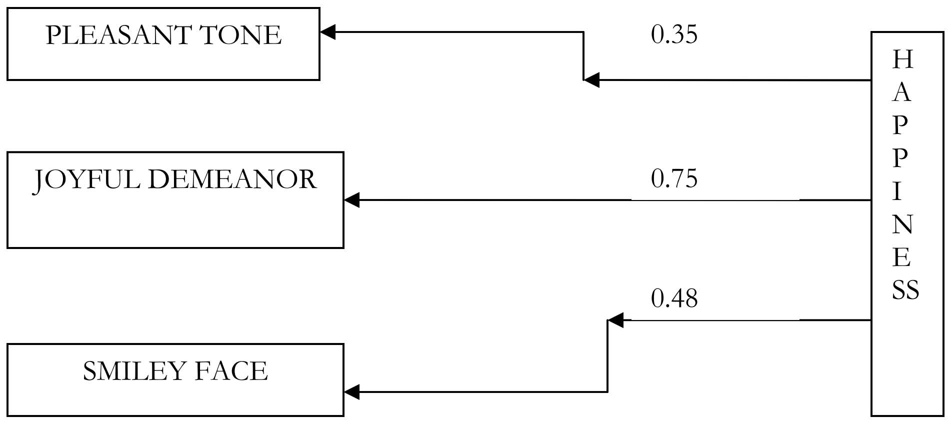
Dimension or Latent Variable	***Indicator or Observed Variables (usually measured by the item questions in a survey)***
HAPPINESS	**Voice tone** **Joyful demeanor** **Smiley face**

Each observed variable is measured with error, yet we would obtain unbiased measures of happiness. This can be done if we assume that the correlations across the observed variables arise from their common relation to the latent variable (local independence).
Similarly, we would like to obtain unbiased coefficients for the relation of happiness to other observed or latent variables (associations or causal effects).

The resulting model would be something like this:
Voice tone = 0.35 * Happiness
Joyful demeanor = 0.75 * Happiness
Smiley face = 0.48 * Happiness

Meaning that an increase in the Happiness of a survey respondent by one unit is shown by an increase in the Voice tone, Joyful demeanor and Smiley face respectively by 0.35, 0.75 and 0.48 (see Figure 17).

Figure 17. Happiness Construct

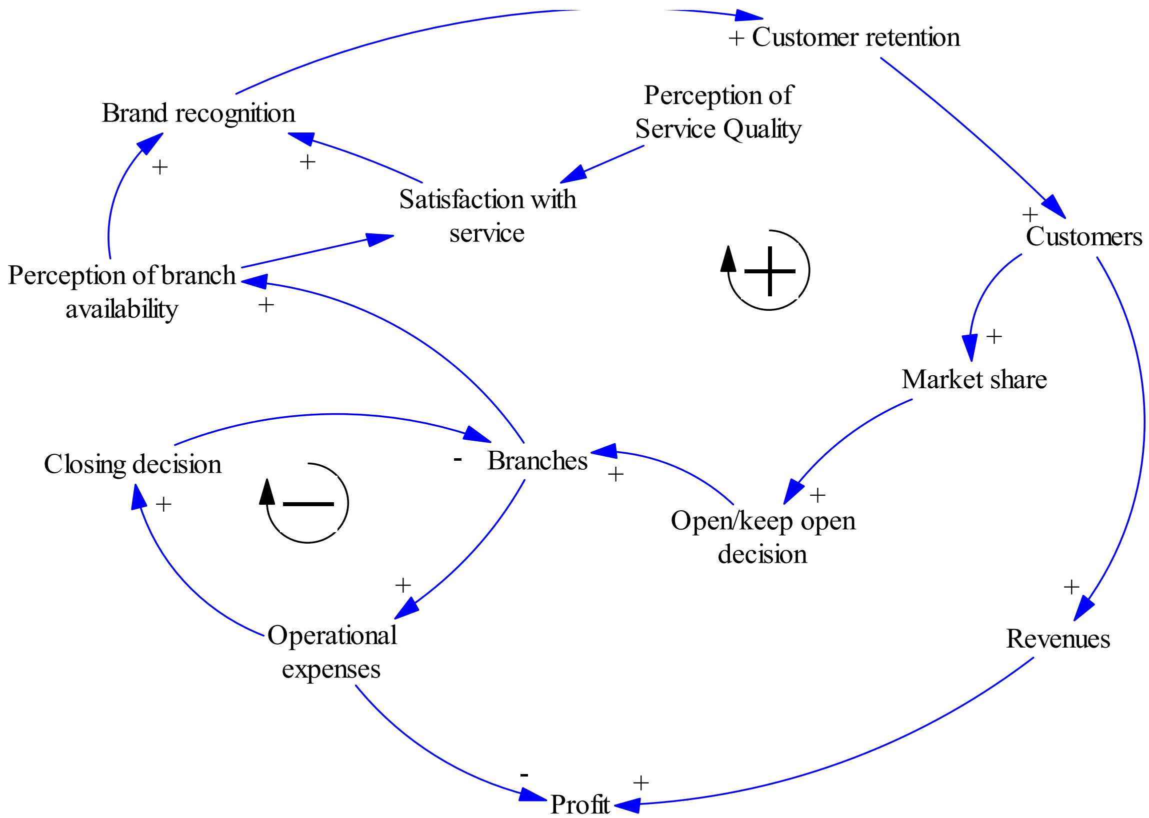


This is a radically different approach than the traditional average of the survey items. In fact, "Happiness" becomes a function that can be calculated and then related to other variables in the problem.

An illustrative example

In our example shown in Figure 16, we know that a level of satisfaction less than indifferent relates to the brand recognition, but we do not know in what magnitude, and how the same vary if the customer is "satisfied" instead. To clarify these, let us assume that the service company in our example wants to explore downsizing the number of branches. In this situation, customers perceive the quality of the services and tend to have certain levels of satisfaction. The extent to such satisfaction increases the loyalty of such customers and thus the recommendation of the service to their family and friends. Based on theory, the modeler could consider that an increase in number of branches increases the perceived service quality, all else being equal. As service quality increases, satisfaction also increases, more than otherwise would have been without enough branches. Again, with higher satisfaction, customer loyalty tends to increase. Let us assume that historical data shows a correlation between number of customers and the opening of new branches, suggesting that when the number of customers in one branch exceeds a certain range, management tends to make the decision of opening a new branch in the vicinity area. Branch availability in turn requires more operational expenses. For a re-structuring program, more expenses seem to be a negative consequence of more branches. More customers obviously will bring more revenue. Assuming, this very simple example accounts for all influencing variables, the right decision is a balance of all these interactions. The causal diagram for this situation is as shown in Figure 18.

Figure 18. Casual Loop Diagram for Restructuring Decisions



If the components of service quality are measured in several survey items, then we could use SEM to uncover the actual mathematical equation of the relationship between these two variables (i.e. between the abstract concept of service quality and the hard number of returning customers). This relationship could have been previously uncovered by CHAID or CART.

Similarly, the construct of service quality in our restructuring problem is measured by ease of service procedures, knowledge of personnel, empathy/helpfulness and convenience of location. In addition, brand recognition is measured by image, logo recognition, uniqueness and bond with customer (Table 6).

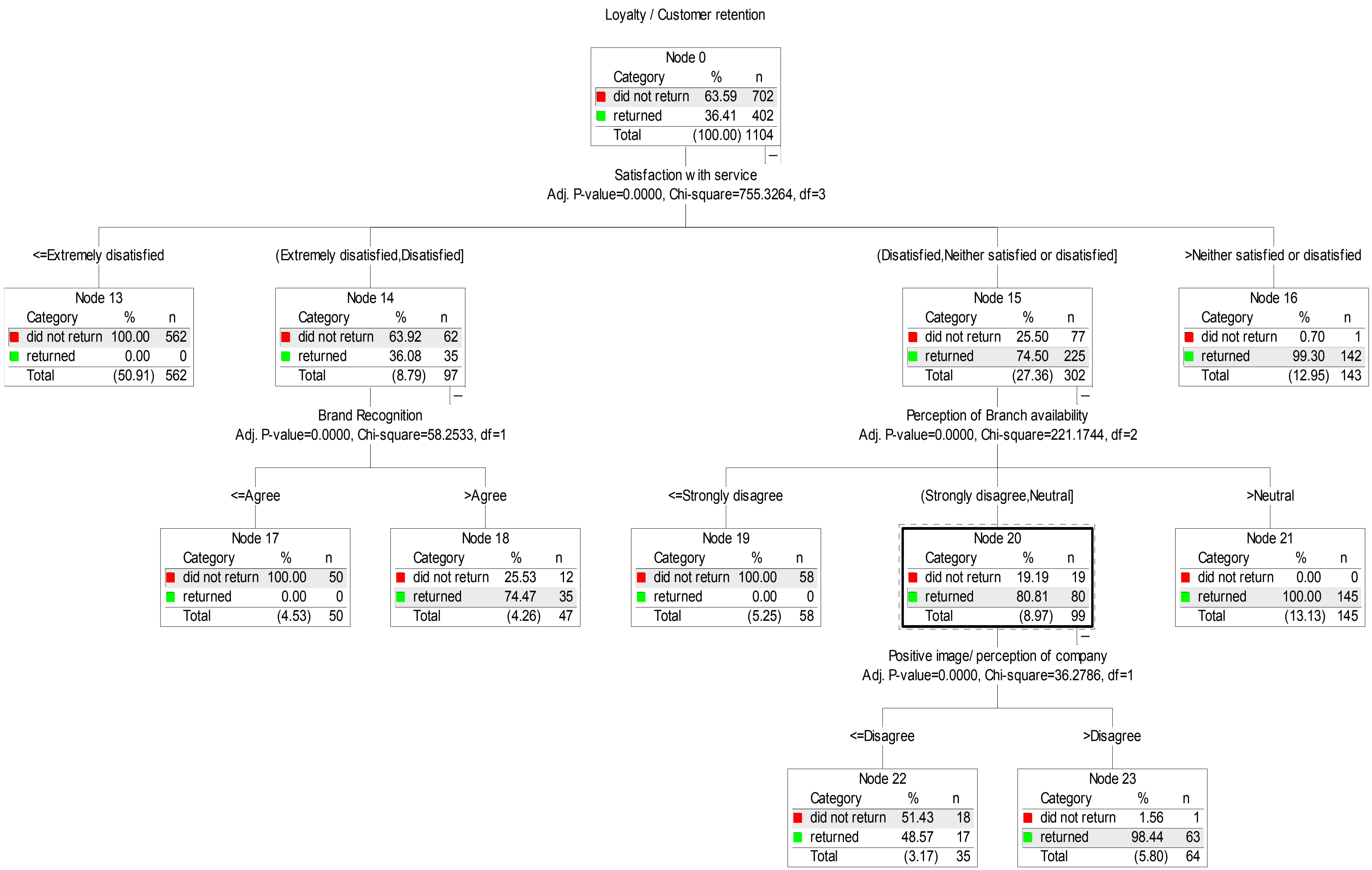
Table 6. Latent and Indicator Variables for the Restructuring Example

Latent variables	Indicators
Perceived Service Quality	Knowledge of personnel
	Ease of service procedures
	Empathy/helpfulness of personnel
	Convenience of location
	Responsiveness to customer needs
Brand/company recognition	Bond with customers – sense of security
	Positive image (setting it apart from others)
	Logo/name recognition
Customer satisfaction	Answer to "How satisfied are you with this service?
Perceived availability of branches	Answer to the question "There is a branch available whenever I need one"

All of the above indicators are part of a survey questionnaire distributed to customers. Thus, the customers' perceived service quality (perceptions about personnel, service and location), satisfaction and brand recognition are captured this way. All other variables are hard data from company's databases. Through customer relationship management systems, one can know whether a customer that gave a bad service quality evaluation and said to be dissatisfied, actually returned to make business in the future. By identifying the exact relationship that makes a customer return or not, it is possible to make the number of customers a stock variable and the flow is influenced by survey results. Further, it is known that a returning customer makes recommendations and referrals to friends and family, of which only 5% of the competitors are gained as new customers.

In our example, other variables measured as independent constructs are loyalty —measured as a binary variable for whether the customer returned or not — and the answer to the question measuring the customer's perceptions of the availability of enough branches of the company. CHAID would produce the tree in Figure 19 showing that the strongest predictors of a returning customer are his/her satisfaction with the service, perception of branch availability, brand or name recognition and having a positive image of the company/service.

Figure 19. Predictors for Loyalty/Customer Retention



We know, however that customer satisfaction is influenced also by the customer's perception of service quality dimensions. Therefore another tree was obtained having customer satisfaction as the dependent variable and all the four items in the construct service quality as potentially independent predictors. The resulting tree is shown in Figure 20. This tree shows that the most important predictor of satisfaction is the empathy or helpfulness of the service provider, followed by the perception of convenience of the location of the branches and ease of service procedures (which includes the time and paperwork involved in each transaction).

One could model these interactions among indicators or items in the survey. One method could be through IF-THEN statements that will account for the likelihood of a customer having a determined perception about the service. For example,

> **IF** the customer agrees or more that the service provider was helpful, exhibit empathy, and found the availability of branch locations as convenient **THEN** the likelihood of the customer being satisfied or extremely satisfied is 58%. However, **IF** the customer had the above characteristics and agreed or more than the service providers was knowledgeable about the service, **THEN** this likelihood of being extremely satisfied jumps to 100%.

We also ran a specific tree to uncover the relationships of the variables with the perception the customer had about the company image (Figure 21). In that we uncover that brand recognition and bond were also important predictors of a positive perception of the company's image, but so was satisfaction.

Having the same type of statements above describing the relationship of customer satisfaction with returning customers expressed in Figure 19, we could build a model including the relationships in Figure 20 and Figure 21. Therefore, one could conceive a model with survey data without using SEM. The model in Figure 22 would depict this model.

Since so far in this model we have not expanded the construct "Service Quality", the model in Figure 23 would be the expanded portion of Perceptions of Service Quality that affect customer satisfaction according to the tree in Figure 20. Here, *empathy of service provider* is the most important factor that affects a positive rating of satisfaction, and all other indicators refine this classification further, indicating they influence the perception of empathy and the final outcome of the evaluation.

However, one should observe that there is really no quantification of the increase/decrease in satisfaction and increase in retention due to the overall increase/decrease in the perception of quality. This is one disadvantage of using only CHAID or CART for modeling purposes. More importantly, SEM is necessary when we do not necessarily want to model the customer's individual reactions to items in the survey but instead we want to model the interaction of service quality as a whole concept (or latent concept) with the number of customers returning.

Using SEM the researcher would calculate the contribution to service quality of each one of its dimensions and then come up with a relationship that relates, not the survey items or dimensions, but the whole concept of service quality to satisfaction and then to loyalty.

Figure 20. Predictors for Satisfaction with Service

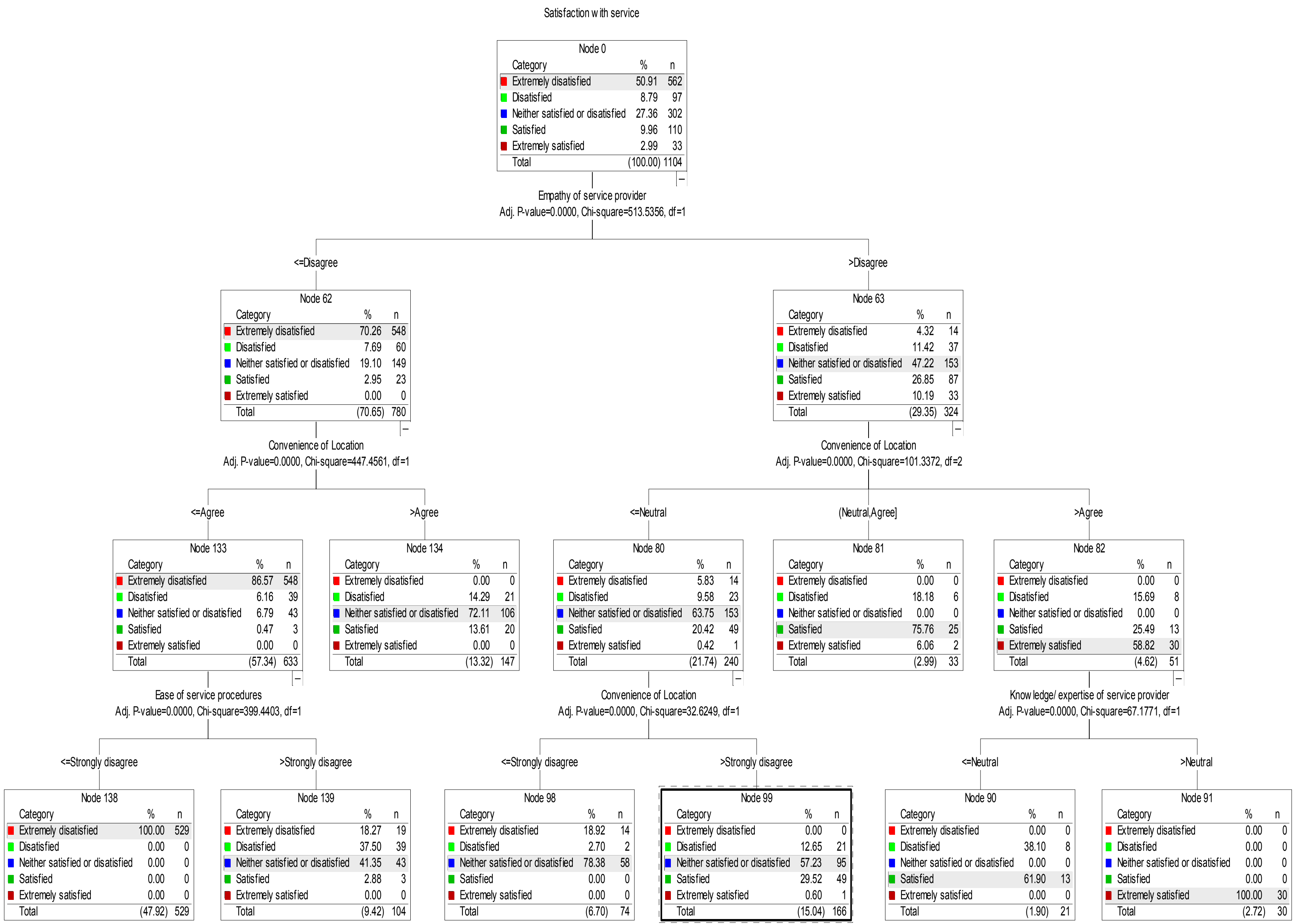


Figure 21. Predictors for Positive Image/Perception

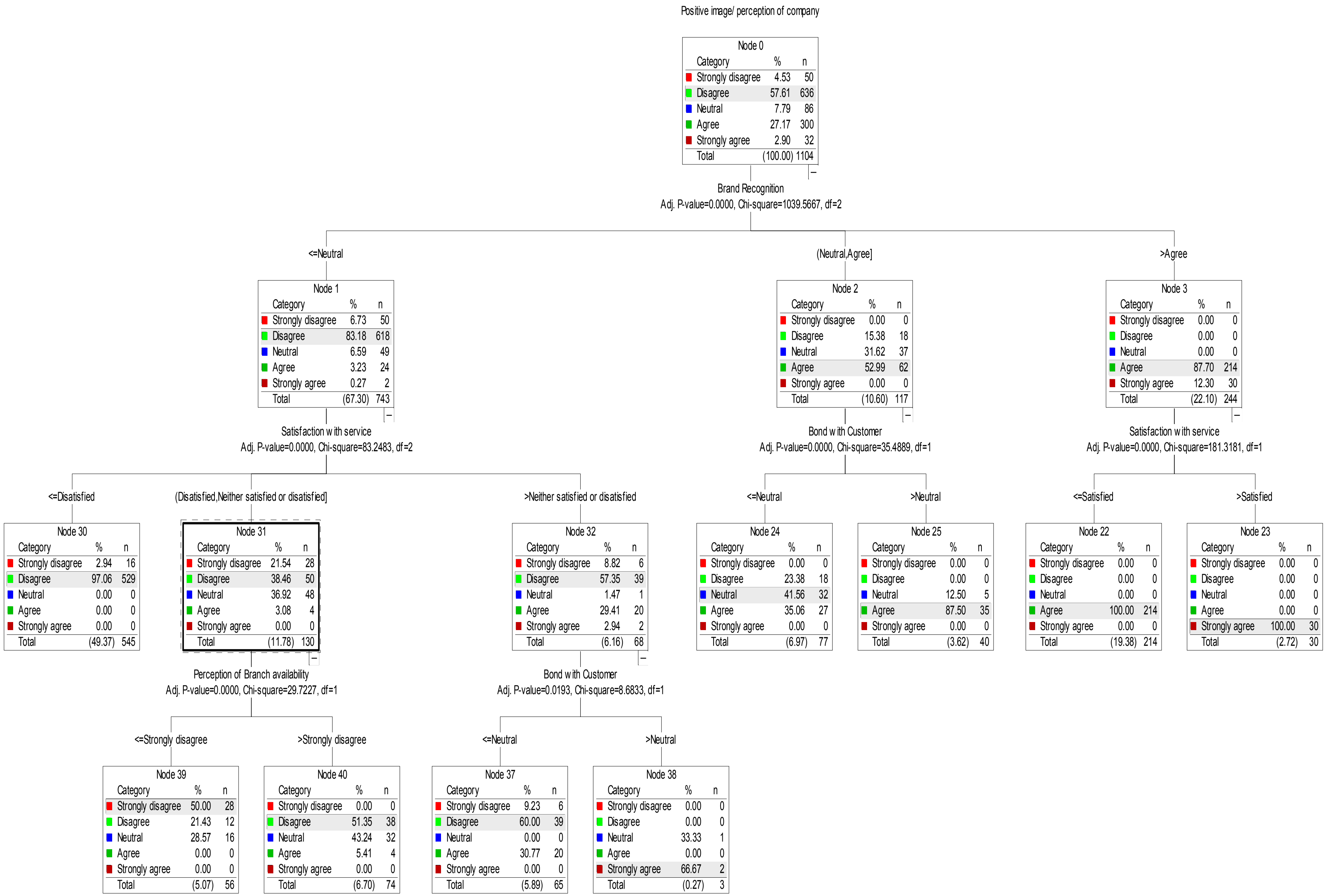


Figure 22. Resulting Causal Loop Diagram after CHAID Exploration

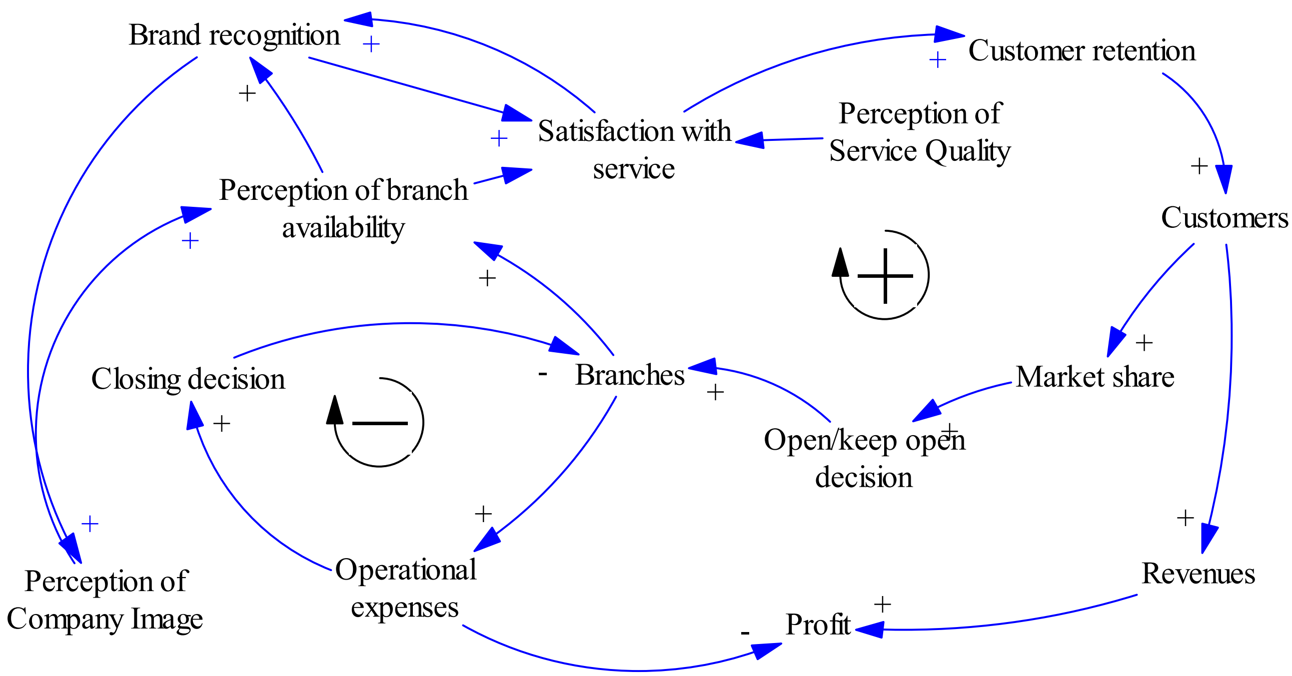


Figure 23. Expanding the Construct Service Quality

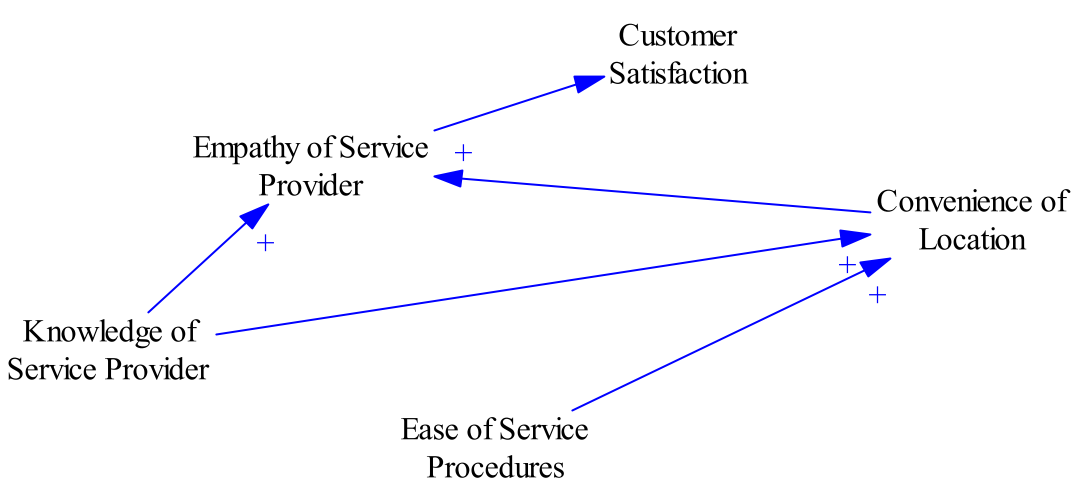
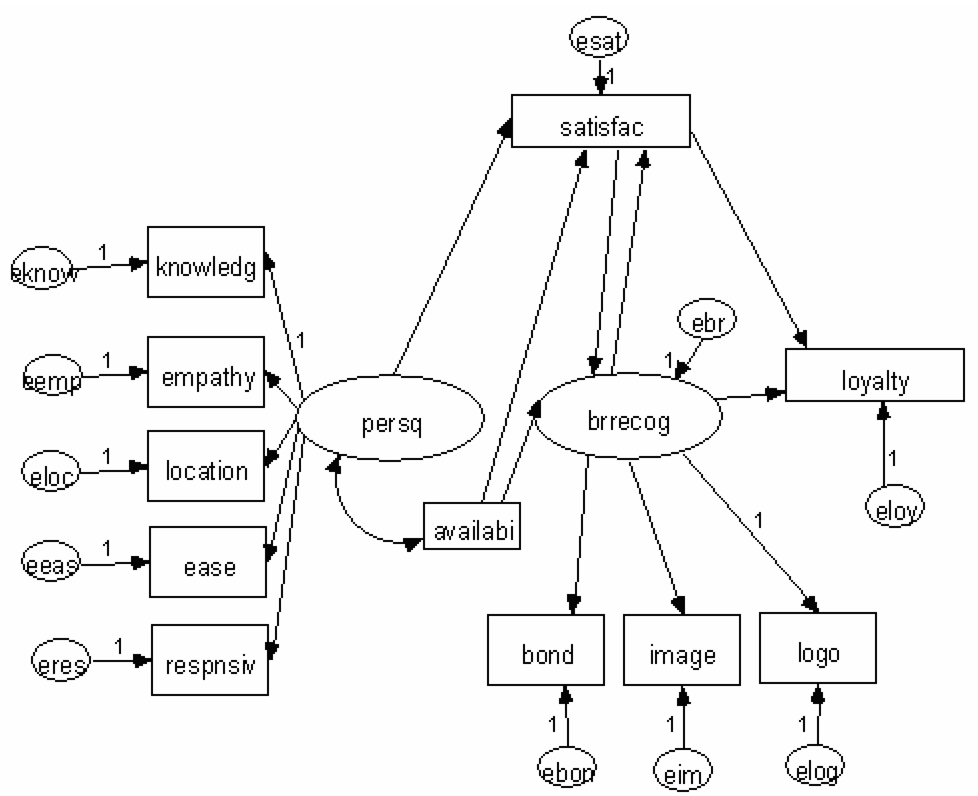


Figure 22 shows how one would model with SEM to represent the diagram in Figure 24. Latent variables are represented by the ellipses and indicators or measured variables by the rectangles. Each measured variable has an error term associated with it represented by the small circles.

While the contribution of each indicator (item in the survey) to the overall service quality will be estimated, the linkage that we will use in SD would be the one from the latent variable service quality to customer satisfaction, which estimates the increase in satisfaction for each unit of service quality. The researcher can then estimate the evaluation provided based on the contributions of all the variables affecting satisfaction.

Figure 24. Modeling the Restructuring Problem in Structural Equation Modeling (SEM)

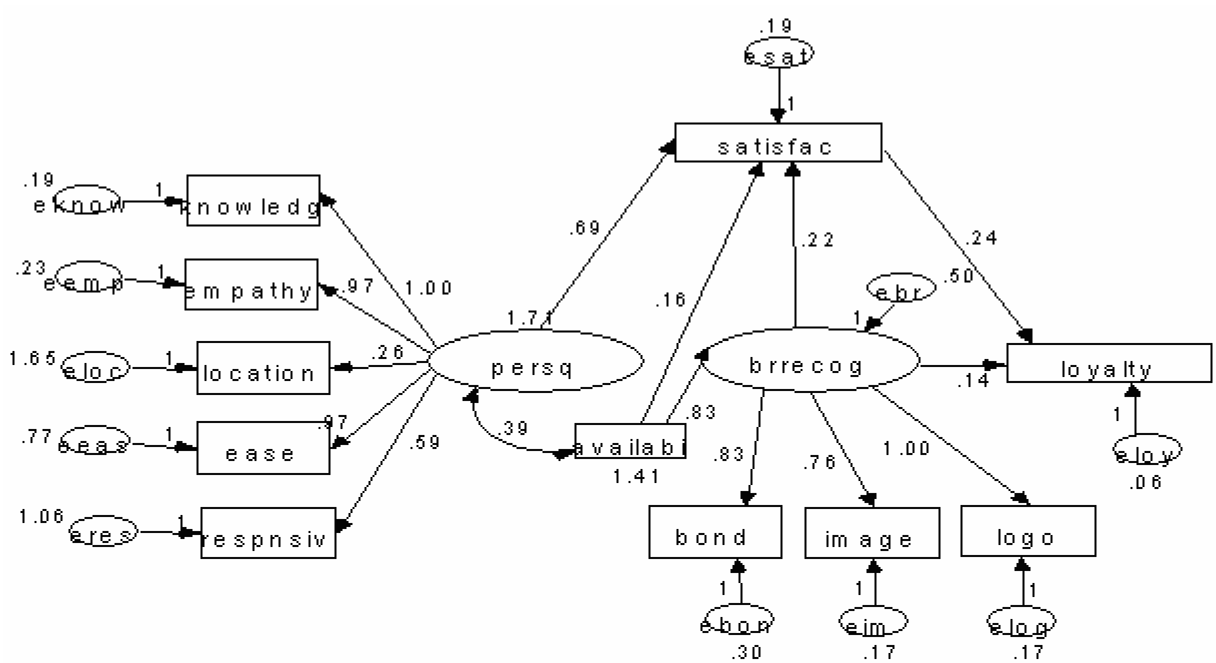


Another good feature of SEM is that it allows the researcher to explore variations to the model and see which one seems to be more appropriate. The commercially available software allows the user to explore alternative models and select the best fit one.

After running the above model, we obtained a series of parameters: estimate coefficients for the equations that link each variable, the covariances, variances, and the correlations estimates for the relationships among variables. To compare models, the researcher can use a number of statistics of goodness of fit. For the above model Chi-square was 6982.9 with 39 degrees of freedom and probability level $p = 0.0001$. All relationships were proven to be significant at the 0.0001 level except for the brand recognition influencing satisfaction which was significant at the 0.004 level with a negative coefficient (meaning that a higher level of recognition of the brand actually reduces the satisfaction, perhaps due to higher expectations) while a higher level of satisfaction increases brand recognition.

We then explored eliminating the two-way relationship from satisfaction to brand recognition, by first eliminating the link from brand recognition to satisfaction, leaving the link from satisfaction to brand recognition. The new model turned out to have a slightly lower Chi-square statistic (6954.5) and 40 degrees of freedom, showing that the two way model might have a better fit. A third model was also explored reversing the direction of the one-way relationship, under the theory that brand recognition influences satisfaction more than satisfaction influences recognition, even though both relationships were significant. This model had a higher fit than the other two with Chi-square of 7016.8. The resulting model with the coefficients is shown in Figure 25.

Figure 25. SEM Model with Parameter Estimates



In summary, for each unit of increase in service quality, the level of satisfaction would increase by 0.69, the latent Brand Recognition will influence satisfaction by 0.22 while the perception of branch availability will influence the evaluation of level of satisfaction by 0.16, and so forth.

Likewise, the latent variables Service quality and Brand Recognition were able to have a dimension, therefore, being linked to other variables in the model. By solving multiple equations, we can show that Service Quality can range between 0.2 and 1.3, 1.3 being high quality and 0.2 low quality. One could interpret this number as the most likely magnitude of service quality (a concept similar to the average of all the customer evaluations) given the other conditions in the model. This is useful when as said at the beginning, a relationship among variables is hidden in large amounts of data.

Table 7. Equations in the System Dynamics Restructuring Model

Relationship	Equation
Service Quality	0.279*Perception of branch availability
Satisfaction	0.683+(Perception of Service Quality*0.694+0.22*Brand recognition+0.16*Perception of branch availability)
Brand recognition	0.83*Perception of branch availability
Perception of branch availability	IF,THEN,ELSE statement based on CHAID results relating distance driven to branch for customers
Loyalty/ customer retention	IF THEN ELSE(Satisfaction with service>2.8,0.993 , IF THEN ELSE(Satisfaction with service<2.8 :AND: Brand recognition>=2.5,0.98,IF THEN ELSE(Satisfaction with service>2.8 :AND: Brand recognition<2.5, 0.423,0.053)))

Table 7 shows the equations input into Vensim for the SD modeling. All of the equations illustrated are linear in nature. Certain models will end up having non-linear relationships that are for example, products of linear combinations or combinations of piece-wise linear functions. Modeling latent variables is a mechanism to parse out measurement error by combining across observed variables (using correlations among variables) and allow for the estimation of complex causal models. In this paper, we show how one can use SEM to establish and quantify causal relationships that can be used later in system dynamics. Other decision variables, such as the Management Open/Close decision were based on pre-determined profitability and market share goals. Another introduced decision rule was that management would not open a new branch unless it had at least 6,500 customers per branch and that it would close a branch any time it had less than 2,000 customers per branch. The model then could be used to evaluate those policies. Data in this example turned out to drive radical retention rules that may not be as realistic, whenever satisfaction and brand recognition was low, the retention rate was minimal (around 5%) therefore the behavior of the level variable *customers* was not very realistic. The SD model created is shown in Figure 26 and
Figure 27 shows the behavior of key variables over time.

Figure 26. Resulting System Dynamics Model for the Restructuring Problem

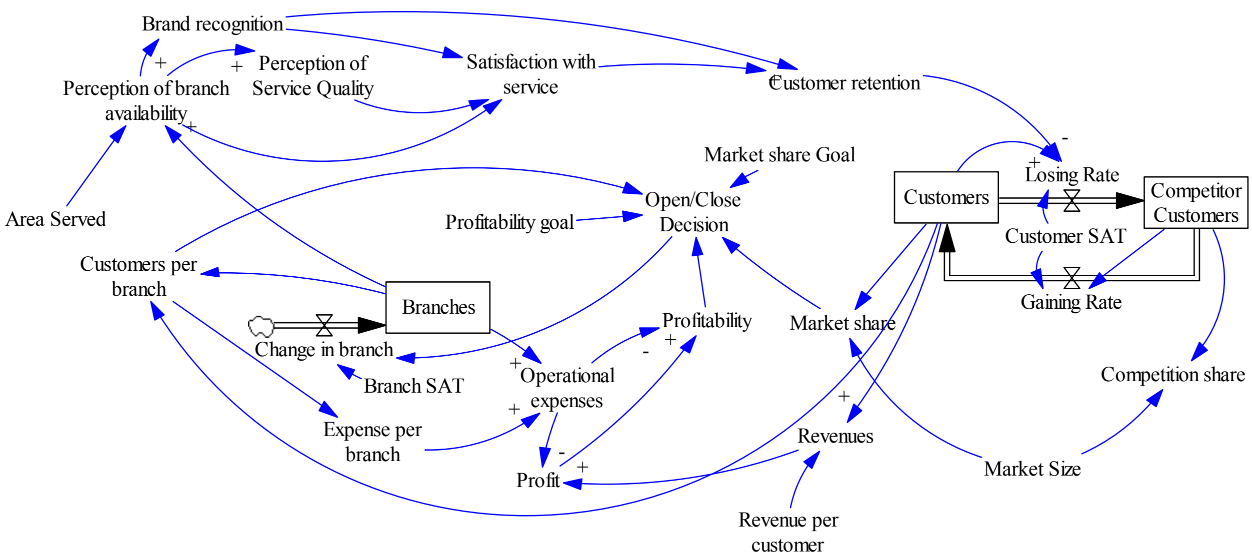
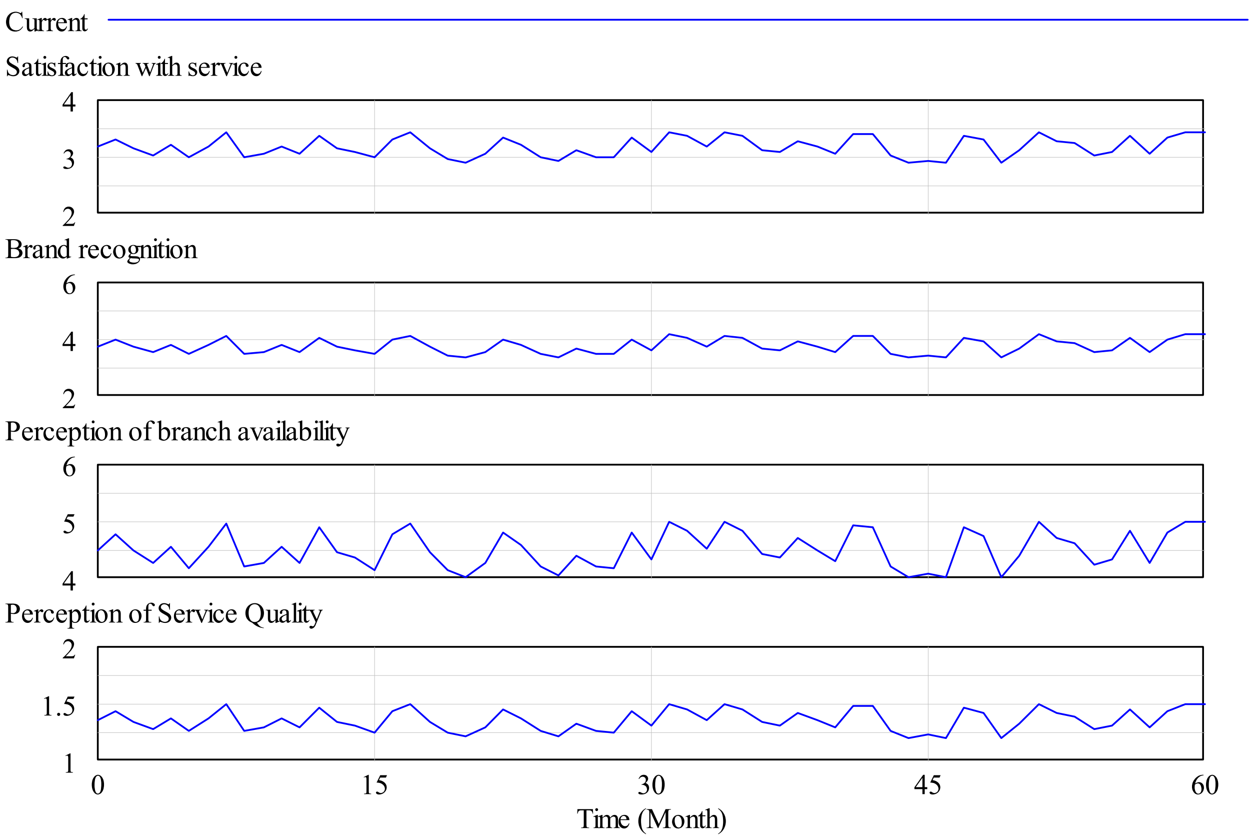
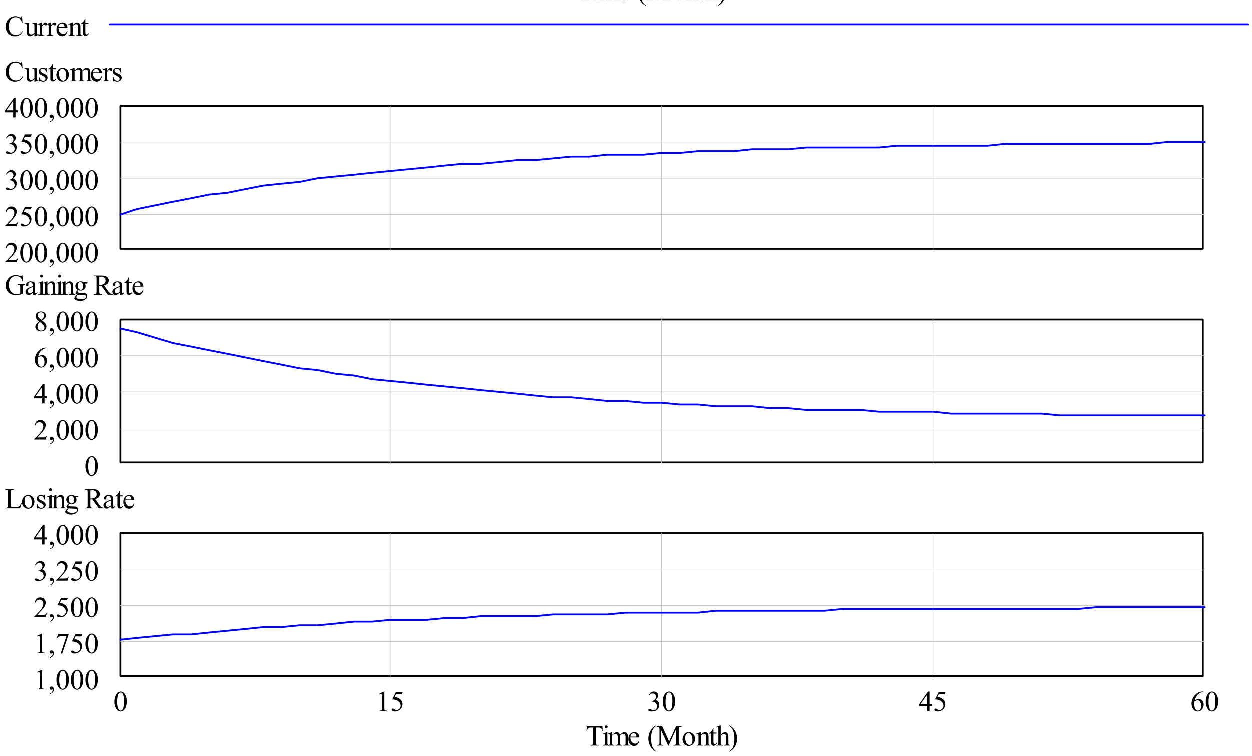


Figure 27. Behavior over time of key variables


Current
Satisfaction with service
4
3
2
Brand recognition
6
4
2
Perception of branch availability
6
5
4
Perception of Service Quality
2
1.5
1
0
15
30
45
60
Time (Month)


Current
Customers
400,000
350,000
300,000
250,000
200,000
Gaining Rate
8,000
6,000
4,000
2,000
0
Losing Rate
4,000
3,250
2,500
1,750
1,000
0
15
30
45
60
Time (Month)

Advantages of using Tree Pruning Methods in combination with SEM

The justification for using Tree Pruning Methods such as CART or CHAID arises primarily when knowledge needs to be extracted from large amounts of data sitting in large databases. The most likely behavior or outcome would then be uncovered regarding variable relationships. SEM can then be used to quantify the impact that a variation in the way respondents answered to constructs measured in survey items would affect the overall system.

In particular, using SEM as a resource for formulating relationships from survey data can prove to be advantageous.

- SEM can be used to either reinforce or challenge preconceived notions about relationships.
- SEM helps to draw associations between abstract concepts and constructs, which otherwise would have been close to impossible.

However, on the down side, there is a need for data and SEM applies linearity assumptions for each pair-wise relationship, which might bring misspecification problems. However, this can be overcome by exploring the fit of non-linear functions. Since a large data set is available, goodness of fit methods using the error term to compare the training set with the test set of data can be explored to adjust the equations.

Conclusions and further research

We have shown how tree data mining methods in conjunction with SEM can be used to explore and confirm relationships in large data sets when the nature, direction and intensity of the relationships among variables are unknown. The main application of the proposed three step process is for modeling problems where non-quantifiable concepts are used, such as the concept of customer satisfaction, or the construct service quality which in terms of data representation are characterized by several items in a survey.

In particular, the above three step process is currently being used to model the effect that proposed restructuring policies imposed purely based on financial performance will have on several variables representing customer perceptions, including customer satisfaction and customer loyalty. Eventually, customer retention will in turn affect revenue and sustainability of operations. Over 1 million customers answered a number of surveys for different branches of a service organization. Millions of data points and over 1000 variables are being explored and significant interactions are being identified. Eventually, a SD model will be run and validated within the company. Further research is needed for validation and non-linearity issues as well as on sensitivity analysis on the weight coefficients by introducing fuzzy mathematical concepts.

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Appendix B – Variables and Units

In alphabetical order of variable name used in system dynamics model

Variable name used in SD model	**Explanation**	**Units**	**Units abbreviation used in SD model**
Age above 25	Fraction of market with age above 25	Dimensionless	Dmnl
Certificate duration	Time validity of the certification received after completion of the course	Year	Year
Change in courses	Change in the number of courses offered during any given year	Courses/Year	Crse/Year
Change in courses per customer	Change in the number of courses offered during any given year divided by the number of customers	Courses/(Year * Customers)	Crse/(Year*Cust)
Change in OS	Change in the percentage of overall satisfaction during any given year	Percentage/Year	Per/Year
Change in refer intention	Change in the percentage of current and past customers that had intentions to refer others to the organization during any given year	Percentage/Year	Per/Year
Change in referrals	Change in the percentage of current and past customers that referred others to the organization during any given year	Percentage/Year	Per/Year
Change in return intention	Change in the percentage of past customers that had intentions to return to the organization during any given year	Percentage/Year	Per/Year
Change in returns	Change in the percentage of past customers that returned to the organization during any given year	Percentage/Year	Per/Year
Change in Rev per cust	Change in the revenue or price charged to each customer for the service during any given year	$/(Customer*Yea r)	$/(Cust*Year)
Change in RV	Change in the percentage of perceived relative value of the service	Percentage/Year	Per/Year
Change in SQ	Change in the percentage of perceived service quality of the service	Percentage/Year	Per/Year
Coeff SQ	Coefficient of impact of environment on service quality	Percentage*Custo mers/Course	Per*Cust/Crse
Competitor revenue per customer	Revenue or price charged to each customer by the competitor for a similar service	$/Customers	$/Cust
Competitor Service Quality	Service quality of the competitor	Percentage	Per
Course completion	Number of customers that completed the course during any given year	Customers	Cust
Course SAT	Course state adjustment time	Year	Year

Courses	Number of courses offerings during any given year	Courses	Crse
Current customers per course	Number of customers divided by the number of courses offered during any given year	Customers/Cours e	Cust/Crse
Customers	Number of current customers during any given year	Customers	Cust
Discrepancy	Comparison of the current state of the system to the target state of the system; ratio of current customers per course to the target customers per course	Dimensionless	Dmnl
Expense	Total operating expenses for the organization related to the service provided; sum of per customer expenses and salaries for instructors for offering the courses	$	$
Expense per customer	Operating expenses for training materials on a per customer basis	$/Customer	$/Cust
Intend to refer	Percentage of current and past customers that had intentions to refer others to the organization during any given year	Percentage	Per
Intend to return	Percentage of past customers that had intentions to return to the organization during any given year	Percentage	Per
Marginal rate of return	Return obtained for every additional dollar invested; ratio of surplus to expenses	Dimensionless	Dmnl
Market penetration	Extent to which the market is penetrated by retaining current and attracting new customers; ratio of the number of current customers to market size during any given year	Dimensionless	Dmnl
Market size	Size of the whole market where the service is being provided	Customers	Cust
Median HHI	Median household income in the market community	$	$
Non-return rate	Number of customers that did not return to the organization when their certification expired during any given year	Customers/Year	Cust/Year
Normal	Percentage of potential customers that enroll for the course without referrals	Percentage	Per
Normal Adoption	Number of potential customers that enroll for the course during any given year	Customers	Cust
Overall satisfaction	Percentage of overall satisfaction during any given year	Percentage	Per

Past Customers	Number of customers who completed the course but whose certification has not expired (is still valid) at any given point in time	Customers	Cust
Population change rate	Rate at which the population of the community changes	1/Year	1/Year
Potential customers	Number of people that could potentially enroll in the course and become current customers	Customers	Cust
Potential customers change rate	Rate at which the number of potential customers changes	Customers/Year	Cust/Year
Referrals	Percentage of current and past customers that referred others to the organization during any given year	Percentage	Per
Referred Adoption	Number of potential customers that enrolled in the course due to referrals during any given year	Customers	Cust
Relative Value	Percentage of perceived relative value of the service during any given year	Percentage	Per
Return rate	Number of customers that did return to the organization when their certification expired during any given year	Customers/Year	Cust/Year
Returns	Percentage of past customers that returned to the organization during any given year	Percentage	Per
Revenue	Total revenue generated from the service operations	$	$
Revenue per customer	Price charge to each customer for the service delivered	$/Customer	$/Cust
Salary	Salary paid to the instructors for each course offered	$/Course	$/Crse
Scale	Range over which certain variables are measured	Percentage	Per
Service Quality	Percentage of perceived service quality of the service	Percentage	Per
Size change	Rate at which the market size changes during any given year	Customers/Year	Cust/Year
Surplus	Amount of money from revenue left over after all expenses have been covered; difference between revenue and expenses; deficits are measured as negative quantities	$	$
Target customers per course	Target number of customers for every course offering set as a policy decision	Customers/Cours e	Cust/Crse
Target number of courses	Target number of course offerings computed based on comparison	Courses	Crse

Appendix C – Survey Instrument

American Red Cross

SERVICE QUALITY QUESTIONNAIRE
Health and Safety Services Training
First Aid and CPR

The American Red Cross is interested in learning about your experience with Health and Safety First Aid and CPR training. Please help us by answering the following questions.

Instructor's name

F.I. . LAST NAME

Please completely fill in the bubbles next to your answer(s). Use black or blue ink only.

EXAMPLE : Will you fill in bubbles completely? ● YES
○ NO

GENERAL INFORMATION

1. Which of the following courses on this page are you evaluating today? (FILL ALL THAT APPLY)
- ○ First Aid
- ○ Adult CPR
- ○ Infant and Child CPR
- ○ CPR for the Professional Rescuer
- ○ AED
- ○ Other Which?

2. How many times have you taken this course?
- ○ This is my first time
- ○ This is my second time
- ○ This is my third time
- ○ More than 3 times

3. Did you take this course for re-certification?
○ Yes ○ No

4. Did you need certification for a job, school, a volunteer position, or another requirement?
○ Yes ○ No

5. Have you taken other Red Cross courses before?
○ Yes ○ No

6. The cost of this course to you is:
○ Just right ○ Expensive ○ Inexpensive ○ Did not pay

7. If you did not pay, mark the appropriate option:
- ○ My employer paid
- ○ This course was free of charge
- ○ I am not sure who paid

8. You consider the length of this course to be:
○ Just right ○ Too long ○ Too short

9. Did you complete the knowledge portion of your course using Web based (computer) technology?
○ Yes ○ No

10. Are you interested in using computer-based learning as part of your Red Cross course in the future?
○ Yes ○ No

ABOUT THE SERVICE YOU RECEIVED

11. Thinking about your experience with this Red Cross course, on a scale from 1 to 6 (with 1 being extremely poor and 6 excellent), please rate each of the following by filling in the bubble that best represents your thinking.

	Extremely Poor 1	Poor 2	Below Average 3	Above Average 4	Good 5	Excellent 6	Does Not Apply 0
Instructor's ability to present information clearly.	○	○	○	○	○	○	○
Instructor's knowledge: ability to answer questions.	○	○	○	○	○	○	○
Inclusion of skills and information that you needed.	○	○	○	○	○	○	○
Quality of course books and videos.	○	○	○	○	○	○	○
Effectiveness in helping you learn skills.	○	○	○	○	○	○	○
Availability/courtesy of Red Cross staff to answer questions.	○	○	○	○	○	○	○
Convenience of the times offered in the course schedule.	○	○	○	○	○	○	○
Convenience of the available course locations.	○	○	○	○	○	○	○
Overall satisfaction with this Red Cross course.	○	○	○	○	○	○	○
Ease of course registration.	○	○	○	○	○	○	○

57156

PLEASE CONTINUE ON BACK--->

12. Thinking about the skills you learned today, please fill in the bubble that represents how you feel about each of the following statements.

	Strongly disagree 1	Disagree 2	Tend to Disagree 3	Tend to Agree 4	Agree 5	Strongly Agree 6	Does Not Apply 0
I feel confident that I know how to identify an emergency situation.	O	O	O	O	O	O	O
I feel prepared to respond to an emergency.	O	O	O	O	O	O	O
Should an emergency arise, I am willing to provide emergency care using the skills I learned today.	O	O	O	O	O	O	O
I feel comfortable responding to an emergency.	O	O	O	O	O	O	O
I would recommend this Red Cross course to a friend.	O	O	O	O	O	O	O

ABOUT YOURSELF

The Red Cross wants to know more about you and your specific needs to better tailor our programs and services to our communities. Please provide us with the following information:

Age Group:

O 12 or younger O 13 to 18 O 19 to 25 O 26 to 40 O 41 to 55 O 56 or older

How did you first learn about this Red Cross presentation?

- O A Red Cross campaign for disaster/emergency preparedness, such as "Together We Prepare."
- O Red Cross ad on TV/ radio
- O Printed material
- O Browsing the Red Cross Web Site
- O From the Federal Government
- O From a Red Cross worker
- O From a friend/ family member
- O At work
- O At school
- O From a social service organization
- O Other Which? [ ]

You are: O Male O Female

You consider yourself to be (FILL ONLY ONE):

- O Hispanic or Latino (of any race)
- O White
- O Black or African American
- O Asian
- O Native Hawaiian or other Pacific Islander
- O American Indian or Alaska Native
- O Two or more races
- O Other Which? [ ]

Your Zip code

[ ][ ][ ][ ][ ]

THANK YOU!

SPACE FOR LOCAL CHAPTER QUESTIONS:

FOR RED CROSS CHAPTER OFFICE USE ONLY:

Where did the training take place?

- O At the Red Cross chapter
- O At work
- O At school
- O At a recreation center or pool
- O At another community service organization

Month service was rendered:

[ ][ ] / [ ][ ]

Month Year

Branch office code (if any)

A B C D E F G H I J K L

O O O O O O O O O O O O

This course was conducted by a Red Cross (FILL ONE):

O Authorized provider instructor O Volunteer instructor O Paid instructor O Leader

Chapter Code (Please fill in the bubbles)

[ ][ ][ ][ ][ ]

0 1 2 3 4 5 6 7 8 9

57156

Appendix D – Text Model for SSC under base scenario

Revenue per customer= INTEG (

Change in Rev per cust,

65)

~ $/Cust

~ |

Change in OS=

IF THEN ELSE(Relative Value=78.7, 0.982*Change in SQ , -100)

~ Per/Year

~ |

Relative Value= INTEG (

Change in RV,

78.7)

~ Per

~ |

Change in Rev per cust=

0

~ $/(Cust*Year)

~ |

Change in RV=

IF THEN ELSE(Service Quality>Competitor Service Quality :AND: Revenue per customer>Competitor revenue per customer\

, 0, -100)

~ Per/Year

~ |

Revenue=

Revenue per customer*Customers

~ $

~ |

Marginal rate of return=

Surplus/Expense

~ Dmnl

~ |

Expense=

Expense per customer*Customers+Salary*Courses

~ $

~ |

Surplus=

Revenue-Expense

~ $

~ |

Discrepancy=

Current customers per course/Target customers per course

~ Dmnl

~ |

Target number of courses=

Discrepancy*Courses

~ Crse

~ |

Competitor revenue per customer=
60
~ $/Cust
~ |

Competitor Service Quality=
40
~ Per
~ |

Change in courses=
(Target number of courses-Courses)/Course SAT
~ Crse/Year
~ |

Course SAT=
1
~ Year
~ |

Normal Adoption=
(Normal*Potential customers)/(Scale)
~ Cust
~ |

Course completion=
Customers
~ Cust
~ |

Referred Adoption=

(Referrals*(Customers+Past Customers)*Potential customers)/(Scale*Market size)

~ Cust

~ |

Customers= INTEG (

Referred Adoption+Normal Adoption-Course completion+Return rate,

2650)

~ Cust

~ |

Potential customers= INTEG (

"Non-return rate"-Referred Adoption-Normal Adoption+Potential customers change rate,

78022)

~ Cust

~ |

Normal=

1.5

~ Per

~ |

Current customers per course=

Customers/Courses

~ Cust/Crse

~ |

Target customers per course=

10

~ Cust/Crse

~ |

Courses= INTEG (

Change in courses,

220)

~ Crse

~ |

Service Quality= INTEG (

Change in SQ,

50)

~ Per [0,100]

~ |

Overall satisfaction= INTEG (

Change in OS,

53)

~ Per [0,100]

~ |

"Non-return rate"=

((Scale-Returns)*Past Customers)/(Scale*Certificate duration)

~ Cust/Year

~ |

Past Customers= INTEG (

Course completion-"Non-return rate"-Return rate,

1986)

~ Cust

~ |

Market penetration=

Customers/Market size

~ Dmnl

~ |

Change in courses per customer=

Change in courses/Customers

~ Crse/(Year*Cust)

~ |

Return rate=

(Returns*Past Customers)/(Scale*Certificate duration)

~ Cust/Year

~ |

Population change rate=

0

~ 1/Year

~ |

Market size= INTEG (

Size change,

82658)

~ Cust

~ |

Size change=

Population change rate*Market size

~ Cust/Year

~ |

Potential customers change rate=

Size change

~ Cust/Year

~ |

Certificate duration=

2

~ Year

~ |

Scale=

100

~ Per

~ |

Age above 25=

0.6

~ Dmnl

~ |

Coeff SQ=

IF THEN ELSE(Age above 25<=0.55881, 0.63 , IF THEN ELSE(Age above 25>0.55881 :AND: Median HHI\

<=43516, 0.28 , IF THEN ELSE(Age above 25>0.55881 :AND:Median HHI>43516 :AND:Median HHI\

<=47628 , 0.57 , IF THEN ELSE(Age above 25>0.55881 :AND: Median HHI>47628 :AND: Median HHI\

<=50025, 0.8 , -100))))

~ Per*Cust/Crse

~ |

Salary=

300

~ $/Crse

~ |

Median HHI=

```
	50000
	~	$
	~		|

Change in SQ=
	Coeff SQ*Change in courses per customer
	~	Per/Year
	~		|

Referrals= INTEG (
	+Change in referrals,
		34)
	~	Per
	~		|

Intend to refer= INTEG (
	Change in refer intention,
		34)
	~	Per [0,100]
	~		|

Returns= INTEG (
	+Change in returns,
		62)
	~	Per
	~		|

Intend to return= INTEG (
	Change in return intention,
		68)
	~	Per [0,100]
	~		|
```

Change in referrals=
0.348*Change in refer intention
~ Per/Year
~ |

Change in returns=
0.651*Change in return intention
~ Per/Year
~ |

Expense per customer=
20
~ $/Cust
~ |

Change in return intention=
0.03*Change in OS
~ Per/Year
~ |

Change in refer intention=
0.404*Change in OS
~ Per/Year
~ |

****
.Control
***~
Simulation Control Parameters
|

FINAL TIME = 20

~ Year

~ The final time for the simulation.

|

INITIAL TIME = 0

~ Year

~ The initial time for the simulation.

|

SAVEPER =

TIME STEP

~ Year [0,?]

~ The frequency with which output is stored.

|

TIME STEP = 0.5

~ Year [0,?]

~ The time step for the simulation.

|

Appendix E – Results for SSC under base scenario

Time (Year)	Courses	Current customers per course	Discrepancy	Target number of courses	Change in courses	Change in courses per customer	Change in SQ
0	220	12.04545	1.204545	265	45	0.016981	0.013585
0.5	242.5	12.21407	1.221407	296.1912	53.69122	0.018127	0.014502
1	269.3456	12.64994	1.264994	340.7207	71.37506	0.020948	0.016759
1.5	305.0331	12.841	1.2841	391.6931	86.66	0.022124	0.0177
2	348.3632	12.8287	1.28287	446.9045	98.54138	0.02205	0.01764
2.5	397.6339	12.71345	1.271345	505.5298	107.8959	0.021343	0.017075
3	451.5818	12.5582	1.25582	567.1056	115.5238	0.020371	0.016297
3.5	509.3437	12.39278	1.239278	631.2184	121.8748	0.019308	0.015446
4	570.2811	12.22924	1.222924	697.4103	127.1292	0.018229	0.014583
4.5	633.8457	12.07164	1.207164	765.1555	131.3098	0.017161	0.013729
5	699.5006	11.92084	1.192084	833.8633	134.3627	0.016113	0.012891
5.5	766.6819	11.77662	1.177662	902.8919	136.21	0.015086	0.012069
6	834.7869	11.63853	1.163853	971.5692	136.7823	0.014078	0.011263
6.5	903.1781	11.50622	1.150622	1039.217	136.0385	0.01309	0.010472
7	971.1973	11.37952	1.137952	1105.176	133.9787	0.012123	0.009698
7.5	1038.187	11.25845	1.125845	1168.837	130.6504	0.011178	0.008942
8	1103.512	11.14315	1.114315	1229.659	126.1476	0.010259	0.008207
8.5	1166.586	11.03384	1.103384	1287.193	120.6068	0.00937	0.007496
9	1226.889	10.93081	1.093081	1341.089	114.2001	0.008515	0.006812
9.5	1283.989	10.83429	1.083429	1391.111	107.1217	0.0077	0.00616
10	1337.55	10.74448	1.074448	1437.128	99.57788	0.006929	0.005543

Time (Year)	Courses	Current customers per course	Discrepancy	Target number of courses	Change in courses	Change in courses per customer	Change in SQ
10.5	1387.339	10.6615	1.06615	1479.112	91.77307	0.006205	0.004964
11	1433.226	10.58538	1.058538	1517.124	83.8988	0.00553	0.004424
11.5	1475.175	10.51605	1.051605	1551.301	76.12634	0.004907	0.003926
12	1513.238	10.45332	1.045332	1581.837	68.59875	0.004337	0.003469
12.5	1547.538	10.39695	1.039695	1608.968	61.42993	0.003818	0.003054
13	1578.253	10.3466	1.03466	1632.955	54.70203	0.00335	0.00268
13.5	1605.604	10.30187	1.030187	1654.073	48.46899	0.00293	0.002344
14	1629.838	10.26235	1.026235	1672.597	42.75916	0.002556	0.002045
14.5	1651.218	10.22759	1.022759	1688.797	37.57935	0.002225	0.00178
15	1670.007	10.19713	1.019713	1702.928	32.92053	0.001933	0.001547
15.5	1686.468	10.17054	1.017053	1715.228	28.76013	0.001677	0.001341
16	1700.848	10.14739	1.014739	1725.916	25.06848	0.001452	0.001162
16.5	1713.382	10.12728	1.012728	1735.191	21.80872	0.001257	0.001005
17	1724.286	10.10986	1.010986	1743.229	18.94312	0.001087	0.000869
17.5	1733.758	10.09479	1.009479	1750.191	16.43372	0.000939	0.000751
18	1741.975	10.08176	1.008176	1756.216	14.2417	0.000811	0.000649
18.5	1749.095	10.07051	1.007051	1761.428	12.3324	0.0007	0.00056
19	1755.262	10.0608	1.00608	1765.934	10.672	0.000604	0.000483
19.5	1760.598	10.05243	1.005243	1769.829	9.230957	0.000522	0.000417
20	1765.213	10.04521	1.004521	1773.194	7.980957	0.00045	0.00036

Time (Year)	Service Quality	Change in OS	Overall satisfaction	Change in refer intention	Intend to refer	Change in return intention	Intend to return
0	50	0.01334	53	0.00539	34	0.0004	68
0.5	50.00679	0.014241	53.00667	0.005753	34.00269	0.000427	68.0002
1	50.01405	0.016457	53.01379	0.006649	34.00557	0.000494	68.00041
1.5	50.02243	0.017381	53.02202	0.007022	34.00889	0.000521	68.00066
2	50.03128	0.017322	53.03071	0.006998	34.0124	0.00052	68.00092
2.5	50.0401	0.016767	53.03937	0.006774	34.0159	0.000503	68.00117
3	50.04863	0.016003	53.04776	0.006465	34.01929	0.00048	68.00143
3.5	50.05678	0.015168	53.05576	0.006128	34.02252	0.000455	68.00166
4	50.06451	0.014321	53.06334	0.005785	34.02558	0.00043	68.00189
4.5	50.0718	0.013482	53.0705	0.005447	34.02847	0.000404	68.00211
5	50.07866	0.012659	53.07724	0.005114	34.0312	0.00038	68.00231
5.5	50.08511	0.011852	53.08357	0.004788	34.03375	0.000356	68.0025
6	50.09114	0.01106	53.0895	0.004468	34.03615	0.000332	68.00268
6.5	50.09677	0.010284	53.09503	0.004155	34.03838	0.000309	68.00285
7	50.10201	0.009524	53.10017	0.003848	34.04046	0.000286	68.003
7.5	50.10686	0.008781	53.10493	0.003548	34.04239	0.000263	68.00314
8	50.11133	0.008059	53.10932	0.003256	34.04416	0.000242	68.00327
8.5	50.11543	0.007361	53.11335	0.002974	34.04579	0.000221	68.0034
9	50.11918	0.00669	53.11703	0.002703	34.04728	0.000201	68.0035
9.5	50.12259	0.006049	53.12038	0.002444	34.04863	0.000181	68.0036
10	50.12566	0.005443	53.1234	0.002199	34.04985	0.000163	68.00369
10.5	50.12844	0.004874	53.12612	0.001969	34.05095	0.000146	68.00378
11	50.13092	0.004344	53.12856	0.001755	34.05193	0.00013	68.00385
11.5	50.13313	0.003855	53.13073	0.001557	34.05281	0.000116	68.00392
12	50.1351	0.003407	53.13266	0.001376	34.05359	0.000102	68.00398
12.5	50.13683	0.002999	53.13436	0.001212	34.05427	9E-05	68.00404
13	50.13836	0.002632	53.13586	0.001063	34.05488	7.89E-05	68.00408
13.5	50.1397	0.002302	53.13718	0.00093	34.05541	6.91E-05	68.00412
14	50.14087	0.002008	53.13833	0.000811	34.05587	6.03E-05	68.00416
14.5	50.14189	0.001748	53.13933	0.000706	34.05628	5.24E-05	68.00419
15	50.14278	0.001519	53.14021	0.000614	34.05663	4.56E-05	68.00421
15.5	50.14355	0.001317	53.14096	0.000532	34.05694	3.95E-05	68.00423
16	50.14423	0.001141	53.14162	0.000461	34.05721	3.42E-05	68.00426
16.5	50.14481	0.000987	53.1422	0.000399	34.05743	2.96E-05	68.00427
17	50.14531	0.000854	53.14269	0.000345	34.05763	2.56E-05	68.00429
17.5	50.14574	0.000738	53.14312	0.000298	34.0578	2.21E-05	68.0043
18	50.14612	0.000637	53.14349	0.000257	34.05795	1.91E-05	68.00431
18.5	50.14644	0.00055	53.14381	0.000222	34.05808	1.65E-05	68.00432
19	50.14672	0.000475	53.14408	0.000192	34.05819	1.42E-05	68.00433
19.5	50.14696	0.00041	53.14432	0.000166	34.05829	1.23E-05	68.00433
20	50.14717	0.000354	53.14452	0.000143	34.05837	1.06E-05	68.00434

Time (Year)	Change in referrals	Referrals	Change in returns	Returns	Customers	Referred Adoption	Potential customers
0	0.001876	34	0.000261	62	2650	1487.834	78022
0.5	0.002002	34.00094	0.000278	62.00013	2961.9121	1826.781	76881.59
1	0.002314	34.00194	0.000321	62.00027	3407.207	2178.299	75658.96
1.5	0.002444	34.00309	0.000339	62.00043	3916.9316	2542.778	74343.59
2	0.002435	34.00431	0.000338	62.0006	4469.0454	2918.01	72932.38
2.5	0.002357	34.00553	0.000327	62.00076	5055.2974	3300.549	71425.75
3	0.00225	34.00671	0.000313	62.00093	5671.0557	3686.168	69826.58
3.5	0.002133	34.00784	0.000296	62.00108	6312.1846	4070.078	68140.02
4	0.002013	34.0089	0.00028	62.00123	6974.1025	4447.109	66373.45
4.5	0.001895	34.00991	0.000263	62.00137	7651.5542	4811.928	64536.56
5	0.00178	34.01086	0.000247	62.00151	8338.6328	5159.263	62641.18
5.5	0.001666	34.01175	0.000231	62.00163	9028.9199	5484.175	60701.12
6	0.001555	34.01258	0.000216	62.00174	9715.6924	5782.303	58731.88
6.5	0.001446	34.01336	0.000201	62.00185	10392.165	6050.104	56750.17
7	0.001339	34.01408	0.000186	62.00195	11051.761	6285.038	54773.41
7.5	0.001235	34.01475	0.000171	62.00204	11688.371	6485.688	52819.13
8	0.001133	34.01537	0.000157	62.00212	12296.594	6651.795	50904.34
8.5	0.001035	34.01593	0.000144	62.0022	12871.926	6784.216	49044.98
9	0.000941	34.01645	0.000131	62.00228	13410.893	6884.795	47255.32
9.5	0.000851	34.01692	0.000118	62.00234	13911.11	6956.187	45547.61
10	0.000765	34.01735	0.000106	62.0024	14371.28	7001.637	43931.7
10.5	0.000685	34.01773	9.52E-05	62.00245	14791.121	7024.739	42414.98
11	0.000611	34.01807	8.48E-05	62.0025	15171.244	7029.226	41002.27
11.5	0.000542	34.01838	7.53E-05	62.00254	15513.014	7018.752	39696
12	0.000479	34.01865	6.65E-05	62.00258	15818.371	6996.761	38496.38
12.5	0.000422	34.01889	5.86E-05	62.00261	16089.676	6966.356	37401.71
13	0.00037	34.0191	5.14E-05	62.00264	16329.546	6930.238	36408.66
13.5	0.000324	34.01928	4.5E-05	62.00267	16540.725	6890.683	35512.66
14	0.000282	34.01944	3.92E-05	62.00269	16725.971	6849.538	34708.21
14.5	0.000246	34.01958	3.41E-05	62.00271	16887.969	6808.252	33989.18
15	0.000214	34.0197	2.97E-05	62.00273	17029.277	6767.919	33349.1
15.5	0.000185	34.01981	2.57E-05	62.00274	17152.277	6729.32	32781.37
16	0.00016	34.0199	2.23E-05	62.00275	17259.16	6692.986	32279.44
16.5	0.000139	34.01998	1.93E-05	62.00277	17351.904	6659.235	31836.96
17	0.00012	34.02005	1.67E-05	62.00278	17432.293	6628.227	31447.9
17.5	0.000104	34.02011	1.44E-05	62.00278	17501.914	6599.998	31106.59
18	8.96E-05	34.02016	1.24E-05	62.00279	17562.164	6574.494	30807.75
18.5	7.73E-05	34.02021	1.07E-05	62.0028	17614.277	6551.603	30546.58
19	6.67E-05	34.02025	9.27E-06	62.0028	17659.338	6531.167	30318.66
19.5	5.76E-05	34.02028	8E-06	62.00281	17698.285	6513.01	30120.04
20	4.97E-05	34.02031	6.91E-06	62.00281	17731.941	6496.941	29947.16

Time (Year)	Normal Adoption	Course completion	Past Customers	Return rate	Non-return rate	Expense	Revenue
0	1170.33	2650	1986	615.66	377.34	119000	172250
0.5	1153.224	2961.912	2814.5	872.4968	534.7532	131988.3	192524.3
1	1134.884	3407.207	3591.831	1113.472	682.4431	148947.8	221468.5
1.5	1115.154	3916.932	4397.477	1363.227	835.5112	169848.6	254600.6
2	1093.986	4469.045	5256.573	1629.553	998.7333	193889.8	290487.9
2.5	1071.386	5055.297	6176.953	1914.879	1173.597	220396.1	328594.3
3	1047.399	5671.056	7160.363	2219.746	1360.436	248895.6	368618.6
3.5	1022.1	6312.185	8205.801	2543.843	1559.058	279046.8	410292
4	995.6018	6974.103	9310.443	2886.295	1768.927	310566.4	453316.7
4.5	968.0485	7651.554	10469.88	3245.736	1989.206	343184.8	497351
5	939.6177	8338.633	11678.19	3620.327	2218.768	376622.8	542011.1
5.5	910.5168	9028.92	12927.96	4007.772	2456.207	410583	586879.8
6	880.9782	9715.692	14210.43	4405.357	2699.858	444749.9	631520
6.5	851.2525	10392.17	15515.67	4810	2947.833	478796.8	675490.8
7	821.6011	11051.76	16832.83	5218.342	3198.074	512394.4	718364.4
7.5	792.2869	11688.37	18150.51	5626.842	3448.411	545223.4	759744.1
8	763.5652	12296.59	19457.06	6031.897	3696.636	576985.4	799278.6
8.5	735.6747	12871.93	20741.1	6429.968	3940.579	607414.3	836675.2
9	708.8298	13410.89	21991.79	6817.704	4178.189	636284.6	871708
9.5	683.2141	13911.11	23199.29	7192.05	4407.592	663419	904222.2
10	658.9755	14371.28	24355.02	7550.348	4627.162	688690.6	934133.2
10.5	636.2247	14791.12	25451.9	7890.402	4835.55	712024.1	961422.9
11	615.0341	15171.24	26484.49	8210.522	5031.722	733392.6	986130.9
11.5	595.44	15513.01	27448.99	8509.535	5214.959	752812.8	1008346
12	577.4457	15818.37	28343.25	8786.772	5384.852	770338.9	1028194
12.5	561.0256	16089.68	29166.62	9042.034	5541.277	786054.8	1045829
13	546.1298	16329.55	29919.8	9275.534	5684.367	800066.7	1061421
13.5	532.6898	16540.72	30604.63	9487.843	5814.47	812495.6	1075147
14	520.6231	16725.97	31223.83	9679.808	5932.107	823470.8	1087188
14.5	509.8377	16887.97	31780.86	9852.497	6037.932	833124.6	1097718
15	500.2365	17029.28	32279.63	10007.12	6132.689	841587.8	1106903
15.5	491.7205	17152.28	32724.36	10145	6217.179	848985.8	1114898
16	484.1915	17259.16	33119.41	10267.47	6292.231	855437.5	1121845
16.5	477.5544	17351.9	33469.13	10375.89	6358.672	861052.6	1127874
17	471.7186	17432.29	33777.8	10471.59	6417.313	865931.8	1133099
17.5	466.5988	17501.91	34049.5	10555.82	6468.93	870165.6	1137624
18	462.1163	17562.16	34288.08	10629.78	6514.256	873835.6	1141541
18.5	458.1986	17614.28	34497.14	10694.6	6553.974	877014.2	1144928
19	454.7799	17659.34	34679.99	10751.28	6588.712	879765.3	1147857
19.5	451.8007	17698.29	34839.66	10800.79	6619.047	882145	1150389
20	449.2074	17731.94	34978.89	10843.95	6645.498	884202.8	1152576

Time (Year)	Surplus	Market penetration	Marginal rate of return
0	53250	0.03206	0.447479
0.5	60536.03	0.035833	0.458647
1	72520.64	0.041221	0.486886
1.5	84751.98	0.047387	0.498986
2	96598.09	0.054067	0.498211
2.5	108198.3	0.061159	0.490926
3	119723	0.068609	0.481017
3.5	131245.2	0.076365	0.470334
4	142750.3	0.084373	0.459645
4.5	154166.2	0.092569	0.449222
5	165388.3	0.100881	0.439135
5.5	176296.8	0.109232	0.429382
6	186770.1	0.117541	0.419944
6.5	196694	0.125725	0.410809
7	205970	0.133705	0.401976
7.5	214520.7	0.141406	0.393455
8	222293.2	0.148765	0.385267
8.5	229260.9	0.155725	0.377438
9	235423.4	0.162246	0.369997
9.5	240803.2	0.168297	0.362973
10	245442.6	0.173864	0.35639
10.5	249398.8	0.178944	0.350267
11	252738.3	0.183542	0.344615
11.5	255533.1	0.187677	0.339438
12	257855.2	0.191371	0.33473
12.5	259774.2	0.194654	0.330478
13	261353.8	0.197556	0.326665
13.5	262651.6	0.20011	0.323265
14	263717.3	0.202352	0.320251
14.5	264593.4	0.204311	0.317592
15	265315.3	0.206021	0.315256
15.5	265912.2	0.207509	0.313212
16	266407.9	0.208802	0.311429
16.5	266821.1	0.209924	0.309878
17	267167.3	0.210897	0.308532
17.5	267458.8	0.211739	0.307365
18	267705	0.212468	0.306356
18.5	267913.8	0.213098	0.305484
19	268091.8	0.213643	0.304731
19.5	268243.5	0.214115	0.304081
20	268373.5	0.214522	0.30352

Appendix F – Results for key variables in SSC for alternate scenarios

Robustness – extreme condition

Initial value of Courses = 1

Time (Year)	Courses	Time (Year)	Courses
0	1	10.5	1387.734
0.5	133	11	1433.625
1	214.5956	11.5	1475.576
1.5	277.6645	12	1513.638
2	334.6938	12.5	1547.934
2.5	390.8241	13	1578.644
3	448.2128	13.5	1605.988
3.5	507.7071	14	1630.215
4	569.5238	14.5	1651.585
4.5	633.5419	15	1670.366
5	699.4381	15.5	1686.817
5.5	766.755	16	1701.189
6	834.9427	16.5	1713.714
6.5	903.3899	17	1724.61
7	971.4508	17.5	1734.074
7.5	1038.474	18	1742.283
8	1103.827	18.5	1749.397
8.5	1166.924	19	1755.557
9	1227.248	19.5	1760.887
9.5	1284.364	20	1765.497
10	1337.937		

Initial value of Courses = 10,000

Time (Year)	Courses	Time (Year)	Courses
0	10000	10.5	1369.714
0.5	5132.5	11	1415.367
1	2714.346	11.5	1457.222
1.5	1527.25	12	1495.315
2	958.801	12.5	1529.75
2.5	701.7412	13	1560.686
3	602.0358	13.5	1588.326
3.5	582.4361	14	1612.899
4	604.1133	14.5	1634.651
4.5	647.4299	15	1653.832
5	702.3144	15.5	1670.691
5.5	763.4484	16	1685.468
6	827.8669	16.5	1698.39
6.5	893.7677	17	1709.668
7	959.9267	17.5	1719.494
7.5	1025.419	18	1728.045
8	1089.489	18.5	1735.477
8.5	1151.5	19	1741.931
9	1210.917	19.5	1747.532
9.5	1267.301	20	1752.391
10	1320.313		

Policy sensitivity

No more than 5 customers per course

Time (Year)	Surplus	Marginal rate of return
0	53250	0.447479
0.5	20786.03	0.121033
1	8223.875	0.038564
1.5	1504.641	0.005944
2	-3769.25	-0.01281
2.5	-9009.91	-0.02668
3	-14698.8	-0.03834
3.5	-21019.6	-0.04872
4	-28053.5	-0.05826
4.5	-35837.1	-0.06719
5	-44378.9	-0.07565
5.5	-53661.8	-0.08374
6	-63643.1	-0.0915
6.5	-74253.4	-0.09898
7	-85398.1	-0.10619
7.5	-96959.1	-0.11311
8	-108800	-0.11974
8.5	-120770	-0.12606
9	-132714	-0.13205
9.5	-144481	-0.13768
10	-155925	-0.14295
10.5	-166920	-0.14784
11	-177359	-0.15234
11.5	-187161	-0.15646
12	-196267	-0.16019
12.5	-204646	-0.16356
13	-212287	-0.16657
13.5	-219199	-0.16926
14	-225406	-0.17163
14.5	-230945	-0.17373
15	-235860	-0.17556
15.5	-240201	-0.17717
16	-244018	-0.17857
16.5	-247363	-0.17978
17	-250286	-0.18084
17.5	-252833	-0.18175
18	-255049	-0.18254
18.5	-256974	-0.18322
19	-258643	-0.18381
19.5	-260090	-0.18432
20	-261342	-0.18476

No more than 15 customers per course

Time (Year)	Surplus	Marginal rate of return
0	53250	0.447479
0.5	73786.03	0.621418
1	93952.88	0.736815
1.5	112500	0.79174
2	130050.8	0.810677
2.5	147261.6	0.812207
3	164520.3	0.80621
3.5	181985.3	0.797259
4	199664.3	0.78733
4.5	217473.2	0.777223
5	235275.5	0.767243
5.5	252905.9	0.757493
6	270188	0.748
6.5	286946.9	0.738776
7	303019.7	0.729829
7.5	318264	0.721177
8	332563.9	0.712843
8.5	345834.8	0.704859
9	358024	0.697256
9.5	369111.1	0.690065
10	379104.6	0.683315
10.5	388038.4	0.677025
11	395966.1	0.671211
11.5	402955.9	0.665877
12	409084.9	0.66102
12.5	414434.6	0.65663
13	419086.9	0.652687
13.5	423121.1	0.649169
14	426611.7	0.646047
14.5	429627.1	0.643291
15	432229.6	0.640868
15.5	434474.1	0.638746
16	436409.1	0.636895
16.5	438077.1	0.635283
17	439515	0.633884
17.5	440754.6	0.632671
18	441823.8	0.631621
18.5	442745.6	0.630714
19	443540.9	0.62993
19.5	444227	0.629253
20	444819.3	0.628669

Behavior mode sensitivity

Population decreasing at 10% per year

Time (Year)	Surplus
0	53250
0.5	60536.03
1	70963.23
1.5	81079.09
2	90384.16
2.5	98927.88
3	106741.7
3.5	113754.4
4	119817
4.5	124745.2
5	128357.4
5.5	130509.5
6	131121.8
6.5	130197.7
7	127831.3
7.5	124201
8	119551.3
8.5	114164
9	108327.5
9.5	102307.3
10	96323.5
10.5	90540.91
11	85066.78
11.5	79957.84
12	75231.22
12.5	70876.59
13	66867.41
13.5	63169.56
14	59747.69
14.5	56568.45
15	53602.53
15.5	50825.16
16	48215.77
16.5	45757.56
17	43436.81
17.5	41242.25
18	39164.39
18.5	37195.27
19	35327.89
19.5	33556.17
20	31874.58

Population increasing at 10% per year

Time (Year)	Surplus
0	53250
0.5	60536.03
1	74062.53
1.5	88500.13
2	103107.8
2.5	118116.2
3	133835.8
3.5	150490.9
4	168223
4.5	187118.6
5	207231.6
5.5	228597
6	251239.9
6.5	275179.3
7	300431.9
7.5	327013.8
8	354941.8
8.5	384235.6
9	414917.8
9.5	447015.4
10	480560.6
10.5	515590.8
11	552150.6
11.5	590290.6
12	630068.4
12.5	671548.5
13	714803
13.5	759911.4
14	806959.5
14.5	856042
15	907258.8
15.5	960718.8
16	1016537
16.5	1074838
17	1135750
17.5	1199411
18	1265967
18.5	1335571
19	1408385
19.5	1484577
20	1564327

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Glossary

Balanced scorecard is an approach that tracks the performance of an organization in four perspectives – customer, internal business, (innovation, growth and learning) and financial.

Balancing loops are feedback loops with negative loop polarity.

Causal link – see linkage.

Chi-Square Automatic Interaction Detection (CHAID) is a methodology used to partition large data sets using multiple chi-squares, find patterns and provide profiles.

Conceptual validation ensures that the model accurately represents reality and captures the concept in the system structure.

Confidence bounds establish ranges within which the behavior will fall with a certain amount of probability.

Control variables change the accumulations of state variables and control the flow.

Customer behavioral intentions are the intentions that the customer forms about his/her future behavior based on the perceptions of the service received.

Customer loyalty is the dependability or faithfulness of the customer to act in a manner that is beneficial to the organization.

Customer perceptions are views/assessment of the customer about the operational attributes used during the service delivery process.

Decision is the chosen rational course of action.

Decision maker is a human being that is capable of making rational decisions.

Decision making is the process of analyzing at least two options based on certain needs and preferences to arrive at a rational course of action keeping in mind the long-term consequences.

Decision model is a mathematical framework representation of a real-life decision problem for the sake of analysis (Dinkelbach, 1990).

Decision problem is the combination of the needs, preferences and options available.

Decision variables are a set of variables that represent each mutually exclusive alternative.

Deficit is the additional amount of money required to cover all expenses after all the revenue has been used. It is the inverse of surplus and is measured as negative surplus.

Dependent variables are variables (in SEM) that receive at least one path (one-way arrow) from another variable in the model.

Dynamic decision models are models that take into consideration the growth and evolution of organizations over a period of time to enable decision making.

Equilibrium is a mode of behavior when the system is at steady state.

Feedback loop is a collection of two or more linkages where one can start at a variable, go around the loop and end at the original variable (Sterman, 2000).

Feedback system is a series of two or more feedback loops with common variables between them (Sterman, 2000).

Flow variables (or flows) – see control variables.

Improvement efforts are any efforts that are made to improve the operation for the benefit and to sustain the organization.

Independent variables are variables (in SEM) that emanate paths but never receive them.

Latent dependents are dependent variables that are not observed.

Latent independents are independent variables that are not observed.

Level variables – see state variables.

Link polarity is the type of effect of a link, positive or negative.

Linkage is a cause-and-effect relationship between variables (Roberts, 1978).

Loop polarity is a characteristic of a feedback loop determined based on the number of negative linkages (zero negative linkages being considered even); as positive (even) or negative (odd) (Richardson and Pugh, 1981).

Manager – see decision maker.

Market penetration is a measure of the ability of an organization to retain current customers and gain new customers. It is computed by dividing the current customer base by the market size.

Method is a set of tasks that need to be performed to achieve a specific objective.

Methodology is the analysis and study of a method.

Model – see decision model.

Model validation is a process that determines if the model and the methodology meet the objectives and provide desired results.

Operational attributes are features or characteristics of the internal operations of a service organization that enable service delivery to the customers.

Performance goals are goals set forth by organizations based on past analyses, experience, mental models, etc. (Sterman, 2000).

Planning horizon is the time period (from start to end) during which the analysis is conducted and the decision made.

Problem – see decision problem.

Rate variables – see control variables.

Reinforcing loops are feedback loops with positive loop polarity.

Relative value is the value perceived by the customer based on the quality of the service received for the price paid in comparison to the quality of similar service offered by competitors for their price (McDougall and Levesque, 2000).

Results validation ensures that the results obtained from the model are close to reality and are useful.

Sensitivity analysis is conducted to determine if the model behavior changes significantly when the input parameters are changed (Law and Kelton, 1991).

Service-Profit Chain (SPC) is a framework for linking service operations to customer's assessments and in turn linking those customers' assessments to the firm's bottom line (e.g. profitability in most cases) (Heskett et al., 1994).

State adjustment time is the time taken to make changes or adjustments to the state of the system.

State variables describe the state of the system with accumulations.

Stock and Flow Diagram is a diagram that graphically represents the relationships between stocks and flows.

Stock variables (or stocks) – see state variables.

Structural equation modeling (SEM) is a methodology used to model interactions, nonlinearities, multiple latent independents measured by multiple indicators, and one or more latent dependents also each with multiple indicators.

Surplus is the amount of revenues left over after all expenses have been covered. It is computed by subtracting expenses from revenue.

Sustainability is the ability of an organization to uphold its state in the market place.

System dynamics is an approach that helps in decision making.

System dynamics modeling is a methodology that captures complex and non-linear relationships between components of a closed boundary system over time (dynamic) and provide solution to problems for better decision making.

System is an assemblage or combination of elements or parts forming a complex or unitary whole (Blanchard and Fabrycky, 1990).

Uncontrollable factors are factors that are outside the control of the organization but have a substantial impact on the operations.

Variables are quantities that change over time (Roberts, 1978).